Journal of Transport & Health 13 (2019) 1–11

Contents lists available at ScienceDirect

Journal of Transport & Health

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

# Integrating multiple transportation modes into measures of spatial food accessibility

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ARTICLE INFO

*Keywords:*
Food access
Spatial measure
Travel modes
Commuting pattern
Health geography

ABSTRACT

*Introduction:* People can access to healthy food via different modes of transportation, such as traveling by car, transit, bicycle and foot. We categorize current measures of food accessibility under an origin-destination-mode framework and find that few of them integrate multiple travel modes. As a result, these measures can bias the identification of truly low-access areas.

*Methods:* To fill this gap, we propose two new measures that integrate sub-populations of various travel modes, and estimate the overall food accessibility of a whole population. Taking Florida, USA, as a study area, we illustrate our measures with actual multiple mode commuting data from the U.S census transportation planning products (CTPP). We then compare the results to those from conventional single-modal measures.

*Results:* The proposed multiple-mode measures tend to estimate a larger population with low accessibility and fewer accessible supermarkets for a census tract, as compared to single-mode measures. The incorporation of multiple travel modes into food accessibility measures also narrows the disparities between urban and rural areas, which are indicated by conventional measures.

*Conclusions:* By considering modal-split subpopulations, our measures offer a more realistic representation of local people's travel for grocery shopping, and thus a better identification of populations with low food access. The finer modeling scale at a subpopulation level provides health and urban planners more flexibility in policy design, in that interventions can be tailored to not only a neighborhood but also a specific subpopulation within it. Such knowledge could improve the cost-effectiveness of food intervention programs.

## 1. Introduction

Food access refers to easiness of a population to reach supermarkets, grocery stores, or other sources of healthy and affordable food (USDA, 2017). Since poor access to healthy food is associated with high risk of obesity, cardiovascular disease, and Type II diabetes (Drewnowski and Specter, 2004), it raises tremendous concern among health policy makers, epidemiologists, and urban planners. A variety of factors have been related to food access, including spatial access to grocery stores, socio-economic status of residents, and built environment of a neighborhood (e.g., public transit infrastructure and food store density), etc. (Walker et al., 2010). Considering these factors, quantitative measures have been developed to model people's grocery shopping behavior, and evaluate food accessibility of neighborhoods (Charreire et al., 2010). The measuring results are often mapped by neighborhood (e.g., census tracts and block groups) to show spatial patterns and help policy makers identify geographic areas of low access.

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https://doi.org/10.1016/j.jth.2019.03.001
Received 7 November 2018; Received in revised form 4 March 2019; Accepted 4 March 2019
Available online 12 March 2019
2214-1405/ 

In a neighborhood, people may travel to supermarkets or grocery stores with various means of transport, including car, public transit, bicycle, and foot (Fuller et al., 2012). However, a majority of food accessibility measures consider only a single travel mode (in most cases by car), simply assuming that all people access healthy food by the same means of transport (Farber et al., 2014; Gustafson et al., 2011; USDA, 2017). This homogenous assumption makes it easy for data collection and computation, but inevitably biases the identification of populations or areas with low food access. For example, food accessibility of carless population can be overestimated when they are assumed to travel by car.

Recently, there is a rising concern on multiple travel modes in food access. Examples include Burns and Inglis' work on food access via car, bus and foot in Melbourne, Australia (2007), Widener's study on transit and auto users in Hamilton County, Ohio (2017), and the research by Su et al. (2017) to map food access by four transportation modes in Shenzhen, China. These studies still used a single-mode accessibility measure, but applied it separately to different travel modes. The researchers then focused on comparing the measures and revealed spatial disparities in food access among different travel modes. Their findings addressed a part of questions concerned by health and urban planners, for example, the time to grocery stores or the number of reachable stores via each travel mode. However, they failed to indicate how many people in a neighborhood experience low food access by all means of transportation, i.e., the overall accessibility. This is because these studies did not consider actual size of subpopulations with different travel modes in a neighborhood, and thus were not able to aggregate low-access subpopulations into an overall index for a whole neighborhood. After all, an effective intervention needs to address not only where food accessibility is low, but also how many people there are underserved. For example, the U.S. Department of Agriculture designates a census tract as a low-access tract if a significant number (more than 500) or share (above 33%) of its population have low food accessibility (USDA, 2017).

To fill this gap, we propose two new measures that integrate sub-populations of various travel modes, and estimate an overall food accessibility for a whole neighborhood. Taking Florida, USA as a case study, we illustrate our measures by using actual multiple mode commuting data from the U.S census transportation planning products (CTPP). In the following section, we present a taxonomy of current food accessibility measures and identify knowledge gaps. The third section describes the methodology of multiple-mode measures for food accessibility, and the fourth section elaborates its application. The last three sections present results, discussion, and conclusions.

## 2. Literature review

### 2.1. Factors of food access

The literature has intensively explored non-spatial and spatial factors associated with food access. Non-spatial factors include income, race, education, perception of the studied populations, as well as the type and price of food stores (Walker et al., 2010). For instance, Morland et al. (2002) reported a three-time difference in the number of supermarkets between non-poor and poor neighborhoods. Block et al. (2004) found that predominantly black neighborhoods have six times more fast-food restaurants than predominantly white neighborhoods. Garasky et al. (2004) argued that rural clients were more likely than their urban/suburban counterparts to perceive their food environment as having an inadequate number of supermarkets.

On the other hand, spatial concern of food access has been mainly focused on geographic distance or travel time to healthy food stores. For instance, the study by Rose and Richards (2004) suggested that those living within a mile or a round-trip travel time of 30 min to their principal food stores consumed more fruits and vegetables than their counterpart did. Other spatial factors regarding built environment have also been studied, such as food store density and public transit availability (Belzer and Autler, 2002; Block et al., 2004). A limited built environment, especially poor access to public transport infrastructure, potentially decrease a neighborhood's chance of obtaining healthy food (Yoon, 2011). Due to strong correlation, these two factors can be considered as proxies of spatial access to food stores.

