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Measuring Access to Improve Public Health – Phase II

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16. Abstract

This study advances transportation access metrics that support public health planning across Massachusetts. Building on Phase I, which focused on food access, Phase II expands the scope to include healthcare, higher education, and parks. The research improves methods to account for walkability, bikeability, and the role of microtransit alongside fixed-route transit. Using consistent statewide datasets and spatial tools such as Conveyal and Replica, the project generates high-resolution access maps to key destinations. Demographic data are integrated to quantify disparities faced by vulnerable populations. To examine links between access and health, geographic random forest models relate accessibility and demographic variables to chronic health outcomes including diabetes, heart disease, and obesity. Results show that access by walking, biking, transit, and driving to essential destinations varies in importance for predicting health outcomes. Limited access to critical destinations among low-income and zero-vehicle households is especially associated with poorer health. The study concludes with policy recommendations to embed access metrics into planning tools, including dashboards that guide equitable transportation investments and promote public health across Massachusetts.

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Measuring Access to Improve Public Health – Phase II

Final Report

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This study to measure access to improve public health was undertaken as part of the Massachusetts Department of Transportation (MassDOT) Research Program. This program is funded with Federal Highway Administration (FHWA) State Planning and Research (SPR) funds. Through this program, applied research is conducted on topics of importance to the Commonwealth of Massachusetts transportation agencies.

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Table of Contents

List of Tables

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List of Figures

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List of Acronyms

Acronym	Expansion
AADT	Annual Average Daily Traffic
CATA	Cape Ann Transportation Authority
CCRTA	Cape Cod Regional Transit Authority
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
FRTA	Franklin Regional Transit Authority
GATRA	Greater Attleboro and Taunton Regional Transit Authority
GIS	Geographic Information System
GPS	Global Positioning System
GWRF	Geographically Weighted Random Forest
GTFS	General Transit Feed Specification
LTS	Level of Traffic Stress
MAE	Mean Absolute Error
MAPC	Metropolitan Area Planning Commission
MART	Montachusett Regional Transit Authority
MassDOT	Massachusetts Department of Transportation
MBTA	Massachusetts Bay Transportation Authority
MSE	Mean Squared Error
MWRTA	Metro West Regional Transit Authority
NWI	National Walkability Index
OLS	Ordinary Least Squares
OSM	Open Street Maps
QC	Quaboag Connector
REJ+	Regional Environmental Justice Plus
RF	Random Forest
RMSE	Root Mean Squared Error
RTA	Regional Transit Authority
SCC	South County Connector
SHAP	Shapley Additive Explanations
SPR	State Planning and Research
U.S.	United States
VMT	Vehicle Miles Travelled
WI	Walkability Index
WRTA	Worcester Regional Transit Authority
Z9	Web Mercator Grid Zoom Level 9

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1.0 Introduction

Transportation is an important determinant of public health. Inequitable access to jobs, food, healthcare, education, and recreation have all been shown to be significant contributors to health disparities. To improve equity in access, metrics that are based on statewide data are needed to systematically identify gaps in access so that actions can be taken by public officials to address them. A study funded by the Massachusetts Department of Transportation (MassDOT) entitled "Measuring Food Access to Improve Health" was a first phase of research on this problem, which focused on metrics and recommendations around food access in Massachusetts [1]. Three important research needs emerged from the study, which are to be addressed in this second phase: 1) metrics of access should account for new transportation services (e.g., microtransit) and the connectivity of transportation infrastructure (e.g., sidewalks); 2) meaningful metrics and analysis should account for the locations of vulnerable populations (e.g., Regional Environmental Justice Plus, REJ+, populations); and 3) access should be measured for more broad determinants of public health, such as healthcare, education, and recreation. Consistent and reproducible methods to measure access and inequities across Massachusetts provide the necessary information to support planning and decision making to improve access and public health.

1.1 Project Overview

MassDOT has been a pioneer in recognizing the connection between transportation and health. These efforts have been ongoing for more than a decade and include health-related design guidelines as expressed through the 2009 Healthy Transportation Compact and the 2013 Healthy Transportation Policy Directive. Recent MassDOT research projects include "Public Health Assessment for Transportation Projects" [2], which identified project scoring criteria and metrics for accounting for health impacts of transportation through multiple pathways such as access, safety, air quality, equity, and physical activity. Access significantly affects many aspects of human life, including access to jobs, food, health care, education, and recreational activities, all of which directly affect health outcomes.

Recognizing the importance of access for public health, a MassDOT project entitled "Measuring Food Access to Improve Health" [1] was a first phase of research to develop metrics specifically related to transportation and food access so that gaps in access can be identified. The first phase provided a systematic method to use statewide data to measure food access and quantify inequities across communities and available modes of transportation. The method uses an analysis tool available to MassDOT called Conveyal, which enables analysis of network travel times by walk/transit, bicycle, and driving. The study also identified some specific shortcomings that, if addressed, would improve the value of access metrics. These shortcomings are in three areas:

1) **Transportation** – The existing analysis tools are limited to a representation of the transportation network that includes fixed route transit services but not new microtransit programs. Furthermore, walking and biking experiences are based only

on network travel distance without other measures of the quality of the walking or cycling environment.

2) **Demographics** – The negative effects of limited access are of greatest concern to vulnerable populations who are more likely to be restricted by the cost, time, or physical mobility required to access opportunities. The access metrics from Phase I focus on the spatial dimension of access (i.e., how many opportunities can be reached within a travel time constraint) and then compare the locations of access gaps with REJ+ communities. A more holistic approach would provide a measure of access that jointly considers the locations of vulnerable populations and food access and to view n the context of health outcomes.

3) **Determinants of Public Health** – MassDOT maintains a data dashboard for jobs access. The Phase I study focused on food access. Public health is affected by access to an array of opportunities that also include education, health care, and recreational activities. The methods for measuring access to food can be extended to other types of opportunities. Together these paint a more complete picture of the role that access plays as a determinant of public health.

This report presents the results of research in each of the three areas described above so that MassDOT is equipped with a comprehensive set of methods and tools for assessing access across the Commonwealth and making transportation investments that improve public health.

1.2 Study Objectives

There are four objectives of this research:

1. To develop methods that account for transportation modes and services (such as walkability, bikeability, and microtransit services) and the quality and connectivity of transportation infrastructure in metrics of access based on travel time and/or cost.

2. To present metrics of access and equity that account for the locations of vulnerable or disadvantaged populations and how these align with the transportation system.

3. To identify metrics and tools that serve needs for planning transportation infrastructure and services that provide access to critical locations associated with public health.

4. To recommend metrics and analyses that can be reproduced with available data to be incorporated into a data dashboard or tool that supports ongoing planning and investment decisions.

There are two intended products of this research: (1) the documentation of metrics and analyses for access to social determinants of health, including methods to account for transportation services and infrastructure and to account for vulnerable populations; and (2) recommendations for how data should be presented and utilized in data dashboards to support planning and decision-making. These products should support MassDOT’s existing initiatives as well as other entities such as municipalities and regional planning agencies.

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2.0 Research Methodology

The research approach for this study consists of four main components: a literature review that focuses on how access is measured for non-driving modes of transportation (e.g., walk, bicycle, transit) and describes the current state of the art; relevant data sources are identified for transportation, critical destinations, demographics, and public health outcomes; a method is developed for measuring access at a fine spatial scale so that aggregations are weighted by the concentrations of affected populations; finally, modeling methods are used to link measures of access with observed public health outcomes. Together, these methods provide ways to consistently analyze data to reveal where investments to improve access will affect the most vulnerable populations and where the impact on public health will be greatest.

The research methods developed in this study leverage datasets that are already compiled by the Commonwealth of Massachusetts and tools that MassDOT currently uses for spatial and travel demand analysis. The results of these analyses are presented in Section 3.0. Implications for planning transportation investments are discussed in Section 4.0.

2.1 Literature Review

A general review of literature on measuring access is provided in the final report for Phase I [1]. For measuring access to destinations that are associated with social determinants of health, such as food retailers, methods that count the number of destinations that can be reached within a travel time constraint are used to quantify access. To measure access by private car, a spatial analysis of a network of links associated with traffic speeds is used to define the area that can be reached within a time limit, known as an isochrone. A standard approach is to use the same concept to quantify access by walking, bicycling, or using transit based on walking speed, biking speed, and transit schedule. However, the experience of travelers by these modes is affected by other factors related to the quality of the transportation infrastructure, characteristics of the built environment, and the structure of transit services available. This review focuses on these mode-specific considerations.

Accessibility is an important component in transportation planning and plays a critical role in measuring social equity. Research by Vecchio et al. [3] and Dempsey et al. [4] underscores that an equitable society necessitates the elimination of social and environmental exclusion. The concept of exclusion frequently occurs in specific geographical areas characterized by socio-economic difficulty, where disadvantaged living conditions are prevalent and access to public services and amenities is comparatively limited [4, 5]. Accessibility, in this context, is defined by the extent to which individuals can access various destinations, particularly through walking and cycling. Enhancing walkability and bikeability, as McNeil [6] points out, can significantly improve people's quality of life.

Furthermore, the effectiveness of walking and cycling as transportation modes is contingent on the quality and interconnectedness of infrastructure, particularly for journeys not made by car. While current tools predominantly evaluate travel time across transportation networks, there is a recognized need for additional data. This data should effectively measure how pedestrian- and cyclist-friendly different environments are, thereby contributing to a more comprehensive understanding of accessibility by walking, bicycling, and transit in urban planning.

2.1.1 Walkability

Multiple studies have focused on assessing walkability accounting primarily for built environment factors such as residential density, retail building floor area, intersection density (indicating street network connectivity), and land use mix [7]. Street-level characteristics such as sidewalk condition, traffic safety, security, comfort, and attractiveness have also been considered to allow for a more comprehensive assessment of the walk experience [8, 9, 10, 11].

The various metrics that have been proposed to assess walk accessibility are typically time-based, i.e., number of locations of a certain type of destination (e.g., grocery stores or healthcare facilities) that can be reached from a census block group centroid within a certain travel time threshold [12], maximum walking time between a census block group's centroid and essential amenities, or percentage of residents who live within a certain travel time threshold from destinations of interest [13]. However, these metrics do not consider the quality of pedestrian infrastructure in terms of both surface and connectivity, built environment characteristics (e.g., building density), presence of transit, or other location-specific factors that could be affecting one's desire and ability to walk to destinations of interest.

In response to these limitations, several studies have incorporated quantifiable elements of the built environment, such as block length and intersection density, land use related characteristics, as well as socioeconomic characteristics such as population density to assess neighborhood walkability [14, 15]. Frank et al. [7] defined walkability at the census block group level, as a function of intersection density, residential unit density (i.e., number of residential units per unit of land area allocated for residential uses), retail building density (i.e., ratio of the floor area of the retail building to the floor area of the retail land), and land use diversity index. The latter is evaluated by considering five land use categories: residential, retail, entertainment (including restaurants), office, and institutional (including schools and communal institutions). This metric was then used to assess the relationship between neighborhood walkability and residents' physical activity levels, demonstrating that higher walkability scores were positively associated with increased walking and overall physical activity among adults. A related study by Sallis et al. [16] also showed that residents in more walkable neighborhoods engaged in more physical activity and had a lower obesity risk, regardless of income. However, these studies did not consider street-level characteristics such as the presence of pedestrian infrastructure and surface quality.

The National Walkability Index (NWI), which was developed by the Environmental Protection Agency (EPA) to compare walkability across neighborhoods, also takes into consideration attributes related to the built environment [17]. This index was developed using factors such as intersection density, proximity to transit stops, and diversity of land uses. The index is ranked from 1 to 20. The weights assigned to the index are calculated according to the following formula:

$$NWI\ Score = \frac{w}{3} + \frac{x}{3} + \frac{y}{6} + \frac{z}{6} \tag{1}$$

where w, x, y, and z stand for a census block group's ranked score across all block groups in an area, for intersection density, proximity to transit stops, employment mix, and employment and household mix, respectively. Although the NWI score itself takes a continuous numerical value between 0 and 20, it is often categorized as shown in Table 2.1. However, there has been limited quantitative analysis on how the NWI relates to pedestrian activity levels, such as walking, shopping, and visiting places.

Table 2.1 National Walkability Index (NWI) score categories [17]

Category	Score Range
Least Walkable	1.0 – 5.75
Below Average Walkability	5.76 – 10.50
Above Average Walkability	10.51 – 15.25
Highly Walkable	15.26 – 20.00

A walkability index (WI) was developed by Arellana et al. [11] that accounts for observable and non-observable factors associated with security, traffic safety, sidewalk condition, comfort (e.g., presence of trees), and attractiveness (e.g., presence of parks and green zones). Arellana et al. [11] used the discrete choice model to estimate the weights of WI by taking data from two sections of the rank perception survey. The response from both ranks of five non-observable factors and the components of each factor. WI is estimated by

$$Walkability = \sum_{m \in M} P_m^* \sum_{c \in C_m} P_{cm}^* C_{cml} \tag{2}$$

where P_m^* is the weight of the non-observable factor m; P_{cm}^* is the weight of the component c associated with the non-observable factor m; and C_{cml} is the measurement variable level for component c associated with non-observable factor m corresponding to a sidewalk l. In the context of calculating the WI, the component factors are based on data related to traffic safety, security, comfort, and attractiveness. The parameters of the model are then fitted with data on observed walking route choices.

Privately-motivated efforts have also resulted in walkability metrics that account for built environment and population characteristics. An example of an index that has incorporated the aforementioned factors is the Walk Score, which is a proprietary tool offering a quantifiable measure of walkability to various destinations around an address. Despite the fact that its methodology specifics are not published, this tool has been acknowledged for its effectiveness in measuring neighborhood walkability [18, 19, 20] and has been extensively used in studies exploring residential location choice [21], house values, crime statistics [22], and cardiometabolic health [23].

In many cases, the goal of a walkability score is to predict the likelihood that a trip will be made by walking or to estimate the number of walking trips that will be made in a network. For this study, the focus is on accessibility, so a measure of walkability will be used to account for the characteristics of a walking trip beyond simple travel time that affect its feasibility.

2.1.2 Bikeability

Like walking, bicycle access is not adequately characterized by network travel distance, alone, because environments vary in how conducive they are to safe, comfortable, and convenient bicycling. Kellstedt et al. [24] define *bikeability* "as the extent to which the actual and perceived environment is conducive and safe for bicycling," although no universal definition has been established. Bikeability varies by location based on physical characteristics of the built infrastructure such as surface quality, presence of bike lanes, existence of buffers from other road users, and slope.

Translating the bikeability of infrastructure into the likelihood that people will actually use bicycles to travel requires consideration of the perceptions and attitudes of people themselves. A typology of bicyclists, known as the "Four Types of Cyclists," categorizes people in one of the following categories based on their level of comfort and willingness to ride in various conditions [25], as described in Furth et al. [26] with estimates of group sizes from Dill and McNeill [27]:

- **Strong and fearless** (4%) – Willing to ride in almost any situation;
- **Enthused and confident** (9%) – Willing to ride on busy, wide roads if a designated bicycling space (bike lane or shoulder) is provided;
- **Interested but concerned** (56%) – Uncomfortable next to fast traffic or negotiating with traffic on busy roads; and
- **No way, no how** (31%) – No interest in riding a bike.

Of these categories, only the 4% of the population that are characterized as "strong and fearless" could be expected to ride a bicycle on any type of road in the road network to meet their access needs. The majority of people are willing to consider using a bicycle but are sensitive to the perceived safety and comfort of the route. Those characterized as "no way, no how" include individuals who are averse to cycling merely by attitude as well as the significant number of people who are unable to bicycle either because of a disability or other limitations.

In an effort to map network connectivity for different levels of cyclist comfort, Mekuria et al. [28] proposed a classification scheme for road links based on the level of traffic stress (LTS) that would be acceptable for each of the cyclist types described above. Table 2.2 defines the four LTS classifications as presented in Furth et al. [26]. These categories are determined using road characteristics such as the lane count, speed limit, presence and width of bike lanes, and presence of parking lanes. The criteria for determining LTS have been updated over the years; the most recent one is LTS v2.2 [29].

Table 2.2 Levels of traffic stress (LTS) [26]

Level	Description
LTS 1	Demands little attention to traffic from cyclists and attractive for a relaxing bike ride. Suitable for almost all cyclists, including children trained to safely cross intersections. On road sections, cyclists are either physically separated from traffic or are in an exclusive bicycling zone next to a slow traffic stream with no more than one lane per direction, or are in mixed traffic with a low-speed differential and demanding only occasional interactions with motor vehicles. Next to a parking lane, cyclists have ample operating space outside the zone into which car doors are opened. Intersections are easy to approach and cross.
LTS 2	Presents little traffic stress but demands more attention than might be expected from children. On road sections, cyclists are either physically separated from traffic or are in an exclusive bicycling zone next to a well-confined traffic stream with adequate clearance from a parking lane, or are on a shared road where they interact with only occasional motor vehicles with a low-speed differential. Where a bike lane lies between a through lane and a right-turn lane, it is configured to give cyclists unambiguous priority where cars cross the bike lane and to keep car speed in the right-turn lane comparable to bicycling speeds. Crossings are not difficult for most adults.
LTS 3	Offers cyclists an exclusive cycling zone (e.g., bike lane) requiring little negotiation with motor traffic, but in close proximity to moderately-highspeed traffic or mixed traffic requiring regular negotiation with traffic with a low speed differential. Crossings may be stressful but are still considered acceptably safe by most adult pedestrians.
LTS 4	Requires riding near to high-speed traffic, or regularly negotiating with moderate-speed traffic, or making dangerous crossings.

The LTS concept has been validated in studies of various demographic groups, which have confirmed that cyclists prefer to use streets with lower LTS, even if routes are not the shortest path [30, 31]. For measuring access by cycling, the LTS designation allows for analysis of network connectivity constrained by a maximum LTS [26]. Thus, LTS is an important additional constraint to consider in the calculation of access by bicycle, because most users will limit the set of streets that they will use to those corresponding to their level of comfort.

2.1.3 Transit Access

Three different approaches are often used to evaluate accessibility for fixed-route transportation: level of access to transit stations, accessibility to a single destination, and accessibility to several possible destinations [32]. Proximity to public transportation stops does not fully reflect transit travel time, thus failing to provide a comprehensive understanding of actual transit accessibility from origin to destination. Furthermore, the accessibility to specific destinations is not suitable for mesoscale studies that aim to capture the impact of land use supply. Thus, our main objective is to assess the level of access for different types of destinations and using various transit services.

Mavoa et al. [33] determined the service area by analyzing the travel time requisite to reach 17 distinct land-use sites using public transit and walking. It was estimated that there would be a 10-minute delay at each transit stop when there is a change in commuting patterns or public transportation routes. The locations were classified into five distinct domains: education, finance, health, retail, and social/recreational. They then assigned an accessibility score to each destination based on the sum of the average domain accessibility scores. The authors also computed the mean number of trips per hour per grid block to evaluate the extent of public transportation service. The limitations of this method include a predetermined waiting period for the vehicle and the allocation of identical importance to the five categories. The first problem may be resolved by using Conveyal's journey time (i.e., travel time) estimations, while the second needs additional literature and statistics to assess the attractiveness of different destinations to the residents.

Grengs [34] estimated fixed route transit accessibility by using the exponential form of the gravity model as in Equation 3.

$$A_i = \sum_j O_j e^{-\beta T_{ij}} \tag{3}$$

Where A_i is the transit accessibility indicator for residents in zone i; O_j represents the attractiveness factor, based on the number of opportunities in destination zone j; β is a constant that varies by purpose, indicating how sensitive an opportunity's attractiveness is to travel time; and T_{ij} is the average travel time needed from zone i to j. Different values of β obtained by Grengs [34] can be found in Table 2.3, which has been observed from automobile trips from the 2005 Michigan Department of Transportation household travel survey. Some variations of this formula do not use an exponential function to represent the travel time effect but use different travel impedance functions like linear decay functions [35], while others include both travel time and transit fares, using th e hourly wage to convert fare into equivalent units of time to evaluate access values [5].

2.1.4 Microtransit

Microtransit offers several advantages over fixed route transit, including improved service quality, reduced operational expenses, and increased convenience in areas with low demand for transportation services [35]. Microtransit is typically implemented to serve three main purposes: providing transportation for the first and last mile of a journey, filling gaps in transit coverage, and replacing fixed routes. Its goal is to connect passengers to and from fixed route transit stops or stations, expand transit coverage to areas that are currently underserved, and potentially eliminate or reduce the need for existing transit routes.

Table 2.3 β-values for transit access by trip purpose [34]

Trip Purpose	β
Convenience Stores	0.3967
Libraries	0.3521
Religious Organizations	0.2934
Social visits	0.2297
Banks	0.1865
Supermarkets	0.3899
Restaurants	0.3228
Shopping	0.2811
Hospitals	0.2067
Childcare facilities	0.3763
Schools	0.3204
Services	0.2784
Medical clinics	0.1981

Identifying microtransit service areas is crucial for recognizing and addressing gaps in the existing public transportation network. Examining service regions ensures that microtransit is implemented in places where it can most effectively enhance people's accessibility. Erdoğan et al. [36] identified the places where microtransit services are needed. They presented a thorough answer by introducing a Multi-Criteria Decision-Making Framework that combines two important factors: the Microtransit Propensity Index and the Weighted Accessibility Score. By analyzing data from Prince George's County, they claim that the approach is better in determining the most favorable places. Nevertheless, the research supported a more sophisticated strategy that highlighted the importance of making decisions based on data and allowing planners to balance multiple objectives.

Understanding the preferences, expectations, and behavior of prospective microtransit users is critical for catering to unique user demands and increasing user satisfaction. Preference surveys enable transportation planners to use a design strategy that prioritizes the needs and preferences of users. Rossetti et al. [37] investigated the commuting preferences of individuals in the United States (U.S.) regarding microtransit services, using a metric that measures the value of time. The research used preference surveys and mixed logic models to identify the demographic characteristics associated with a higher likelihood of interest in microtransit. The findings indicated that males, younger passengers, persons with higher levels of education, and those who already utilize public transportation are more inclined to express interest in microtransit. Their work emphasized the need to consider cultural and infrastructural differences when interpreting the value of time, highlighting the necessity of context-specific factors.

Hansen et al. [38] focused on developing a framework for assessing and evaluating the performance of public microtransit services. The research suggested a range of assessment metrics, such as arrival time, total passenger boardings, cost efficiency, and operational effectiveness, to assess the success of microtransit in relation to the objectives established by the agency. Nevertheless, acknowledging the necessity for adaptability, Hansen et al. [38]

proposed modifying assessment metrics under particular service performance and zone classifications.

2.2 Summary of Available Data and Tools

The Phase I study focused on food access across Massachusetts, and the analyses relied primarily on the representation of transportation modes available within the spatial analysis tool Conveyal. Food retailer data was obtained from the Metropolitan Area Planning Council (MAPC). Transportation network data was based on the representation of the road network in Open Street Maps (OSM) and fixed-route transit services as documented in General Transit Feed Specification (GTFS) datasets from Regional Transit Authorities (RTAs). Although some traffic speed data is available through Conveyal based on speed limits and traffic congestion data, speeds for walking and bicycling are assumed to be the same regardless of the infrastructure they travel on.

The goal of this research is to develop methods to measure access that are reproducible across the whole Commonwealth of Massachusetts and over time. The measures also need to be detailed enough that the effects of investments in transportation infrastructure or services can be reflected in the quantitative access measures. To meet this need, a comprehensive review of available data sets that are relevant to measuring access to the various destinations that are considered determinants of health and the observed public health outcomes were analyzed by utilizing the tools available for transportation demand and spatial analysis.

2.2.1 Data Available in Massachusetts

Activities during nonwork trips mostly focus on shopping, education, health services, political engagement, and recreation [39]. In order to assess the level of access in relation to various types of infrastructure, we gathered data on the geographical distribution of Food Retailers and Farmers Markets, Colleges and technical schools, Urgent care facilities, Pharmacies and emergency rooms, as well as parks. Most of these data sources are currently available to MassDOT from the US Census Bureau or through MassGIS.

2.2.1.1 Transportation Data

1. **Road Inventory 2024** – The Massachusetts Road Inventory is a shapefile with data on every road link in the Commonwealth of Massachusetts. This data includes information about speed limits, the existence and dimensions of sidewalks, and data on the presence of bicycle infrastructure [40]. This provides link-specific data on which spatial analysis of travel routes can be based.

2. **Bike Inventory 2024** – The Massachusetts Bike Inventory is a shapefile that complements the road inventory by documenting bicycle infrastructure that is not on a road network [41]. This includes the extensive networks of separated bicycle

infrastructure and multi-use paths, many of which provide links to the bicycle network with low LTS.

3. **Fixed Route Transit Data** – Stop locations, routes, and schedules for fixed route transit services operated by the Massachusetts Bay Transportation Authority (MBTA) and the 15 RTAs in Massachusetts are documented in the General Transit Feed Specification (GTFS) format. This data is already utilized by many wayfinding platforms, and provides the basis of measuring access by transit using spatial analysis tools.

4. **Microtransit Services** – Microtransit provides on-demand service within a specific service area during specific hours of operation, but there is no pre-defined route or schedule of operations. These services are not included in the GTFS data for conventional transit services, so data specific to microtransit is needed in order to characterize the access provided by these systems. A shapefile of all microtransit service area boundaries and information about hours of operation are available for all microtransit services in Massachusetts. Specific trip records for the South County Connector (SCC), centered in Great Barrington, and the Quaboag Connector (QC), centered in Ware, have been provided by those services for a more detailed analysis of waiting times and travel speeds.

2.2.1.2 Critical Destinations for Public Health

1. **Food Retailers and Farmers Markets data** – The Metropolitan Area Planning Council offers an extensive database of food retailers, encompassing crucial information such as store names, addresses, and precise latitude/longitude coordinates [42]. This data is derived from records spanning the years 2016 to 2021. A challenge with the food retailer data is that more recent MAPC retailer data does not include square footage of the stores, which was used as a proxy measure for the variety of foods available in the Phase I study.

2. **Urgent Care, Community Health Centers, and Emergency Rooms** – Urgent care center, community health clinic, and hospital emergency room data have been collected from the Commonwealth of Massachusetts for 2024. The dataset captures 58 retail clinics, 150 urgent care centers, and 75 acute care hospitals in Massachusetts [43].

3. **Colleges and Technical Schools** – Colleges and university data is from December 2018, including adult education, business school, community college, divinity school, public and private colleges and universities, technical colleges and schools, and vocational schools. [44].

4. **Parks** – Park areas are observed from Mass.gov and published in November 2023. We select the categories of parks of federal, DCR-State parks recreation, DCRS, DCR-Urban Parks recreation, County, and municipal to be included in the accessibility to park measurements [45].

2.2.1.3 Demographic and Public Health Data

1. **Census Data, American Community Survey** – Census data encompasses information regarding the spatial allocation and habitation patterns of census blocks and census block groups [46]. Those data were published by the US Census Bureau and were updated in 2020.

2. **Environmental Justice (EJ) regions** – The data is obtained from MassGIS [47] for 2022 and originates from the Executive Office of Energy and Environmental Affairs. The EJ population is determined based on the median annual household income, minority representation, and proficiency in the English language. Of the 4,985 block groups in Massachusetts, 2,604 are identified as EJ regions.

3. **Regional Environmental Justice Plus (REJ+) Communities** – The REJ+ designation expands on the EJ definition by accounting for household car ownership, disability, and age. These are all socioeconomic characteristics that affect a person's ability to use the transportation system to access critical destinations. The REJ+ data provide the most comprehensive definition to identify disadvantaged or vulnerable communities for which access is an important concern [48].

4. **Health Outcome Data** – Data on population health characteristics, aggregated at the town level, are available from the Massachusetts Department of Public Health's Community Health Data Tool [49]. The data include health outcomes for chronic conditions (e.g., cancers, diabetes, heart disease, obesity) as well as rates of communicable diseases, health behaviors, mortality, and measures of well-being.

2.2.2 Tool: Conveyal

Conveyal is a spatial analysis tool that uses road network data, transportation mode speeds, and fixed-route transit network and schedule data as reported in the General Transit Feed Specification (GTFS) by each transit agency. Conveyal performs network analysis functions that include calculating travel time from origin to destination by various modes: walking, bicycling, driving, and fixed-route transit with walk or drive access.

A useful feature of Conveyal is that it can determine the area that can be accessed from a specific origin point within a defined travel time constraint using the existing road network. The software can also compare this accessible area with a set of geocoded points provided by the analyst to identify which points can be accessed within the travel time constraint. Furthermore, this analysis procedure can be batched to compute accessible areas and the number of accessible points for a large number of origin points in a single analysis run. In the context of measuring food access, Conveyal was used in the Phase I project to count the number of supermarkets that could be reached from the centroid of each of the 1,472 census tracts in Massachusetts by four constraints: 10 minutes walking, 10 minutes bicycling, 30 minutes walk-access to fixed route transit, and 10 minutes driving.

Conveyal is limited by the level of detail in the transportation network data. Links on the street network, for example, are associated with speeds based on speed limits or data on traffic conditions, so travel times are representative of realistic travel times on the network. There is currently no comprehensive database of pedestrian and bicycle facilities that includes walking or bicycling speed or accessibility, so the tool assumes that pedestrians and cyclists travel at a constant speed along the shortest path on the road network. The transit network is represented by the GTFS data, which represents the stop locations and operating schedule of fixed route services, but this does not include the access that may be provided by on-demand services.

2.2.3 Tool: Replica

Replica is a web-based data platform that contains data that captures travelers' behavior. It uses multiple data sources to estimate regional movements of people and patterns of spending that can be tracked over time. The data sources for Replica include:

- *Mobile Location Data* – data from location-based services on mobile devices, vehicle in-dash global positioning system (GPS), and points-of-interest aggregated as sampled data of where people are traveling and how quickly.

- *Consumer/Resident Data* – demographic data from public sources, such as the US Census, as well as other private sources, are used to determine where people live and work as well as people's characteristics, including age, race, income, vehicle ownership, and employment status.

- *Built Environment Data* – land use and zoning data, building data, and transportation network data are used to determine where people participate in activities and which modes can be used for travel.

- *Economic Activity Data* – Credit card, debit card, and cash transactions at point of sale provide information about the levels of spending by time and place as well as how much economic activity is associated with e-commerce.

- *Ground Truth Data* – Data on auto volumes, truck volumes, transit ridership, and bike and pedestrian counts provide points for calibrating and verifying model estimates.

Replica uses extensive modeling methods to extrapolate travel demand patterns from available data sources to quantify origin-destination flows by trip purpose, travel mode, and time of day. Part of the method is to construct a synthetic population that is assigned to these trip flows so that the travel patterns of different demographic groups can be compared. The modeled datasets that are generated by Replica include:

- *Mobility Data* – Network link volumes, weekly origin-destination flows of people by mode and time of day, and weekly estimates of vehicle miles traveled (VMT). Although not currently part of MassDOT's subscription, the tool can potentially report annual average traffic volumes and speeds across the road network as well as intersection turn counts by time of day.

- *Spending Data* – Weekly spending amount merchant location, resident location, and county-to-county flows, by sector (airline hospitality car rental, entertainment recreation, gas stations parking taxis tolls, grocery stores off/on-line, restaurants bars off/on-line, retail off/on-line).

Replica had not been used in the Phase I study but provides some data capabilities that are useful for looking at access patterns across Massachusetts. Although the data provided by Replica are intended to represent total travel flows, they are modeled on a subset of observed traveler behaviors. However, by fusing public and private data sources, these provide the most comprehensive and consistent set of estimated origin-destination flows by mode across the entire Commonwealth of Massachusetts. Since Replica leverages several data sources to estimate mode share for active transportation (e.g., walking and bicycling), some of which are not readily available outside of the platform, this data is useful for gaining insights on where people are choosing to travel by means other than car.

2.3 Measuring Access

Measuring access from a specific location requires spatial analysis to determine the isochrone of reachable area within a travel time constraint. The conventional approach, which was used in Phase I, and which continues to be the method for measuring car access is to specify a travel time constraint and use network analysis to determine the isochrone of reachable area within that travel time limit. Based on the review of literature in Section 2.1 and the availability of data as described in Section 2.2, access measures for walking, bicycling, and microtransit are developed to represent the experience of travel by these modes. This involves development of separate analysis techniques for each of the three modes to account for different constraints in addition to the simple travel time limit.

2.3.1 Measuring Walk Access

One of limits of walk access is the travel time or distance that a person is able or willing to walk, but this does not fully capture the accessibility of a location by walking. The street infrastructure, such as sidewalks and crosswalks, and the characteristics of the built environment, such as the density and diversity of land uses affect how safely, securely, and comfortably a person is likely to feel while walking. These are the factors that determine walkability, as defined in the National Walkability Index (NWI). The approach for measuring walk access is to scale the constraint for walk travel time based on the NWI of the census tract in which the trip originates so that longer walking time is allowed in more walkable environments.

Trip data from Replica includes modeled origin-destination trips across Massachusetts based on a variety of data sources, as described in Section 2.2.3. Each modeled trip includes the census tract of the origin and destination, the distance traveled, and the mode used. This data can be analyzed to determine how the mode share by walking varies by trip distance and location in the state. The mode share can also be interpreted as the likelihood that a person will choose to walk. A conceptual challenge related to measuring access is to determine to what extent the length of a desired trip affects a person's choice to walk or if a person's choice (or limitation) to walk determines how far they are willing to go. This is challenging to disentangle, but the effect of socioeconomic characteristics and NWI on the likelihood to walk has a clearer causal relationship. Appendix A includes a more detailed description of the comparison of regression models that explore these relationships. The results indicate that the NWI and socioeconomic factors explain as much variation in walk mode share as trip distance alone. This implies that NWI is a useful determinant of walking access.

By using data on walking mode share across Massachusetts, the magnitude of the effect of NWI on walk access is calibrated based on the observed relationship between NWI and distances that people are observed to walk in different communities. The proposed method involves four parts.

1. **Measure Walkability** – As described in Section 2.1.1, walkability can be measured in several different ways. The NWI is a useful measure of walkability because it is a nationwide geographic data resource that ranks block groups across the Unites States based on their relative walkability [17]. NWI captures basic physical information about the infrastructure of how the road environment can be used by residents, partially accounting for how safely and comfortably a person can walk in these environments. Although individuals' psychological safety, such as whether the street has a high crime rate, and the width of the walkway are not taken into consideration, the NWI provides a consistent representation of infrastructure for comparing a wide range of communities. The population-weighted average NWI value represents the average walkability of a community in which a Massachusetts resident lives, and this serves as a baseline against which to compare walkability in other settings.

2. **Analyze Modeled Trip Data –** Using Replica, data on shopping trips across Massachusetts is grouped by census tract to characterize the distribution of lengths of trips and the walk mode share by trip length. Shopping trips are selected as the focus for this analysis because that is the trip purpose in Replica that is most closely related to the types of destinations (e.g., food retailers) that are associated with public health outcomes.

3. **Aggregate Walking Data by NWI –** The NWI and Replica trip data are then linked by aggregating the trips in census tracts associated with each of the four levels of walkability, as defined in Table 2.1. Within each walkability category, the walking mode share is plotted against trip distance.

4. **Calculate the Adjustment Factor for Walk Access –** For a given travel time constraint, the walkable distance at an average walking speed of 3.4 km/hr [50] provides a reachable distance. For example, a travel time constraint of 15 minutes is common in the literature [51, 52, 53] and corresponds to a distance of 0.85 km. Using the figure developed in step 3, the expected mode share for this distance is looked up for the walkability curve associated with the average resident, which is defined as the *reference mode share*. At other NWI values, the reference mode share is associated

with different trip lengths, and the ratio of distance to 0.85 provides an NWI-adjusted measure of the distance that can be reached at a comparable level of walk access.

It is expected that trip data from less walkable locations (lower NWI) are associated with lower walk mode share and trip data from more walkable locations (higher NWI) are associated with higher walk mode share. Another way to look at this relationship is that the reference mode share will typically be associated with shorter trips where walkability is low and longer trips where walkability is high. However, the method does not rely on these assumptions, because adjustment factors are defined based on observed walking behaviors.

Once these analysis steps have been completed for Massachusetts, a set of NWI adjustment factors have been defined for the travel time constraint of interest. These factors can be applied to either the travel time constraint or modeled walking speed in each census tract based on the category of NWI to which it belongs. Then, Conveyal calculates isochrones for walk access at each location of interest in a way that accounts for the adjusted walkability in that location.

2.3.2 Measuring Bicycle Access

Like walking, access by bicycle is not sufficiently characterized by the distance that can be traveled on the road network at a fixed biking speed. A key distinction from walking is that bicyclists vary in the level of comfort they experience in traveling on different types of streets and bicycle infrastructure, which is the guiding principle behind the development of the bicycle LTS, described in Section 2.1.2. The approach for measuring bicycle access is to add an LTS constraint to the set of links that travelers are assumed to be able to use for travel within the given travel time constraint.

A comprehensive map of all bikeable links (roads, streets, and paths) in Massachusetts was constructed based on three MassDOT network files. Each link in the Road Inventory 2024 is associated with a speed limit and number of lanes, and an older version of the Road Inventory 2022 provides annual average daily traffic (AADT) measures or estimates for some roads. The Bike Inventory 2024 includes bicycle facilities that are classified as bike lane, separated bike lane, shared use path, or bicycle/pedestrian priority roadway. Some bicycle links are not included in the road inventory, while others can be linked to the road inventory by the Record_ID. The inventories are merged and links that do not permit bicycles (i.e., freeways and expressways) are encoded with a fifth level, denoted LTS 5, to indicate that the link cannot be utilized for bicycle access. This provides a complete GIS map of the bicycle network.