### 2.2. A taxonomy of current food accessibility measures

This research mainly focuses on the spatial or geographic access to healthy food. From a perspective of geography, people's access to healthy food stores is intrinsically a traveling problem that involves three basic elements: the origin, destination, and travel mode. Various types of food access measures have been developed by configuring these three elements differently. Using this origin-destination-mode framework, we classify current food accessibility measures into eight types as shown in Table 1.

Type '*1-1-1*' measure only considers one origin, one destination, and one travel mode for accessing healthy food. The food accessibility is often expressed as travel distance or time from home to the closest supermarket, and mapped by census unit, such as ZIP codes and tracts, to indicate low access neighborhoods. A typical example is the USDA's 'closest facility' model, which considers home location as the only origin, and the closest supermarket as the only destination (USDA, 2017). The travel mode is generalized as Euclidean distance between the origin and destination. Several studies refined this measure by considering realistic road-network distance (Gustafson et al., 2011) and travel time by a specific transport mode, e.g., by automobile (Pearce et al., 2006) or public transit (Farber et al., 2014). Given a threshold of distance or time, this measure can estimate the total number of people with low food access. For example, the USDA uses 1.6 km (1 mile) in urban areas and 16 km (10 miles) in rural areas to identify low-access populations.

Type '*1-n-1*' measure argues that people's access to healthy food should not be limited to the closest one supermarket to their homes, but encompass multiple supermarkets (*n*) around their homes within a time budget, thus termed as 'cumulative opportunity model' (Handy and Clifton, 2001; Horner and Wood, 2014). The travel mode of studied population is often kept homogeneous for

**Table 1**
A taxonomy of food accessibility measures by origin, destination, and mode.

| Origin | Destination | Mode | Examples in the Literature | Travel mode considered |
|---|---|---|---|---|
| *1* | *1* | 1[a] | USDA (2017) | Euclidean distance |
| | | | Gustafson et al. (2011) | Road distance |
| | | | Farber et al. (2014) | Transit |
| | | | Widener (2017) | Car/Transit |
| | | | Burns and Inglis (2007) | Car/Transit/Walking |
| | | | Su et al. (2017) | Car/Transit/Bicycle/Walking |
| *1* | *n* | *1* | CDC (2013) | Euclidean distance |
| | | | Widener (2017) | Car/Transit |
| | | | Farber et al. (2014) | Transit |
| | | | Choi and Suzuki (2013) | Walking |
| | | | Larsen and Gilliland (2008) | Transit/Walking |
| *n* | *1* | *1* | Burgoine and Monsivais (2013) | Road distance |
| *n* | *n* | *1* | Widener et al. (2013) | Car |
| | | | Widener et al. (2015) | Transit |
| | | | Burgoine and Monsivais (2013) | Road distance |
| *1* | *1* | *n* | Addressed in this article | |
| *1* | *n* | *n* | | |
| *n* | *1* | *n* | | |
| *n* | *n* | *n* | | |

[a] Including research that use 'distance' to estimate accessibility.

simplicity of calculation. The food accessibility is expressed as the count number of reachable supermarkets from a neighborhood within a time or distance limit. For example, Choi and Suzuki (2013) estimated the number of grocery stores within certain walking distances from home. The modified retail food environment index (mRFEI), developed by the Centers for Disease Control and Prevention (CDC, 2013), counts the number of healthy food retailers within census tracts of ½ miles from the tract boundary.

Recent studies further argued that people may also travel from non-home places to supermarkets; for example, commuters often shop for grocery on their way back home from workplaces (Horner and O'Kelly, 2007; Leszczyc et al., 2004). Confining people's shopping behavior around their homes can exaggerate poor food access. Thus, type '*n-1-1'* and '*n-n-1'* measures have been proposed to incorporate multiple origins of travel to supermarkets, based on data of commuting workers. Type '*n-1-1'* measure calculates the travel distances or time from both homes and workplaces to their respective closest supermarkets to determine accessibility to healthy food (Burgoine and Monsivais, 2013). Type '*n-n-1'* measure examines the number of supermarkets within certain distance or time limit from both home and workplaces (Widener et al., 2015).

Here, we argue that in addition to multiple origins and destinations, people also access supermarkets by multiple travel modes, e.g., by car, transit, bicycle, and foot. Therefore, type '*n-1-n*' and '*n-n-n*' measures are more realistic representations of people's grocery shopping behavior. As shown in Table 1, these two multiple-mode measures and their real applications remain as a gap in the literature. Most studies relied on the assumption of single travel mode to grocery stores. A few recent studies considered more than one travel modes to access food (Burns and Inglis, 2007; Su et al., 2017; Widener, 2017), but they simply applied a single-mode measure to different travel modes respectively for comparison purposes. Since these studies did not encapsulate multiple travel modes into an ad hoc measure, we still categorize them as studies that used single-mode measures. In this article, we attempt to fill the gap of multiple-mode measures for food accessibility and illustrate their implementation.

## 3. Methodology

### *3.1. 'n-1-n' measure*

To design an '*n-1-n*' measure, we consider two origins (home and workplace), 1 destination (the closest supermarket to each origin), and multiple modes for grocery shopping. First, we assume a study area has $N$ neighborhoods. A neighborhood $i$ (= 1, 2, 3, …, $N$) has a residential population $P_i$, which comprises of subpopulations, $P_{ij}$, who commute to neighborhood $j$ (= 1, 2, 3, …, $N$) for work. For any $P_{ij}$, we further divide it by transportation mode, and denote $P_{ijm}$ as the commuting population between neighborhood $i$ and $j$ with a transportation mode of type $m$ (= 1, 2, 3, …, $M$). Then, the total number of people with low food accessibility in neighborhood $i$, $LA_i$, is the sum of those subpopulations $P_{ijm}$ with low food access, formulated as:

$$LA_i = \sum_{m=1}^{M} \sum_{j=1}^{N} P_{ijm}\delta(i, j, m), \quad \text{and } \delta(i, j, m) = \begin{cases} 1, & t_{i,m} > t_0 \text{ and } t_{j,m} > t_0 \\ 0, & Otherwise \end{cases} \tag{1}$$

where $\delta(i, j, m)$ is a discriminant function to determine whether a subpopulation $P_{ijm}$ has low accessibility. $t_{i,m}$ denotes the travel costs (time or distance) via mode $m$ from home neighborhood $i$ to the closest supermarket, and $t_{j,m}$ is the travel costs from workplace neighborhood $j$ to the closest supermarket. $t_0$ is a predefined threshold of travel costs, beyond which the food accessibility is considered low.