Each link in the combined inventory of road and bike infrastructure is then classified by LTS using a simplified version of the LTS v2.2 [29], because some of the data requirements for the published LTS criteria are not available in the statewide dataset for Massachusetts. For example, the presence of a parking lane is not included in the road inventory, so road links are classified as if there is no parking lane. This classification involves the following steps:

1. Is the link a fully separated bike path or protected bike lane?
   a. If yes, LTS 1
   b. If no, proceed to 2
2. Does the link have a separated bike lane (i.e., with physical separation from traffic)?
   a. If yes, LTS 2
   b. If no, proceed to 3
3. Does the road have a conventional bike lane?
   a. If yes, assign LTS based on criteria in Table 2.4
   b. If no, assign LTS based on criteria in Table 2.5
4. Any road on which bicycle access is not permitted is classified as LTS 5, which is effectively eliminated from the bikeable network for all users.

Table 2.4 Bicycle LTS criteria for roads with bike lanes by speed limit

# Lanes	AADT	≤ 25 mph	30 mph	35 mph	40 mph	45+ mph
1 thru lane per direction or contraflow	≤ 1500	1	1	2	3	3
1 thru lane per direction or contraflow	> 1500	2	2	2	3	3
2 thru lanes per direction	-	2	2	2	3	4
3+ lanes per direction	-	3	3	3	4	4

Table 2.5 Bicycle LTS criteria for roads without bike lanes by speed limit

# Lanes	AADT	≤ 25 mph	30 mph	35 mph	40 mph	45+ mph
1 thru lane per direction or contraflow	≤ 1500	1	2	2	3	3
1 thru lane per direction or contraflow	> 1500	2	3	3	4	4
2 thru lanes per direction	-	3	3	3	4	4
3+ lanes per direction	-	3	4	4	4	4

The encoded map of bikeable links with LTS designations is then uploaded into Conveyal for the spatial analysis of bicycle access. The measured bicycle access from a point is the number of reachable destinations of interest within the time constraint of 15 minutes, limited to using only links with LTS 2 or lower.

2.3.3 Measuring Transit Access with Microtransit

Measuring transit access for fixed route services requires a spatial analysis of the distance that must be walked to reach a transit stop, the time spent waiting until the next scheduled departure(s), the time spent on-board scheduled transit vehicle services, and the time spend walking after disembarking to reach the final destination.

Conveyal has built-in capabilities to analyze the reachable area within an isochrone based on stop, route, and schedule data that each agency records in the GTFS format (Figure 2.1). Because the amount of waiting time depends on when a person starts their trip relative to the published service schedule, Conveyal calculates access measures for different percentiles of travelers, assuming a uniform distribution of starting times during the analysis time period. A screenshot from Conveyal (Figure 2.2) shows a cumulative plot of the number of reachable supermarkets from a point near downtown Springfield, Massachusetts, for a weekday from 9:00 – 11:00am. Within 45 minutes, the number of reachable supermarkets by transit may be as low as 20 for a person who would have to wait for a full headway and would effectively just walk, or it may be over 80 supermarkets for a person who is able to time their travel to not wait at all for a scheduled bus. The median reachable area is shown on the map in blue shading and corresponds to access to 43 supermarkets. Users of transit systems with headways exceeding 10 minutes are more likely to plan their trips according to the published schedule [54]. Trip start times are not likely to be uniformly distributed during across the service headway, because most people plan to arrive at transit stops just a few minutes before the scheduled departure. Therefore, a low percentile of the travel times calculated from the uniform distribution of trip start times is more indicative of the time that transit passengers actually spend waiting. In this study, the 5th percentile is used to represent the relatively small amount of time that passengers must wait relative to long headways when they are able to plan their travel in advance.

Newer microtransit services have a different operating structure, so they are not represented in GTFS, and therefore, the conventional transit access analysis methods do not account for the access provided by these services. Microtransit services operate on demand within a specified service area and are either booked in advance or in real-time using an app. Figure 2.3 is a schematic that shows the basic elements of a microtransit trip. It starts when a passenger requests to be picked up at a point of origin at a preferred time. The passenger then waits for an assigned vehicle to arrive and pick them up. Then, the passenger rides within the microtransit vehicle until being dropped off at their preferred destination. This ride may be a direct point-to-point ride (e.g., as a taxi would serve a single passenger) or the passenger may experience a longer ride while the vehicle deviates to pick up or drop off other passengers.

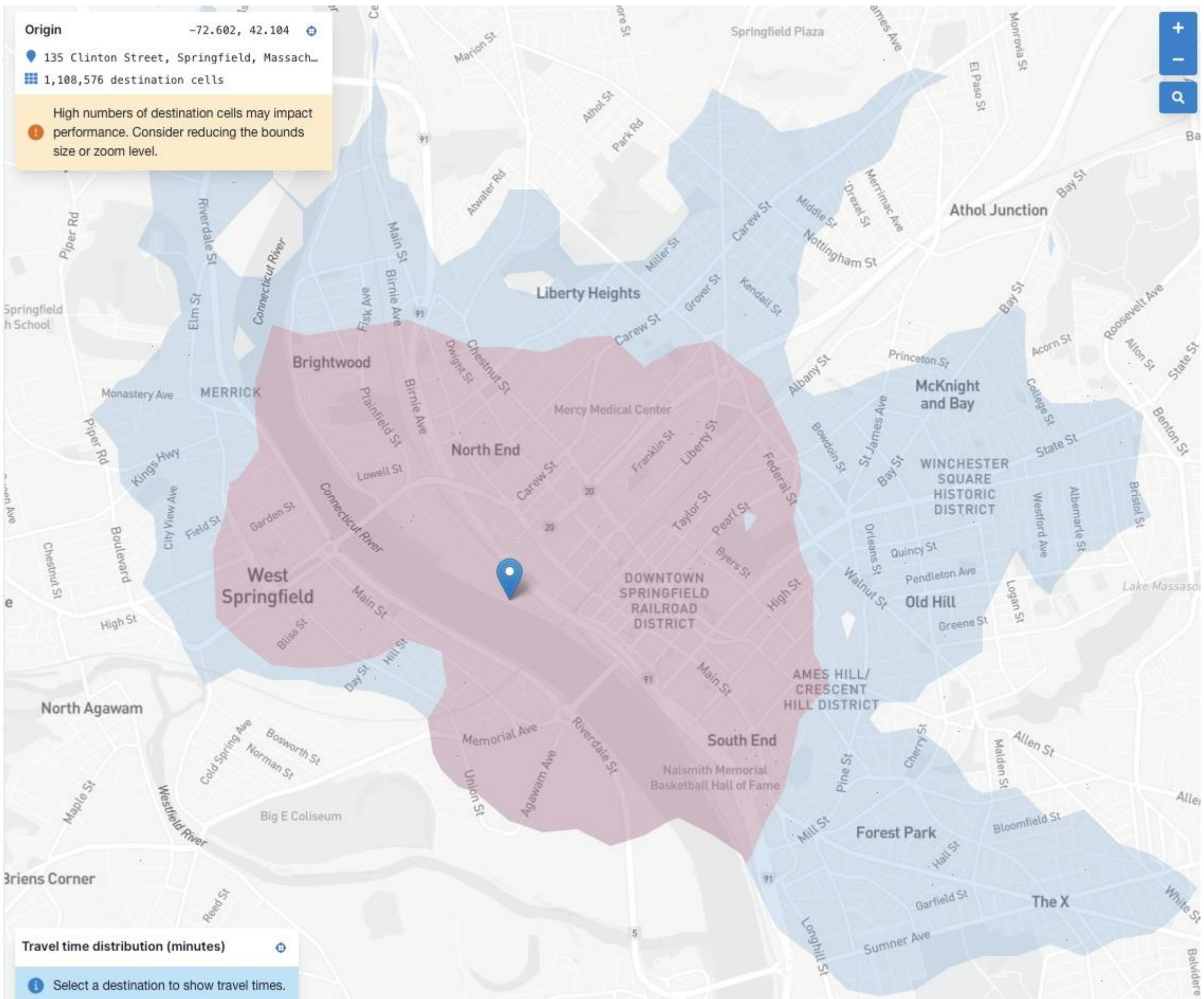

Figure 2.1 Screenshot of isochrones for walking and fixed route transit in Conveyal

The access that is provided by the microtransit service is limited by how far that passenger can travel in the vehicle after the waiting time has been subtracted from the total travel time constraint. In reality, the waiting time and travel time depend on many factors such as the number of vehicles in the microtransit fleet, the number of other people requesting to travel at the same time, and the size of the service area. To measure access for planning purposes, it is more useful to characterize the average or median experience, as shown for fixed route transit (Figure 2.2).

A simple model for microtransit service consists of estimating the maximum distance that can be traveled within the travel time constraint by the average microtransit customer. This requires estimating or calculating the average waiting time experienced by customers, t_w, during which no distance is traveled, and the distance that can be traveled in microtransit with the remaining time. This requires calculating the ratio of the average speed of a microtransit vehicle, v_m, compared to the average speed of a private car, v_c,

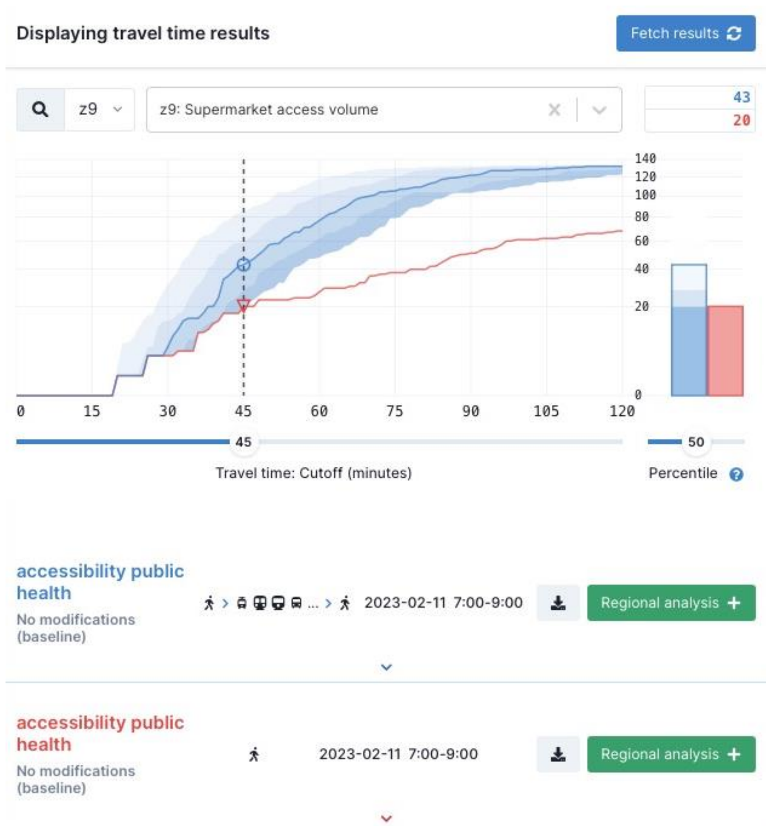

Figure 2.2 Screenshot of cumulative access to supermarkets by walk and fixed route transit (50th percentile) in Conveyal

Figure 2.3 Sequence of events for a microtransit trip

$$\alpha = \frac{v_m}{v_c} \tag{4}$$

where v_m and v_a represent the average speed on the network from origin to destination, including delays for traffic signals, congestion, and any other stops. If a microtransit service operates like a taxi, in which passengers are carried directly from their origins to their destinations without intermittent stops, then $\alpha = 1$. A microtransit service that shares operations among multiple customers would introduce some in-vehicle delays to riders as the vehicle deviates to make additional pick-up and drop-off operations, in which case, $\alpha < 1$.

The values of t_w and α can be calculated for a specific microtransit service based on analysis of individual trip records that include the following attributes:

- Date and time of trip pick-up request – For an advanced reservation, this is the time that the customer requested to be picked up; for a real-time booking, this is the time that the request was submitted
- Date and time of actual trip pick-up
- Location (address or latitude/longitude) of trip pick-up
- Date and time of actual trip drop-off
- Location (address or latitude/longitude) of trip drop-off

The difference between the requested pick-up time and the actual pick-up time represents the waiting time experienced by the passenger. In the event that a vehicle picks up a passenger before the requested time, this is assumed to be 0 minutes of waiting time. The average observed waiting time is a useful estimate of t_w.

The difference between the actual pick-up time and the actual drop-off time is the time that the passenger spent traveling within the microtransit vehicle. This time depends on how far the passenger traveled and whether or not the vehicle made stops to pick up or drop off other passengers en route. An access measure is intended to identify the maximum distance that could be reached by a traveler, whereas the actual trips made can be over shorter distances. In order to quantify how fast microtransit vehicles operate, it is necessary to compare the observed travel time by microtransit to the hypothetical travel time that would have been experienced using a private car. This requires that the origin-destination car travel times are estimated for each observed microtransit trip. Conveyal includes functionality to estimate car travel times for specific origin-destination points, but there are other tools (e.g., Google maps) that perform the network analysis to identify a car's route and expected travel time. The straight-line distance from origin to destination is the same for both the observed microtransit trip and the hypothetical car trip, so it follows from equation (4) that the value of α is the travel time by car divided by the travel time by travel time by microtransit. Therefore, network analysis of the set of microtransit trip records provides an estimated value of α for the service area of interest.

Although Conveyal does not have built-in functionality to model access by microtransit, the t_w and α parameters allow the microtransit isochrone to be calculated as if it were a delayed and slowed car to account for the additional waiting time for pick-up and the detours to serve other passengers. A second constraint is then introduced to limit the reachable area to the spatial extent of the microtransit service area. The true isochrone of the area that can be reached by microtransit is the intersection of the microtransit service area boundary and the estimated distance that can be reached based on t_w and α. If the time constraint of interest is denoted by T, then the modified time constraint used in Conveyal for a car analysis to represent the area that can be reached by microtransit is T_m, which is calculated as:

$$T_m = \alpha(T - t_w) \,. \tag{5}$$

Finally, a combined transit access metric should account for the number of destinations that can be reached by either fixed route transit or microtransit. In locations where there are both fixed route and microtransit operations, it is important not to double count the destinations that can be reached by both services. In many cases, microtransit provides greater access than fixed route such that the reachable points by fixed route transit are a subset of the access provided by microtransit. However, near microtransit service boundaries, there may very well be destinations that can only be accessed by fixed route services. The transit access must be measured by first identifying the specific set of points that can be reached by fixed routes, then identifying the specific set of points that can be reached by microtransit, and finally counting the number of unique points in the union of those two sets. This measure of transit access accounts for the presence of microtransit services and the extent of the boundary. Depending on the granularity of microtransit trip data analysis, the effect of fleet size and crowding on the microtransit system can also be reflected in the access provided by the system, because larger fleets can reduce waiting time for service and more crowding can increase circuity of rides from origin to destination.

2.3.4 Implementing Access Measures

Each of the mode-specific access measures defined above is designed for implementation using Conveyal. The modes and constraints of interest are as follows:

1. Walk Access, adjusted for NWI
2. Bicycle Access, limited to LTS 2
3. Public Transit Access, including microtransit services, where provided
4. Car Access

Expanding on the Phase I study, access is now measured to a variety of destinations that are considered relevant to public health. The following sets of locations (as described in Section

2.2.1.2) have been uploaded as points of interest for Conveyal to quantify access within the isochrones for each mode:

- Supermarkets
- Urgent Care
- Community Health Clinic
- Emergency Rooms
- Colleges and Technical Schools
- Parks

The analysis of access is conducted across Massachusetts for each point on a one-unit Web Mercator grid at zoom level 9 (z9), which is spaced 305.75 meters (0.19 miles) apart. At this scale, access is measured at 216,000 points across the state, providing a high-resolution map of access. The fine spatial resolution allows for aggregation of access measures to larger geographic scales in a way that can account for the variation in access across space. The maps are useful for looking at the specific spatial patterns of access across the state.

In the Phase I study, access measures were evaluated at census block group centroids, because that is the spatial resolution of demographic data. However, the geometric centroid of a block group may not be representative of the average level of access across the area, especially for larger block groups in rural areas. Figure 2.4 shows how the scale of the grid compares with the size of census block groups in the vicinity of Holyoke, Massachusetts. In urban areas, where block groups are small, only a few grid points are associated with a block group and there is not much variation in the level of access. In rural areas with much larger block groups, the level of access can vary significantly within the block group. Rather than measuring access only at the block group's geometric centroid, the access for a block group is now represented by the average of the measured access for all grid points contained within it. The average census block group in Massachusetts contains 43 grid points.

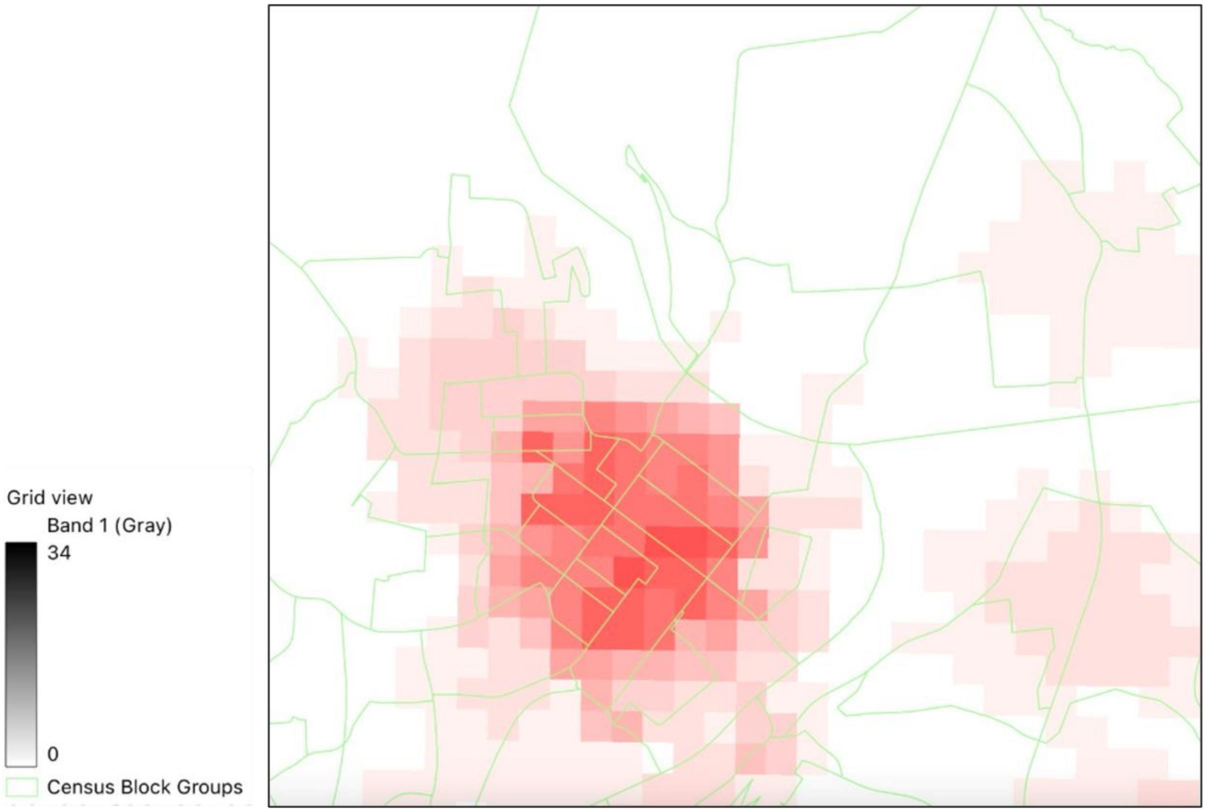

Figure 2.4 Relative scale of Web Mercator Grid z9 and census block groups, Holyoke, Massachusetts

A further level of aggregation is needed to measure access at larger geographic scales, such as municipalities, which is the level at which public health data is available. Although it is possible to simply average the measured access of all grid points within a municipality, this would give equal weight to every location whether it is populated or not. The purpose of analysis to link access measures with demographic and public health data is to make inferences about the effect of transportation access on the people who experience it. Therefore, it is more meaningful to measure access for a municipality as the population-weighted access of each block group within it, because population data is available at the block group level. The result is a measure of access that is representative of the average resident of a municipality rather than the average location. This is important in larger, rural municipalities where the population may be concentrated in a town center rather than outlying farms and forests, and the measure of access that is most related to those residents' experiences would be the access from where people reside. There are 351 municipalities in Massachusetts, so the average municipality contains 14 census block groups and 616 grid points.

2.4 Identifying Access Gaps

A comprehensive perspective is taken to assess the vertical equity among different groups, specifically focusing on the REJ+ group defined by MassDOT. This group highlights all disadvantaged communities impacted by compounded burdens related to transportation access, health, environmental, economic resilience, and social disadvantages. Vertical equity accounts for the fact that different groups have varying needs for access by walk, bicycle, or transit, particularly because groups with restricted access to vehicles depend more heavily on these modes. Linking access measures with demographic data is important for identifying the access gaps that affect these population groups. Two types of analysis are conducted to identify access gaps.

The first approach is to evaluate the equity of access across Massachusetts collectively. As introduced in the Phase I study, the Lorenz curve and Gini coefficient are constructed to evaluate the distributional impact of access across a population of interest. The Lorenz curve is constructed by ranking the block groups from least to greatest measured access, multiplying the measured access in each block group by the population of the block group to create a weighted measure of total access, and then plotting the cumulative total access (vertical axis) against cumulative population (horizontal axis). A line of slope 1 is called the *line of equal opportunity* and would indicate equal access for all individuals, and curvature below that line indicates unequal distribution of access. The Gini coefficient is a quantitative measure of equity calculated by dividing the area between the line of equal opportunity and the Lorenz curve by the total area under the line of equal opportunity. A Gini coefficient of 0 signifies that every individual has equal access, whereas an index of 1 indicates extreme inequity where no community has access except for one community that has exclusive access to infrastructure [55]. In this study, a comparison of accessibility between REJ+ communities and the general communities is conducted to identify the access gap.

The second approach is to map access gaps to identify where they exist. One drawback of the REJ+ designation in Massachusetts is that it is a binary indicator: either a block group is categorized as an REJ+ community, or it is not. The result is that about 45% of the population of Massachusetts live in an environmental justice community. It would be useful to account for the size of the disadvantaged population in each block group so that the relative need can be compared across communities. For the purposes of transportation access, two dimensions of REJ+ criteria are likely the most important indicators of reliance on non-car transportation modes for meeting critical needs: low-income population and population in zero-car households, which are available from the U.S. census at the block group level. In this context an access gap is defined as either the number of people with income below the poverty level or the number of people in zero-car households that cannot access a supermarket or health care provider by walking or transit. This allows access gaps to be revealed in places that may not meet percentage thresholds to count as an REJ+ community but where a significant need exists.

2.5 Modeling Access and Public Health Outcomes

The goal of this study is to capture the relationship between different forms of accessibility and public health outcomes, such as diabetes, heart disease, and obesity, aligned with a previous MassDOT project focused on incorporating health outcomes in project prioritization [2]. The literature that currently exists on geographic modeling patterns related to transportation typically uses statistical models such as machine learning techniques and linear regression [56, 57]. As shown in Figure 2.5, the purpose of this study is to determine what kinds of access significantly affect public health and how the relative importance of these types of access differs geographically among towns. Knowing these differences helps to decide where and what kinds of infrastructure should be built to ensure fair access and enhance public health results, thus contributing to bettering communities. Including demographic data ensures that we consider population heterogeneity and capture additional key variables influencing health. For instance, the proportion of low-income and zero-vehicle households identifies disadvantaged groups who might find it difficult to obtain basic needs including food and healthcare [58]. Age is also highly related with the diseases investigated in literatures [59, 60, 61].

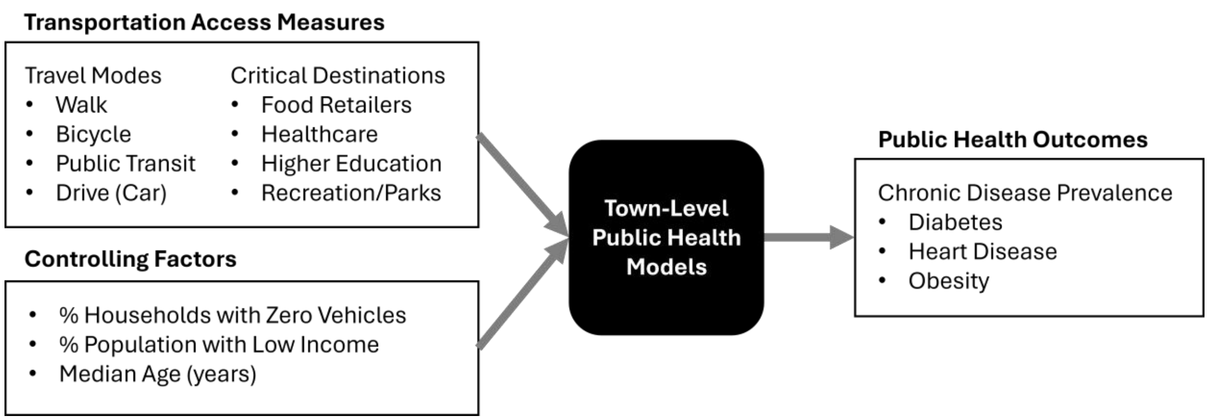

Figure 2.5 Framework for modeling access and public health

The independent variables representing different types of access exhibit some degree of multicollinearity. Therefore, we first adopted ridge regression as a representative linear regression model in place of ordinary least squares (OLS) to model public health outcomes. Unlike OLS, which assumes that independent variables are linearly independent, ridge regression introduces a small L2 regularization penalty to stabilize the regression estimates. This reduces variance substantially without sacrificing much interpretability [62]. While it is technically possible to eliminate regressors to address multicollinearity, we chose not to specify a reduced-access model that includes only a limited set of access types. This is because of our goal of capturing the full range of travel options and opportunities that people can access within an interval of time that has been scientifically defined, considering their physical mobility patterns and lifestyles. Causal inference and OLS-based model selection are inappropriate in this situation because of the complex interactions between these choices that affect health outcomes [63]. The model's performance is evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

Machine learning techniques are increasingly used in supervised learning settings to uncover indirect and non-linear relationships between access and geographic information. For example, in Phase I of this study, a gradient boosting model was employed to link food access with demographic and socioeconomic explanatory variables [12]. In this second phase, we model the non-linear relationship between independent and dependent variables in this phase using Geographically Weighted Random Forest (GWRF). Specifically, GWRF is a local, non-parametric spatial machine learning technique that uses observations from the *n* closest towns to capture local variation while fitting a random forest model at each location in the studied area [64, 65]. The model's performance, as well as the deviation in local variable importance, is evaluated to assess spatial heterogeneity. Spatial non-stationarity is revealed through differences in the importance of predictors across locations.

Algorithm 1 (Appendix B) presents the pseudocode of the GWRF model. GWRF determines the optimal number of neighbors for each local Random Forest (RF) model by minimizing the sum of local RMSE values. A Gaussian kernel is employed to effectively capture spatial patterns, assigning higher weights to observations that are spatially closer to the target location, i.e., nearby observations have a greater influence on the local model than those locations that are further away. A smaller bandwidth leads to larger variance in local estimates, while a larger bandwidth leads to larger bias.

The model's performance is evaluated using metrics consistent with those used in ridge regression, enabling direct comparison of two modeling approaches. A key output of GWRF is the estimation of local feature importance via Shapley Additive Explanations (SHAP) values, which reveal how the contribution of each predictor varies across space and help identify locations that are most sensitive to changes in specific variables. Specifically, SHAP provides an equitable, symmetric, and consistent solution that accounts for the marginal contribution of each feature [66, 67].

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3.0 Results

The results of this research are presented in five parts. First, three subsections present the access measures developed for walking, bicycling, and transit/microtransit services, as described in Section 2.3. An interactive version of the maps presented in this section is available online:
https://experience.arcgis.com/experience/79d94b86eedd456da5ebec901e7df41b/

3.1 Walk Access with Walkability

Measurement of walk access begins with walkability. The NWI at each block group is obtained from the EPA as shown in Figure 3.1 with the full gradation of colors representing the numerical value of the NWI score. As expected, the NWI score is highest in densely populated urban areas and lowest in sparsely populated rural areas. Many suburban communities are also below average walkability. Of the 6.8 million trips that are modeled in Replica for a typical weekday, 14.6% are completed by walking, but these are not uniform across the state. Figure 3.2 shows the percentage of trips in each block group that are completed by walking. Not surprisingly, the walking mode share is higher in urban areas and lower in rural areas in a pattern that shows correlation with the NWI score.

Modeled trip data from Replica have also been extracted and analyzed by trip distance. For very short trips, less than 0.5 miles, almost all trips are completed by walking. The walking mode share quickly drops as the trip length increases with a very low share of trips longer than 3 miles. As discussed in Appendix A, the direction of causality between trip length and walking mode share is ambiguous. To some extent urban areas allow people to reach critical destinations within shorter distances, so walking is a more viable mode choice. Likewise, for people who do not have access to a car, walking may be the most readily available and therefore, trips are limited to the distance that can be walked.

Grouping Replica trip data by NWI category, the mode share by walking is plotted against trip length in Figure 3.3. The higher curve associated with higher NWI scores indicates that more people are willing to walk longer distances in more walkable communities. The curves for the least walkable and below average walkability nearly overlap indicating that walking behaviors do not differ significantly across all NWI values below the average. All of the curves also converge to near zero mode share for distances above 2.5 miles.

The population weighted average NWI in Massachusetts is 11.27, which falls into the above average walkability category by the national ranking. Figure 3.3 shows that 20% of trips of length 1 mile are completed by walking, compared to 1.6 miles for the same walking mode share in above-average NWI regions. The same walking mode share applies to a trip distance of only 0.65 miles in the below-average NWI regions. These ratios are used to proportionally increase or decrease the travel time constraint in Conveyal for measurement and mapping of walk accessibility across Massachusetts. Figure 3.4 shows how changing the NWI category changes the relative walk access isochrone from a point in Great Barrington, Massachusetts.

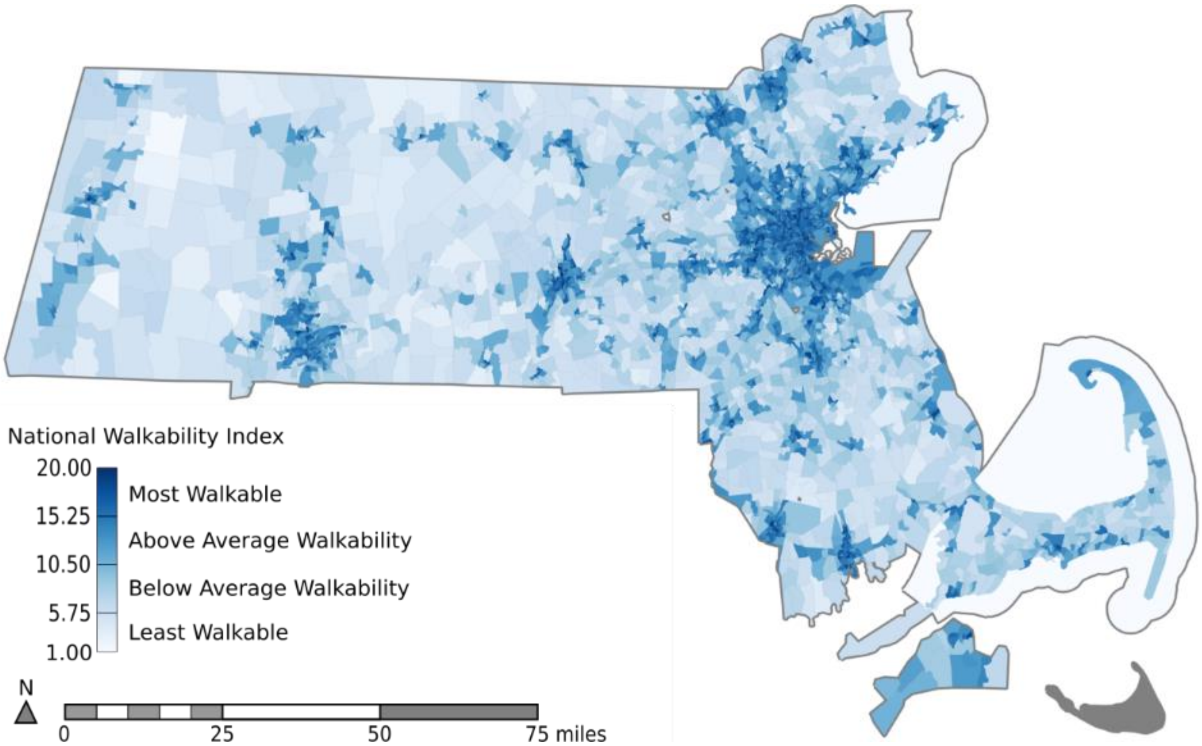


Figure 3.1 National Walkability Index (NWI) by census block group in Massachusetts

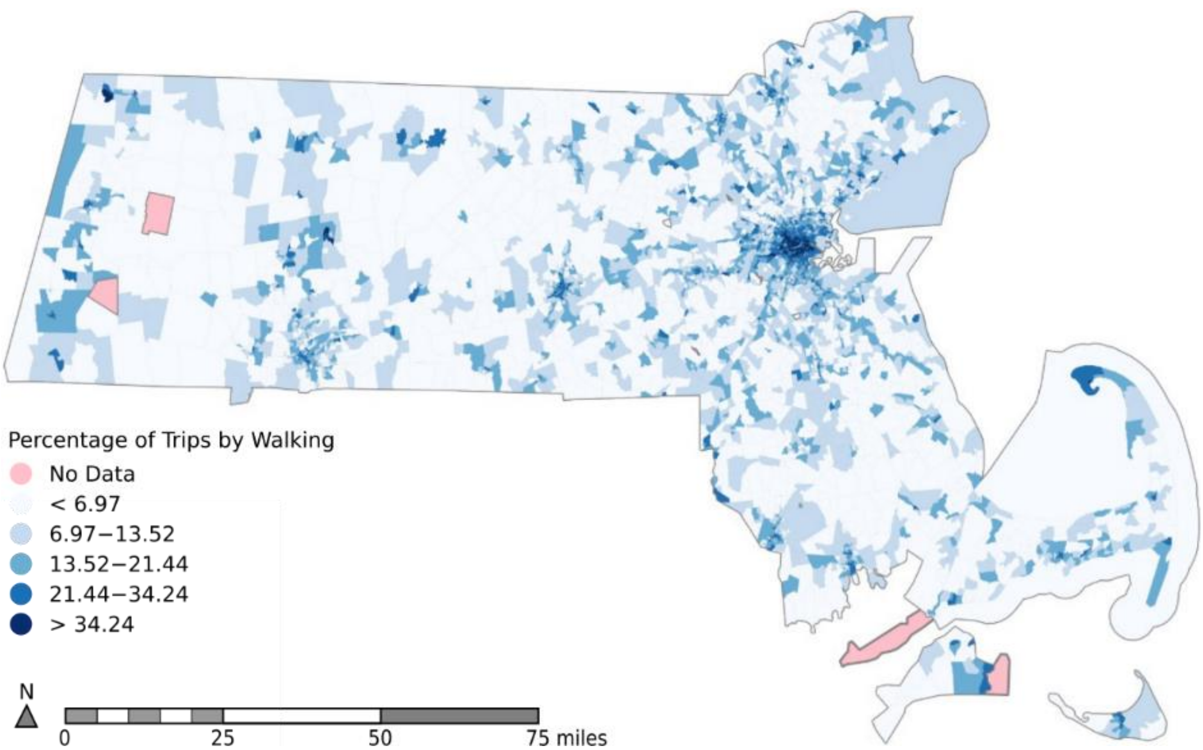


Figure 3.2 Percentage of trips by walking in Massachusetts

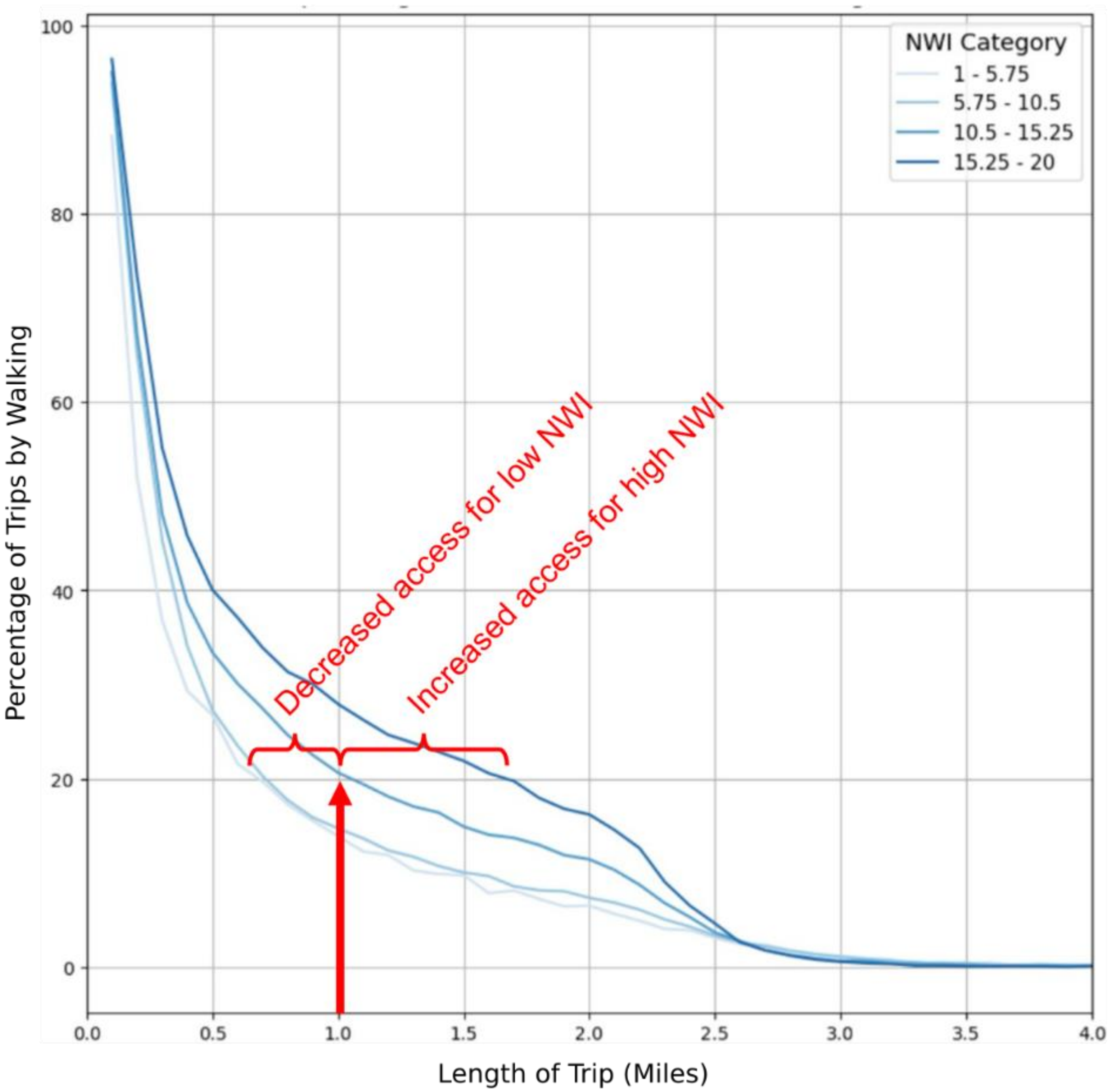


Figure 3.3 Mode share by trip distance for each NWI category

A more walkable environment makes longer walking distances as accessible as shorter distances in less walkable environments. This access measure accounts for factors like infrastructure and land use that make a community more walkable so that the effect of investments on walk access can be measured.

Maps of the NWI-adjusted walk access measure on the unit Web Mercator Grid Zoom Level 9 (Z9) are included in Appendix C for access to supermarkets, urgent care facilities, community health centers, emergency room facilities, colleges and technical schools, and parks.

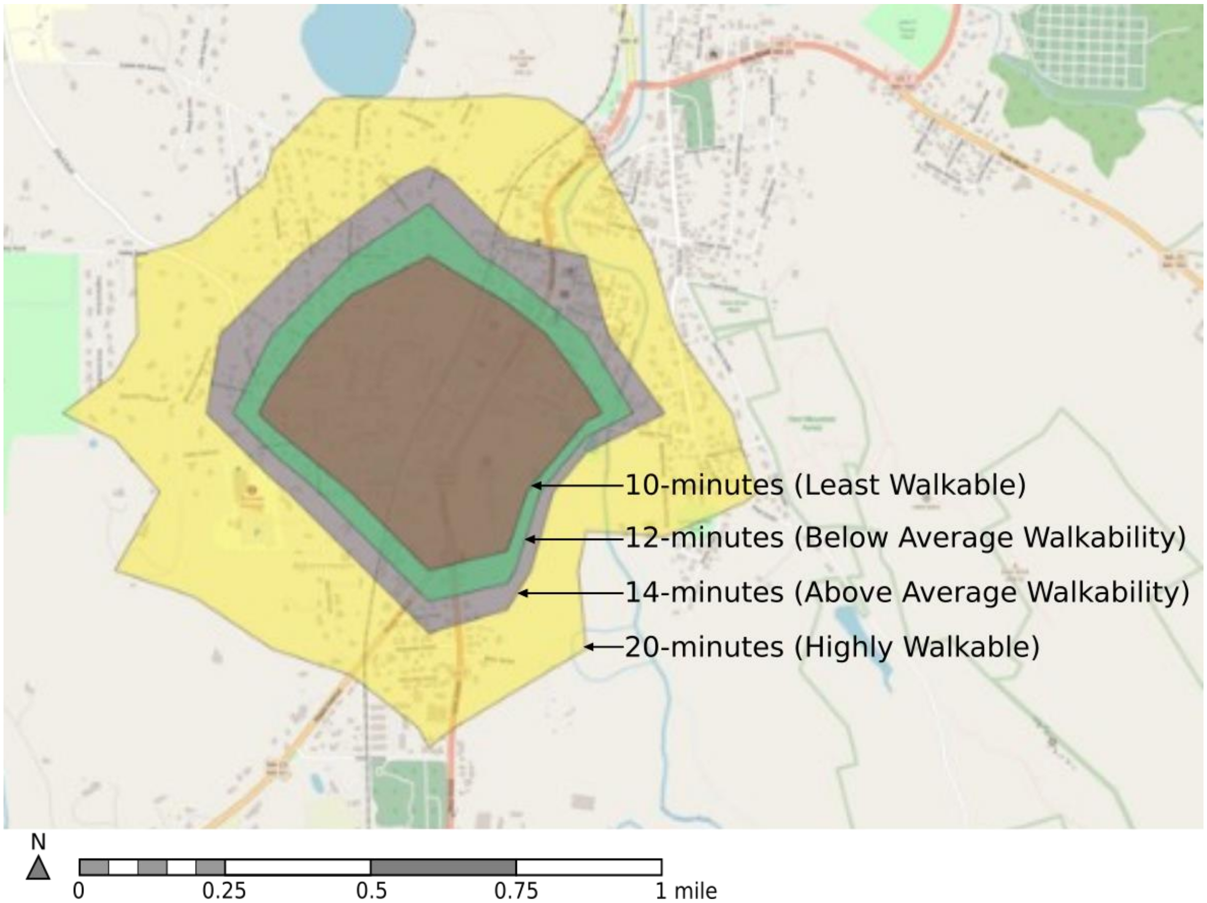


Figure 3.4 Example comparison of NWI-adjusted walk access isochrones from a point in Great Barrington, Massachusetts

3.2 Bicycle Access with LTS

Bicycle access is measured based on a travel time constraint and limiting travel paths to a maximum LTS. For the purposes of this study, a limit of LTS 2 is used, because this corresponds to the preferences and attitudes of the majority of potential cyclists. Using the method described in Section 2.3.2, each link on the road or bicycle network in Massachusetts is classified by a LTS value as shown in Figure 3.5. A view of Boston (Figure 3.6) shows more clearly how each link of the network is classified and how the designation can vary from one block to the next depending on bicycle infrastructure treatments, lane configurations, speed limits, and AADT. These figures show that every road and bicycle network link across Massachusetts are included in the LTS analysis, and that the designation can vary from block to block to provide a high-resolution representation of the network that can be used for bicycle access with an LTS constraint. An interactive version of this map and access to the shapefile with the LTS designation for each link is available online at: https://umass-amherst.maps.arcgis.com/apps/dashboards/3aa28477a7c74dde9ca481150be1702a.

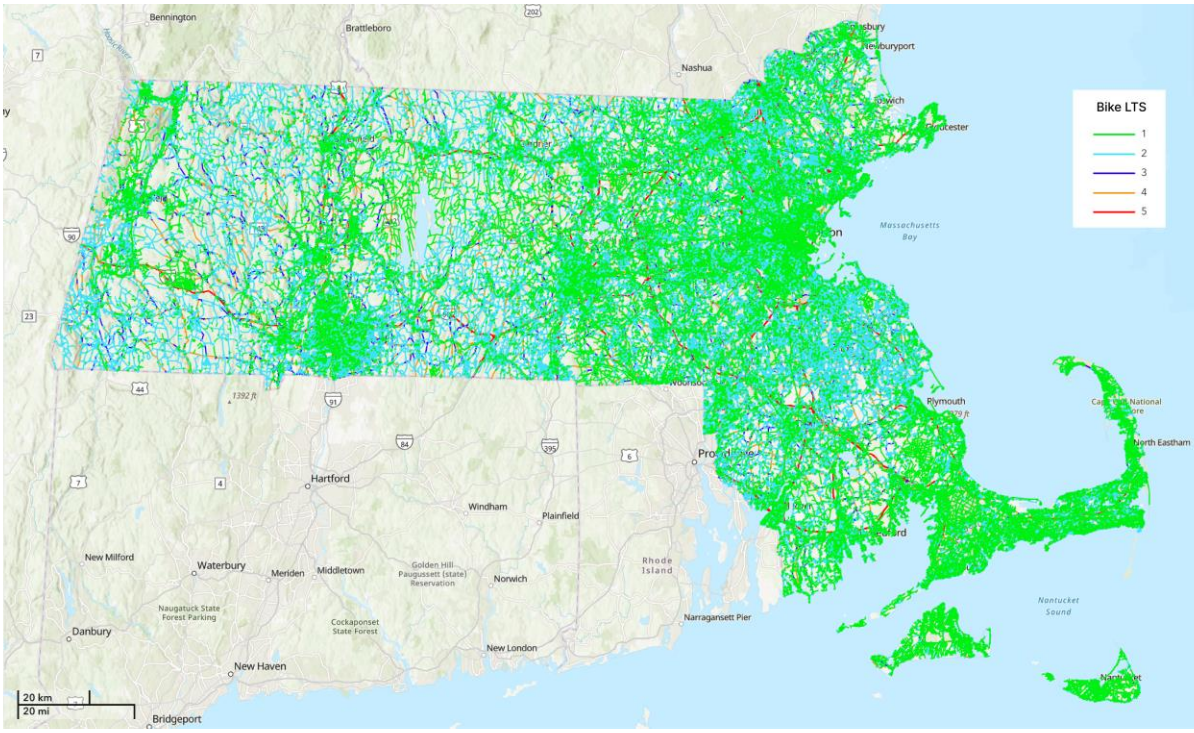


Figure 3.5 Bike LTS map of Massachusetts

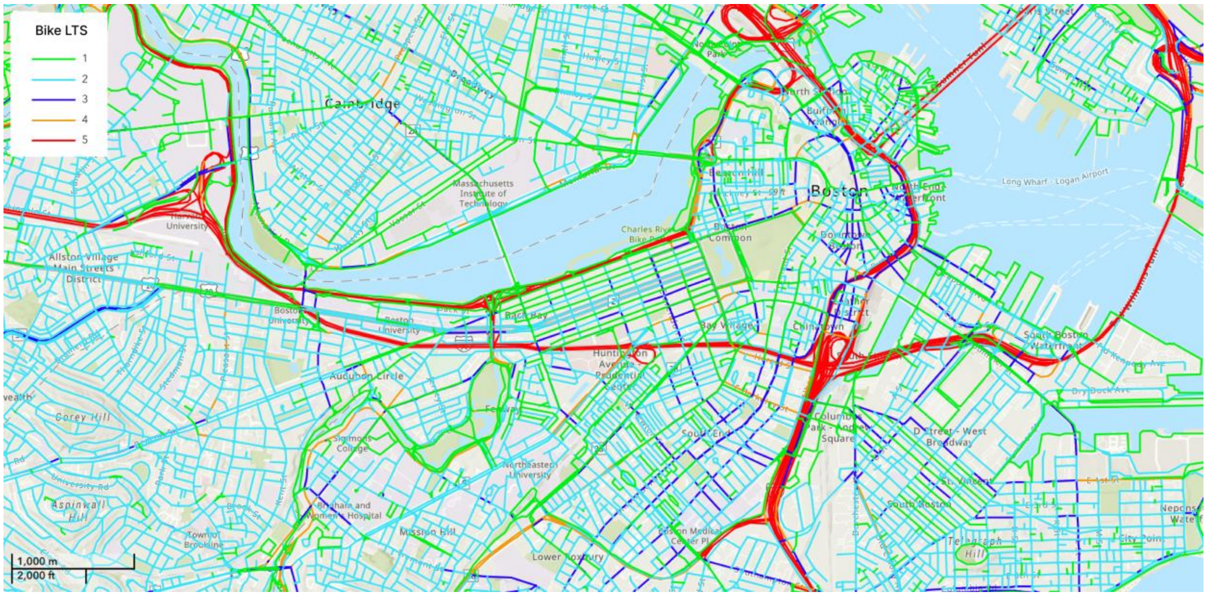


Figure 3.6 Bike LTS Map in Boston, Massachusetts

Maps of the LTS-limited bicycle access measure on the unit Web Mercator Z9 are included in Appendix C for access to supermarkets, urgent care facilities, community health centers, emergency room facilities, colleges and technical schools, and parks.

3.3 Transit Access with Microtransit

Fixed route transit services in Massachusetts are run by the MBTA and 15 RTAs. As described in Section 2.2, the stops, routes, and schedules are coded in the GTFS format, which is the basis for transit access analysis in Conveyal. Fixed route transit routes are supplemented by microtransit services. Operational details for 10 microtransit services are listed in Table 3.1. The spatial coverage of fixed transit routes and microtransit services across Massachusetts are shown on the map in Figure 3.7.

The access provided by microtransit services is modeled using the method described in Section 2.3.3. Three months of trip record data, from February through April 2024, were provided by the SCC (centered in Great Barrington, Massachusetts, shown as the light blue service area in Figure 3.7) and the QC (centered in Ware, Massachusetts, shown as the brown service area in Figure 3.7). These services operate in sparsely populated rural parts of Massachusetts that otherwise have limited fixed route transit service. Data for the SCC reveal that, on average, passengers experience a waiting time of $t_w = 5$ minutes and the relative speed of microtransit is $\alpha = 0.8$ times the speed of private cars.

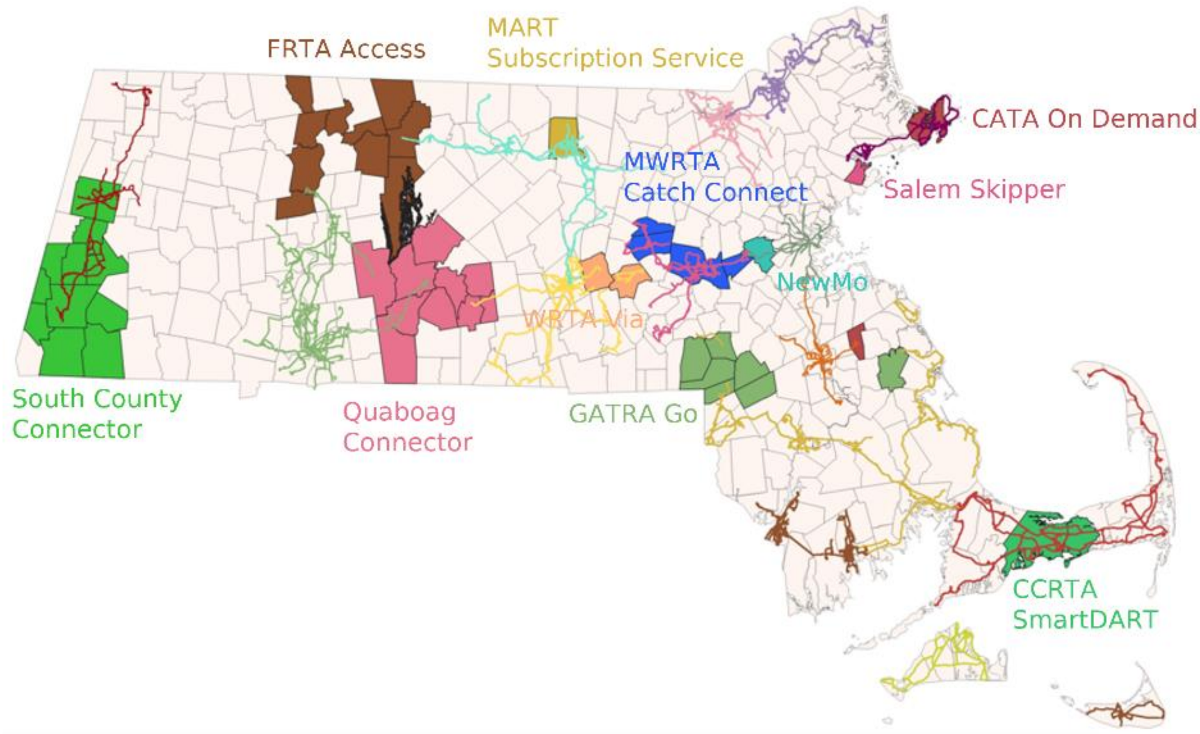


Figure 3.7 Microtransit service areas and fixed transit routes in Massachusetts

Table 3.1 Summary of microtransit services in Massachusetts

Service name	Service hours	Price($/trip)	Waiting time	Website
CATA On-Demand	M-F 7:30am-8pm	2	/	https://canntran.com/cataondemand/
FRTA Access	M-F 5:30am-7:30pm S-S 9:30am-5:30pm	within zone 3 between zone 4	30min	http://frta.org/getting-around/frta-access-program/
GATRA GO	Coastline, Explore:7am-5pm; Seacoast: M-F 7:30-5:30pm, Sat 9-5pm, Sun 12pm-5pm; United: M-F 6:30-8pm, Sat 9-8pm, Sun 12pm-6pm	2 (United and Seacoast) 0 (Coastline and Explore)	/	https://www.gatra.org/gatra-go/
NewMo	M-F 7am-6:30pm S-S 9am-12pm for seniors	3 for Seniors 1 for low-income residents 4 other users	30 min before 12 noon; 45 min in afternoon	https://www.newtonma.gov/government/seniors/transportation
MART Subscription Service	/	Monthly base	up to 20 min	https://www.mrta.us/service/
Salem Skipper	M-Thur 7am-10pm, F 7am-12am, Sat 10am-12am, Sun 10am-8pm	2 before 7pm, 3 after 7pm, 1 for senior	/	https://www.salemma.gov/mobility-services/pages/salem-skipper
CCRTA SmartDART	M-Sat 7:30-6pm	3	/	https://capecodrta.org/schedules-services/smartdart/
CATCH Connect: MWRTA	M-F 6:45am-6:45pm Wellesley S-S 8am-6pm Framingham/Natick M-F 6:45am-6:45pm, Sat 8am-6pm Hudson	2	/	https://www.mwrta.com/catch
Via - WRTA	M-F 7am-7pm	2	/	https://therta.com/demand-response/via/
SCC	M-F 6am-9pm S-S 7:30am-8pm	2 within one town; 4 between towns. Discounted tickets for seniors (60+)	/	https://www.tritown.org

The implementation of the microtransit access model is illustrated for an example point in Stockbridge, Massachusetts (Figure 3.8). The median isochrone for 30 minutes by fixed route transit is shown in dark blue, and reaches only a small area because fixed route transit service is so limited given the long headways. The locations of supermarkets are shown by triangles, and there are no accessible supermarkets by fixed route transit. For comparison, the accessible isochrone for 30 minutes by car is shown in pink and allows 23 stores to be reached. The isochrone for 30 minutes by microtransit is modeled using Equation 5 with $t_w = 5$ minutes and $\alpha = 0.8$ to obtain $T_m = 20$ minutes. This is the yellow area, which is smaller than the pink area corresponding to access by car with $T = 30$ minutes. Finally, the South County Connector (formerly, Tri-Town Connector) is limited to the service area defined by the nine municipalities shaded light blue. The area that can be reached within the microtransit isochrone and that is within the service area includes 15 supermarkets.

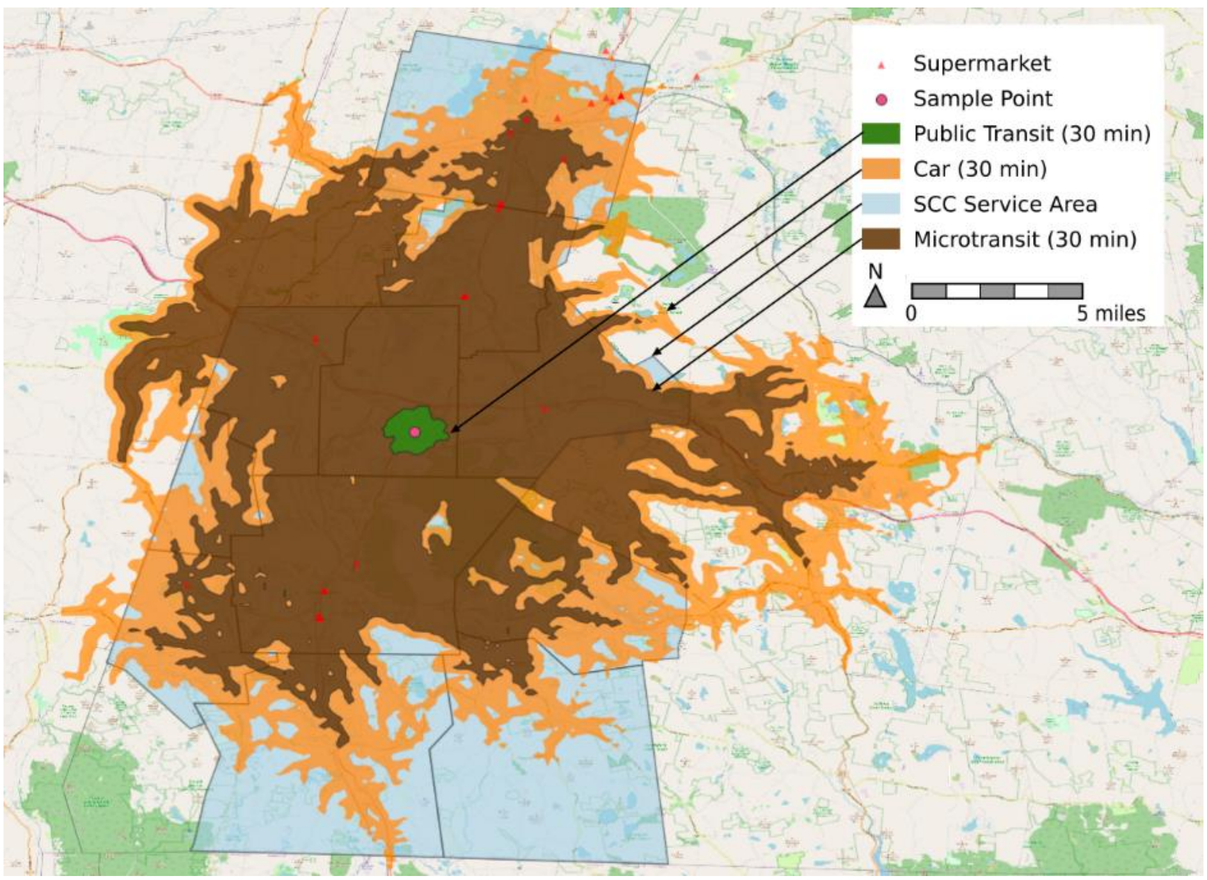


Figure 3.8 Comparison of isochrones for car, fixed route, and microtransit from Stockbridge, Massachusetts

Maps of the combined fixed route and microtransit access measures for public transit on the unit Web Mercator Z9 are included in Appendix C for access to supermarkets, urgent care facilities, community health centers, emergency room facilities, colleges and technical schools, and parks.

3.4 Access Gaps and Demographics

3.4.1 Equity Analysis

The first analysis of access gaps and demographics is a statewide evaluation of equity using Lorenz curves and Gini coefficients. In Phase I, access was compared across all census block groups in Massachusetts. Using the revised access metrics, aggregated to census block groups, Figure 3.9 shows the Lorenz curves and Gini coefficients for access by walking, transit/microtransit, and driving. To make a fair comparison between modes, a limit of 45 minutes was used for transit access, with an additional NWI-adjusted constraint of 15 minutes maximum walking time to reach the nearest transit stop. The results show that access is more equitable statewide by driving than by other modes. It is observed that 58.39% of the population is unable to reach a supermarket within an NWI-adjusted walking distance, while 55.47% cannot access one within an NWI-adjusted transit distance trip. Figure 3.10 shows a comparison of the Lorenz curves with only fixed-route transit and a combined system or fixed-route and microtransit.

To account for potential inequities for people who do not have access to a car, this study focuses on comparing equity by transit and walking modes for REJ+ communities versus the general population.

Table 3.2 shows the Gini coefficients for NWI-adjusted walk access among census block groups designated as REJ+ communities versus the statewide data. A high Gini coefficient represents greater inequity, so walk access is actually greater in magnitude and slightly more equitable among REJ+ communities than that statewide trend. This is likely because urban areas are more likely to be classified as REJ+, and these locations also tend to be more walkable. However, this raises concern, because there are low income and zero-car households in non-REJ+ block groups. These populations are vulnerable to limited transportation access regardless of their neighbors' socioeconomic characteristics.

3.4.2 Access Gap Analysis

There are many suburban and rural parts of Massachusetts that have low access when measured in absolute terms (see maps in Appendix C), but for planning and policy analysis it is more important to identify where vulnerable populations experience a lack of access to critical destinations that can affect quality of life and wellbeing and overall health outcomes. As described in Section 2.4, this study focuses on the people with incomes below the poverty line and zero-car households as particularly vulnerable population groups. These include people for whom the cost of making a car trip may be prohibitively expensive or not possible, and therefore, these individuals are more likely to rely on non-car modes to meet critical transportation access needs.

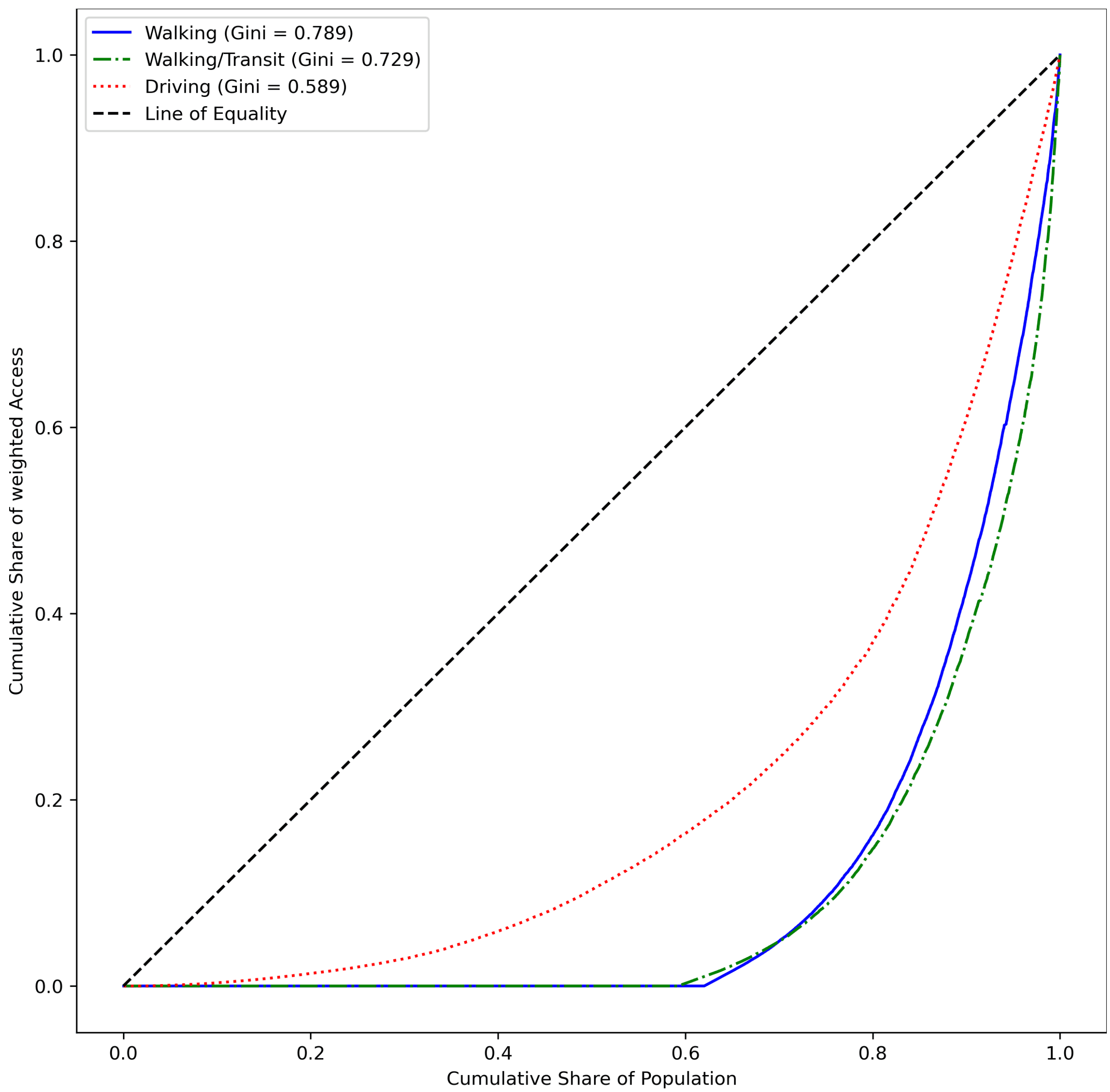


Figure 3.9 Lorenz curves for supermarket access in Massachusetts

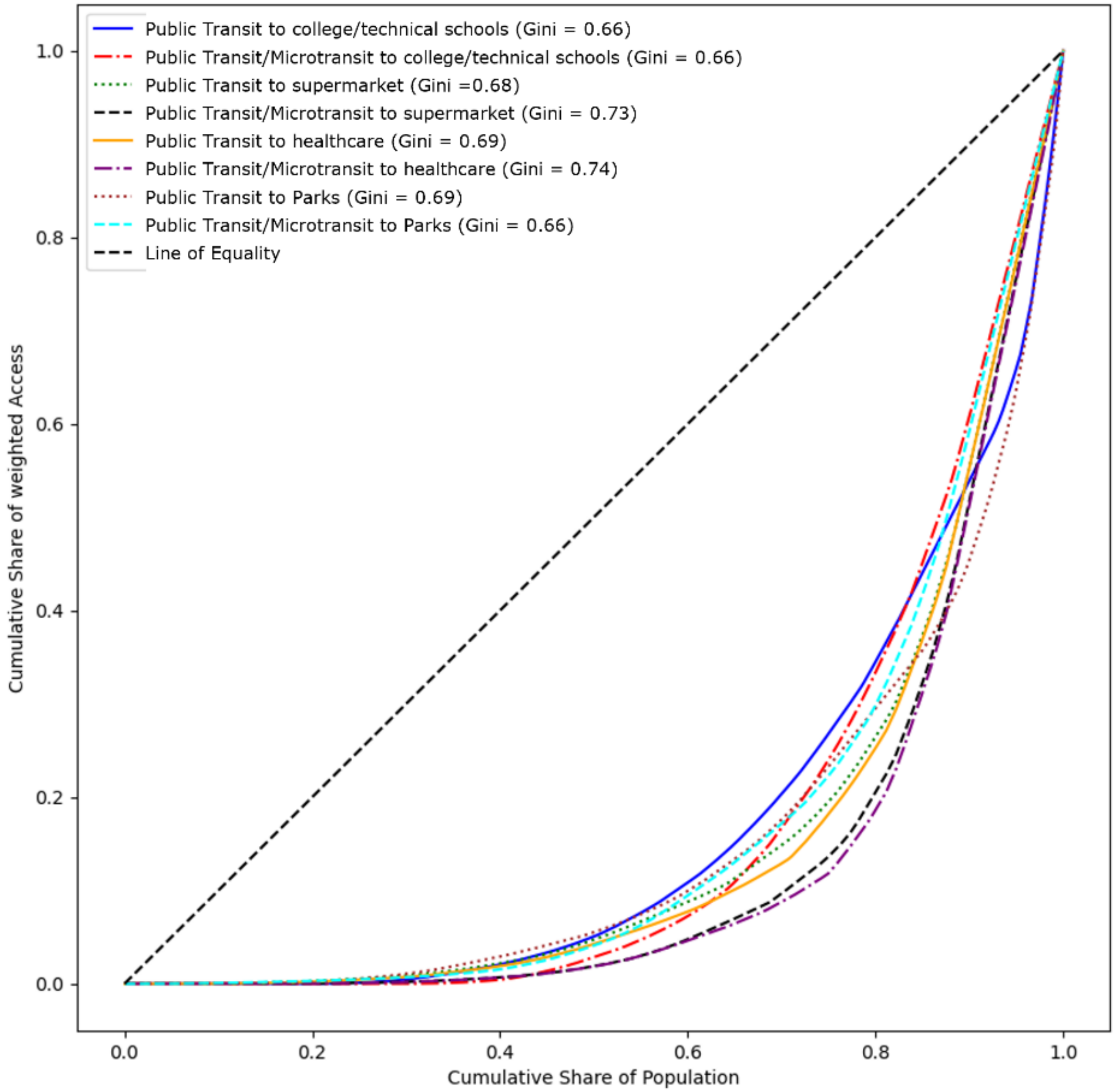


Figure 3.10 Comparative Lorenz curves of public transit and microtransit accessibility in Massachusetts

Table 3.2 Walking access equity for REJ+ and general population

Destination Type	Average Access for REJ+ Block Goups	Gini Coefficient for REJ+ Block Goups	Average Access for All Block Groups	Gini Coefficient for All Block Groups
Supermarket	3.644	0.644	2.039	0.789
Urgent Care	0.116	0.893	0.087	0.926
Community Health Center	0.457	0.813	0.275	0.904
Emergency Room	0.078	0.930	0.067	0.956
College or Technical School	0.043	0.960	0.024	0.976
Park	0.052	0.954	0.053	0.958

Considering transit or walk access, Figure 3.11 shows each census block group in Massachusetts for which there is no access to any supermarket (green), no access to any healthcare provider (red), or no access to either a supermarket or healthcare provider (blue) within 15 minutes. A closer look at the populations of each of these block groups shows that a significant percentage of the REJ+ population has access to a supermarket or healthcare provider by walk or transit (Table 3.3). Note that only the most urban areas provide access to both supermarkets and healthcare for individuals without access to a car. The map also shows the REJ+ block groups with black shading, and many of the locations without access are located outside of the designated REJ+ communities.

These access gaps are linked to the two types of data on the size of the vulnerable populations. Figure 3.12 shows for each block group that has no access to a supermarket or healthcare provider by walk or transit the number of people with income below the poverty level. A darker shade of blue indicates a larger size of the vulnerable population. Red shaded block groups are the REJ+ communities. Note that many dark blue block groups indicate a high number of people in poverty even in places that are not designated as REJ+, perhaps because the total population is high enough that the population in poverty does not exceed that required threshold for REJ+ designation. Likewise, Figure 3.13 shows the number of households with no car available for each block group.

Together, the maps show that the REJ+ designation, alone, does not represent the locations where there are relatively large numbers of people who are vulnerable to a lack of transportation access. The maps show that for the populations that are most likely to have difficulty using a car, either because of affordability or availability, there are communities with demonstrated need outside of the largest urban core areas. The lack of fixed route transit service outside of larger urban areas puts many of these users at a distinct disadvantage, because the distances required to reach destinations are far and there are not adequate alternatives for walking or using transit safely and effectively to get there.