### 3.2. 'n-n-n' measure

For the '*n-n-n*' measure, we also consider two origins (home and workplace), multiple destinations (supermarkets within a time/distance limit), and multiple modes for grocery shopping. With the same notation above, we define the food accessibility $O_i$ for a neighborhood $i$ as a population-weighted sum of reachable supermarkets:

$$O_i = \frac{\sum_{m=1}^{M}\sum_{j=1}^{N} P_{ijm} S(i, j, m)}{\sum_{m=1}^{M}\sum_{j=1}^{N} P_{ijm}} \quad (2)$$

where $S(i,j,m)$ counts the number of supermarkets accessible from either home neighborhood $i$ or work neighborhood $j$ via travel mode $m$ within a time threshold $t_0$, computed as:

$$S(i, j, m) = \sum_{k=1}^{R} \sigma(i, j, k, m); \quad \sigma(i, j, k, m) = \begin{cases} 1, & t_{i,k,m} \le t_0 \ or \ t_{j,k,m} \le t_0 \\ 0, & Otherwise \end{cases}$$

$R$ denotes the total number of supermarkets in the entire study area, and $k$ (=1, 2, 3, ..., $R$) represents any one of them. $\sigma(i, j, k, m)$ determines if a supermarket $k$ is accessible. $t_{ikm}$ and $t_{jkm}$ represent the travel costs from home and workplace to a supermarket $k$ via travel mode $m$. $S(i,j,m)$ is weighted by its corresponding subpopulation $P_{ijm}$, and then summed up to the neighborhood level.

For illustration, we applied these two new measures to census tracts of Florida, USA, and compare the results to those from other types of measures in Table 1.

## 4. A case study: Re-evaluating food accessibility in Florida

### 4.1. Study area

According to the 2015 food access research atlas of USDA, there are 1829 out of 4172 census tracts in Florida falling into the low access (LA) category (Fig. 1a). The LA census tracts are defined as: *census tracts where a significant number (at least 500 people) or share (at least 33 percent) of the population is greater than 1 mile (1.*6 km*) from the nearest supermarket, supercenter, or large grocery store for an urban area or greater than 10 miles (*16 km*) for a rural area* (USDA, 2017). About 4.83 million individuals live in these tracts, with a vast majority of them (4.71 million) residing in urban areas and only 0.12 million in rural areas.

The USDA atlas only considers people's travel from homes to supermarkets. In reality, the national household travel survey (NHTS, 2001) in Florida shows that a significant proportion (21%) of trips for 'buying goods' were workplace-based, rather than home-based. In this case study, we re-evaluated the food accessibility by considering multi-origin, multiple travel mode of people upon real road networks.

### 4.2. Data collection and parameter estimation

Four sets of data were collected to parameterize our proposed measures in Section 3, including the data for origins, destinations, transportation networks, and regional travel survey.

#### 4.2.1. Origins

We assumed that the studied population can travel to supermarkets from two types of origins, namely homes and workplaces. We downloaded 4172 census tracts in Florida from the US Census Bureau (USCensus, 2010) to represent where people live and work. To depict their commuting behavior between homes and workplaces, we acquired the CTPP data, which were derived from 2006 to 2010 5-year American Community Survey published by American Association of State Highway and Transportation Officials (AASHTO, 2010). This data product is designed to help transportation analysts and planners understand people's commuting behavior. As exemplified in Fig. 1b, the CTPP data include which census tracts people live, which census tracts they work, and how many people commute between any pair of census tracts and by which travel mode (car, transit, bicycle, or walk). We downloaded the most recent CTPP flow data of workers 16 years and over between their home and workplace tracts. For each travel mode (by car, transit, bicycle, and walk), we built a 4172 by 4172 matrix to record the number of commuters between any pair of home and workplace tracts, i.e., $P_{ijm}$ in Eqs. (1) and (2). For those who are under 16 years (mostly young and school-aged children) and who do not work (retired people), we presumed their 'workplace' tracts the same as home tracts, and their transportation modes to supermarkets followed the same distribution of workers in the same census tract.

To calculate the travel time to supermarkets, we generalized all home and workplace locations in a census tract onto the mean center of the census tract. The mean center was further weighted by census-block populations to account for uneven population distribution.