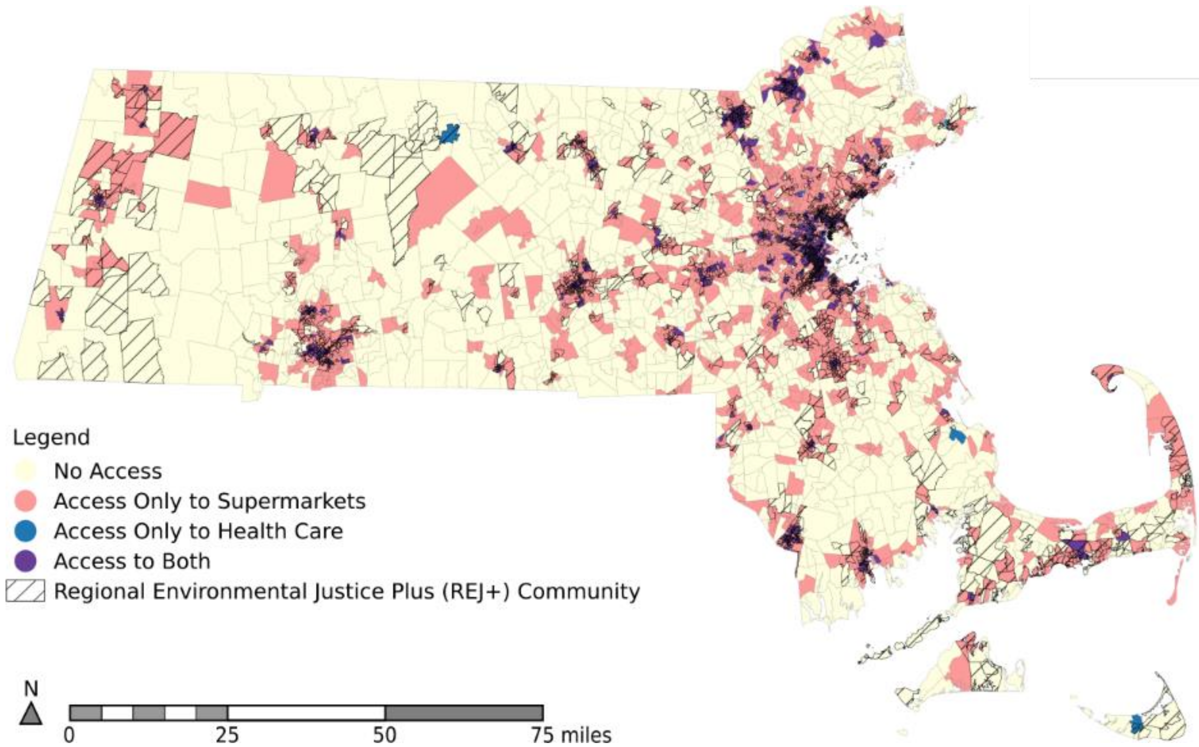


Figure 3.11 Block groups without access to a supermarket and/or a healthcare provider by transit or walking in Massachusetts

Table 3.3 REJ+ and Non-REJ+ populations with access to critical destinations

Destination Type	% of REJ+ Population	% of Non-REJ+ Population
Food & Healthcare	20.7%	29.9%
Only Food	24.0%	28.9%
Only Healthcare	32.8%	33.0%
No Access	22.5%	8.3%

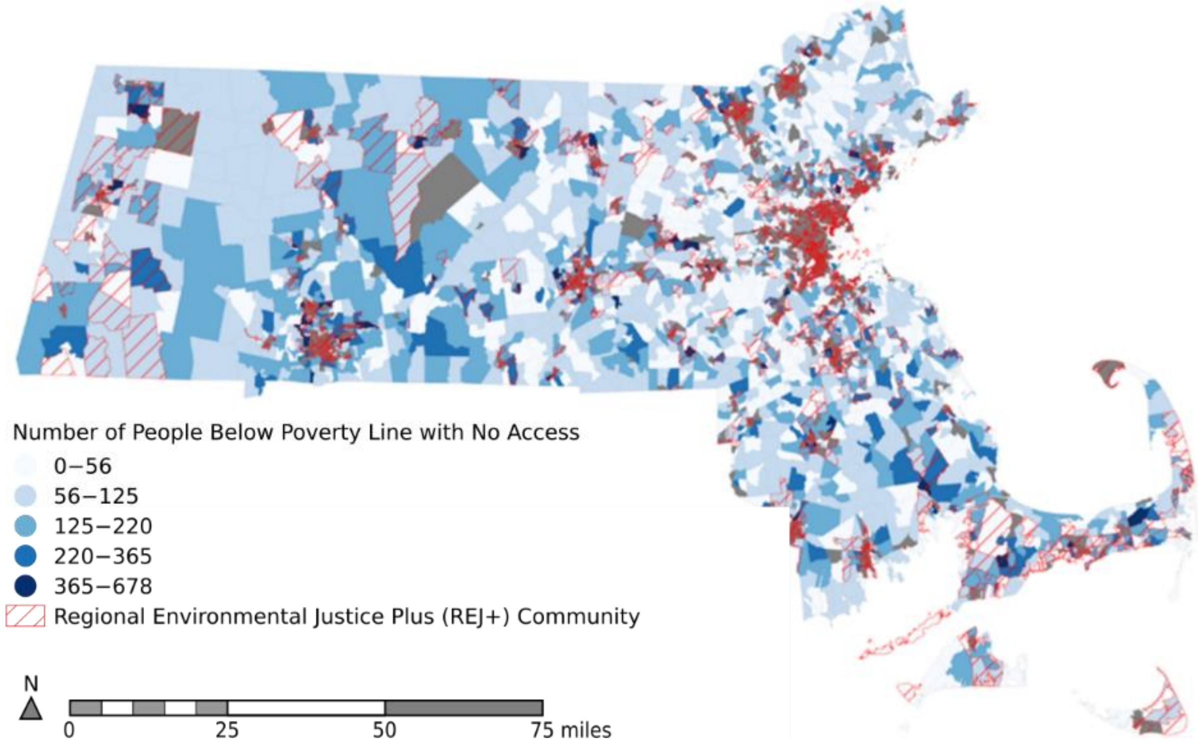


Figure 3.12 Number of people with income below poverty level that have no access to supermarkets or healthcare

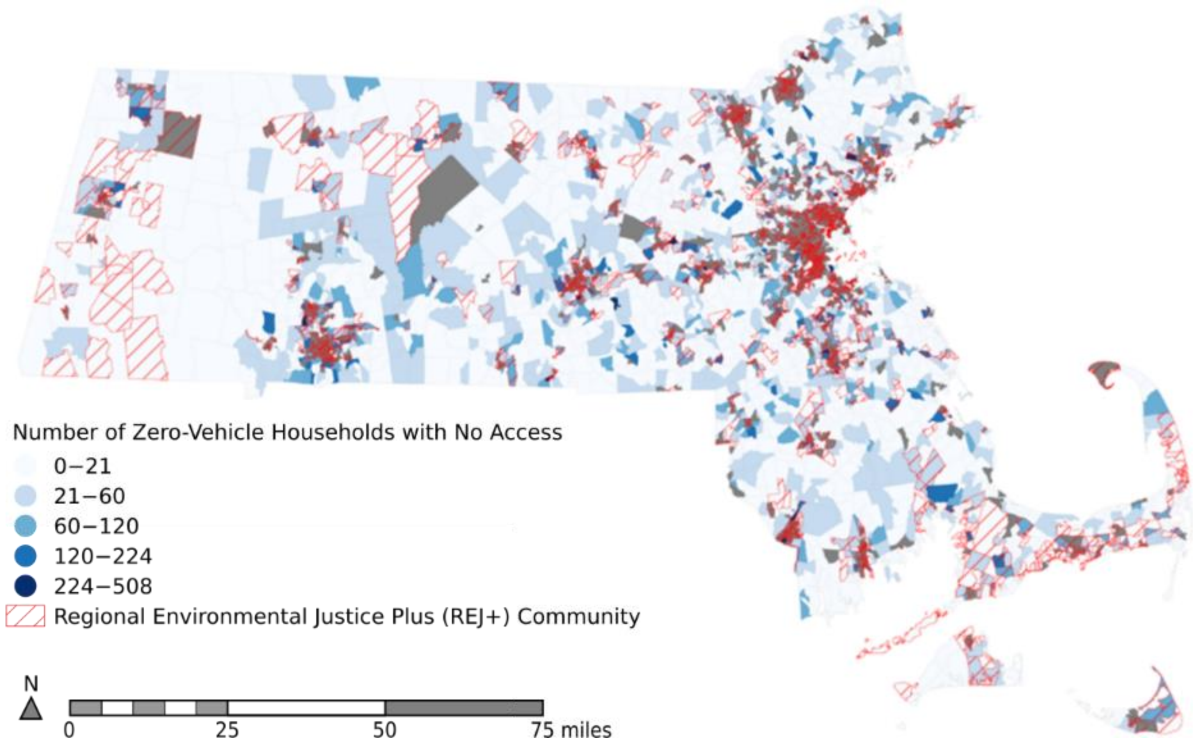


Figure 3.13 Number of zero-vehicle households that have no access to supermarkets or healthcare

3.5 Access and Public Health Outcomes

The final analysis for this study focuses on linking access measures with public health outcomes. Understanding this connection is the motivation of the study, which is to identify measures of transportation access that are associated with public health. The hypothesis is that spatial disparities in public health across Massachusetts can be at least partially explained by disparities in transportation access. Models that quantify this relationship and predict public health outcomes from access measures can be used as a tool to plan and assess transportation system investments that affect access and therefore have an impact on public health outcomes.

There are three public health outcomes that are considered to be closely associated with lifestyle [2], and these are the focus of this study because it is believed that these diseases and conditions are most closely associated with access to healthy foods, regular preventative healthcare, and physical exercise [68, 69]:

- Diabetes
- Heart Disease/Hypertension
- Obesity

There are truly many interacting factors that affect whether a particular individual will develop one or more of these conditions, but the purpose of this study is to step back and investigate larger community-wide trends. As explained in Section 2.5, the approach is to build models to link disease outcomes as the dependent variable to demographic and transportation access measures as the independent variables. Since community health data is provided at the municipality level, demographic data is evaluated at the municipality level and access measures are aggregated by a population-weighted average of the block groups within each municipality.

Three important socioeconomic independent variables are considered for all models. The median age of the population varies considerably across the state, as shown in Figure 3.14. Younger populations are concentrated around college towns, such as Amherst and Williamstown, whereas senior populations are more prevalent in the Berkshires and Cape Cod. Income is measured by the poverty rate, as shown in Figure 3.15. Although the poverty rate tends to be higher in urban areas, there are populations with low incomes in rural areas, particularly in the western part of the state. The third variable is household vehicle ownership (Figure 3.16), which indicates the share of the population that has limited access to a private vehicle at home.

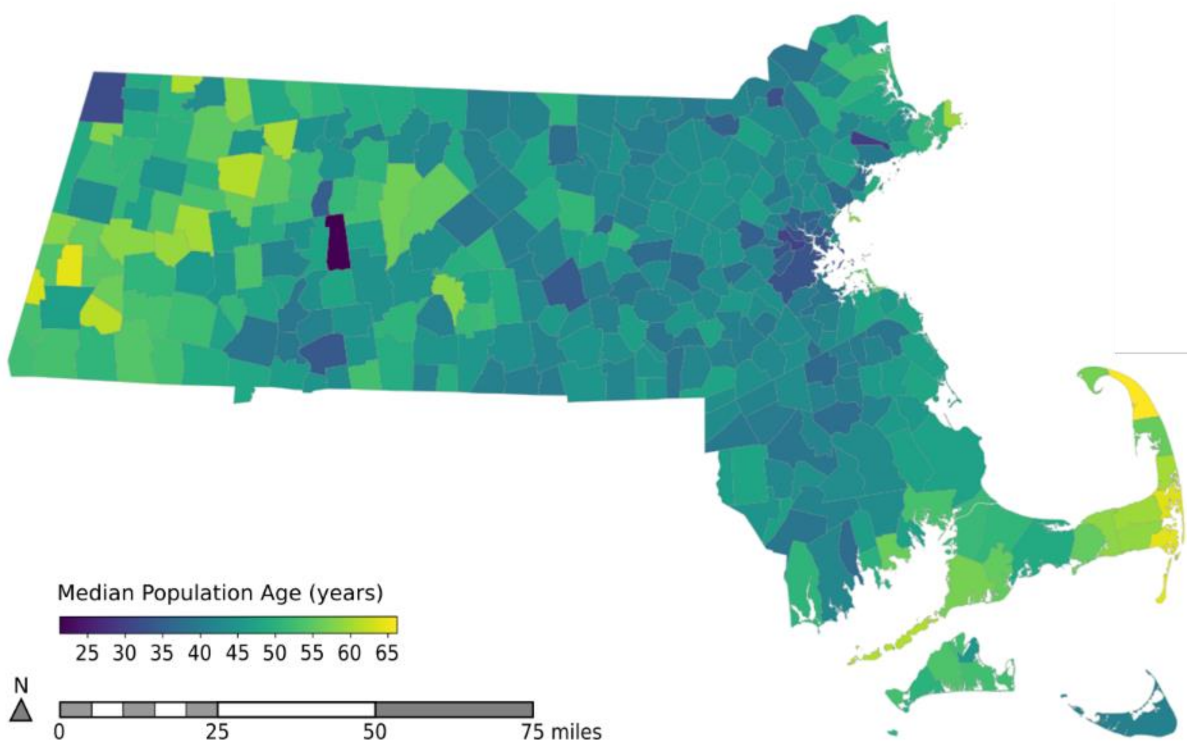


Figure 3.14 Median age by municipality in Massachusetts

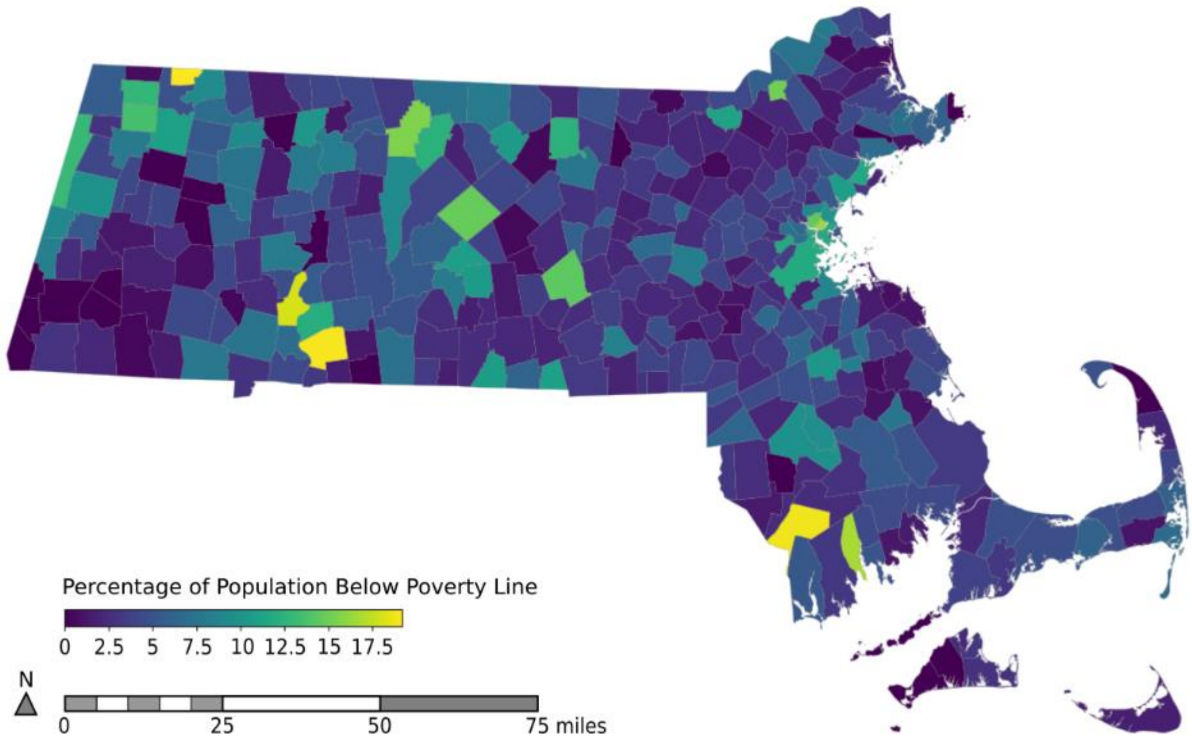


Figure 3.15 Percent of population below poverty line in Massachusetts

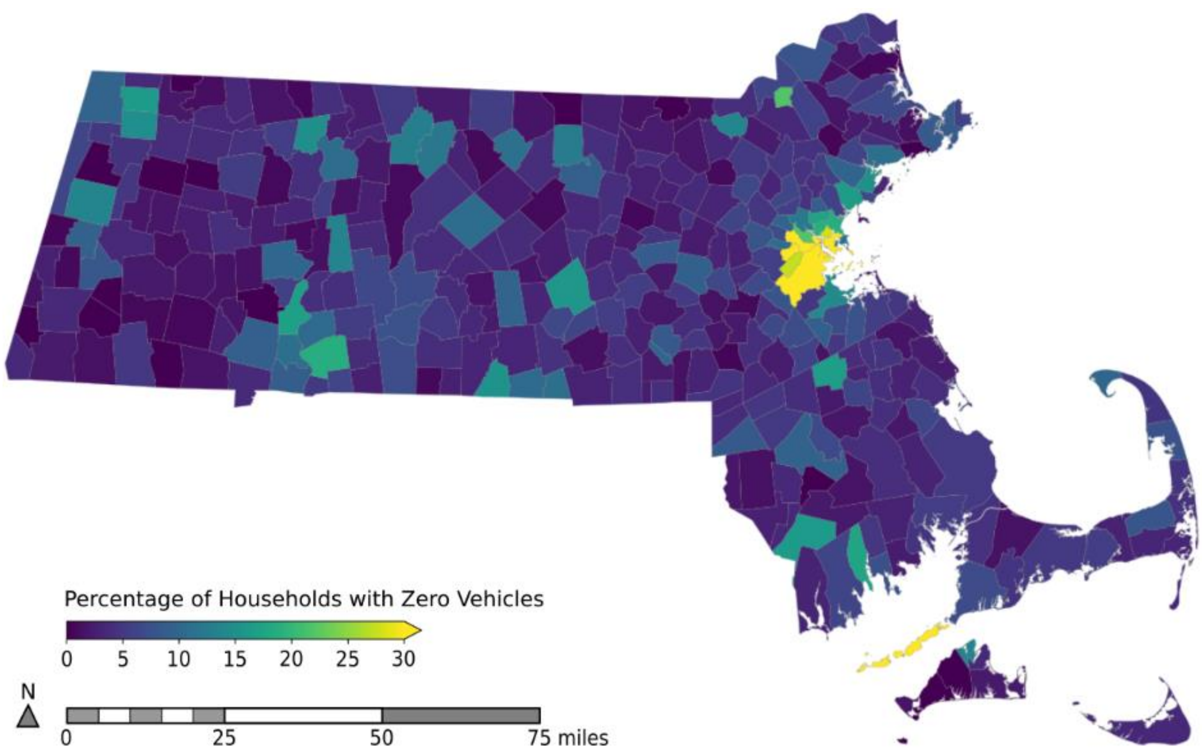


Figure 3.16 Percent of households with zero vehicle ownership

Transportation access is represented by 16 independent variables: access to four destination types (supermarkets, healthcare providers, colleges and technical schools, and parks) by four transportation modes (walk, bicycle, transit/microtransit, and car). Together with the socioeconomic variables, these were used to fit three types of models for the three public health conditions of interest: rates of diabetes, heart disease, and obesity.

The performance of ridge regression, the global RF model, and the GWRF model is presented in Table 3.4. The Moran's I values for health outcomes indicate different degrees of spatial clustering, with obesity having the most significant clustering. Although the ridge regression technique is designed to obtain the best performance for linear regression, the model fit is much worse than the RF or GWRF approaches, especially for diabetes and obesity. Analyzing the spatial distribution of health outcomes can guide targeted actions and resource allocation, ensuring that regions with concentrated high-risk populations receive appropriate priority. The GWRF model outperforms the global RF by accounting for the spatial relationships in the data.

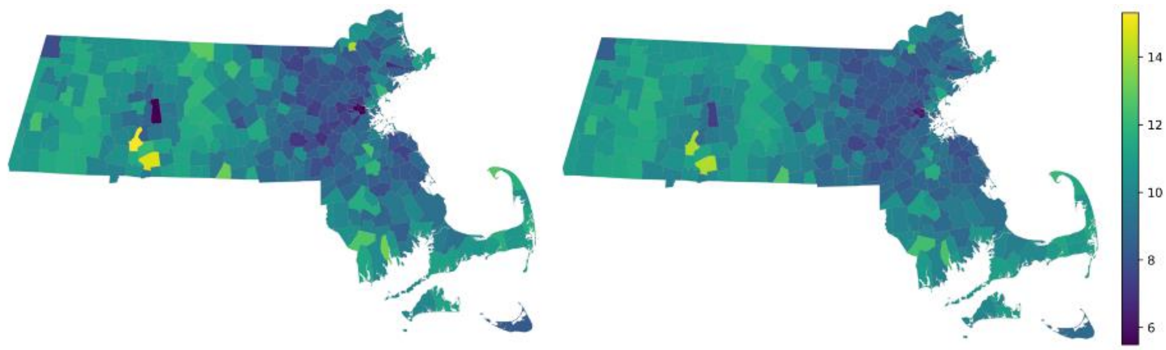
The model reveals quantitative linkages between accessibility and public health in Massachusetts, providing empirical evidence on the relative importance of different types of opportunities as determinants of population health outcomes. The following subsections provide additional details about the relationship between access and public health outcomes. Additional maps of SHAP values for each access mode and destination type are provided in Appendix D.

Table 3.4 Comparison of model performance for public health outcomes

Health Outcome	Moran's I	Model	MSE	RMSE	MAE
Diabetes Rate	0.2550	Ridge	1.0095	1.0047	0.8247
Diabetes Rate	0.2550	Global RF	0.1306	0.3613	0.2784
Diabetes Rate	0.2550	GWRF	0.1083	0.3291	0.2357
Heart Disease Rate	0.2507	Ridge	0.0544	0.2332	0.1769
Heart Disease Rate	0.2507	Global RF	0.0671	0.2590	0.1978
Heart Disease Rate	0.2507	GWRF	0.0489	0.2212	0.1701
Obesity Rate	0.5125	Ridge	9.7310	3.1195	2.5056
Obesity Rate	0.5125	Global RF	1.3102	1.1447	0.8904
Obesity Rate	0.5125	GWRF	1.0138	1.0069	0.7703

3.5.1 Access and Diabetes

Figure 3.17 shows the distribution of the diabetes rate across Massachusetts as a percentage of the population. Higher values indicate a broader population diabetic prevalence. Suffolk County has a low diabetes rate, compared to the western parts of the state, which show rather higher rates. The hyperparameters selected for the GWRF model are as follows: number of trees = 163, maximum depth of each individual decision tree = 16, and minimum number of samples required to split an internal node = 2. The median age across metropolitan areas shown in Figure 3.14 shows that populations of Berkshire County and Cape Cod are primarily older, which is associated with higher vulnerability to negative health effects. Consistent with these spatial patterns, the GWRF regression results (Figure 3.17) indicate that the model reasonably captures the spatial heterogeneity of the dependent variable.



a) Observed b) Predicted (GWRF)

Figure 3.17 Diabetes rate (percent of population)

The spatial variance feature SHAP importance, which quantifies the explanatory power of each independent variable, are shown in decreasing order in Table 3.5. The median age and the percentage of low-income population are the two most significant factors among all independent variables, as they reflect the heterogeneity of the population group and provide essential information regarding the obstacles faced by that demographic. Subsequently, the accessibility of automobiles to supermarkets, along with the percentage of zero-vehicle ownership, underlines the significance of car availability in influencing diabetes prevalence. With a car available at the household level, individuals can visit a greater number of stores and other opportunities, resulting in a broader selection of healthy foods and increased options for physical activities, hence reducing their likelihood of obtaining diabetes. Furthermore, the access to public transit and biking is very important, as it influences individuals' choices and provides coverage for residential areas increasing access to multiple destinations and the potential for additional physical activity through biking.

Table 3.5 Top 10 SHAP feature weights for diabetes

Rank	Variable	Mean Weight	Std. Weight
1	Percent Low Income	0.9454	0.9618
2	Median Age	0.3359	0.5281
3	Percentage of Zero-Vehicle Ownership	0.2671	0.2129
4	Transit Access to Health Care	0.2250	0.3028
5	Car Access to Supermarket	0.0990	0.1785
6	Transit Access to Supermarket	0.0895	0.1111
7	Car Access to Health Care	0.0632	0.0846
8	Transit Access to College	0.0491	0.0423
9	Car Access to Park	0.0476	0.0737
10	Transit Access to Park	0.0421	0.0298

Appendix D contains maps of the local factor SHAP relevance for access across various modes and to each of the destination types. Unlike the global feature importance, which provides an average measure across the entire dataset, local feature importance emphasizes the variability in predictor influence at specific locations and assists in the identification of prospective spatial patterns. These maps reveal spatial non-stationarity, evaluating the correlation between access and disease prevalence across different regions. The findings indicate that walk access is generally of low significance regarding diabetes prevalence, whereas transit access holds greater importance in urban and suburban communities compared to rural areas. Bike access is of general stationary importance, but it is more significant in suburban communities. This may result from the combination of the geographical dispersion of opportunities and the approximately nine times increase in reachable areas that biking offers compared to walking. Additionally, car access demonstrated the highest SHAP importance. Its feature importance was particularly pronounced in rural areas, as validated in Figure 3.13, which indicates that these locations generally have fewer households without a vehicle. Finally, for the cumulative access of all modes, the SHAP significance emphasizes the cluster where access is significantly explanatory for diabetes. However, Cape Cod has a low SHAP significance in terms of access, possibly due to its status as a favored residence for retirees, as indicated by the large number of people aged 65 or older.

A sensitivity analysis was performed to model the predicted effect on diabetes rate if access were increased 50% for walk (Figure 3.18), bike (Figure 3.19), or transit/microtransit (Figure 3.20). The scale indicates the predicted decrease in diabetes rate following the increase in access. Greater values indicate locations where an increase in access is expected to have a greater benefit in terms of reducing the diabetes rate. The three maps illustrate similar regions across different modes. To improve transportation infrastructure in regions designated as very sensitive (sensitivity > 1) for each mode, specific improvements may be contemplated. In areas with high pedestrian sensitivity, investments in pedestrian infrastructure and features that make communities more walkable would be beneficial. In areas with high bicycle sensitivity, the establishment of dedicated bike lanes would improve access and health. In regions that have high transit sensitivity, improving fixed route public transportation services or implementing microtransit options, especially in suburban and rural communities, would improve access to advance health outcomes. Access by fixed route transit also depends on pedestrian infrastructure as users need to walk to and from transit stops.

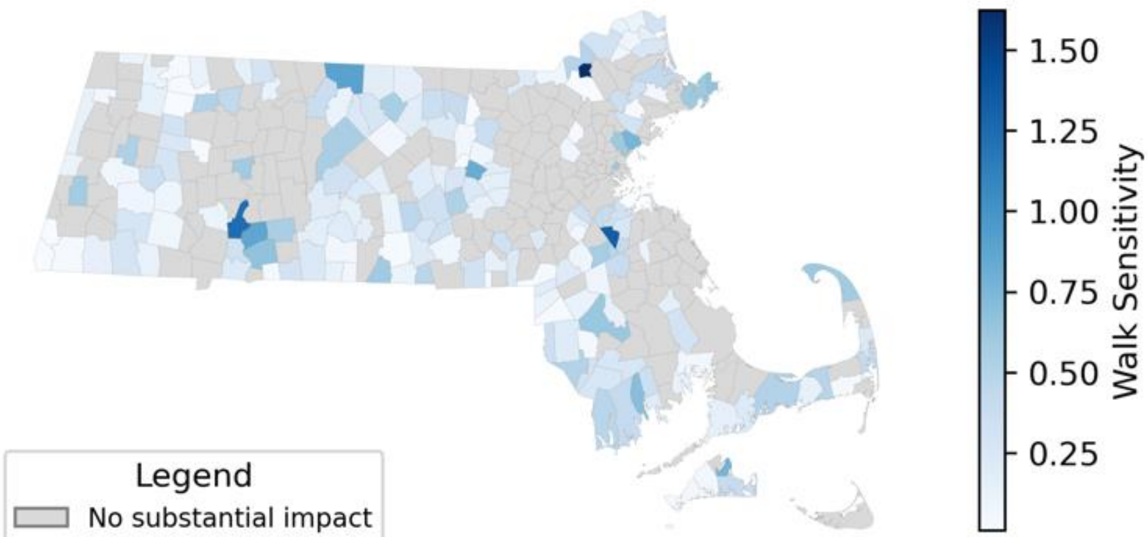


Figure 3.18 Sensitivity map for walking and diabetes

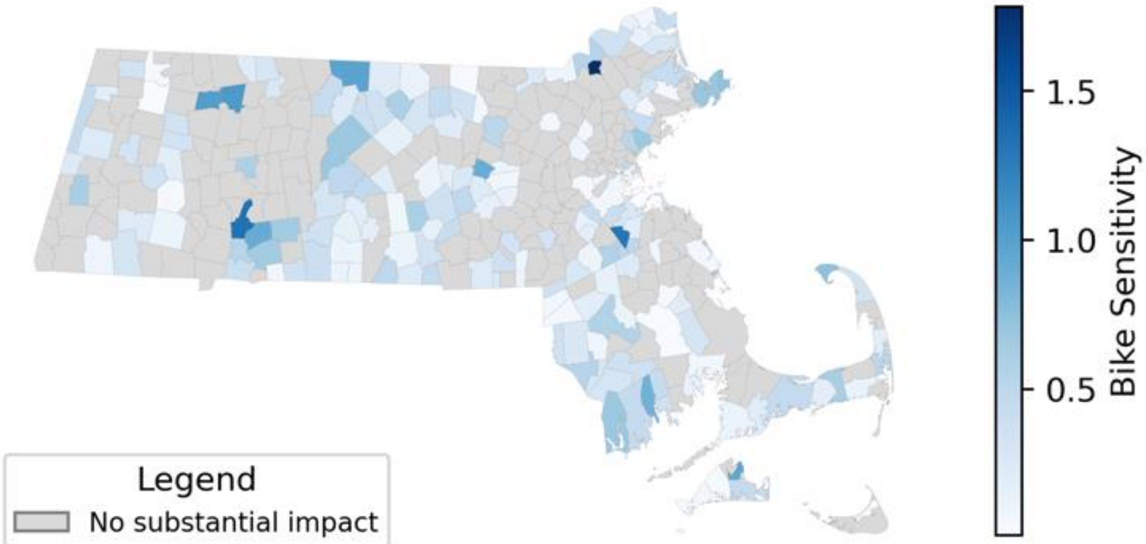


Figure 3.19 Sensitivity map for biking and diabetes

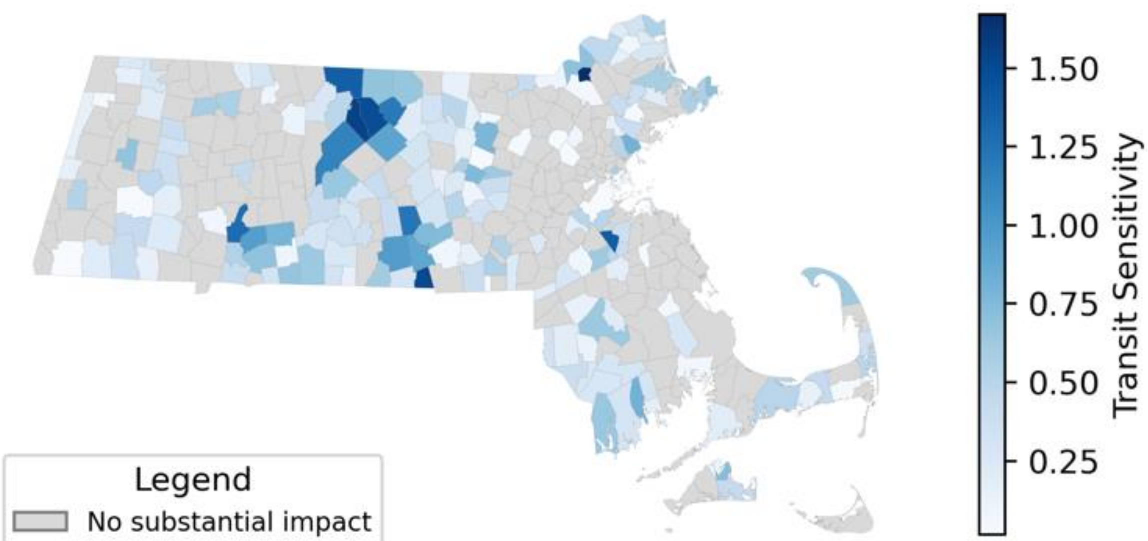
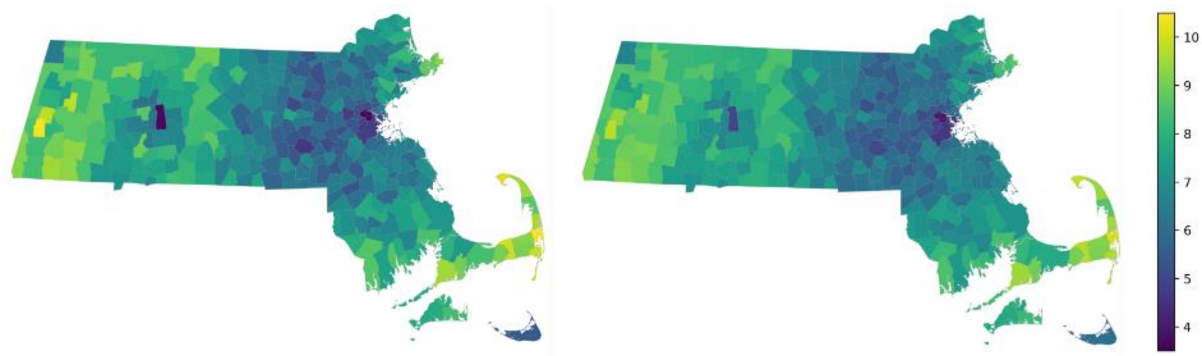


Figure 3.20 Sensitivity map for transit/microtransit and diabetes

3.5.2 Access and Heart Disease

Figure 3.21 illustrates the geographic distribution of heart disease prevalence among the population in Massachusetts. Increased values signify greater prevalence of heart disease within the population. Amherst, Cambridge, and Somerville display a lower incidence of heart disease in comparison to Stockbridge and Cape Cod, which demonstrate relatively higher rates. The hyperparameters chosen for the GWRF model include: number of trees set at 194, maximum depth of each decision tree at 48, and a minimum of 2 samples required for splitting an internal node. The GWRF regression results align with these spatial patterns, demonstrating that the model effectively captures the spatial heterogeneity of the dependent variable.



a) Observed b) Predicted (GWRF)

Figure 3.21 Heart disease rate (percent of population)

Table 3.6 presents the spatial variance feature SHAP importance, measuring the explanatory power of each element. The median age and percentage of the low-income population remain notable as significant factors among all independent variables. The car access to supermarkets, transit access to healthcare, and bicycle access to parks are important factors that exceed 5%.

Table 3.6 Top 10 SHAP feature weights for heart disease

Rank	Variable	Mean Weight	Std. Weight
1	Transit Access to Health Care	0.3983	0.3883
2	Median Age	0.3588	0.4667
3	Percentage of Low Income	0.3448	0.2511
4	Percentage of Zero Vehicle Ownership	0.1298	0.1133
5	Transit Access to Supermarket	0.0699	0.0437
6	Car Access to Health Care	0.0466	0.0425
7	Transit Access to College	0.0390	0.0402
8	Transit Access to Park	0.0365	0.0284
9	Car Access to College	0.0353	0.0546
10	Bike Access to Health Care	0.0310	0.0261

Appendix D presents maps illustrating the local factor SHAP relevance for access across different modes and multiple destinations. In line with the diabetes SHAP importance map, findings suggest that walk access is generally of low significance in relation to heart disease prevalence. In contrast, transit access is of greater importance and is more geographically concentrated, presenting higher SHAP importance in areas served by public transportation. This likely reflects the fact that locations with more transit service provide more varied transit access values that can provide some explanation for variations in health outcomes. It may also reflect the fact that transit service is, by design, provided to communities that use it to access critical destinations. High SHAP importance does not necessarily mean that transit access is high; it means that the value has strong importance in explaining the health outcome. Access by bike and car follows a similar trend to the diabetes SHAP local importance plot. However, access by car in the southwestern part of Massachusetts for heart disease has declined compared to diabetes. The prevalence of heart disease in Cape Cod is of lesser significance compared to other regions, indicating that demographics (specifically age) play a crucial role in predicting the percentage of rate of heart disease in this area.

Lastly, the sensitivity maps for walking (Figure 3.22), biking (Figure 3.23), and transit/microtransit (Figure 3.24) show how the relative importance of access by each of these modes varies across Massachusetts. The scale indicates the predicted decrease in heart disease rate following the increase in access. The three maps show that sensitivity to access varies somewhat by mode. Although there is not a specific regional concentration of communities with high sensitivity to access, the values tend to be higher in the suburban and rural parts of the state. Communities on the North Shore and in Central Massachusetts are relatively more sensitive to transit/microtransit access than elsewhere in the state, reflecting an opportunity for transportation investments to improve public health.