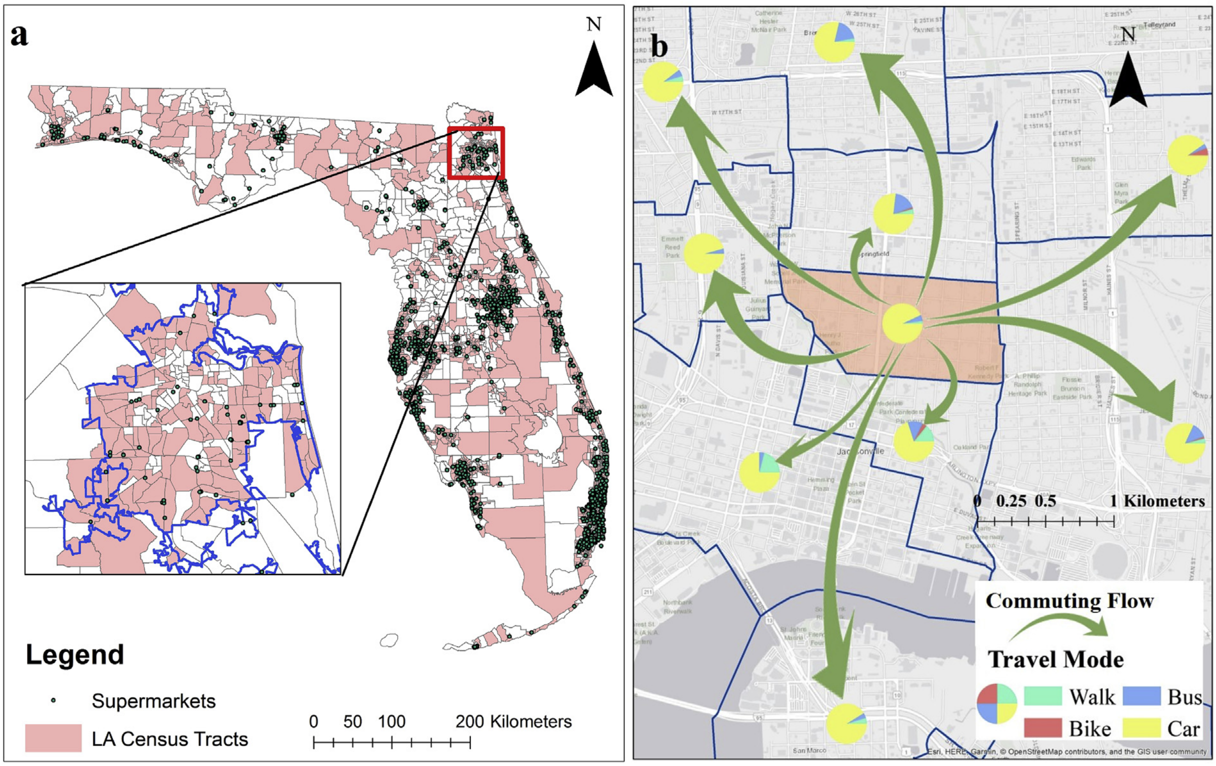


**Fig. 1.** a) USDA defined low access (LA) census tracts in Florida, and locations of supermarkets for healthy food. The inset map shows the urbanized area of Jacksonville, the largest city in the state; b) An illustration of the CTPP data showing the commuting flows from the central census tract (red) to surrounding tracts. The pie-charts indicate the share of each travel mode in a commuting flow. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

#### *4.2.2. Destinations*

Destinations in this study included all supermarkets, supercenters, or large grocery stores in Florida. We acquired the most recent points of interest (POI) data from the OpenStreetMap, an open geographic data source (Geofabrik, 2016). A total of 1307 locations with a type of supermarket or green-grocery (all referred to "supermarket" for short) were subset for analysis (Fig. 1a).

#### *4.2.3. Transportation networks and travel time estimation*

We estimated the travel time between origins and destinations ($t_{i,m}$ in Eq. (1) and $t_{i,k,m}$ in Eq. (2)) based on real transportation networks, including a road network (USCensus, 2010) and a public transit network (FTIS, 2008). For people commuting by car or motorcycle, they traveled via the road network with speed limits set in Table A1 (in Appendix). For people commuting by bicycle and walk, they followed the road network with a constant speed of 16.7 km/h (10 miles per hour) and 4.8 km/h (3 miles per hour), respectively (Browning et al., 2006). For people using public transit, they traveled through the transit network with a constant speed of 16 km/h (10 miles per hour), according to 2016 Public Transportation Fact Book (Neff and Dickens, 2017). We used ArcGIS Network Analyst to estimate the travel time between any pair of origin and destination by any travel mode.

#### *4.2.4. Florida regional household travel survey*

The threshold travel time ($t_0$) in Eqs. (1) and (2) is a key parameter to determine low food accessibility. We estimated this parameter from real Florida household travel records, which were collected by the National Household Travel Survey (NHTS, 2001). This survey provides detailed records about 12,110 trips of 2615 respondents from 1316 households in Florida during the survey period. Each trip contains information about its intended stop, purpose of stop, and travel cost in minute from the previous stop. For each respondent, we constructed a trip chain by linking consecutive stops according to time sequence. We then identified 1498 trip chains with at least one trip for a purpose of 'buying goods'. For each trip chain, we calculated the total travel time from either the home or work stop (depending on which one is closer) to the stop of 'buying goods'. The statistics showed that the median time cost for shopping from home or workplace was 20 min (Figure A1 in Appendix), which was set as the threshold time $t_0$ to define 'low access'.