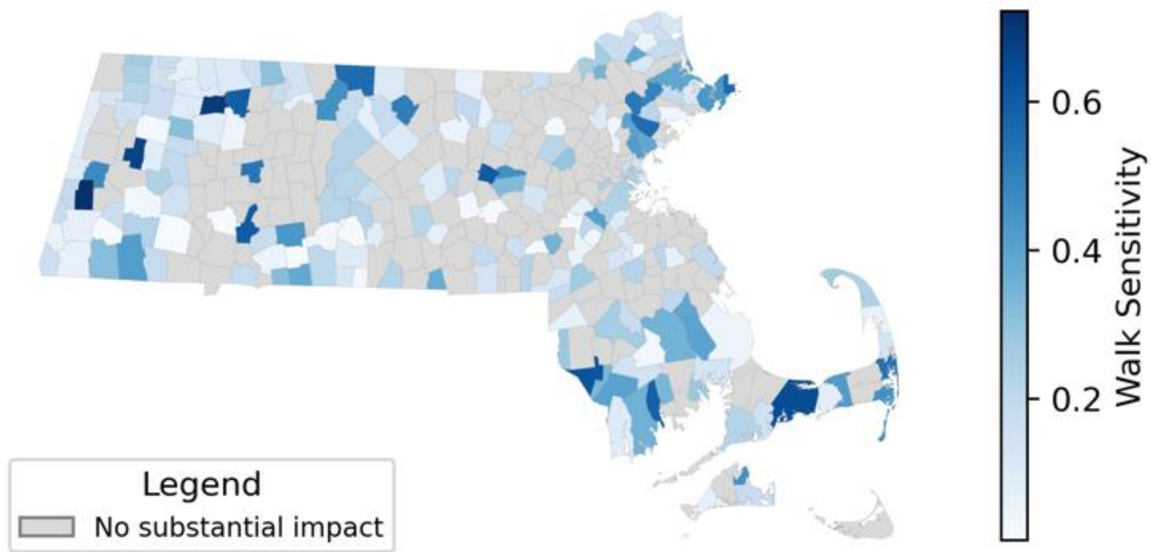


Figure 3.22 Sensitivity map for walking and heart disease

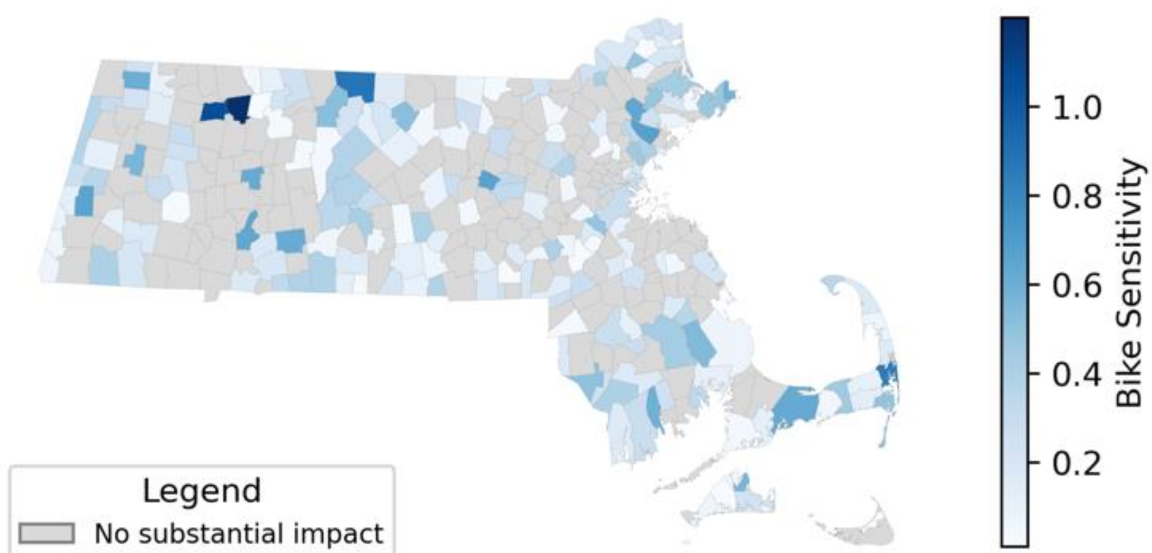


Figure 3.23 Sensitivity map for biking and heart disease

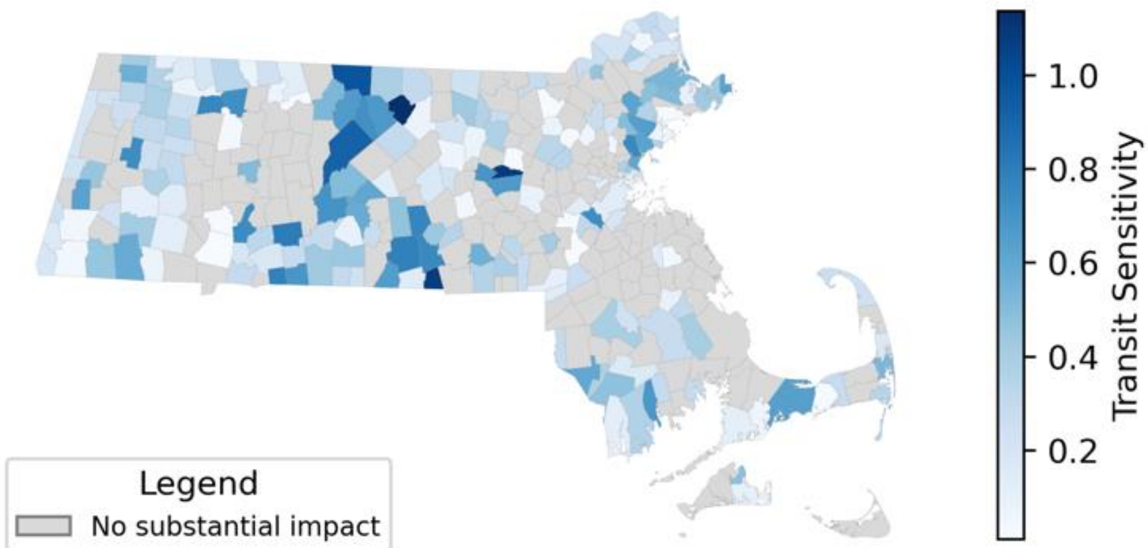
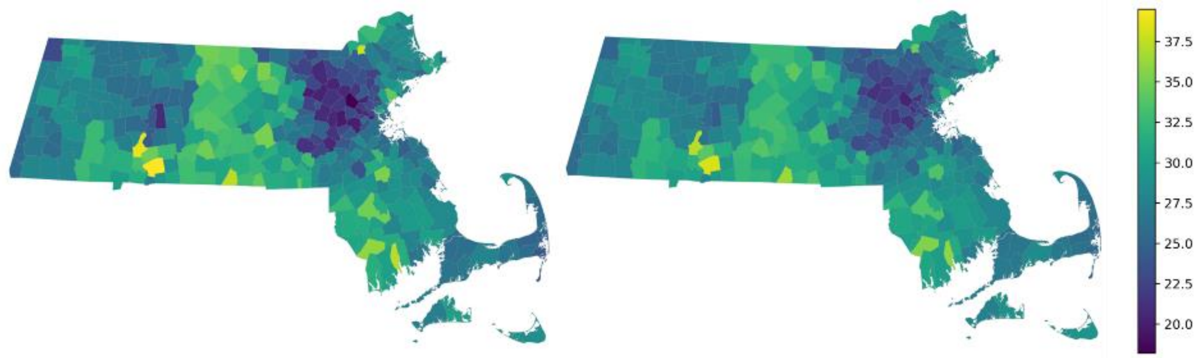


Figure 3.24 Sensitivity map for transit/microtransit and heart disease

3.5.3 Access and Obesity

Figure 3.25 illustrates the geographic distribution of obesity prevalence among the population in Massachusetts. Municipalities with lighter colors have a higher prevalence of obesity throughout the population. Obesity has the strongest geographical connections across the three dependent variables, with the figure indicating that Worcester County has a greater obesity rate than the other parts of the state, while Middlesex County demonstrates a lower obesity rate than the rest of Massachusetts. The hyperparameters chosen for the GWRF model include the following: number of trees set at 291, maximum depth of each decision tree at 31, and a minimum of 2 samples required for splitting an internal node. The GWRF regression results align with these spatial patterns, demonstrating that the model effectively captures the spatial heterogeneity of the dependent variable.



a) Observed **b) Predicted (GWRF)**

Figure 3.25 Observed and modeled obesity rate (percent of population)

Table 3.7 presents the spatial variance feature SHAP importance. The percentage of low-income individuals is the most significant variable, indicating a strong correlation between economic conditions and obesity, perhaps due to limited access to nutritious food and exercise facilities. Transit access to health care is ranked second, indicating that public transportation may significantly influence access to health care services and obesity rates. A large percentage of zero-vehicle ownership suggests that family car ownership may dramatically affect an individual's daily activity habits and health. The influence of public transportation and vehicle access on health-related amenities (e.g., hospitals, supermarkets, parks) is notably substantial. Moreover, enhancements in cycling infrastructure could lower the rate of obesity.

Appendix D includes maps illustrating the local factor SHAP relevance for access across different modes and multiple destinations. Consistent with the other two SHAP importance maps, the findings indicate that walk access is generally of minimal value affecting obesity prevalence. However, transit access is of crucial significance compared to access by bicycle and vehicle, particularly in Greater Boston. This highlights the significance of public transportation in facilitating residents' access to commuting and activities, hence potentially reducing the risk of obesity. The impact of car access is more evident especially in the suburbs north of Boston. This may be because vehicles are the primary way of accessing health resources for residents in suburban areas. The influence of bicycle access on obesity is widespread throughout the state, especially in suburban and certain rural regions, with its average effect greater than that of vehicles. This indicates that enhanced bicycle infrastructure could promote physical activity and decrease obesity rates.

Table 3.7 Top 10 SHAP feature weights for obesity

Rank	Variable	Mean Weight	Std. Weight
1	Percentage of Low Income	1.7340	1.5433
2	Transit Access to Health Care	1.0617	0.8309
3	Car Access to Health Care	0.5536	0.4643
4	Percentage of Zero Vehicle Ownership	0.4666	0.3961
5	Car Access to Supermarket	0.3123	0.3316
6	Car Access to Park	0.2661	0.2354
7	Transit Access to Supermarket	0.2270	0.2172
8	Median Age	0.1856	0.3353
9	Transit Access to Park	0.1404	0.1226
10	Bike Access to Supermarket	0.1258	0.2083

Lastly, the sensitivity maps for walking (Figure 3.26), biking (Figure 3.27), and transit (Figure 3.28) show how the relative importance of access by each of these modes varies across Massachusetts. Sensitivity to transit/microtransit access is particularly high in Central Massachusetts communities, where obesity rates are higher than other parts of the state, which suggests that transit improvements that improve access to critical destinations would have a beneficial impact on public health outcomes. Sensitivity for walk access is also elevated in these communities, and investments to improve walkability would have the dual benefits of making fixed-route transit more accessible and provide more opportunities for physical activity.

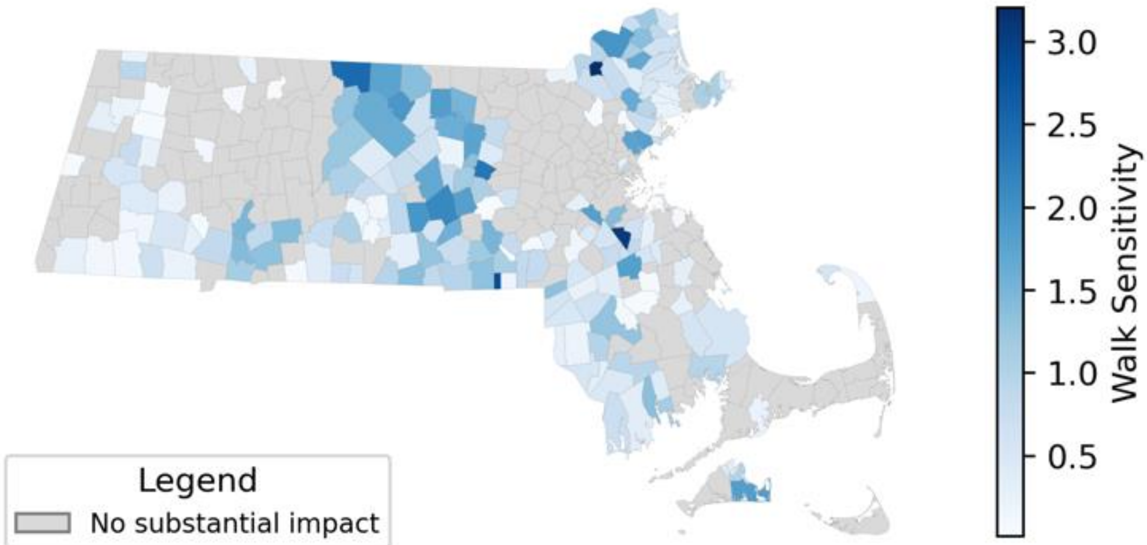


Figure 3.26 Sensitivity map for walking and obesity

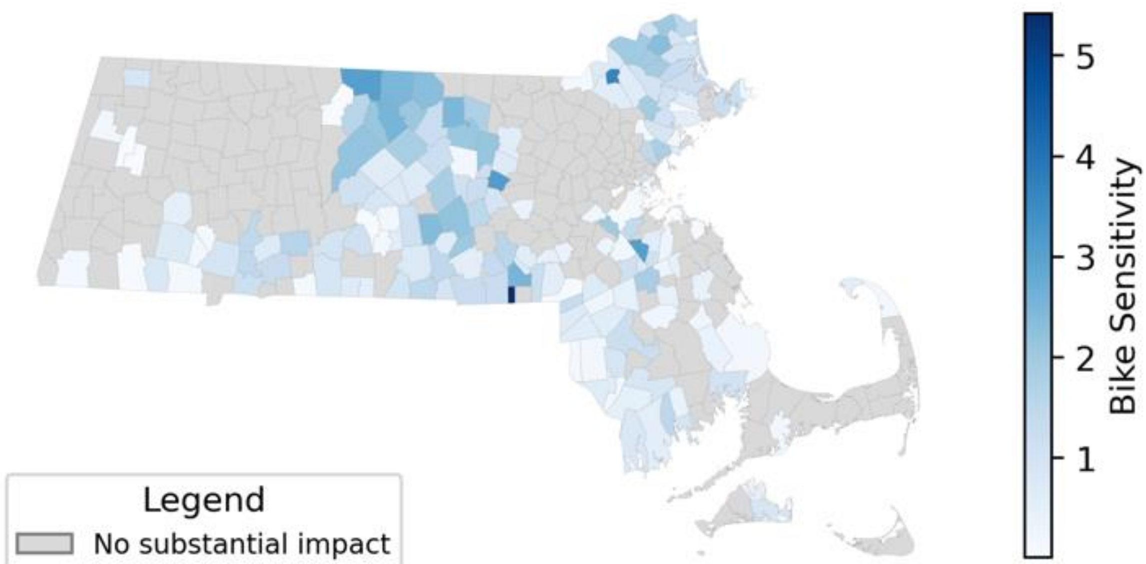


Figure 3.27 Sensitivity map for biking and diabetes

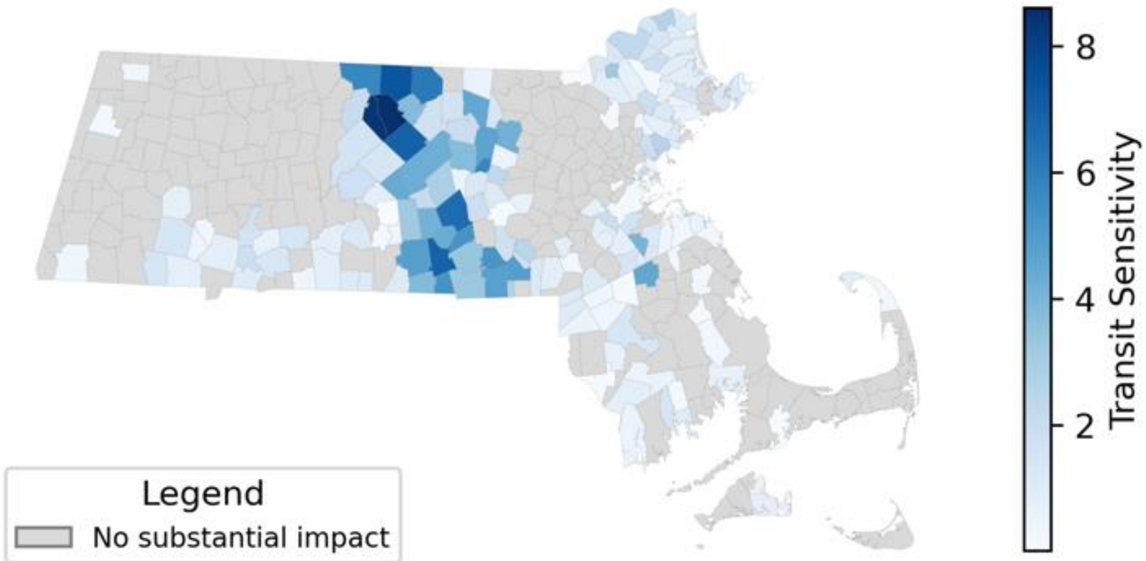


Figure 3.28 Sensitivity map for transit/microtransit and heart disease

4.0 Implementation and Technology Transfer

This research study provides two types of information. First, reproducible methods are developed and documented for the goals of the project. Three of these contributions are related to the development of improved access metrics:

1. **Walk Access Metric Accounting for Walkability** – A measure of walking access is developed that links a nationally available NWI for walkability with walking mode share data that reveals how far people are willing to walk in different types of environments. This method can be replicated anywhere in the U.S. where Replica has data to estimate the mode share of trips by walking. It can also be used to track changes in walking access over time as the built environment and walking behaviors change.

2. **Bike Access Metric Accounting for Bikeability** – A measure of bicycle access is developed that makes use of the current state-of-the-art in assessing bikeability with LTS. The LTS is defined based on characteristics of the road and bicycle infrastructure that relate to the level of comfort for various classes of cyclists. A procedure is presented to estimate the LTS for every road and bicycle path link in Massachusetts based on available data in the Road Inventory and Bike Inventory so that existing data sources are leveraged rather than having to collect additional measurements. This method can therefore be applied across all communities in Massachusetts and any other community in the country for which the required inputs for the LTS methodology are available. As investments are made in road and bicycle infrastructure, which update the Road Inventory, the LTS value will reflect these changes and so will the measured bike access.

3. **Transit Access Metric Accounting for Microtransit** – A method that uses the capabilities of existing datasets and spatial analysis tools is developed to account for the effect of microtransit on transit access. Although conventional fixed route transit is coded in GTFS and already built into Conveyal's spatial analysis capabilities, microtransit has a fundamentally different operating structure by providing on-demand service within a defined service area. The proposed method is based on an estimated waiting time and factors for microtransit speed relative to private cars. These values are calculated from samples of data from SCC and QC, but estimated values can also be modeled based on the characteristics of a microtransit service area (e.g., service area size, demand rate, fleet size) [70].

In addition to proposing improved access metrics, this study also provides a method for linking these measures to demographic and public health information to gain insights about where there are gaps in access and where investment to improve transportation access would be most impactful thorugh the following two contributions:

1. **Identifying Populations Experiencing Low Access** – Although the maps of measured access for walk, bike, transit, and car show where there are spatial gaps in transportation access, it is more important to understand who is experiencing those

limitations. Based on the definitions of the REJ+ designation, the two criteria that are most closely associated with a vulnerability for lack of transportation access are low income and lack of access to a vehicle. The proposed analysis method links transportation access gaps with census data on the size of the vulnerable population in each block group to provide a quantitative measure of the magnitude of the access disparity for those who are most reliant on non-driving modes of transportation.

2. **Linking Access Metrics with Public Health Outcomes** – The causes of chronic health conditions are complex, but a modeling method is presented that links access measures with health outcomes, using data that are available for every municipality in Massachusetts. In addition to interpreting the relative importance of various explanatory factors in statistical terms, the model provides a consistent method for counterfactual sensitivity analysis: i.e., what would be the effect of an improvement in access on public health? The sensitivity results show where investments to improve transportation access by walk, bike, transit, or car are expected to have the greatest impact on improving health

The second type of information resulting from this study is a snapshot of the proposed access metrics and their linkages to demographics and public health. These are presented both as maps in the report and GIS layers that can be viewed on interactive maps online or downloaded to supplement other analyses. The following shapefiles have been prepared as described in this report:

1. Access Metrics Mapped at Web Mercator Grid Z9
    a. Supermarket Access Metrics
        i. Supermarkets, Walking, 15 minutes
        ii. Supermarkets, Biking, 15 minutes
        iii. Supermarkets, Fixed-Route Transit, 45 minutes
        iv. Supermarkets, Microtransit, 45 minutes
        v. Supermarkets, Driving, 15 minutes
    b. Health Care Access Metrics
        i. Urgent Care Centers, Walking, 15 minutes
        ii. Urgent Care Centers, Biking, 15 minutes
        iii. Urgent Care Centers, Fixed-Route Transit, 45 minutes
        iv. Urgent Care Centers, Microtransit, 45 minutes
        v. Urgent Care Centers, Driving, 15 minutes
        vi. Community Health Centers, Walking, 15 minutes
        vii. Community Health Centers, Biking, 15 minutes
        viii. Community Health Centers, Fixed-Route Transit, 45 minutes
        ix. Community Health Centers, Microtransit, 45 minutes
        x. Community Health Centers, Driving, 15 minutes
        xi. Emergency Rooms, Walking, 15 minutes
        xii. Emergency Rooms, Biking, 15 minutes
        xiii. Emergency Rooms, Fixed-Route Transit, 45 minutes
        xiv. Emergency Rooms, Microtransit, 45 minutes
        xv. Emergency Rooms, Driving, 15 minutes
    c. College and Technical Schools Access Metrics

            i. Colleges and Technical Schools, Walking, 15 minutes
            ii. Colleges and Technical Schools, Biking, 15 minutes
            iii. Colleges and Technical Schools, Fixed-Route Transit, 45 minutes
            iv. Colleges and Technical Schools, Microtransit, 45 minutes
            v. Colleges and Technical Schools, Driving, 15 minutes
    d. Park Access Metrics
        i. Parks, Walking, 15 minutes
        ii. Parks, Biking, 15 minutes
        iii. Parks, Fixed-Route Transit, 45 minutes
        iv. Parks, Microtransit, 45 minutes
        v. Parks, Driving, 45 minutes
2. Demographics
    a. Percentage of Households with Low Income
    b. Percentage of Households with Zero-Vehicle Ownership
3. Public Health Model Results
    a. Diabetes Results
        i. Diabetes Rates, Observed
        ii. Diabetes Rates, Predicted
        iii. Total SHAP Importance for All Accessibility Modes, Diabetes
        iv. Walk Access Sensitivity, Diabetes
        v. Bike Access Sensitivity, Diabetes
        vi. Transit Access Sensitivity, Diabetes
    b. Heart Disease
        i. Heart Disease Rates, Observed
        ii. Heart Disease Rates, Predicted
        iii. Total SHAP Importance for All Accessibility Modes, Heart Disease
        iv. Walk Access Sensitivity, Heart Disease
        v. Bike Access Sensitivity, Heart Disease
        vi. Transit Access Sensitivity, Heart Disease
    c. Obesity
        i. Obesity, Observed
        ii. Obesity, Predicted
        iii. Total SHAP Importance for All Accessibility Modes, Obesity
        iv. Walk Access Sensitivity, Obesity
        v. Bike Access Sensitivity, Obesity
        vi. Transit Access Sensitivity, Obesity

These files are available online at: https://umass-amherst.maps.arcgis.com/home/item.html?id=098c4c84f94f481d9daee7259d1b3d14. Additionally, the prepared shapefiles with the following data are available to support future analyses using Conveyal or other spatial analysis software:

1. Walkability by Census Block Group
2. Bicycle Level of Traffic Stress (LTS) Network
3. Microtransit Service Areas
4. Critical Destinations in Massachusetts
    a. Supermarkets

b. Health Care Centers (including urgent care, community health centers, and emergency rooms)
c. College and Technical Schools
d. Parks

A third outcome of this project to facilitate implementation and technology transfer is a set of resources for communicating these results and tools to planners and decision makers. A concise version of the final presentation is designed for communicating this research to practitioners, such as staff in the MassDOT Office of Transportation Planning, Office of Performance Management and Innovation, and MassDOT Rail & Transit Division. Additionally, a set of concise directions for how to repeat the analyses in this report using Conveyal is provided so that they can be conducted more readily by others.

The results of this research can be implemented by building the proposed metrics into data dashboards that are used to support decision-making by MassDOT, metropolitan planning organizations, and local governments. Even without implementing new data platforms, the existing results that are presented and linked in this report can be used to identify the relative levels of access across Massachusetts to support short-term funding allocation decisions and long-term strategic planning. As an example, this research can be used to revise project scoring criteria for the MassDOT highway project prioritization process to incorporate additional criteria that more directly account for health outcomes and mode-specific access. Moreover, this would utilize readily available datasets created through this project.

5.0 Conclusion

This study represents a significant advancement in understanding and measuring the intersection of transportation access and public health in Massachusetts. Building on Phase I's foundation of food access, this second phase expanded the scope to include healthcare, higher education, and recreation access, while incorporating nuanced multimodal accessibility metrics as well as data on demographics and exploring the relationship between access and public health outcomes. The result is a set of replicable methods that allow planners, public health professionals, and policymakers to assess how transportation systems support or hinder health outcomes across Massachusetts.

One important contribution of this study is the development of access measures that account for the specific characteristics and limitations of each transportation mode.

- Walk access is affected by walkability as indicated by the NWI, so suburban and rural communities are even less accessible by walking than a simple distance-based measured would imply.
- Bike access is affected by bikeability as indicated by LTS, because most people are only comfortable and willing to ride a bicycle on streets with low volumes and slow speeds unless dedicated and protected bicycle infrastructure is provided.
- Transit access needs to account for microtransit because these on-demand services are providing a significant increase in transit access in the suburban and rural areas where they operate. Measuring the increase in transit access when microtransit is introduced is important for identifying communities which justify investments in microtransit.

A second contribution is linking these access metrics to demographic data to consider how access disparities affect different populations, especially those with limited access to private cars. While the access metrics alone describe the level of access for a certain point in space, linking these measures with demographic data reveals the number and characteristics of the people experiencing limited access. This is useful for identifying locations where low access affects a large number of vulnerable people, which can also be interpreted as the locations where investments to increase access would benefit the greatest number of people in need. The results of the demographic analysis include the following findings:

- Access by car is relatively more equitable across Massachusetts census block groups than other modes, which suggests that the access disparity is worse for people who do not have access to a car.
- Access by walking and transit is slightly more equitable among block groups designated as REJ+ communities than non-REJ+ block groups, which is a consequence of the fact that REJ+ communities are more likely to be in dense, urban areas. A consequence of this, however, is that vulnerable populations living outside of the REJ+ block groups are likely at an even greater access disadvantage. Therefore, it

is important to recognize the size of the vulnerable population in each block group regardless of the REJ+ designation.

A third contribution is using models to characterize the relationship between transportation access and the prevalence of chronic diseases such as diabetes, heart disease, and obesity. High resolution access metrics are aggregated to population-weighted municipality level measures that can be included as independent variables in GWRF models to explain and predict public health outcomes. Evaluation of the local SHAP variable important factors shows significant spatial heterogeneity of these access-health relationships, underscoring the importance of place-based strategies. The results of this analysis include the following findings:

- Transportation access is a significant determinant of public health outcomes, especially in communities with larger populations with low income or residing in zero-vehicle households.

- The relative importance of access by different modes and to different destination types varies significantly across municipalities, so investments to improve transportation access do not have the same impact on public health outcomes statewide. The largest impacts are in the communities with elevated prevalence of chronic disease, which means that investments in the communities with the greatest need are likely to result in the greatest benefits.

- Modes that provide more access are stronger determinants of public health than modes that provide less access. For people who are not able to drive, this often means that increasing transit or microtransit access is likely to have the largest benefit for public health.

The methods developed in this study, including the development of access metrics and integration with demographic and public health datasets, provide actionable, scalable resources for evaluating how infrastructure investments can promote public health equity. These tools enable planners and decision makers to go beyond conventional metrics like proximity or average travel time and instead evaluate functional, multimodal access in a more holistic, people-centered framework. By accounting for factors such as walkability indices, bicycle level of traffic stress (LTS), transit headways, and microtransit service areas, these models allow agencies to simulate the effects of proposed projects or service changes on vulnerable populations.

The methods and findings presented in this report provide a systematic and replicable approach for quantifying and comparing access across Massachusetts. The focus on identifying access gaps that affect vulnerable populations and the impacts on public health results in quantitative tools for measuring the benefit of transportation investments that improve access for Massachusetts citizens.

6.0 References

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Appendix A. Analysis of Walking Mode Share

To understand the relationship between walkability and walk access, this study included an analysis of walking mode share based on modeled trip data from Replica, NWI, and socioeconomic data from the U.S. census.

The method involves the examination of two distinct sets of independent variables in order to explain the dependent variable. We use separate linear regression models for each set and assess the related R-squared values. The dependent variable in the study is the percentage of trips completed by walking at the census block group level. The two sets of independent variables consist of: 1. The distance of the complete trip traveled from the home location in each census tract by each individual; and 2. Sociodemographic characteristics, including the percentage of households without car ownership, the percentage of low-income individuals, and the National Walking Index (NWI). By comparing the R-squared values of these two models, we can assess how well each set of independent variables explains the variation in walking trips.

The NWI captures basic physical information about the infrastructure of how the road environment can be used by residents, partially accounting for how safely and comfortably a person can walk in these environments. Although individuals' psychological safety, such as whether the street has a high crime rate, and the width of the walkway are not taken into consideration, we believe the NWI can represent the infrastructure condition. Therefore, in our second set of variables, we account for not only the residential profile, but also urban geographic information. The residential profile examines the diversity of household information, including socioeconomic characteristics, that indicate alternative transportation choices beyond walking. Individuals who don't own any vehicles have limited options for transportation, whereas individuals with a low income have a more constrained budget for traveling. Urban geographic effects reflect the impact of the neighborhood environment (land use and urban geometry) on the willingness of individuals to walk. Residing in a rural region often poses challenges in accessing preferred places within a feasible walking distance.

It is thus possible to determine how much information the sociodemographic data provides by comparing the two regression models to the shopping-related travel patterns that we can directly explore from predicted travelers' Origin-Destination (OD) data, specifically analyzing the percentage of people who traveled by walking in each census tract. This comparison helps us assess whether there is a causal relationship between sociodemographic attributes and the proportion of people who walk for their trip or whether sociodemographic data has the same explanatory power as trip lengths.

By categorizing the forecasted OD data according to the original trip locations, we aggregate data on passengers' behaviors. The number of trips for different modes was aggregated at the census block group level based on the origin of each individual's trip. The focus is exclusively on shopping trips that are conducted from home. The reason for this is because shopping trips represent an important portion of urban travel, which has been on the rise, and they have a noticeable effect on traffic congestion and air pollution. Shopping trips also provide people with greater flexibility compared to trips for other destinations [71, 72, 73].

Through the analysis of shopping trips, we may enhance accessibility and public health by comprehending the factors that influence individuals' transportation mode preferences, considering their personal situations and geographical surroundings. This enables us to identify and provide priority to communities that have significant gaps in access, therefore supporting planning and decision-making.

Figure A.1 shows a correlation matrix of the relevant explanatory variables, which include three categories of distance ranges (0-0.5 miles, 0.5-2.4 miles, 2.4-3.2 miles), NWI, percent of population in poverty, and the percent of population in zero-car households as independent variables and the percent of trips completed by walking as the dependent variable. The walkability index has a clear causal relationship to the walking mode share because a more walkable environment can encourage people to walk but a person's choice to walk does not directly change the infrastructure that determines walkability. The causal relationship represented by the correlation between trip distance and walking mode share is more ambiguous, because it is not clear whether people choose nearby destinations and then walk because they are close or they choose to walk and then select a destination that is a short distance away. Table A.1 shows that a regression model to predict walking mode share based on NWI has similar explanatory power as a regression based on trip distances. Since it also has a clearer causal relationship, NWI is used to predict walking mode share.

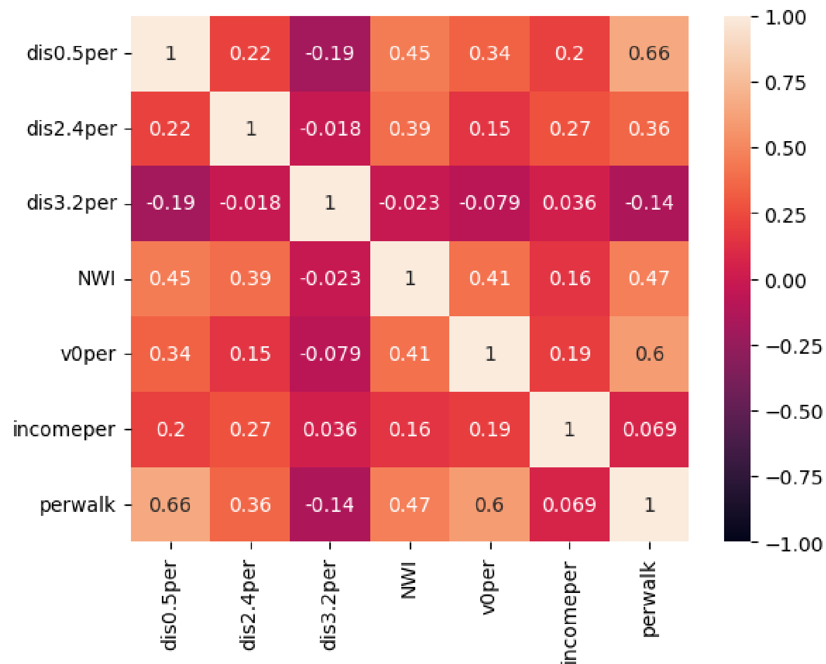

Figure A.1 Correlation matrix of variables for walk mode share models

Table A.1 Comparison of linear regression models to predict walk mode share

Model	R-squared (R^2)	Mean Squared Error (MSE)
Distance Variables	0.428	0.00367
Social Demographic	0.437	0.00362

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Appendix B. Pseudocode for GWRF

Algorithm 1: Geographically Weighted Random Forest (GWRF)
Input:
Dataset: $D = (x_{\text{i}}, y_{\text{i}}, u_{\text{i}}, v_{\text{i}})^{\text{n}}{}_{i=1}$
Parameters: number of trees T, candidate neighbor sizes $K = \{k_1, k_2, ..., k_{\text{p}}\}$
Output:
Spatially varying predictions $\hat{\text{y}}_{\text{i}}{}^{\text{n}}{}_{i=1}$ and SHAP-based local variable importance
Step 0: Determine Optimal $\boldsymbol{mtry*}$ from Global RF
Train a global Random Forest on full dataset D using cross-validation to obtain optimal $mtry*$
Step 1: Standardize Input Features
For each predictor x_j: $x_{\text{j}}' = \frac{(x_{\text{j}} - \mu_{\text{j}})}{\sigma_{\text{j}}}$
Step 2: Bandwidth Optimization (Select best $\boldsymbol{k}$)
Initialize $RMSE_{best} \leftarrow \infty$;
foreach $k \in K$ **do**
  foreach $observation\ i = 1, ..., n$ **do**
    Identify k nearest neighbors of $(u_{\text{i}}, v_{\text{i}})$ to form D_{i};
    Compute Gaussian weights: $w_{\text{ij}} = exp(-\frac{d_{\text{ij}}{}^2}{2b_{\text{i}}{}^2})$;
    // b_{i} is the distance to i's k^{th} nearest neighbor
    Fit local weighted Random Forest RF_{i} with T trees and $mtry*$ features
    Predict $\hat{\text{y}}_{\text{i}}{}^{(\text{k})}$ as average over all trees;
  Compute global performance metrics:
    $MSE(k) = \frac{1}{n}\sum_{i=1}^{n}(y_{\text{i}} - \hat{\text{y}}_{\text{i}}{}^{(\text{k})})^2$;
    $RMSE(k) = \sqrt{MSE(k)}$;
    $MAE(k) = \frac{1}{n}\sum_{i=1}^{n}\left|y_{\text{i}} - \hat{\text{y}}_{\text{i}}{}^{(\text{k})}\right|$;
  if $RMSE(k) < RMSE_{best}$ **then**
    $RMSE_{best} \leftarrow RMSE(k)$;
    $k* \leftarrow k$; Save predictions and SHAP values;
Step 3: Final Local Model with Optimal k*
foreach $observation\ i = 1, ..., n$ **do**
Identify $k*$ nearest neighbors of $(u_{\text{i}}, v_{\text{i}})$;
Compute Gaussian weights w_{ij};
Fit weighted Random Forest RF_{i} with T trees and $mtry*$ features;
Predict $\hat{\text{y}}_{\text{i}}$ as average over all trees;
Compute local SHAP values for feature importance;
Step 4: Final Evaluation and Output
Compute final performance: MSE, RMSE, MAE;
Return $\{\hat{y}_{\text{i}}\}$ and $average\ SHAP$ maps of local variable importance.

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Appendix C. Maps of Access Measures

Interactive versions of all maps are available online at https://umass-amherst.maps.arcgis.com/home/item.html?id=098c4c84f94f481d9daee7259d1b3d14.