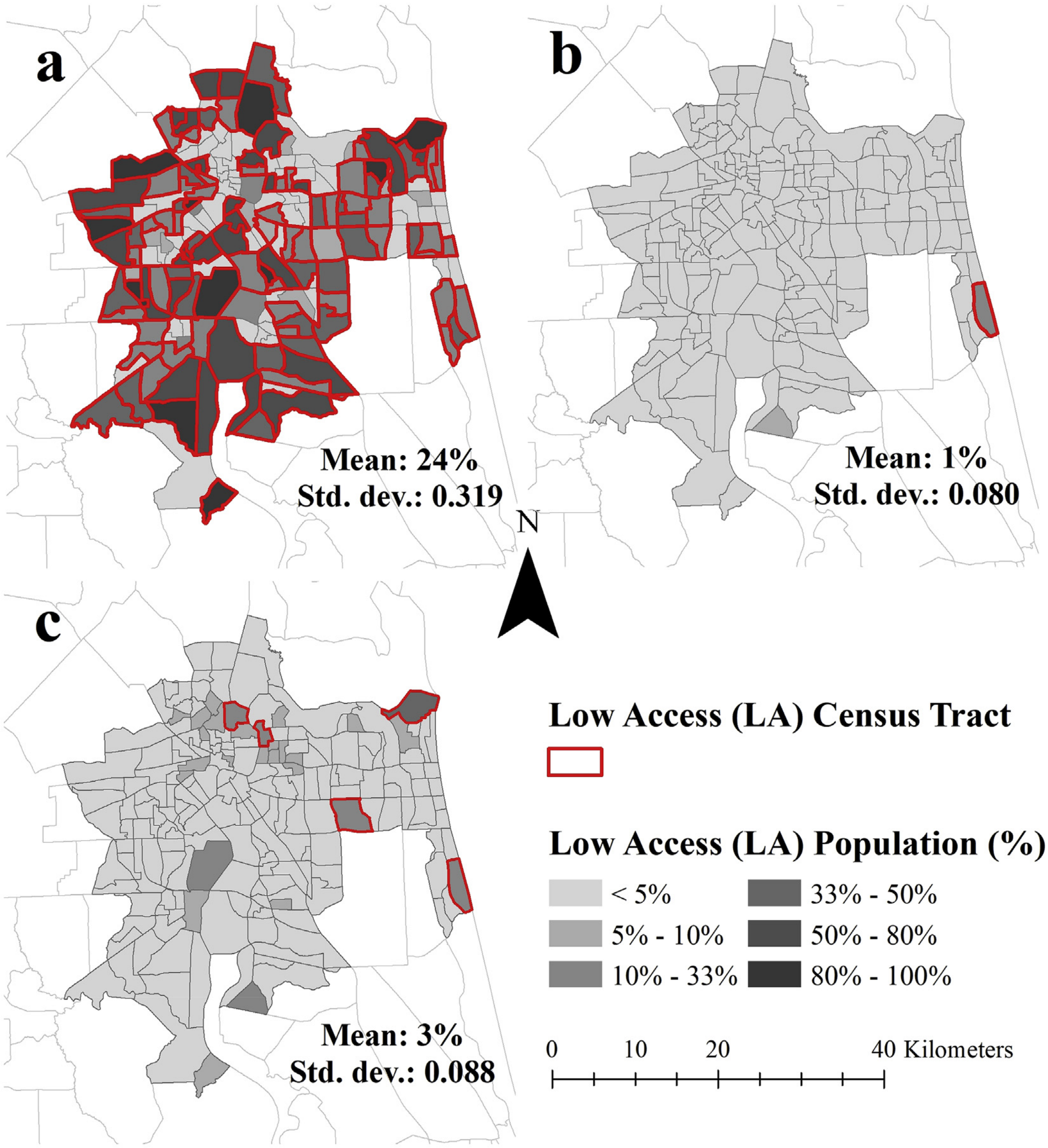


**Fig. 2.** Percentage of LA population by census tract in Jacksonville, FL, along with the mean and standard deviation, estimated by: a) '*1-1-1*' measure (the USDA version), b) '*n-1-1*' measure (the single mode), and c) '*n-1-n*' measure (the multiple modes).

## 5. Results

### 5.1. '*n-1-n*' measure

The proposed '*n-1-n*' measure considers two origins (home and workplace), one destination (the closest supermarket to origin), and multiple travel modes for shopping (Eq. (1)). We applied it to Florida's census tracts to estimate the percentage of LA population, and then compared the results to those derived from the *1-1-1* measure (used by USDA), and the '*n-1-1*' measure (same as the '*n-1-n*' measure except that people only travel by car). For clarity, the maps in Fig. 2 only show the urbanized area of Jacksonville, FL, while the estimates for the entire Florida are presented in Figure A2 in Appendix.

The three measures produce distinct patterns of food accessibility in the city of Jacksonville, FL. The '*1-1-1*' measure (used by USDA) estimates one extreme case (Fig. 2a), where an average of 24% of population in a census tract have low food accessibility. A vast majority of census tracts have more than 33% population with low accessibility and are considered as LA tracts. The '*n-1-1*' measure shows the other extreme case (Fig. 2b), where almost all census tracts have less than 5% LA population and only one census tract is identified as the LA tract (LA population > 33%). Our proposed '*n-1-n*' measure indicates an intermediate state between those two extremes (Fig. 2c), where a few scattered census tracts possess large LA populations and five of them are considered as LA tracts.

**Table 2**
Estimated total LA population and census tracts for entire Florida by three measures.

| Measure | LA Population | | | | | No. of LA Tracts |
|---|---|---|---|---|---|---|
| | Total | Car | Transit | Bike | Walk | |
| *1-1-1* | 4,831,112 | - | – | – | – | 1829 |
| *n-1-1* | 236,784 | 236,784 | – | – | – | 135 |
| *n-1-n* | 479,859 | 228,378 | 20,932 | 9508 | 221,041 | 179 |

Further, we computed the total LA population and LA tracts for entire Florida from the three measures (Table 2). The USDA's '*1-1-1*' measure estimated 4.83 million LA population and 1829 LA tracts, approximately 10–20 times greater than those from the other two measures. The '*n-1-1*' measure (single-mode) estimated the fewest LA population (0.24 million) and LA tracts (135), given all people shopping food by car. When adding more travel modes, the proposed '*n-1-n*' measure doubles the LA population to 0.48 million. It is noteworthy that the proposed '*n-1-n*' measure allows an assessment of LA sub-population by travel mode, while the other two measures cannot (Table 2). People shopping food by walk is the 2nd largest LA sub-population in Florida, followed by people shopping by car.

The urban-rural disparities in food access is often of interest (Table 3). The USDA's *'1-1-1'* measure indicates a significant 'urban disadvantage', in that 28.7% of urban population, versus 5.1% of rural population (ratio = 5.6:1), have low food accessibility. In contrast, the *'n-1-1'* measure suggested a remarkable 'rural disadvantage', because of a much higher percentage of LA population in the rural area than the urban area (ratio = 1:17.3). The proposed '*n-1-n*' measure that considers multiple travel modes also shows a 'rural disadvantage', but the disparity between rural and urban is much narrower than single-model estimation (ratio = 1:4.8).

### 5.2. *'n-n-n' measure*

The proposed *'n-n-n'* measure considers two origins (home and workplace), multiple destinations (several supermarkets within 20 min to origins), and multiple travel modes for grocery shopping (Eq. (2)). We applied it to estimate the number of accessible supermarkets by Florida's census tract, and then compared the results to those derived from the *n-n-1* measure (with a single-mode by car). Both single-mode (Fig. 3a) and multiple-mode (Fig. 3b) measures showed similar radial patterns. That is, census tracts near the city center have more accessible supermarkets, which gradually decreases outward to the city periphery. However, the single-mode measure tends to estimate higher accessibility than the multiple-mode measure (Fig. 3c), and the over-estimation can reach 25% at some neighborhoods.

## 6. Discussion

The USDA's *'1-1-1'* measure tends to suggest a 'pessimistic' scenario that identifies a large number of LA people and LA tracts (Fig. 2 and Table 2). A major reason lies in its assumption of a single origin (from home location) for grocery shopping. For rural areas, this assumption could be reasonable, because rural census tracts are often large in size and rural residents are more likely to live and work in the same census tracts. This assumption, however, is particularly vulnerable in the urban area, where the census tracts are relatively small in size and many urban residents live and work in different census tracts. An urban resident could live in a census tract, where there is a low access to healthy food vendors, but commute daily to another tract, where there are many healthy food vendors, thus providing an opportunity for healthy grocery shopping (Widener, 2013). This explains why the USDA's *'1-1-1'* measure produces an exceptionally high percentage of LA population in the urban area. The *'n-1-1'* and *'n-1-n'* measures relax this assumption by considering workplaces as additional origins, and thus produce fewer LA population and LA tracts.

Among the three measures, the *'n-1-1'* measure provides an 'optimistic' estimation for the fewest LA population and LA tracts (Fig. 2 and Table 2). As commonly seen in the literature, this measure assumes all people in a census tract shop by car. Since traveling by car offers a higher speed than other modes (by bike, bus, and walk), this assumption expands people's activity space within a certain time limit and subsequently increases their opportunities for healthy food. This assumption can be realistic in the rural area, where the travel mode for commuting is relatively uniform and predominated by car in the US (as exemplified in Fig. 4b). In the urban area, this assumption becomes problematic since the travel modes to work can be more diverse due to well-developed public transit system, bike lanes, and sidewalk (Fig. 4a). Therefore, the *'n-1-1'* measure offers more reliable estimates in the rural areas than

**Table 3**
Estimated LA population (% in state total) in urban and rural Florida by three measures.

| Measure | LA population | | |
|---|---|---|---|
| | Urban | Rural | Ratio of Urban-Rural % |
| *1-1-1* | 4,709,992 (29%) | 121,120 (5%) | 5.6:1 |
| *n-1-1* | 71,232 (1%) | 165,552 (7%) | 1:17.3 |
| *n-1-n* | 282,704 (2%) | 197,155 (8%) | 1:4.8 |

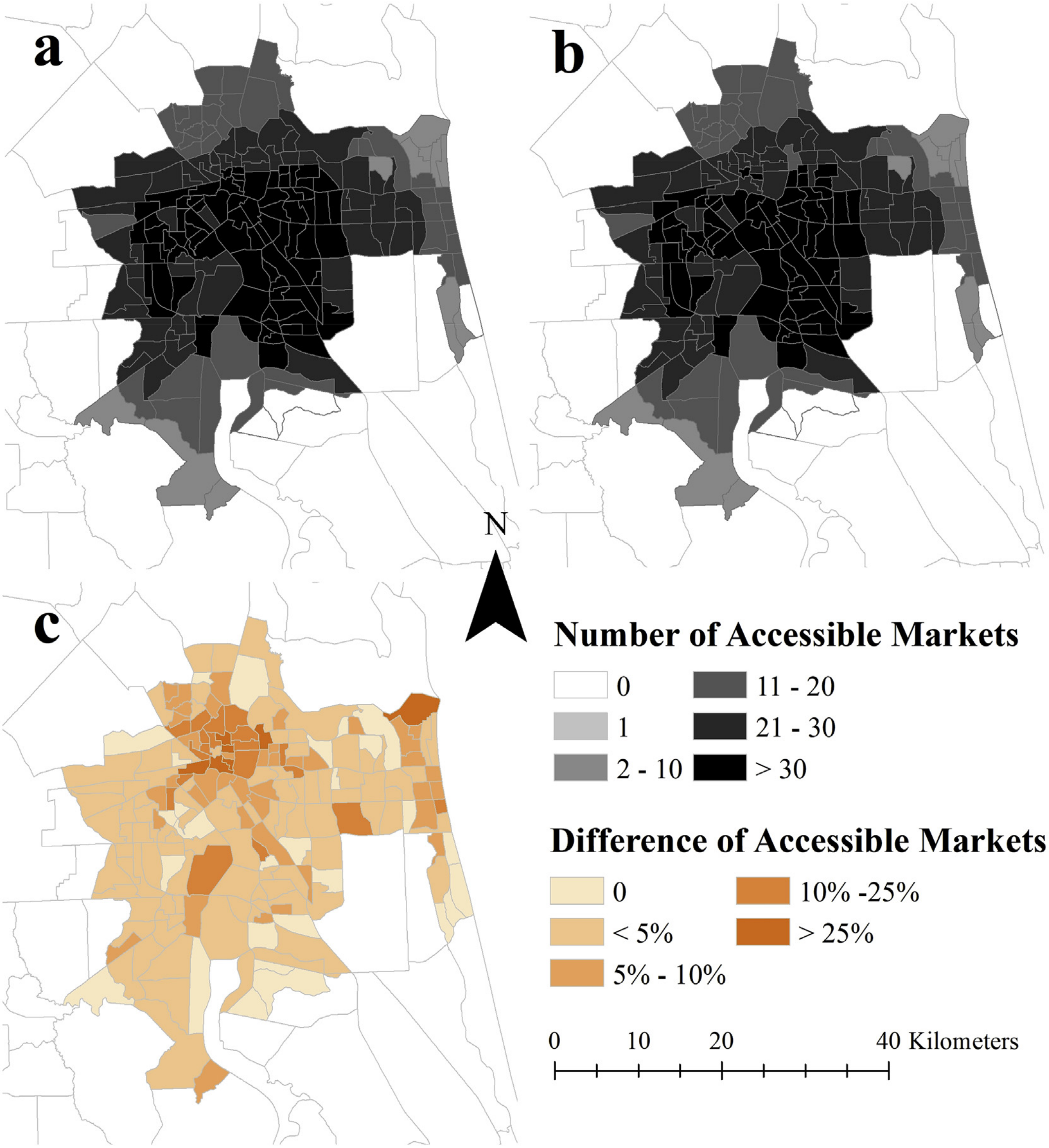


**Fig. 3.** The number of accessible markets within 20 min in Jacksonville, FL, estimated by a)'*n-n-1*' measure, and b) '*n-n-n*' measure. c) the difference between a) and b) in percentage.

the urban areas.