Supermarket Access

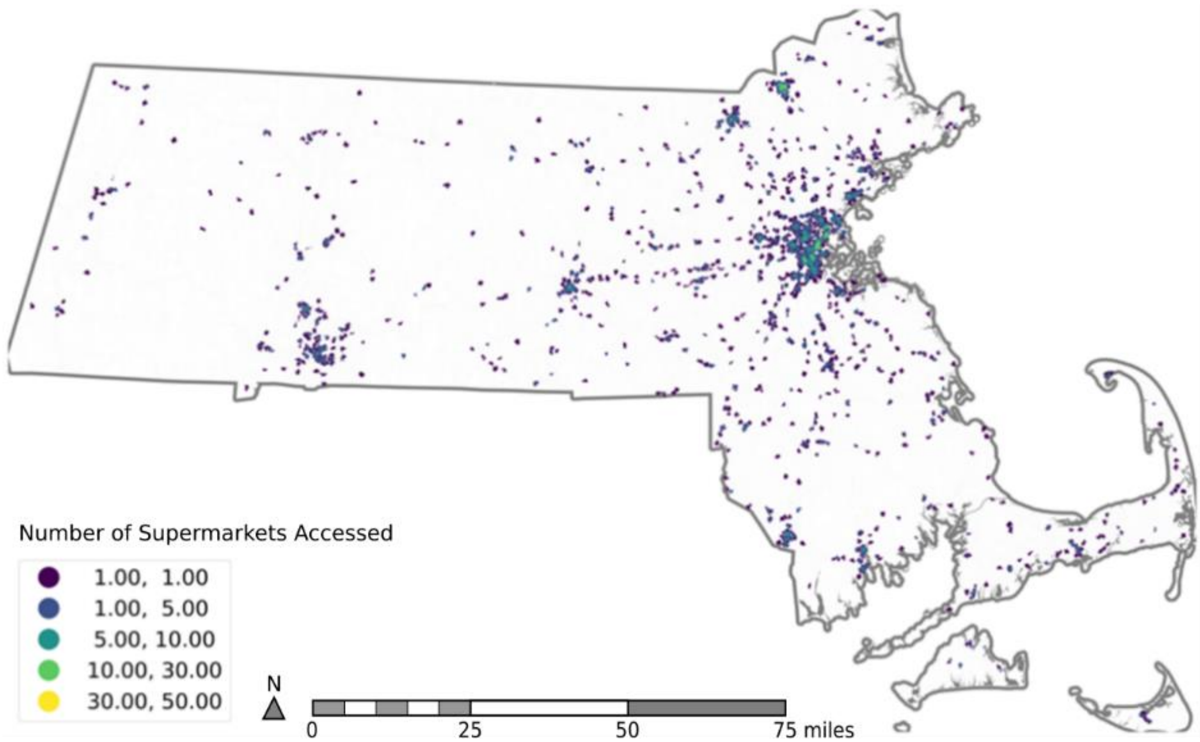

Figure C.1 Supermarkets within 15 minutes NWI-adjusted walk access

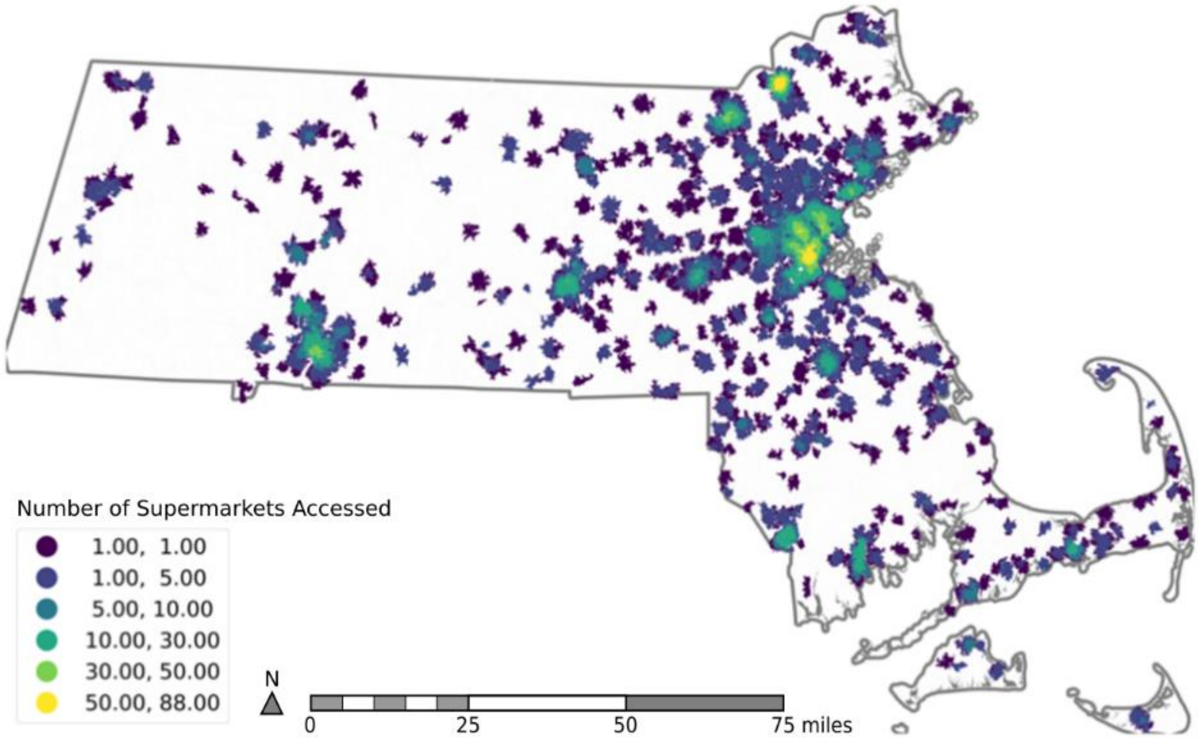

Figure C.2 Supermarkets within 15 minutes LTS 2 bicycle access

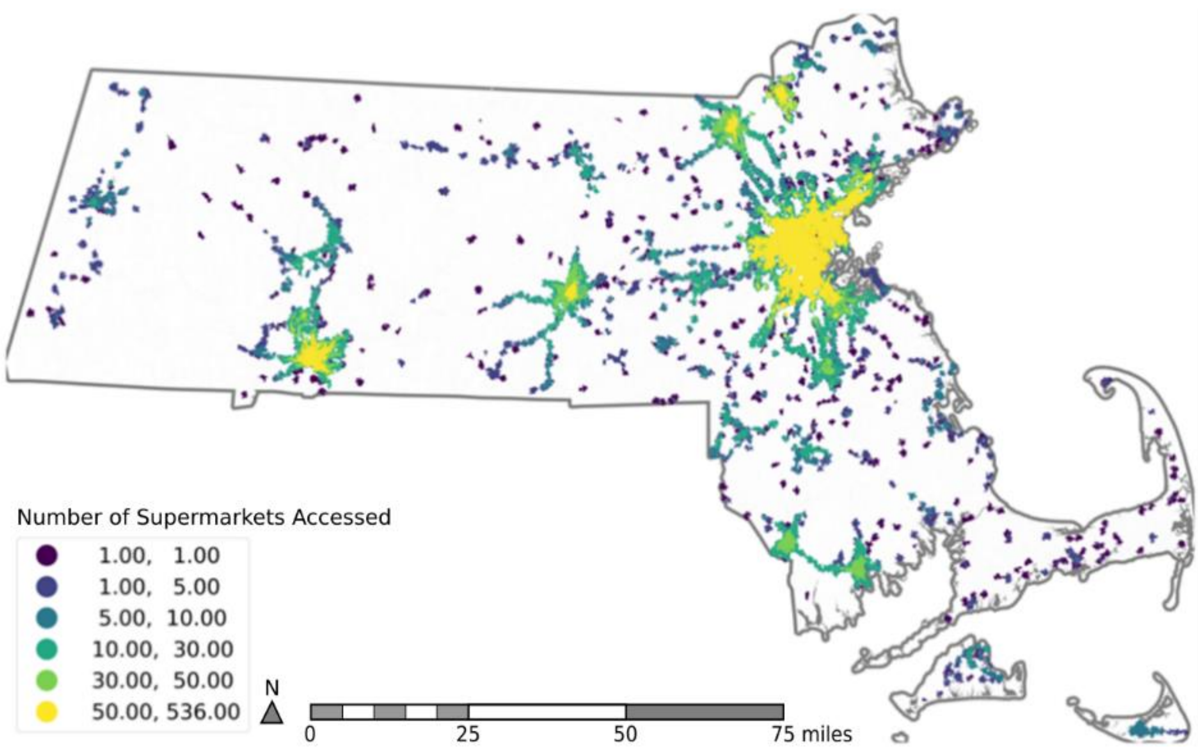

Figure C.3 Supermarkets within 45 minutes fixed route transit

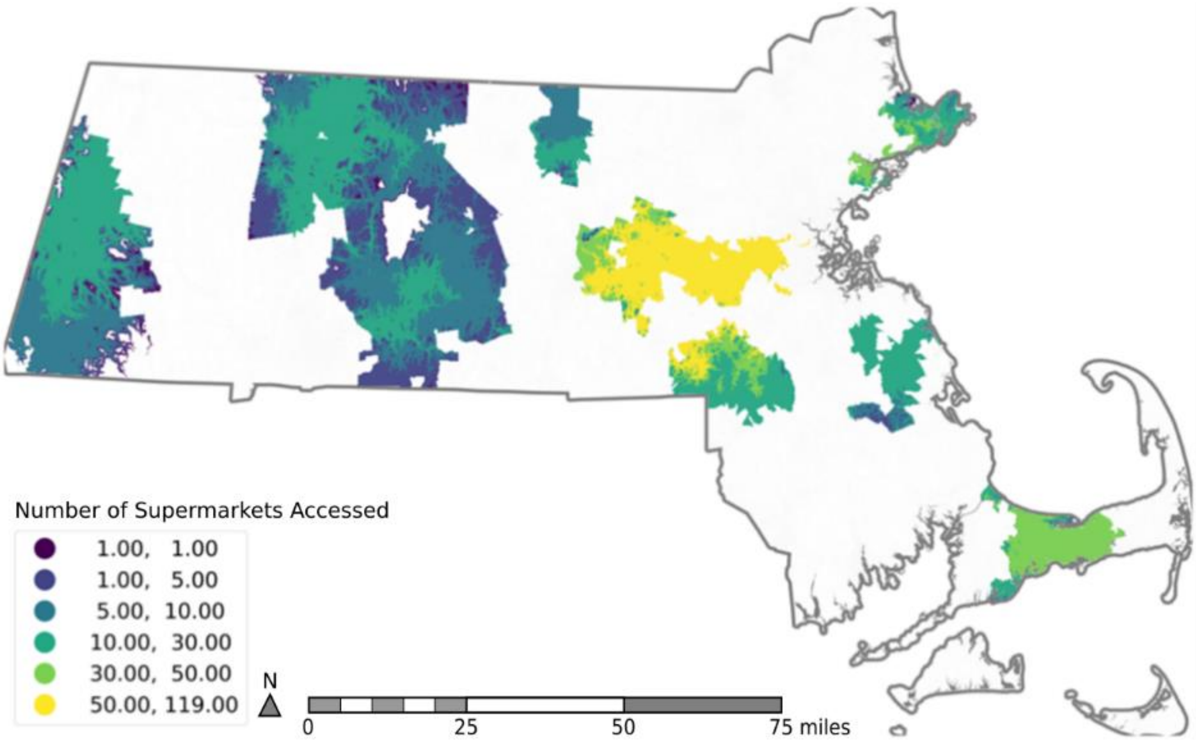

Figure C.4 Supermarkets within 45 minutes microtransit

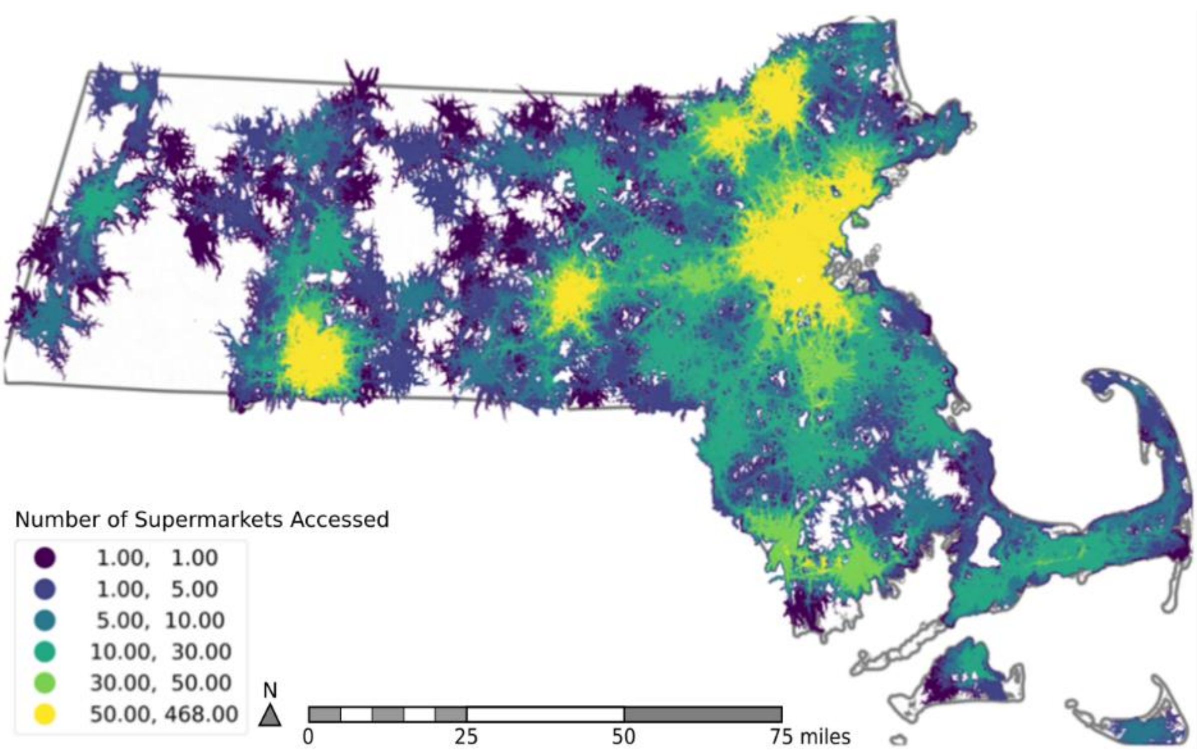

Figure C.5 Supermarkets within 15 minutes driving

Urgent Care Provider Access

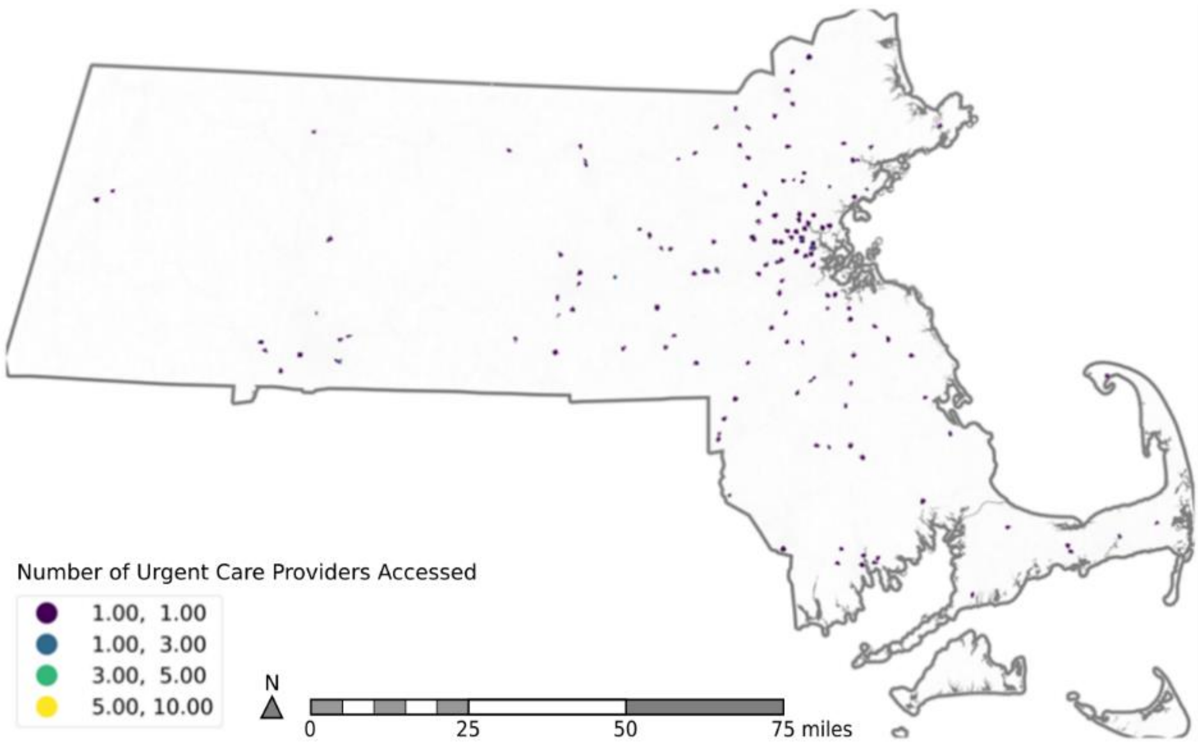

Figure C.6 Urgent care providers within 15 minutes NWI-adjusted walk access

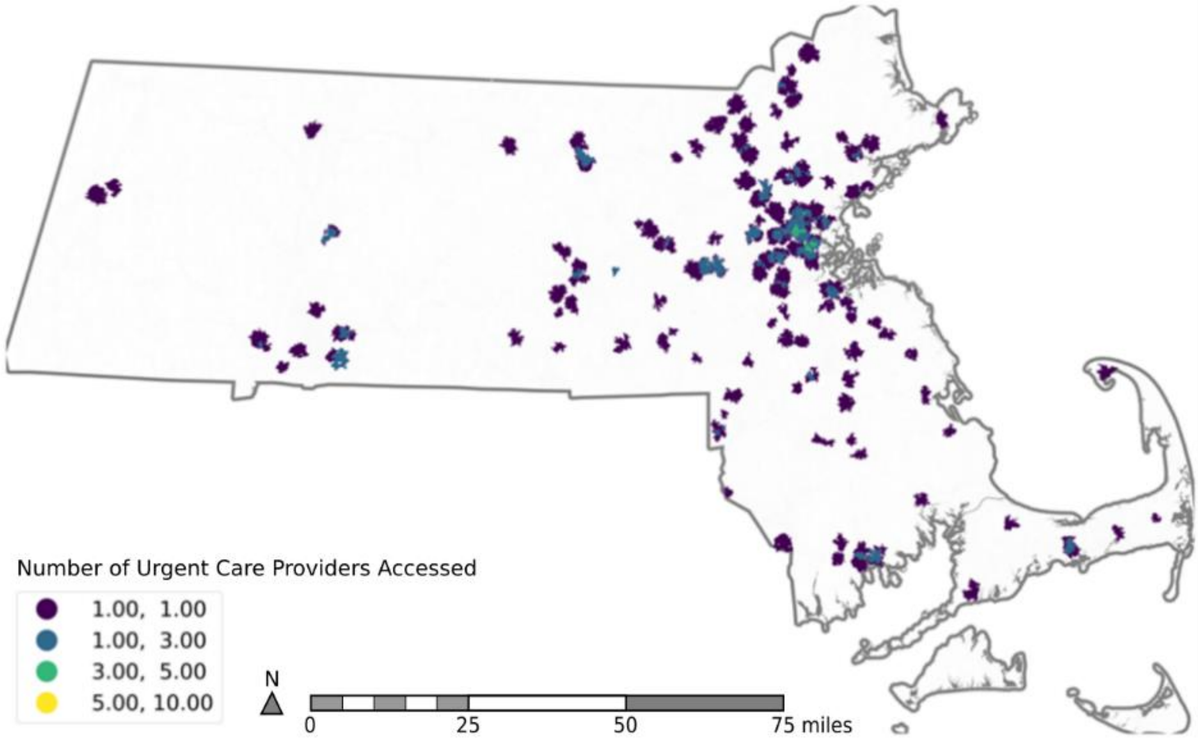

Figure C.7 Urgent care providers within 15 minutes LTS 2 bicycle access

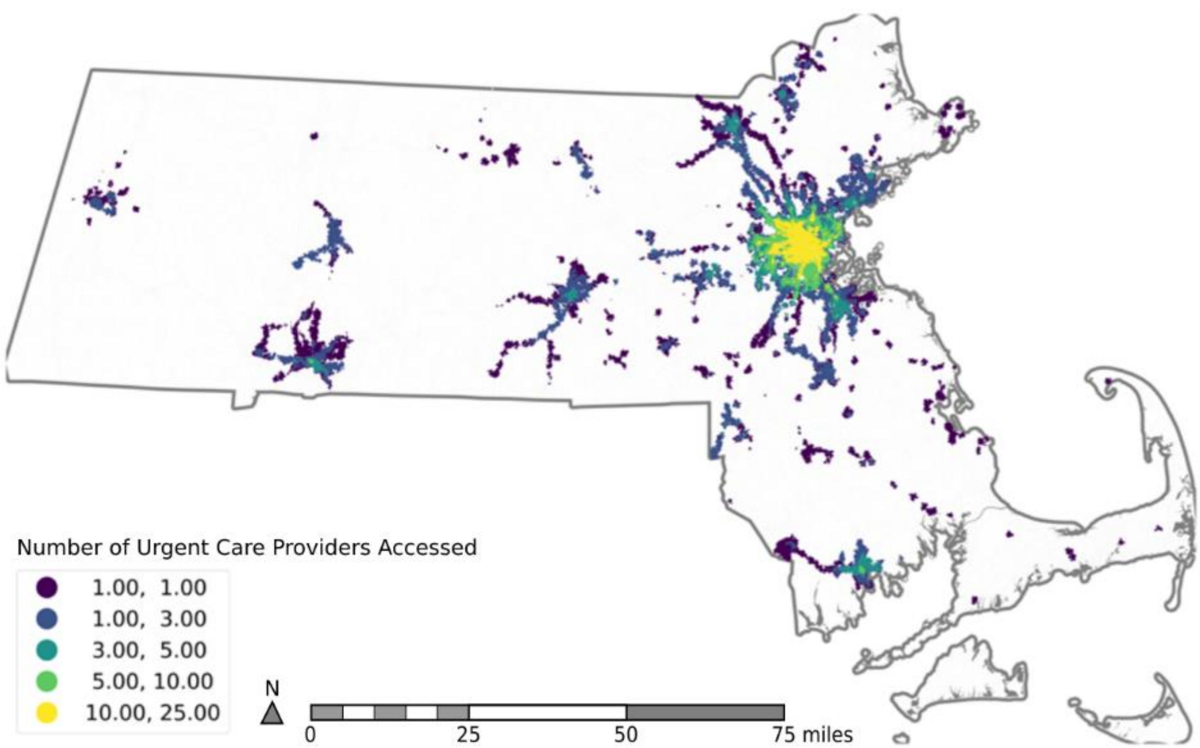

Figure C.8 Urgent care providers within 45 minutes fixed route transit

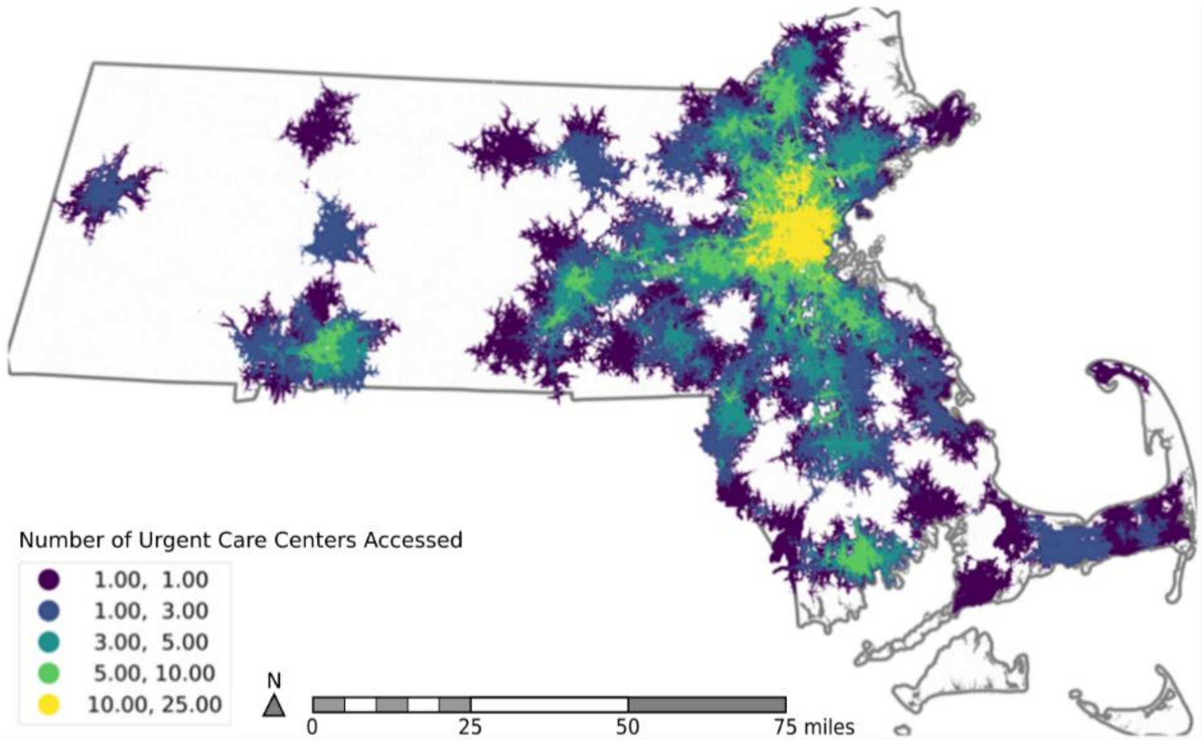

Figure C.9 Urgent care providers within 15 minutes driving

Community Health Clinic Access

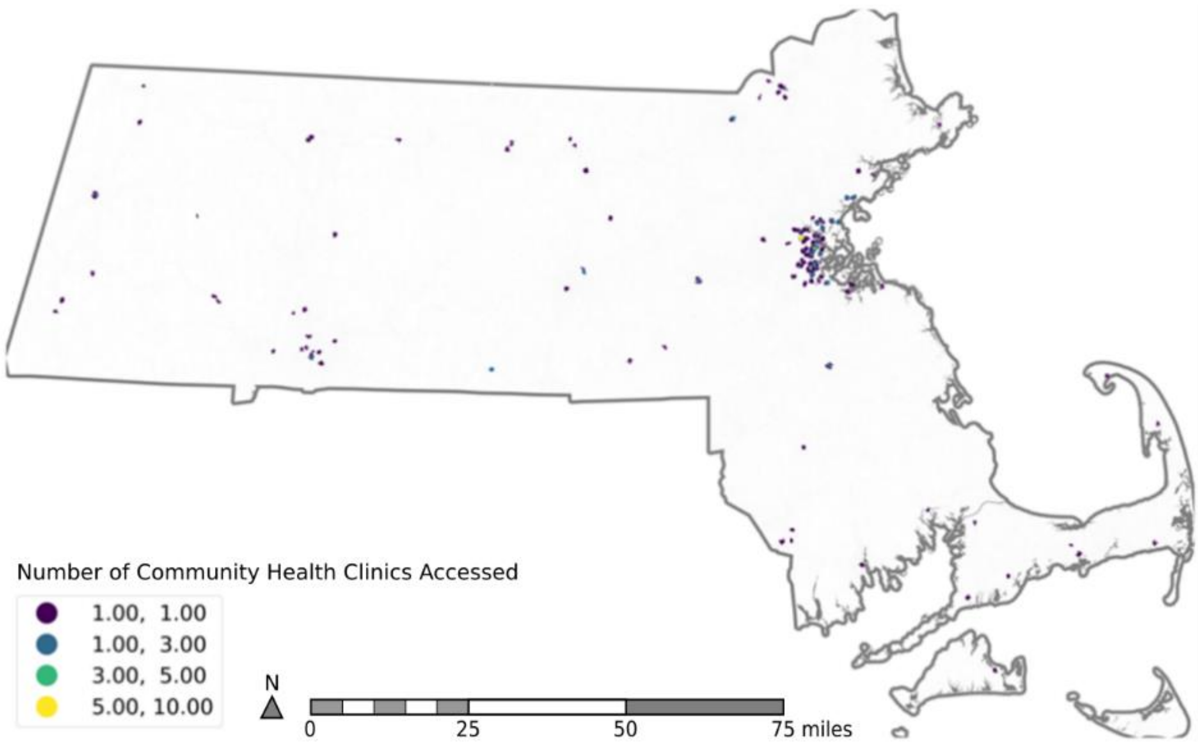

Figure C.10 Community health clinics within 15 minutes NWI-adjusted walk access

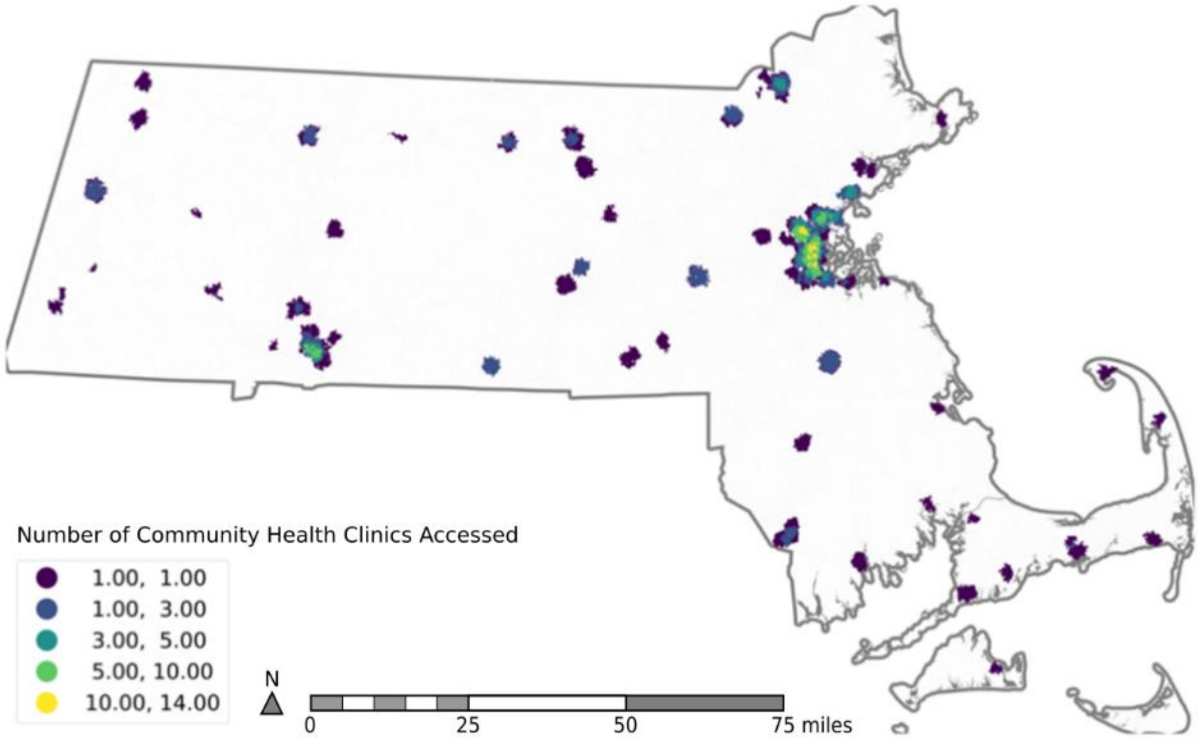

Figure C.11 Community health clinics within 15 minutes LTS 2 bicycle access

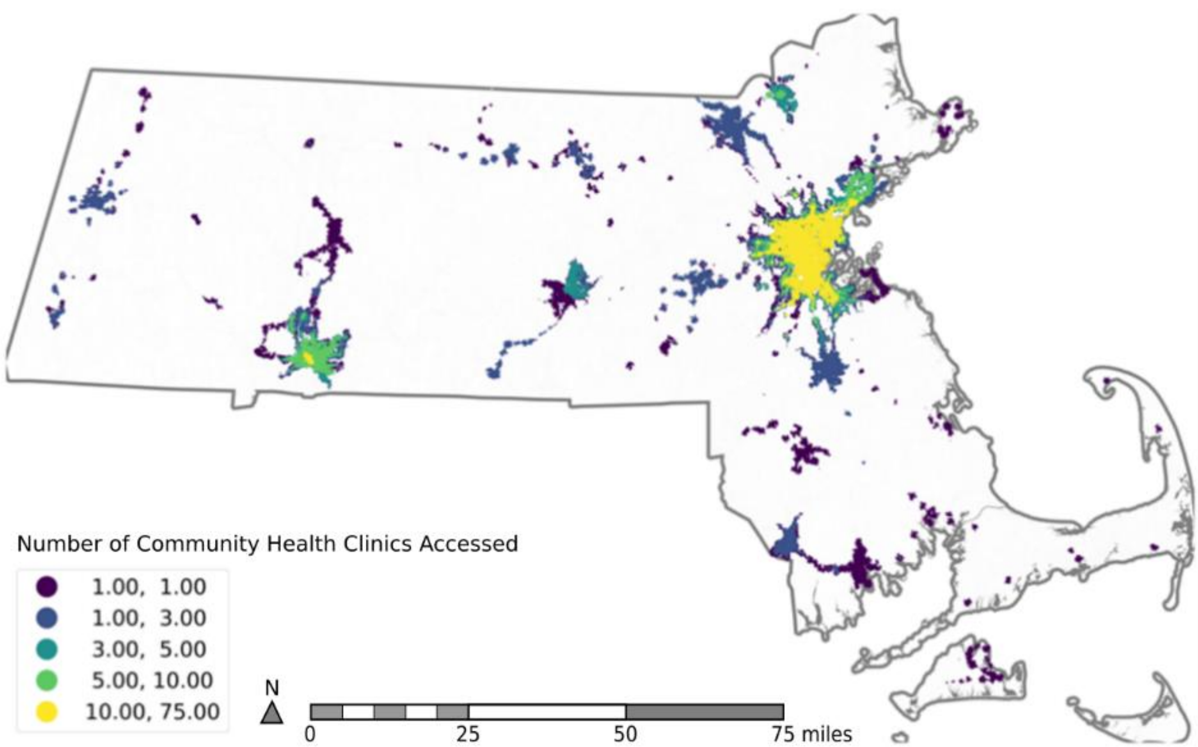

Figure C.12 Community health clinics within 45 minutes fixed route transit

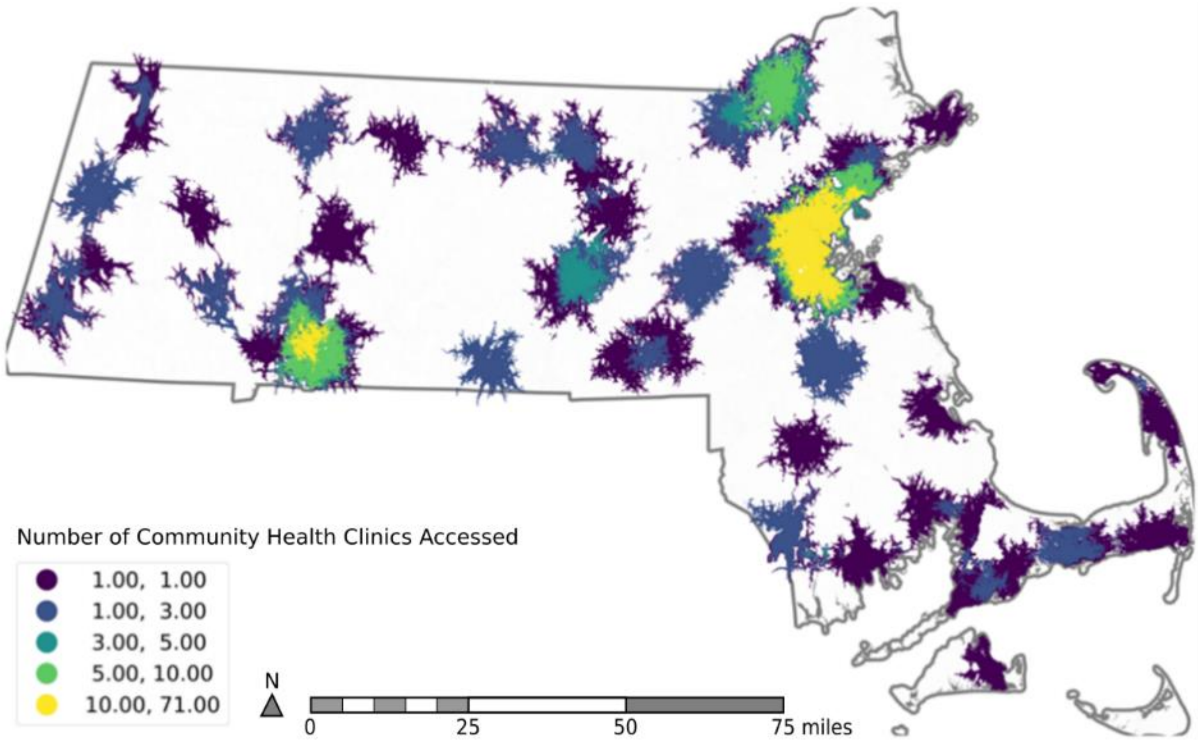

Figure C.13 Community health clinics within 15 minutes driving

Emergency Room Access

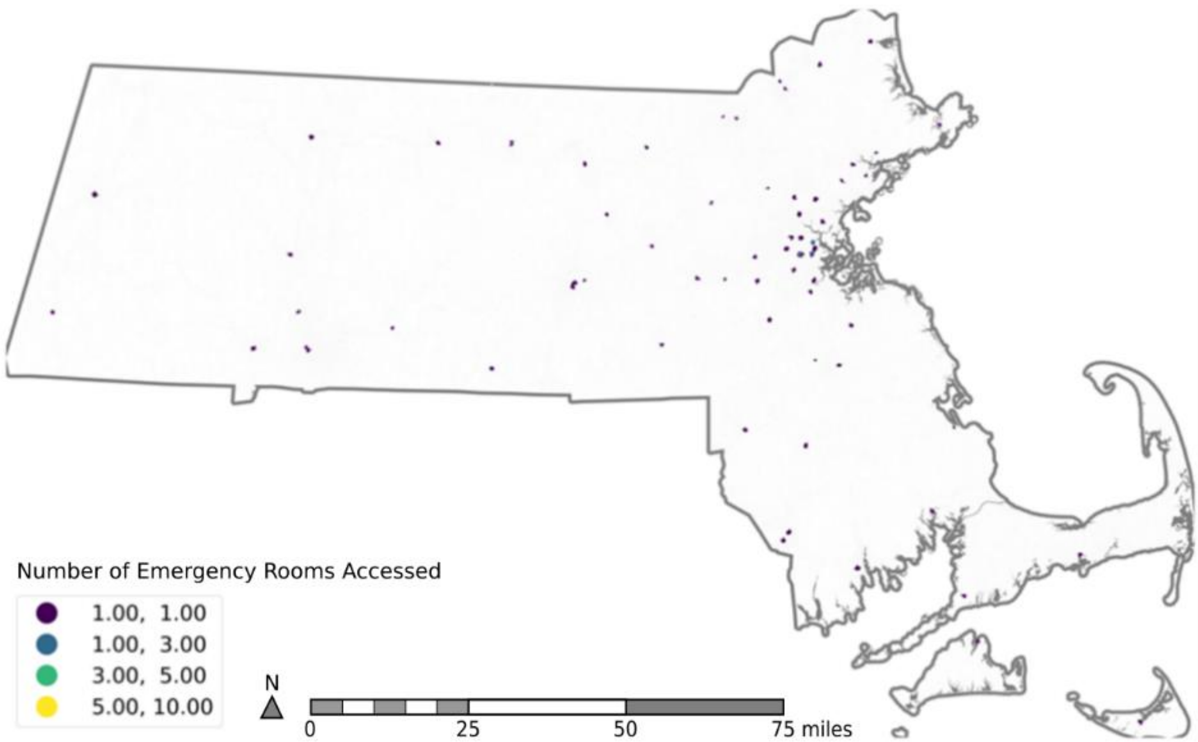

Figure C.14 Emergency rooms within 15 minutes NWI-adjusted walk access

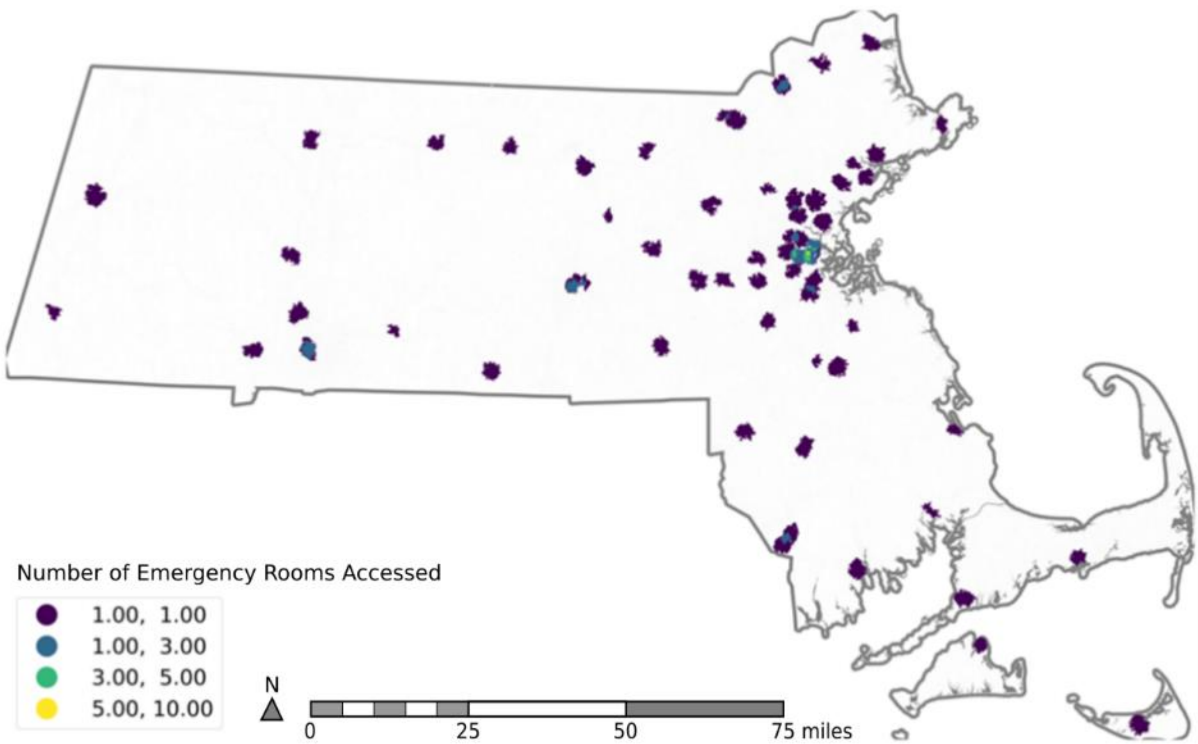