Our proposed *'n-1-n'* measure addresses the limitations of the previous two and provides a 'realistic' scenario between those two extremes. It considers homes and workplace as multiple origins for grocery shopping, and thus produces much lower estimates than the USDA's measure. Further, it incorporates multiple travel modes into the estimation, so that it identifies more LA population in the urban area than the single-mode measure does, but similar LA population in the rural area (Table 2). For the same reason, the proposed *'n-n-n'* measure estimates fewer accessible supermarkets than the *'n-n-1'* measure does (Fig. 3).

From a perspective of policy making for food access improvement, a good measure needs to address questions of 'where' and 'whom' to target. Our multiple-mode measures outperform the previous in answering those questions. In term of 'where', the multiple-mode measure can better identify low food access areas that are otherwise missed by the single-mode measure (as shown in Fig. 2). This is important for precise targeting in policy design. With regard to 'whom', the proposed measure allows researchers to look deeper into the modal-split populations within a neighborhood, which previous measures cannot offer (Table 2). This is a benefit from modeling at the subpopulation level in a neighborhood, which reveals who, not 'all', have low access in a targeted neighborhood. In this sense, there should be no 'one-fit-to-all' policy for every neighborhood, but instead policies customized to the subpopulation(s) that really needs improvements in a neighborhood. For example, if there is a large portion of walking subpopulation with low food access in a targeted neighborhood, the investment should weigh on constructing more walking trails to grocery stores.

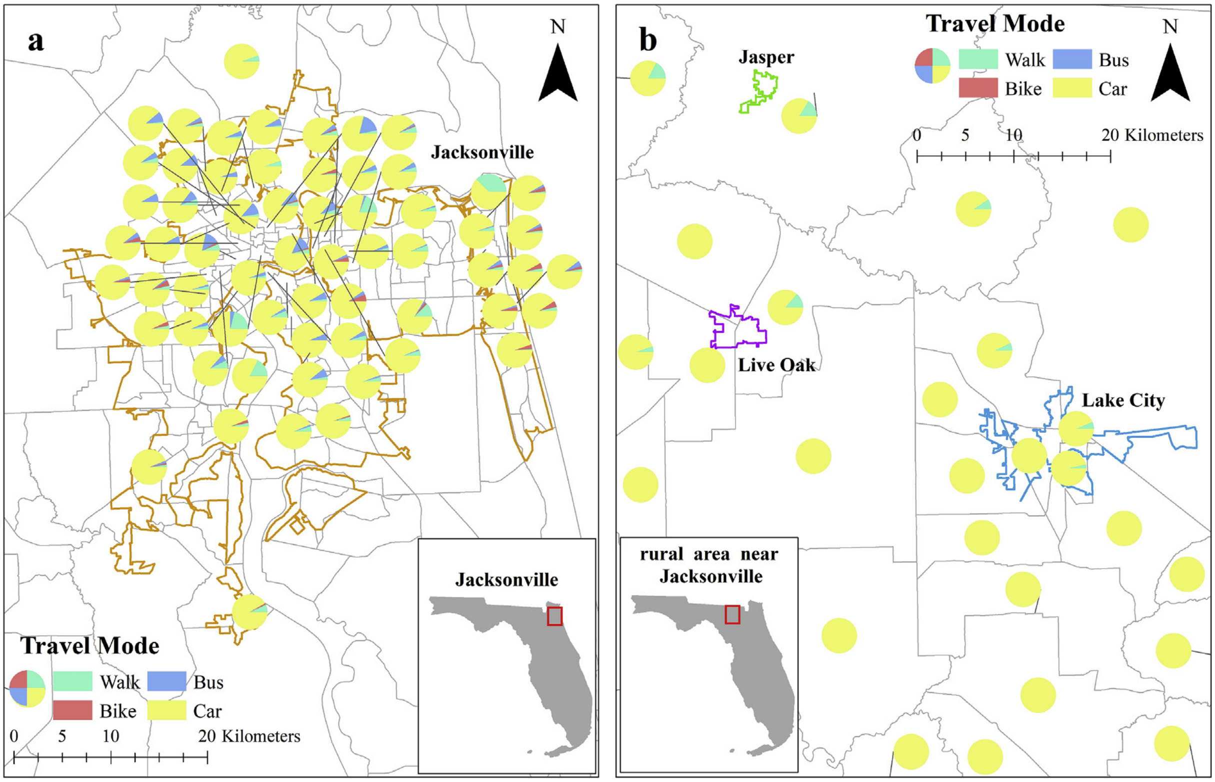


**Fig. 4.** Pie-charts show the shares of each travel mode for commuting for census tracts in: a) the urban area of Jacksonville; tracts with over 95% of people traveling by car are not displayed for clarity; b) the rural area (with small towns) near to Jacksonville.

If the case is the public-transit population, the policy can be adding mobile food markets, e.g., food booths, near to bus stops.

Overall, the integrative multiple-mode approach we propose here is generalizable and scalable for other studies. First, we only discuss the *'n-1-n'* and *'n-n-n'* measures in this research, both of which consider multiple origins and multiple modes for grocery shopping. The other two types of measures listed in Table 1, i.e., the *'1-1-n'* and *'1-n-n'* measures, can be seen as simplified versions, in which only one origin (home location) is represented. Eqs. (1) and (2) can be modified accordingly for implementation. Second, since the CTPP data is published at the state, county, census tract, and traffic analysis zone (TAZ) levels, our multiple-mode measures for food accessibility can be scaled up and down to meet the need of policy makers. Because the CTPP data (or similar data products) are available not only for the United States but also many other countries, this approach can also be easily expanded to the entire US or other countries for nationwide planning purpose. Third, the concept of using modal-split subpopulations as basic modeling units (in Eqs. (1) and (2)) can be extended more broadly to any type of subpopulations, for example, by age, income, race, and education. This would allow an integration of non-spatial factors into spatial measure of food accessibility, thus offering a more comprehensive evaluation for a neighborhood.

This research is also subject to several limitations that warrant future studies. First, the travel time threshold for grocery shopping was set constant in our model, while it can vary by origin (home versus workplace) and by travel mode. Different threshold values can be estimated by further grouping the travel records by origin and by mode, and then parameterized into our proposed model. Second, the key commuting data used in this study, the CTPP data, only have information about the working population (workers over 16), while the travel pattern of non-working population (children and seniors) is unknown. We assumed that both populations have the same travel modal distributions, which could differ in a census tract. A shopping behavior survey oriented to the non-working population would help relax this assumption. Third, the data used in this research is sufficient for illustration purpose but should be improved for policy making. For instance, the open source data on supermarkets may be incomplete, and the classification may not be accurate either. The public transit network data do not have schedule, transfer, and waiting time information. Alternatively, commercial databases for businesses (such as the ReferenceUSA database), as well as the General Transit Feed Specification (GTFS) data, could be more reliable data sources.

## 7. Conclusions

A neighborhood, such as a census tract or ZIP code, is often the basic modeling unit in many food accessibility measures. The population within a neighborhood are assumed homogeneous, i.e., the same origin, food environment, and travel mode. Here, we emphasize heterogeneity among people, even in the same neighborhood, who can have different origins, food opportunities, and travel modes in their grocery shopping. We advocate the use of subpopulations (in a neighborhood) as basic modeling units to represent such heterogeneity, and propose an integrative multiple-mode measure to evaluate the overall accessibility of a neighborhood. By considering modal-split subpopulations, our measures offer a more realistic representation of local people's travel pattern, and thus a better identification of sub-populations with low food access. Further, the finer modeling scale provide health and urban planners more flexibility in policy design, in that interventions can be tailored not only to a neighborhood but also to sub-populations within it. Such knowledge could improve the cost-effectiveness of food intervention programs.

### Financial disclosure

This research was partially supported by the University of Florida Informatics Institute Seed Fund 2016.

## Appendix

Table A1
Criterion for assigning speed limits to road segments

| Road Type[a] | Road Subtype[a] | Speed limit (miles/hour)[b] |
|---|---|---|
| Primary | Interstate Highway | 70 |
| | US Route | 65 |
| Secondary | State Highway | 60 |
| | State Route | 55 |
| | County Highway | 50 |
| | County Route | 45 |
| Local | Local, neighborhood, and rural road, city street | 30 |
| Ramp | N/A | 25 |
| Others | N/A | 20 |

[a] Road types and subtypes are classified by the Florida Geographic Data Library.
[b] Speed limits are assigned according to the Florida Department of Transportation (http://www.dot.state.fl.us/trafficoperations/FAQs/SpeedLimitFAQ.shtm).

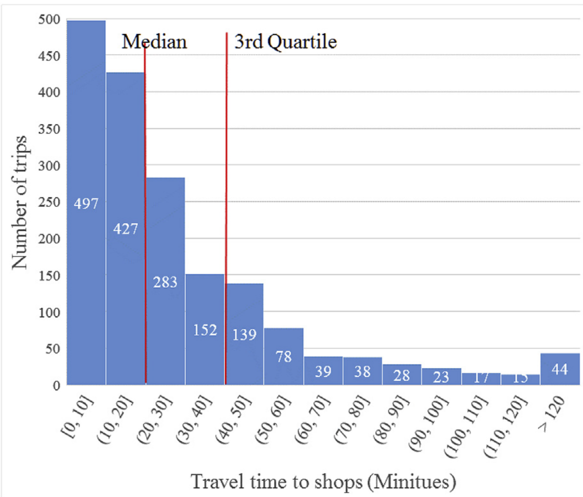


**Fig. A1.** Trip frequency distribution of travel time for 'shopping good', derived from the NHTS 2001. The median (20 min) and 3rd quartile (40 min) travel time are also labeled.

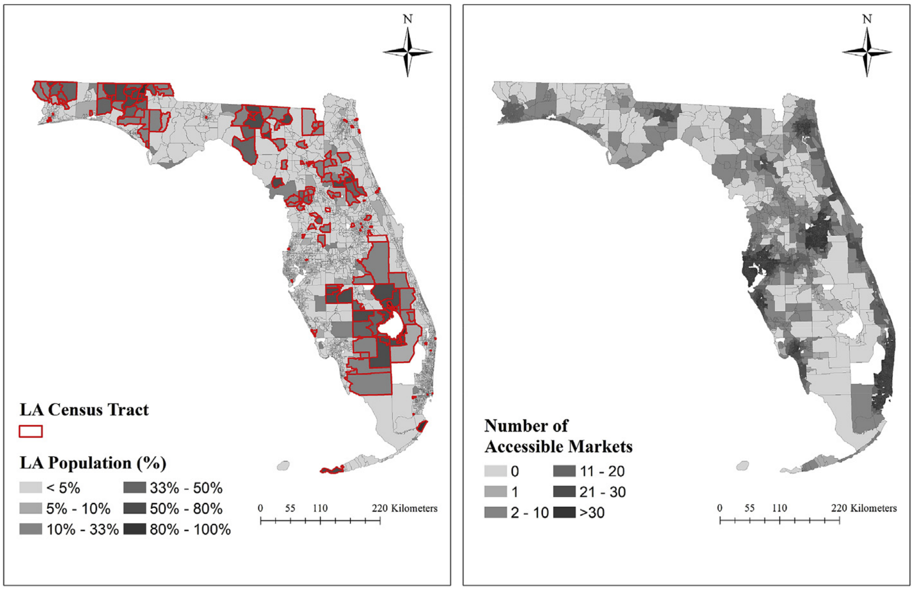


**Fig. A2.** Left: The percentage of LA population by census tract estimated by the *'n-1-n'* measure for the entire Florida state; Right) The number of accessible markets by census tract estimated by '*n-n-n*' measure for Florida.

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