Figure C.15 Emergency rooms within 15 minutes LTS 2 bicycle access

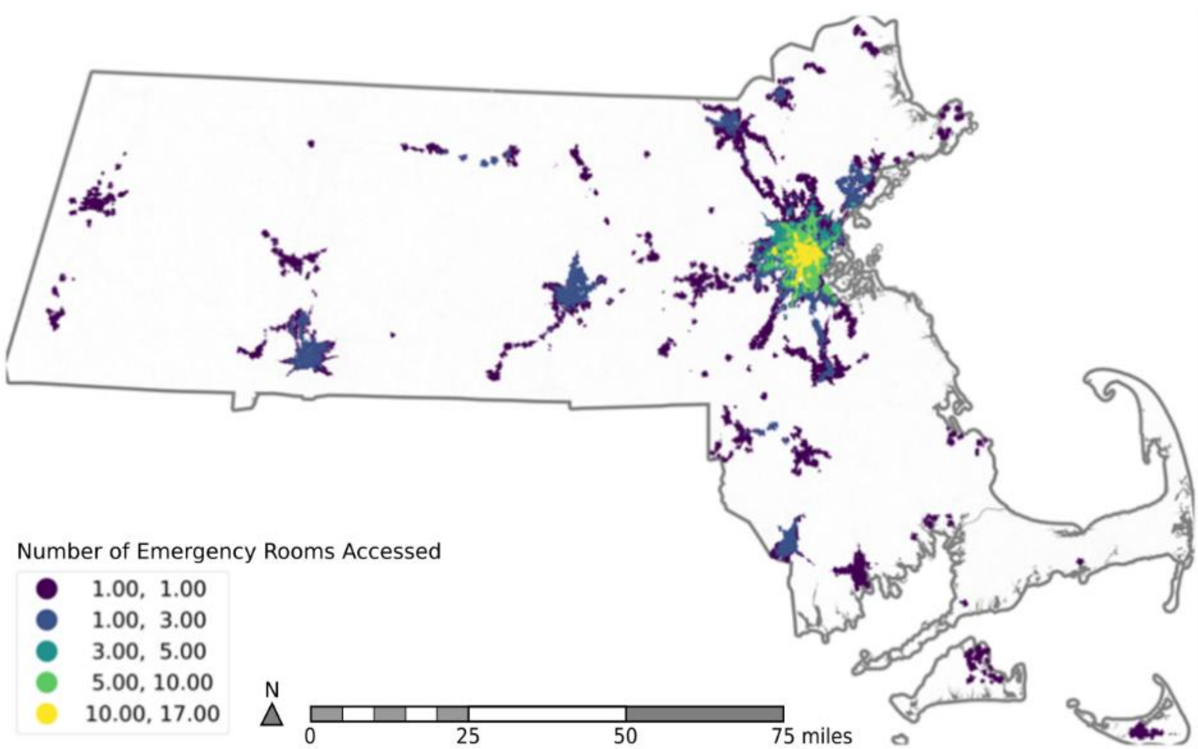

Figure C.16 Emergency rooms within 45 minutes fixed route transit

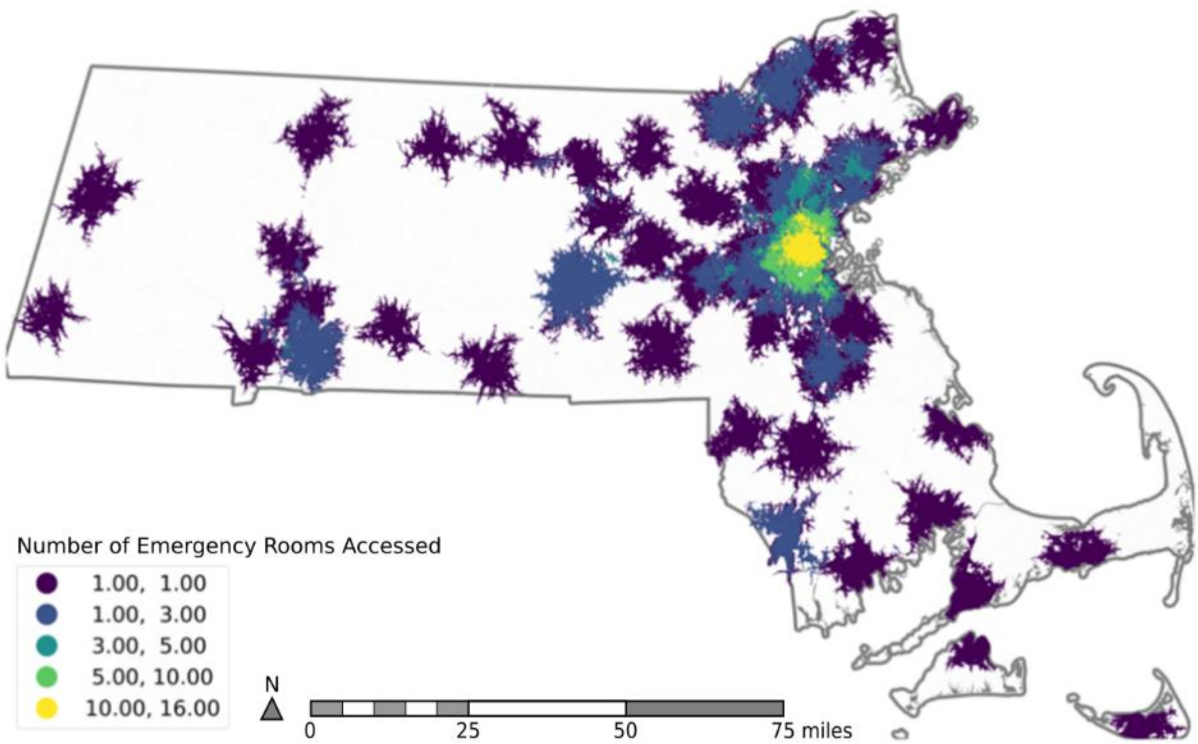

Figure C.17 Emergency rooms within 15 minutes driving

Health Care Access

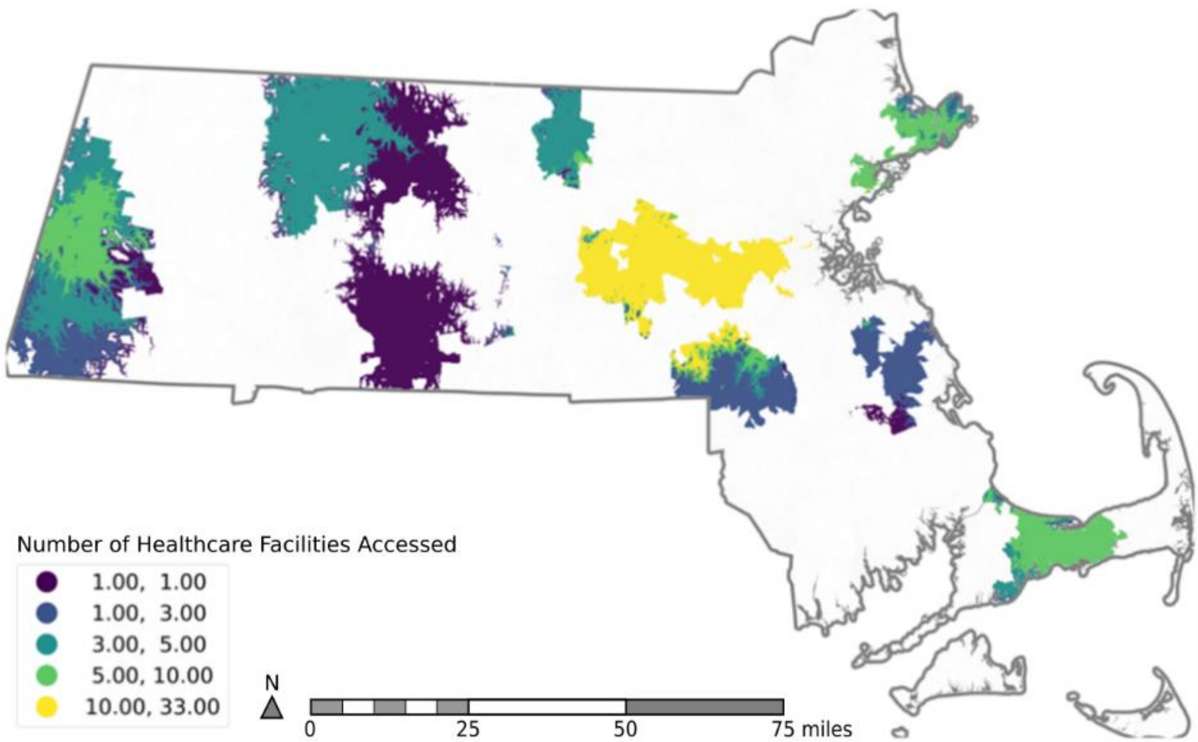

Figure C.18 Health care facilities within 45 minutes microtransit

College and Technical School Access

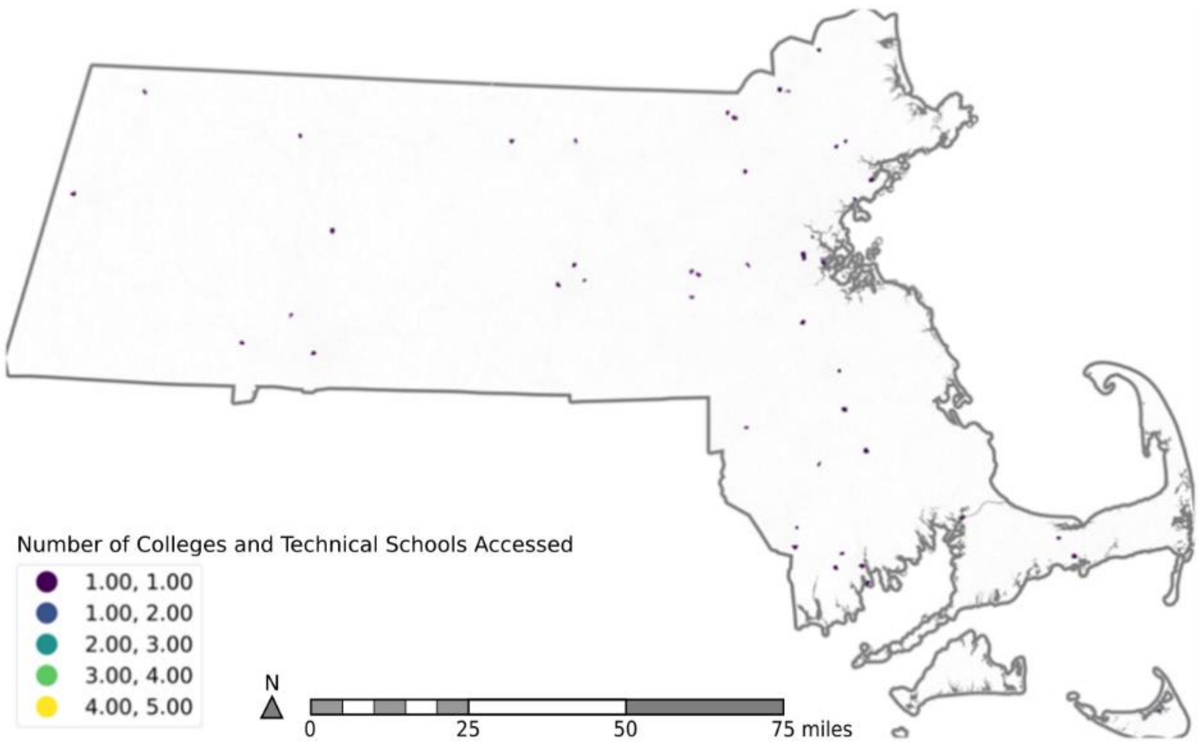

Figure C.19 Colleges and technical schools within 15 minutes NWI-adjusted walk access

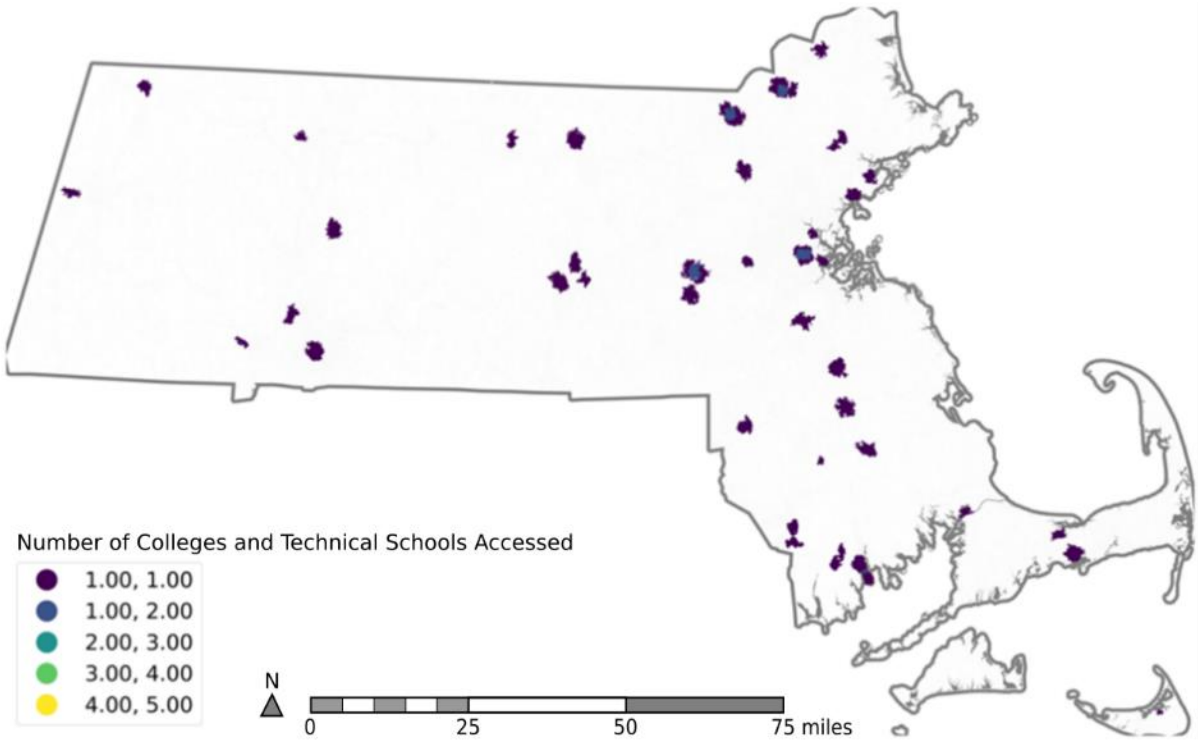

Figure C.20 Colleges and technical schools within 15 minutes LTS 2 bicycle access

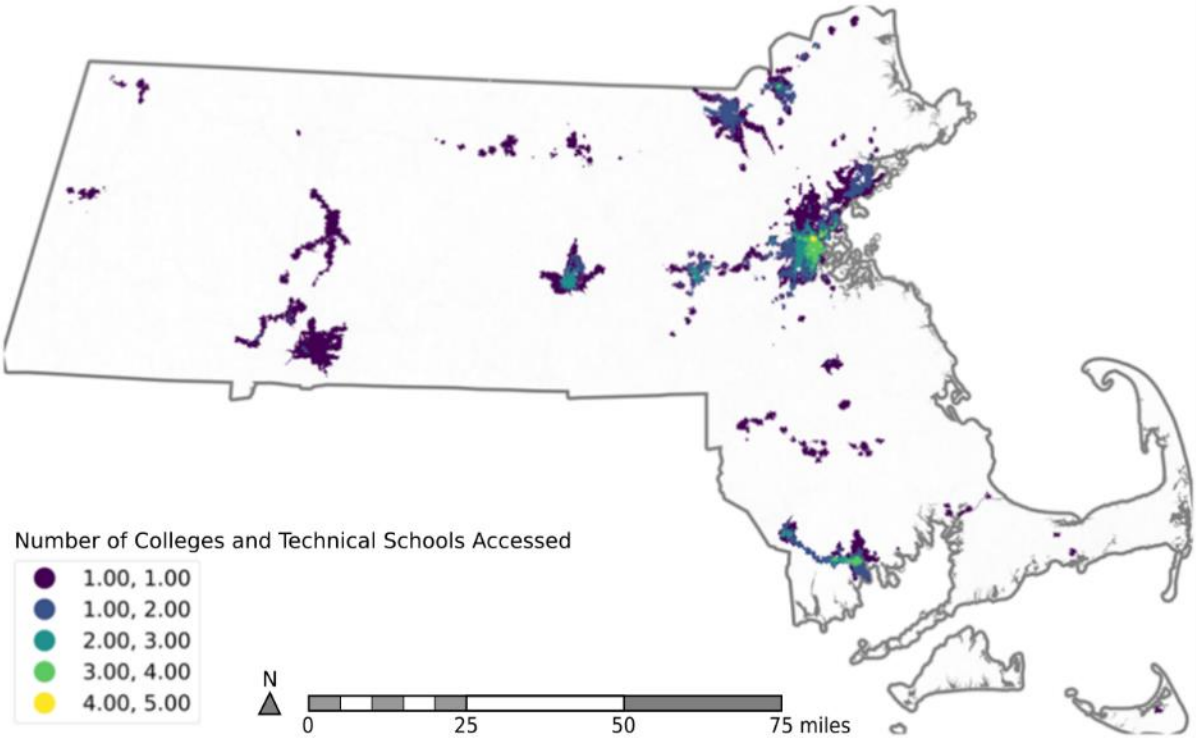

Figure C.21 Colleges and technical schools within 45 minutes fixed route transit

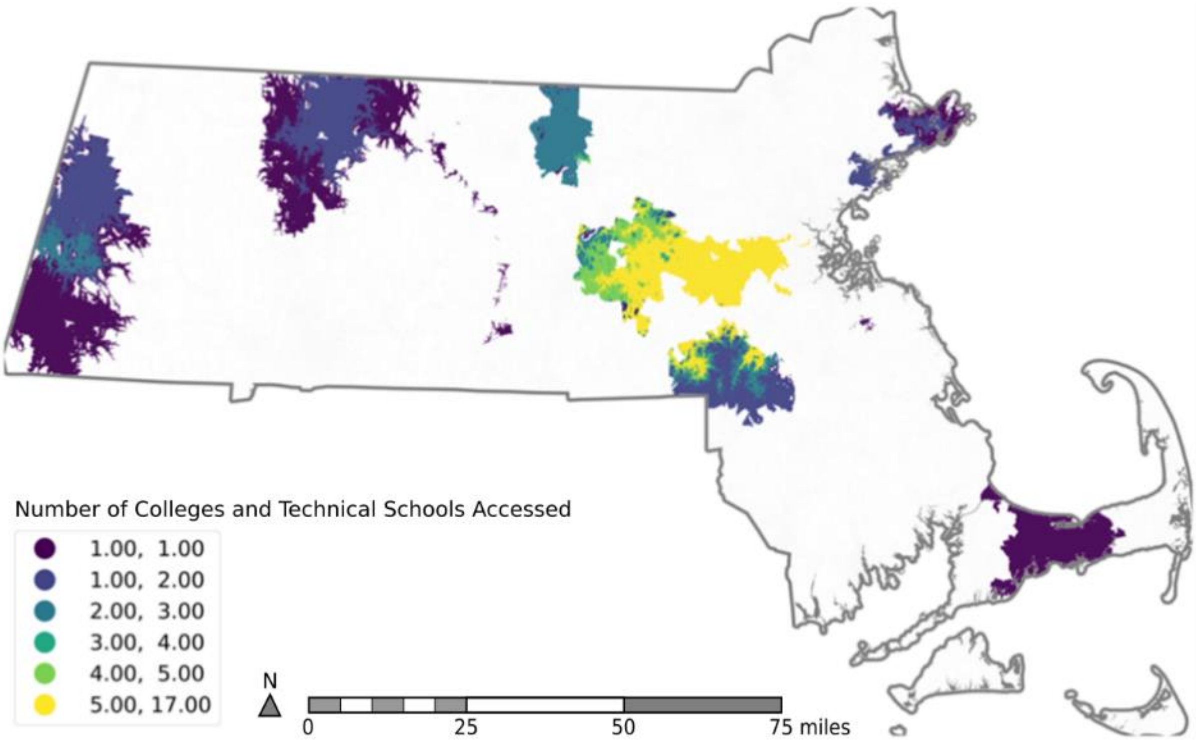

Figure C.22 Colleges and technical schools within 45 minutes microtransit

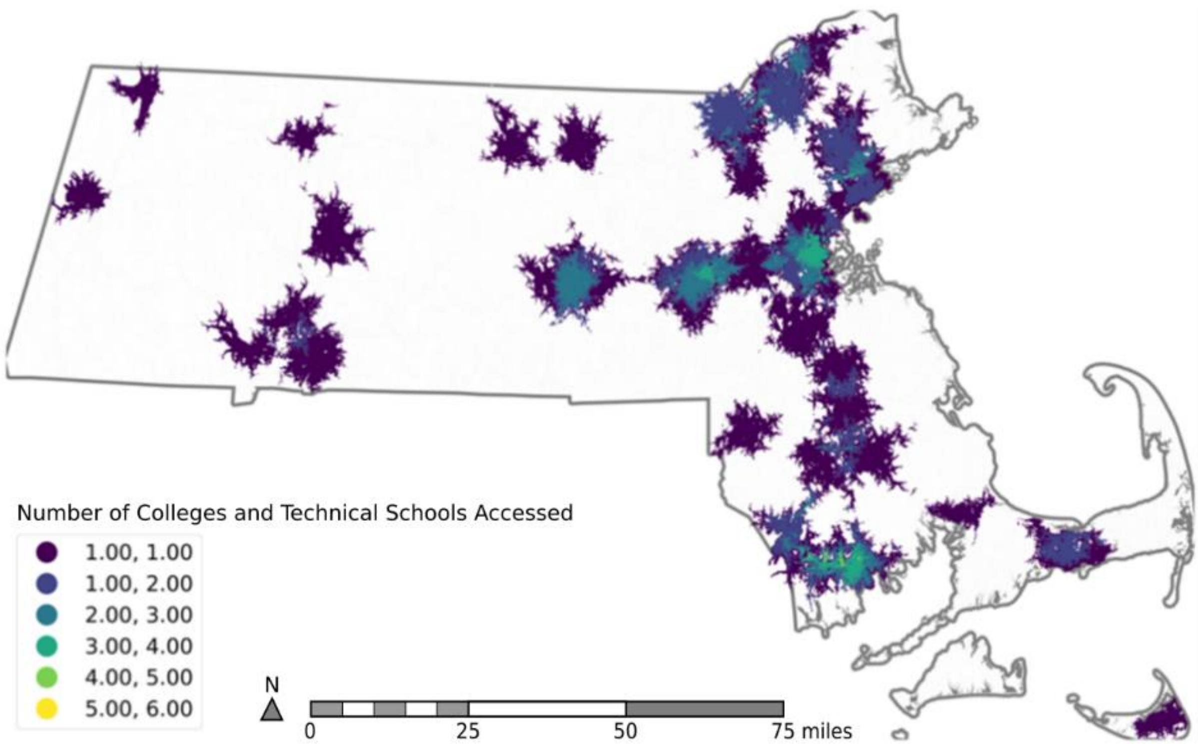

Figure C.23 Colleges and technical schools within 15 minutes driving

Parks Access

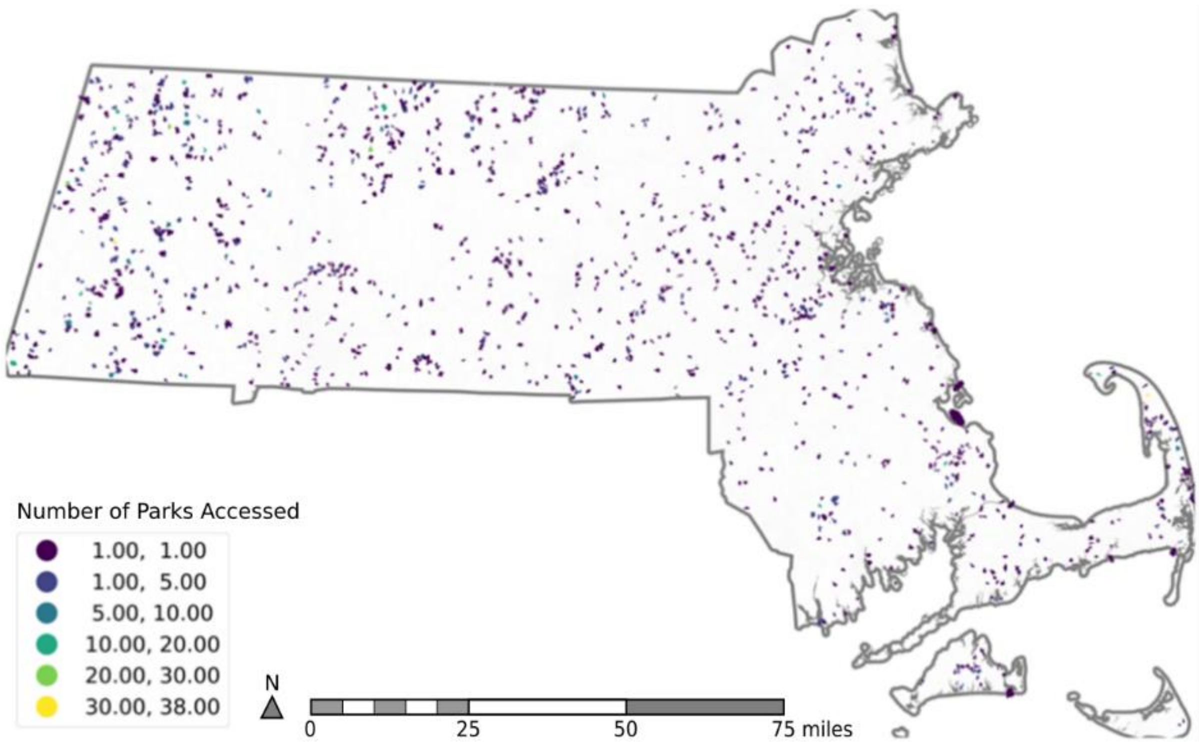

Figure C.24 Parks within 15 minutes NWI-adjusted walk access

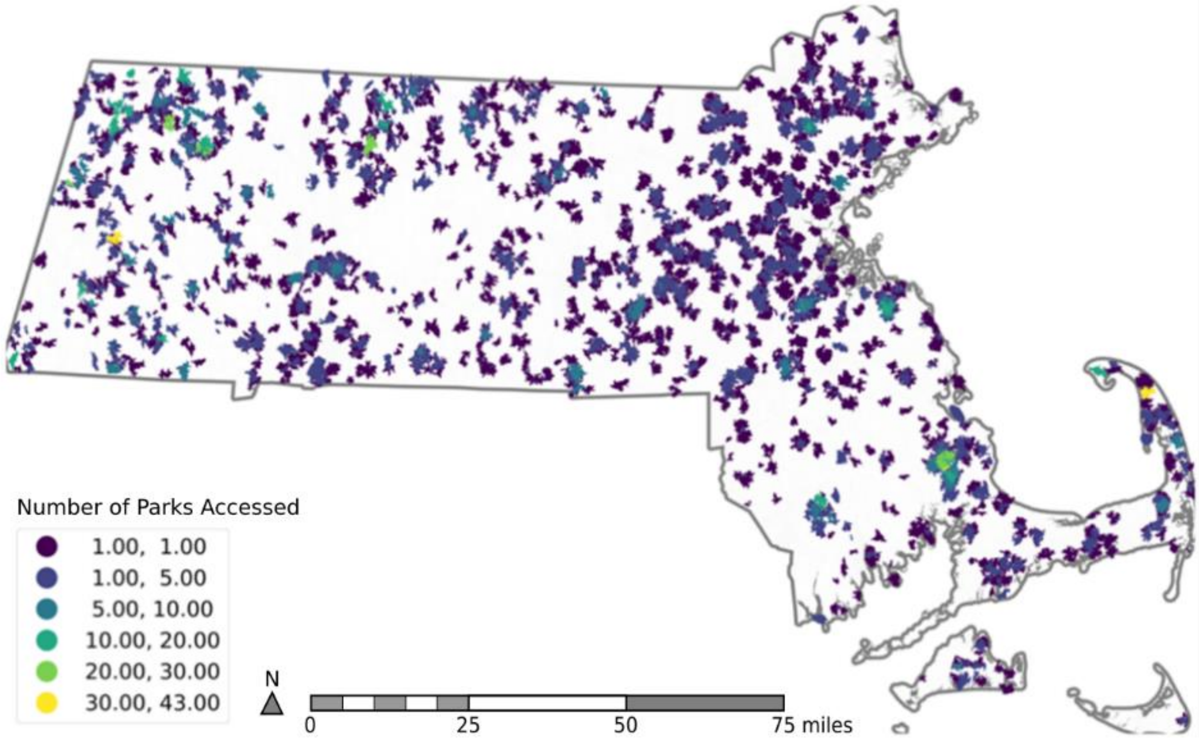

Figure C.25 Parks within 15 minutes LTS 2 bicycle access

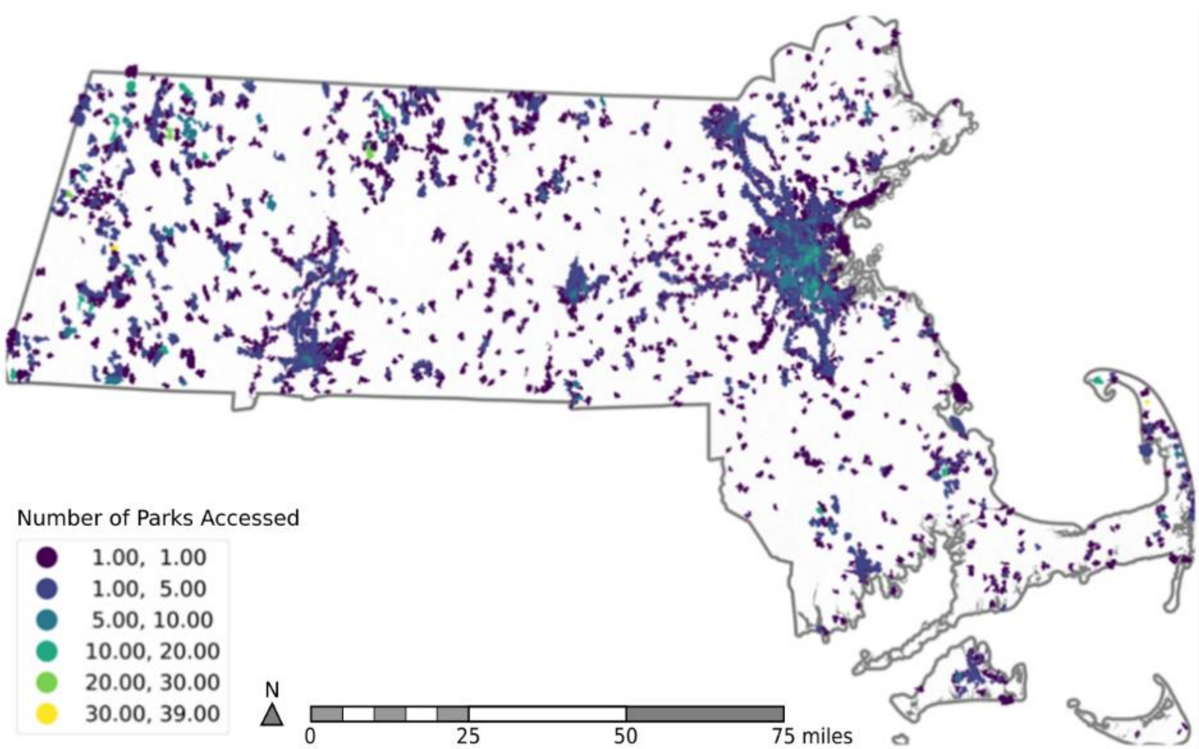

Figure C.26 Parks within 45 minutes transit

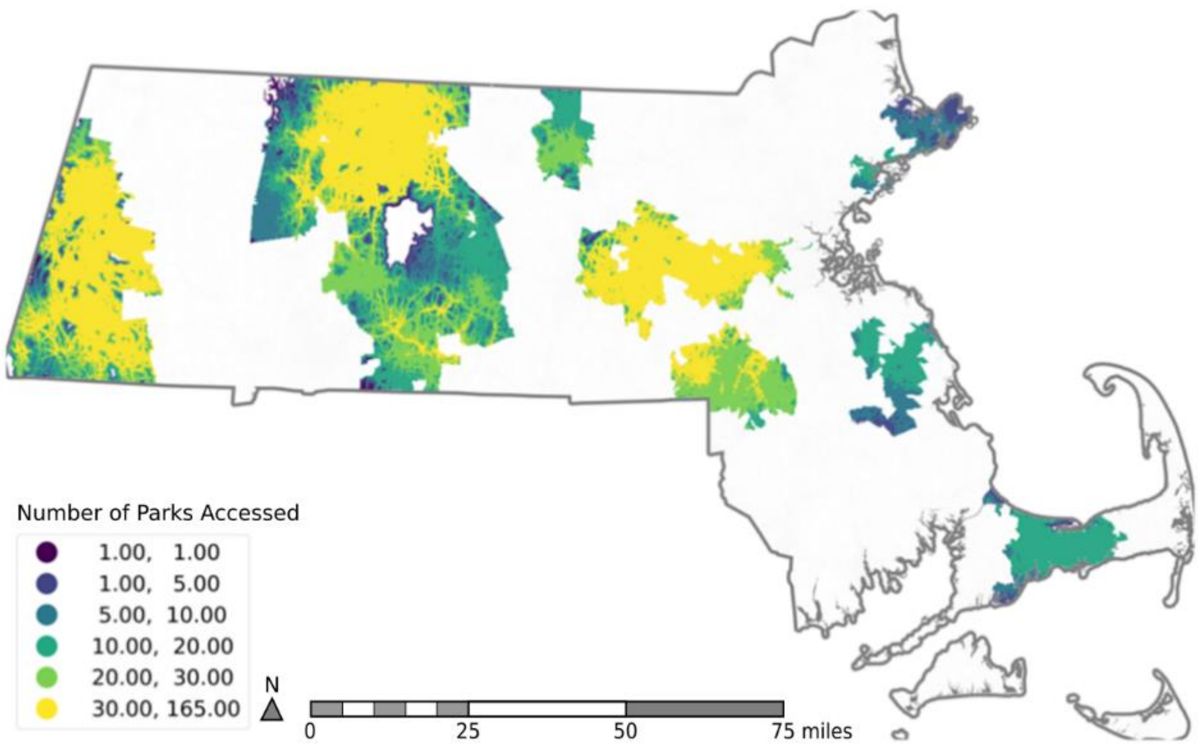

Figure C.27 Parks within 45 minutes microtransit

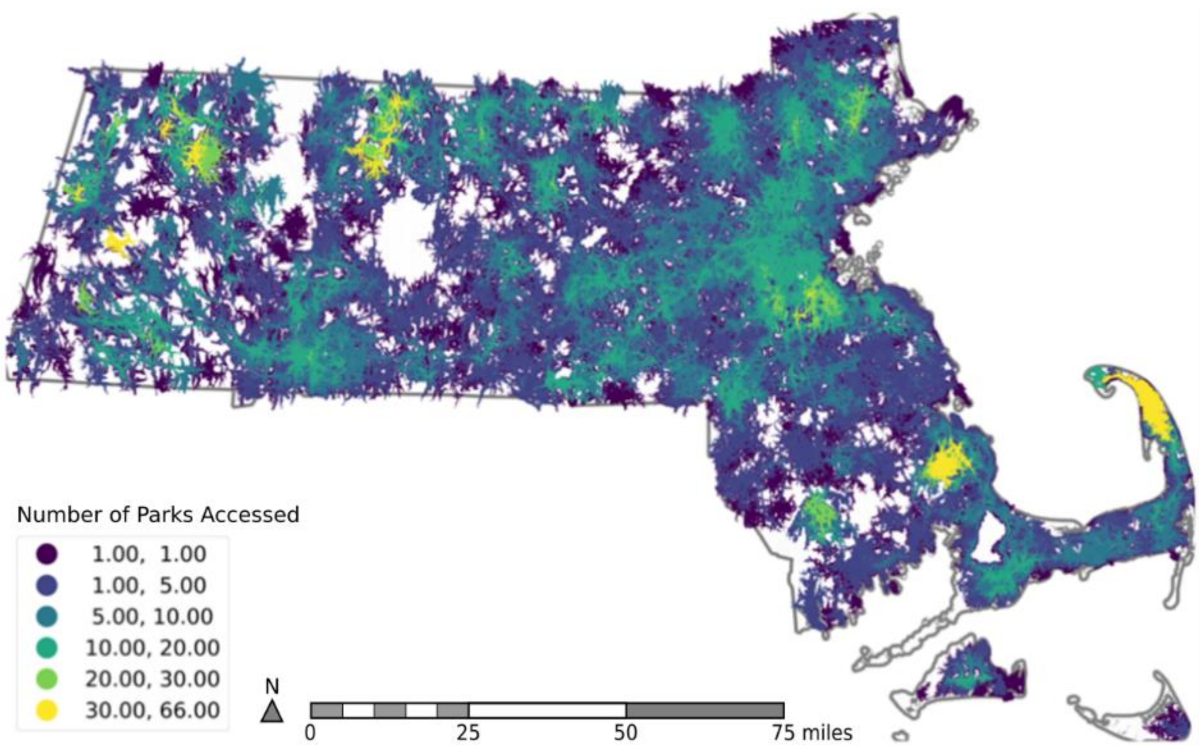

Figure C.28 Parks within 15 minutes driving

Appendix D. Maps of Local SHAP Factors

Interactive versions of all maps are available online at
https://experience.arcgis.com/experience/79d94b86eedd456da5ebec901e7df41b/.

Diabetes Prevalence

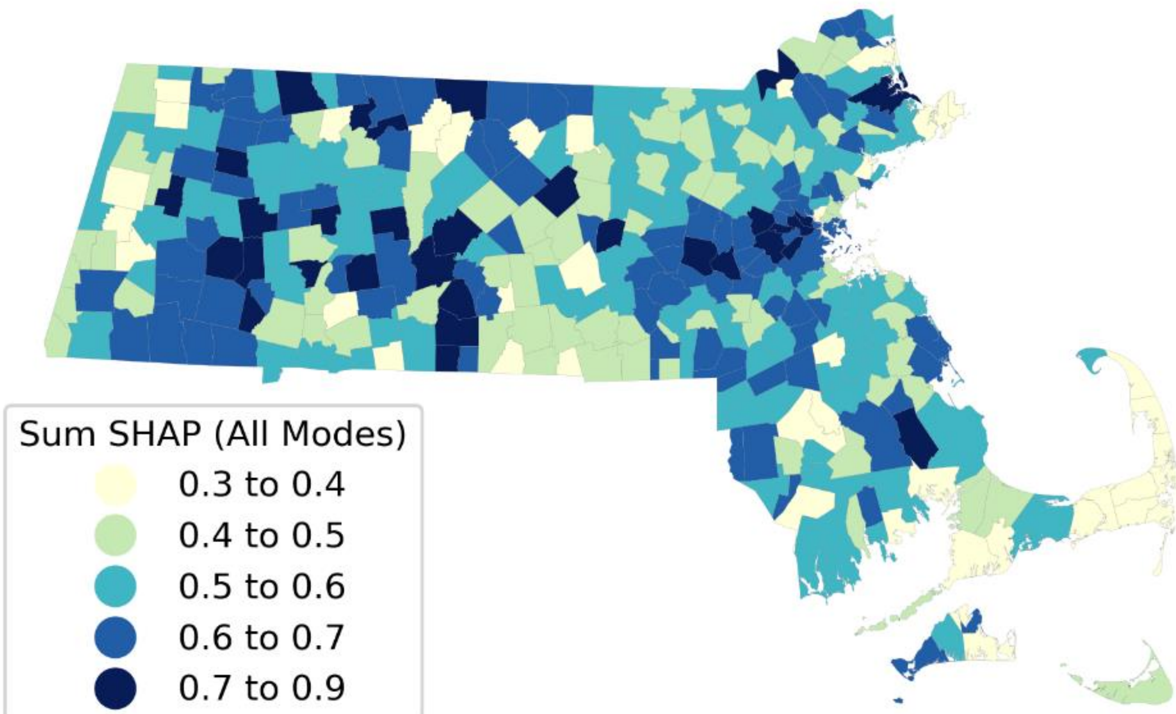

Figure D.1 Normalized SHAP value of all modes – Diabetes

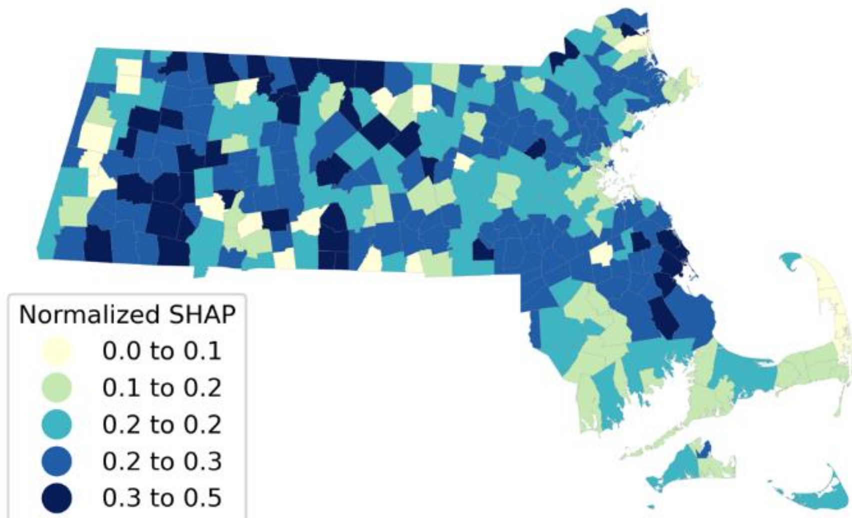

Figure D.2 Normalized SHAP value supermarket access – Diabetes

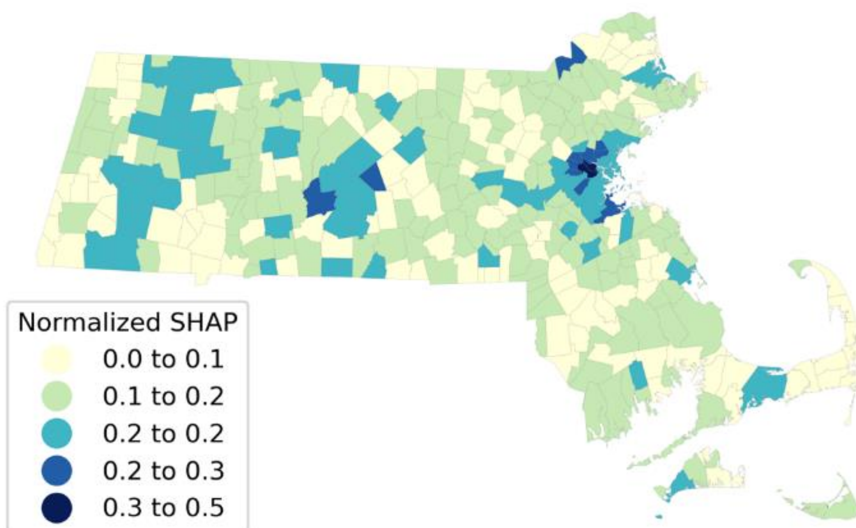

Figure D.3 Normalized SHAP value healthcare access – diabetes

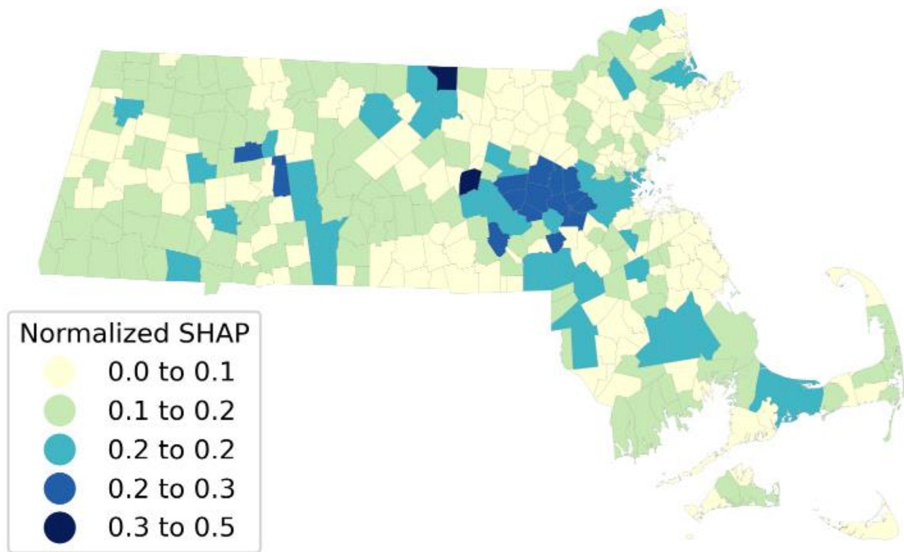

Figure D.4 Normalized SHAP value college and technical schools access – Diabetes

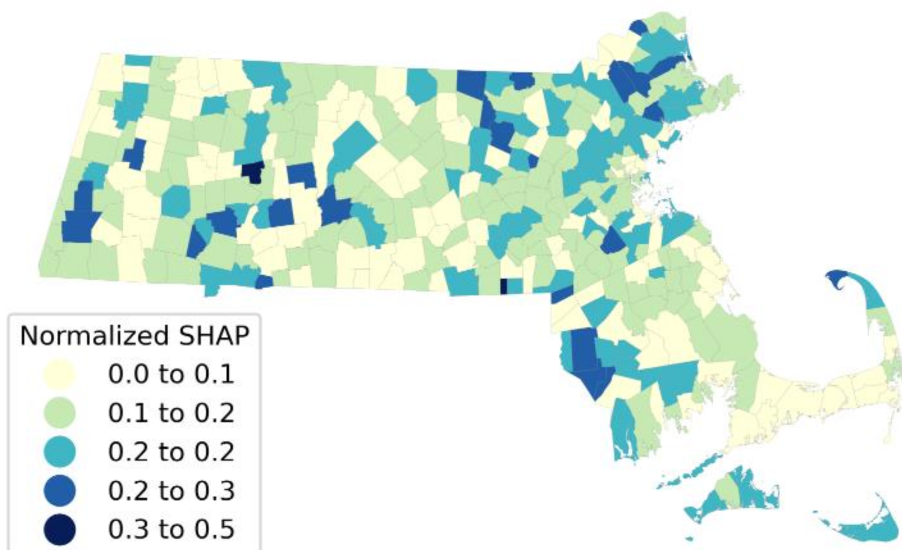

Figure D.5 Normalized SHAP value park access – Diabetes

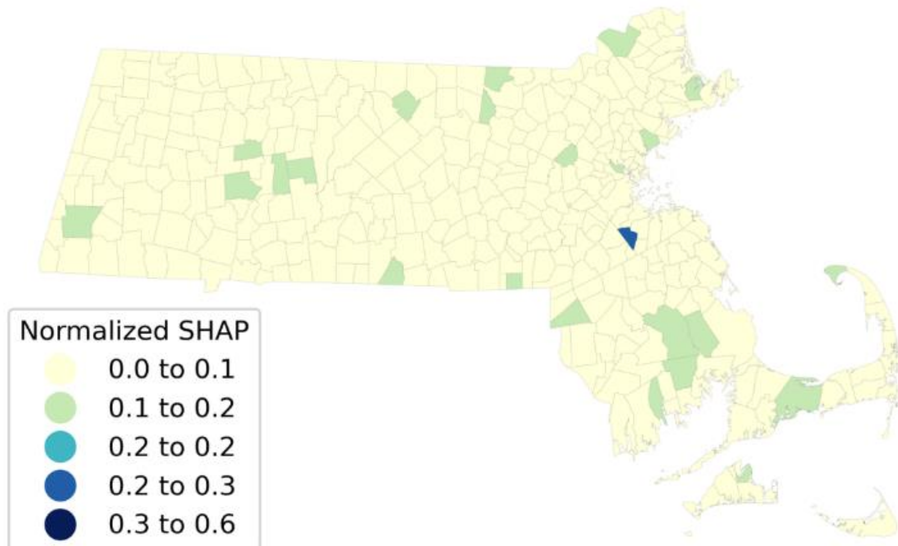

Figure D.6 Normalized SHAP value walk access – Diabetes

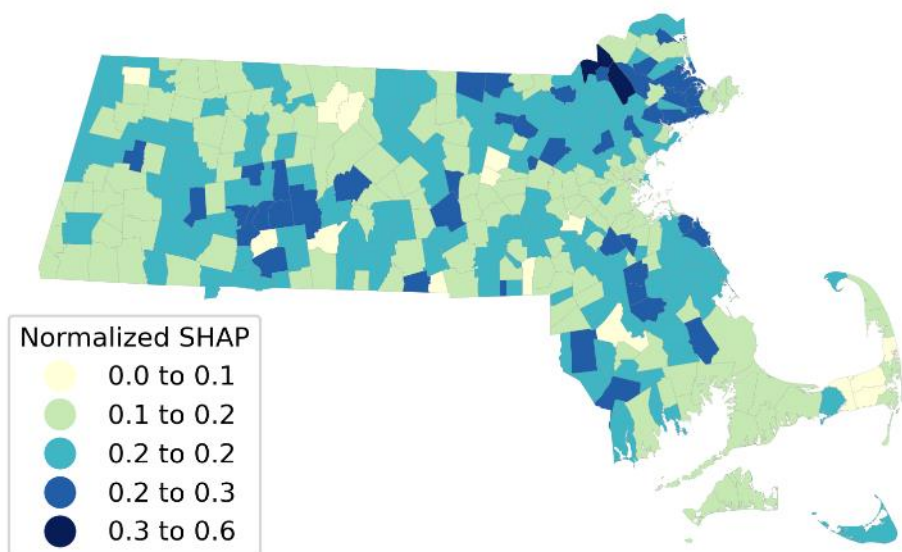

Figure D.7 Normalized SHAP value bike access – Diabetes

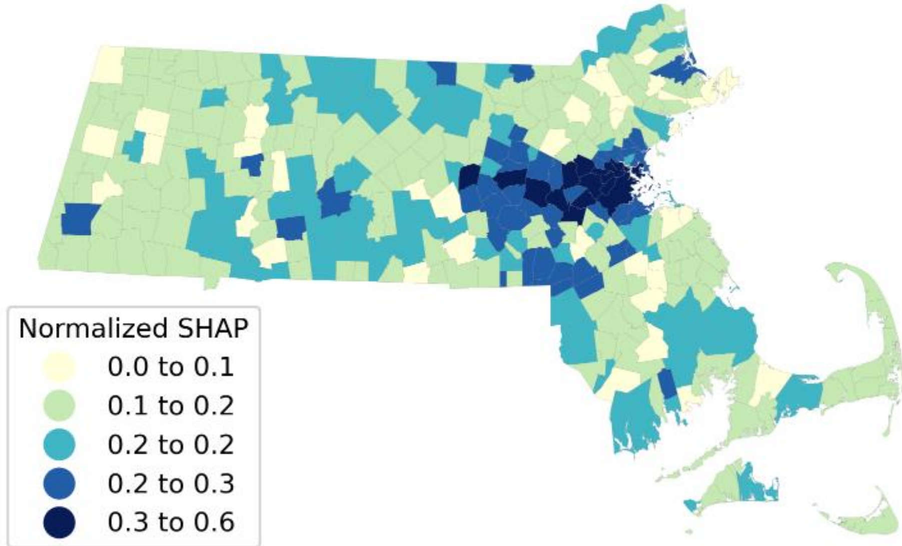

Figure D.8 Normalized SHAP value transit/microtransit access – Diabetes

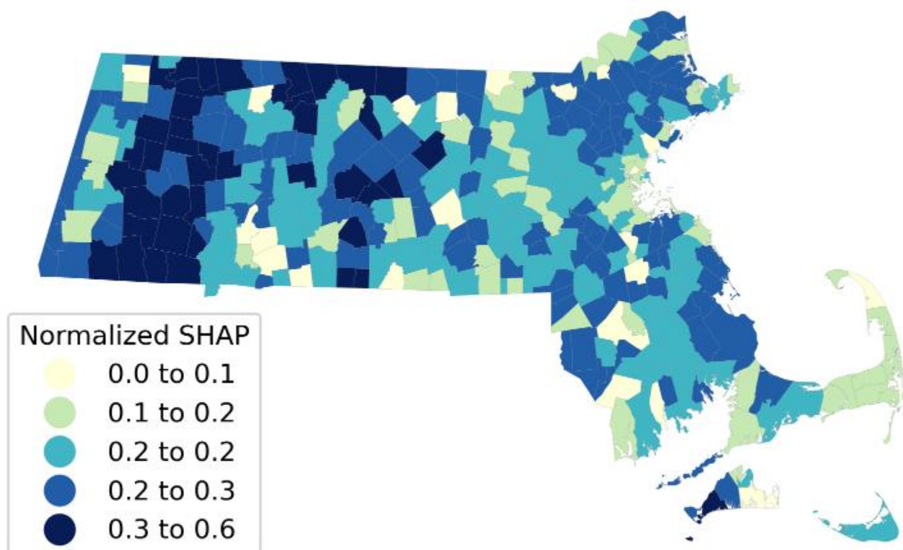

Figure D.9 Normalized SHAP value car access – Diabetes

Heart Disease Prevalence

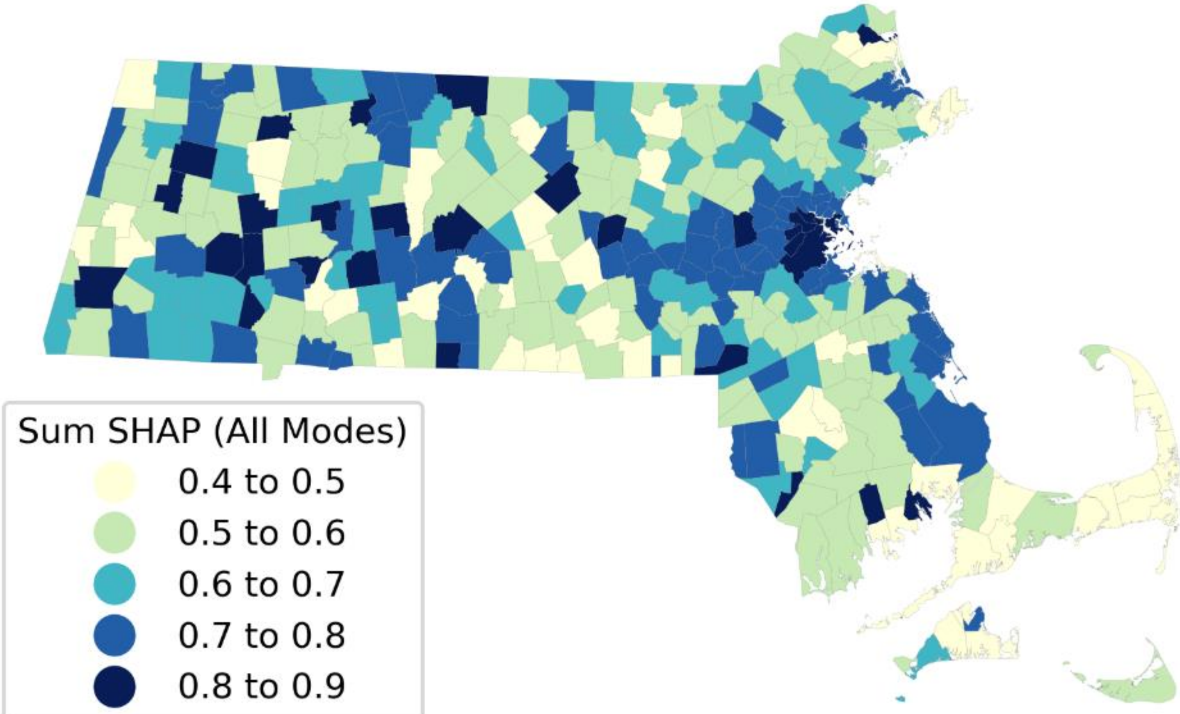

Figure D.10 Normalized SHAP value of all modes – Heart Disease

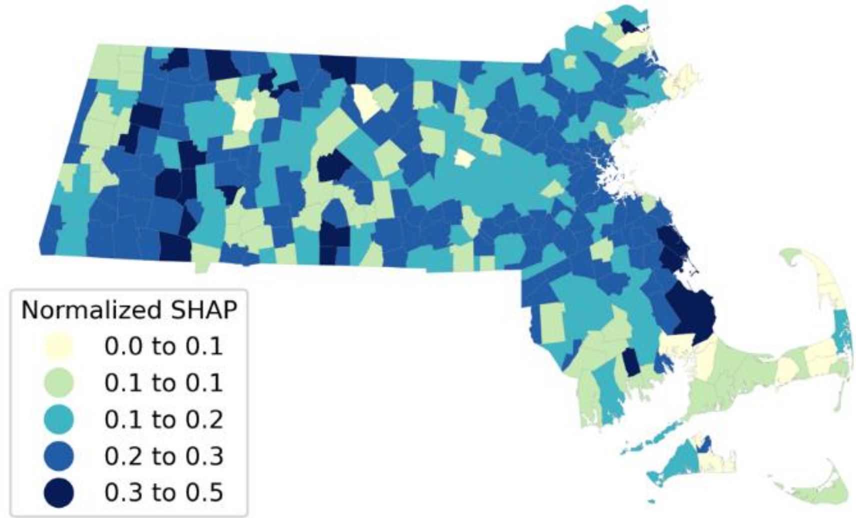

Figure D.11 Normalized SHAP value supermarket access – Heart Disease

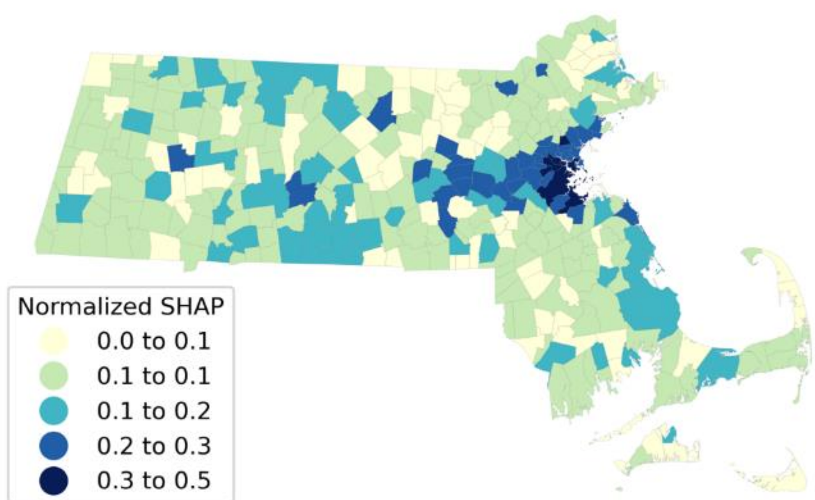

Figure D.12 Normalized SHAP value healthcare access – Heart Disease

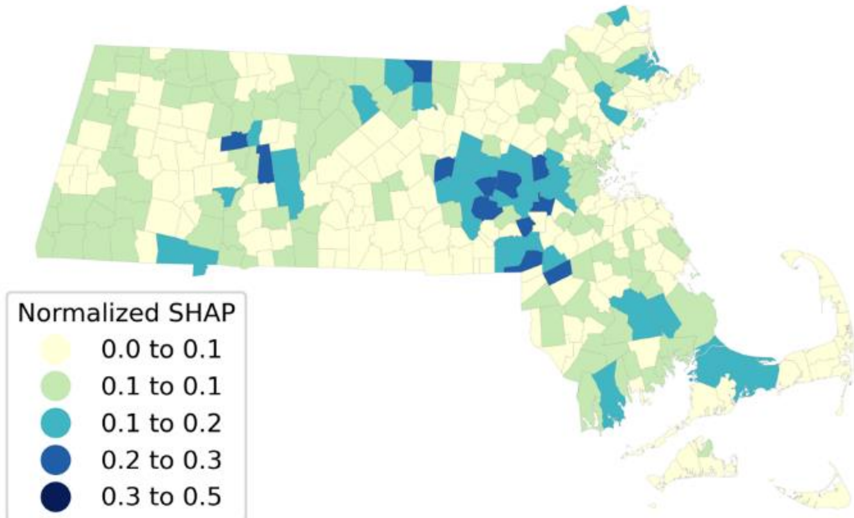

Figure D.13 Normalized SHAP value college and technical schools access – Heart Disease

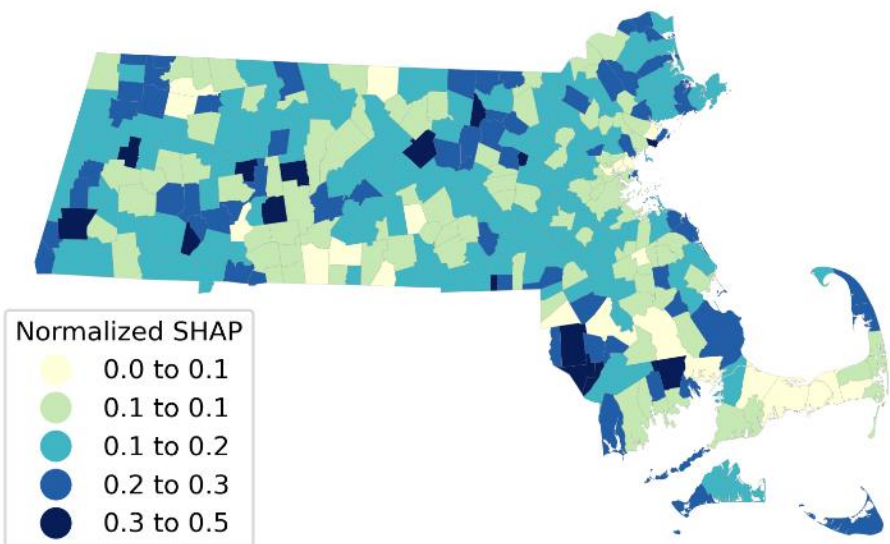

Figure D.14 Normalized SHAP value park Access – Heart Disease

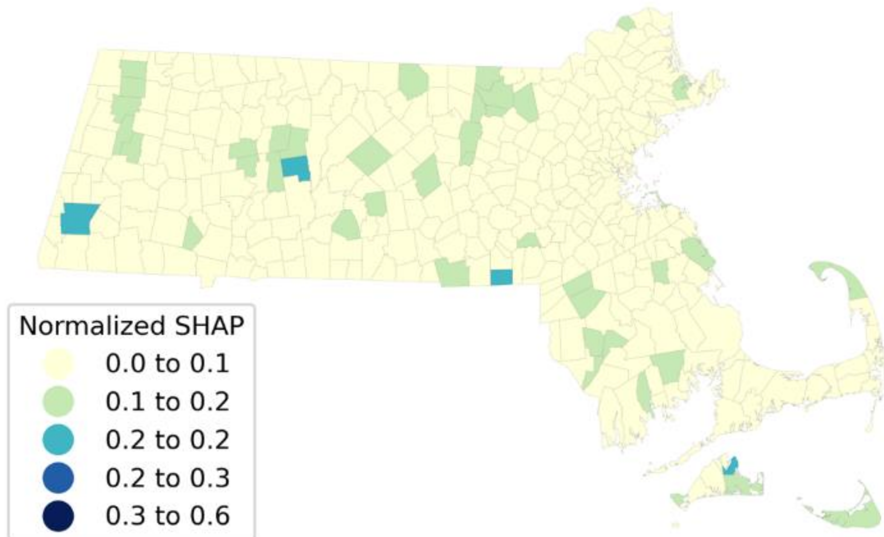

Figure D.15 Normalized SHAP value walk access – Heart Disease

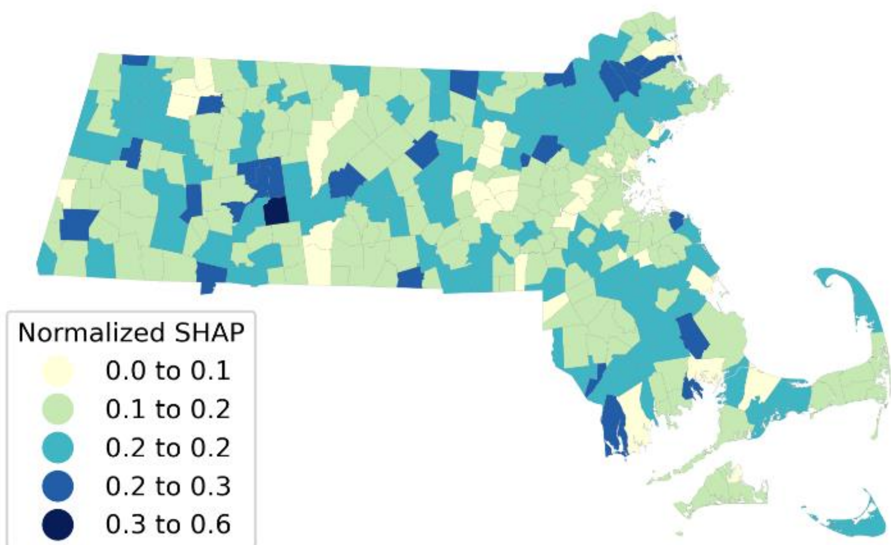

Figure D.16 Normalized SHAP value bike access– Heart Disease

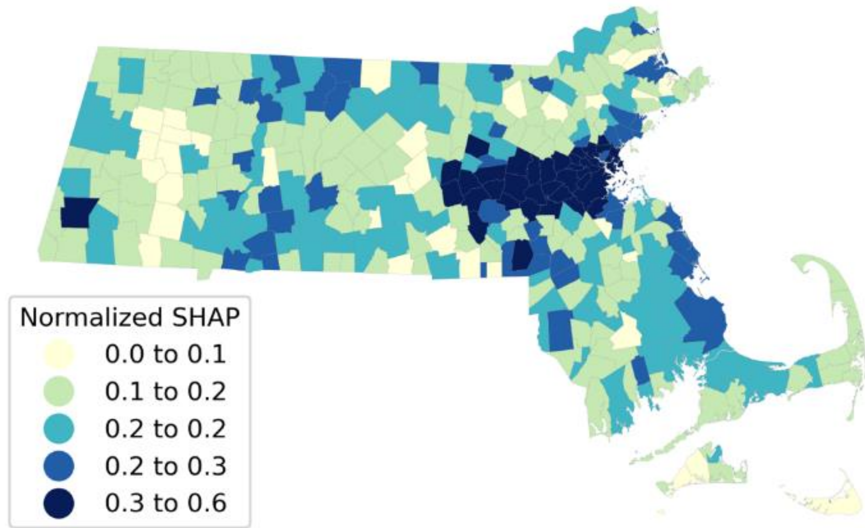

Figure D.17 Normalized SHAP value transit/microtransit access – Heart Disease

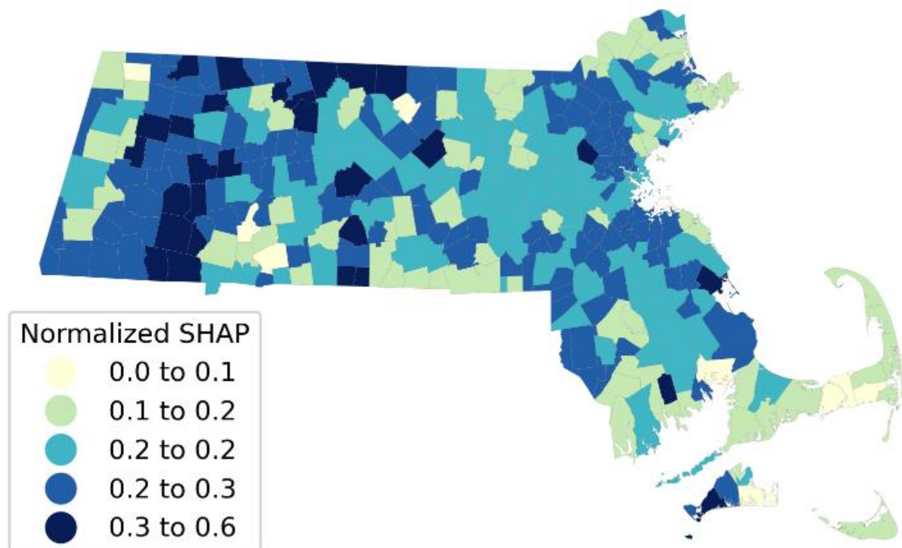

Figure D.18 Normalized SHAP value car access – Heart Disease

Obesity Prevalence

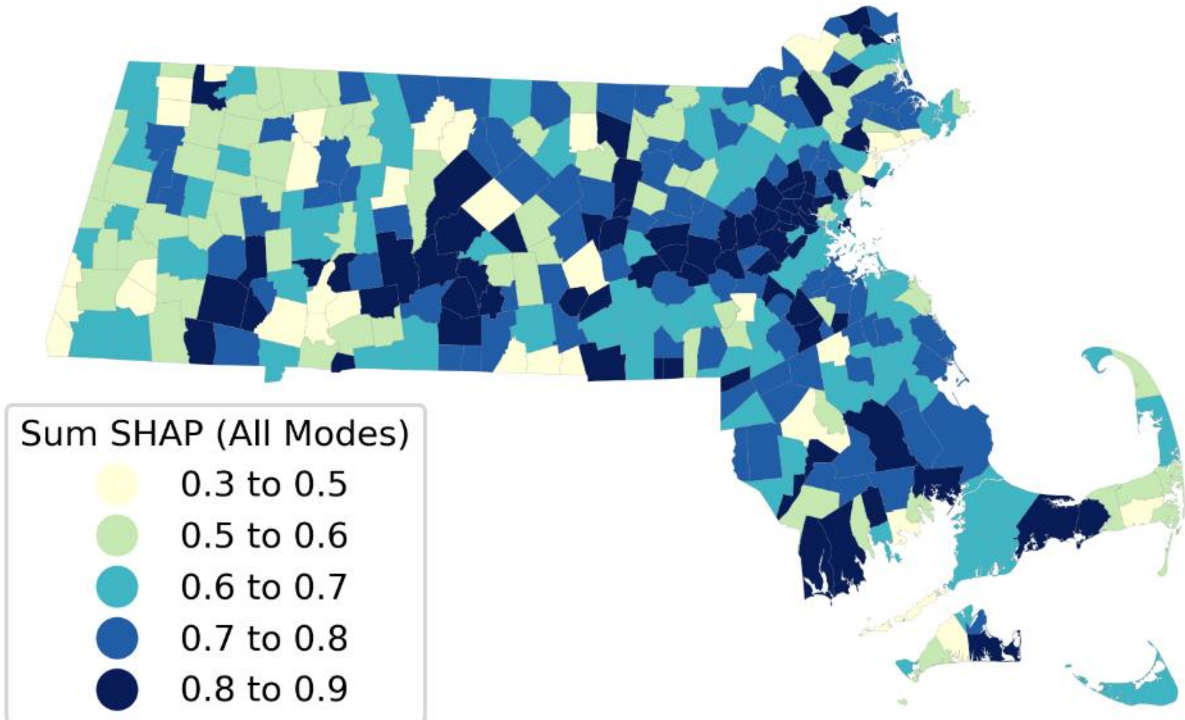

Figure D.19 Normalized SHAP value of all modes – Obesity

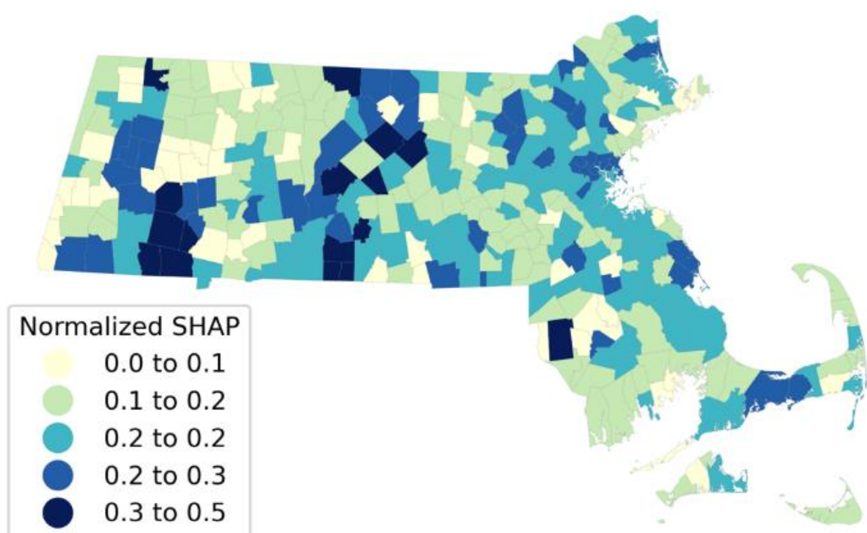

Figure D.20 Normalized SHAP value supermarket access – Obesity

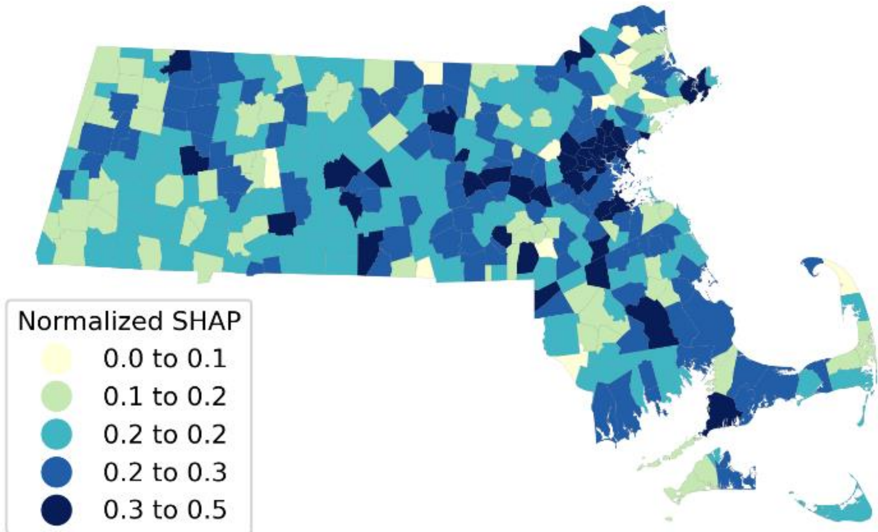

Figure D.21 Normalized SHAP value healthcare access – Obesity

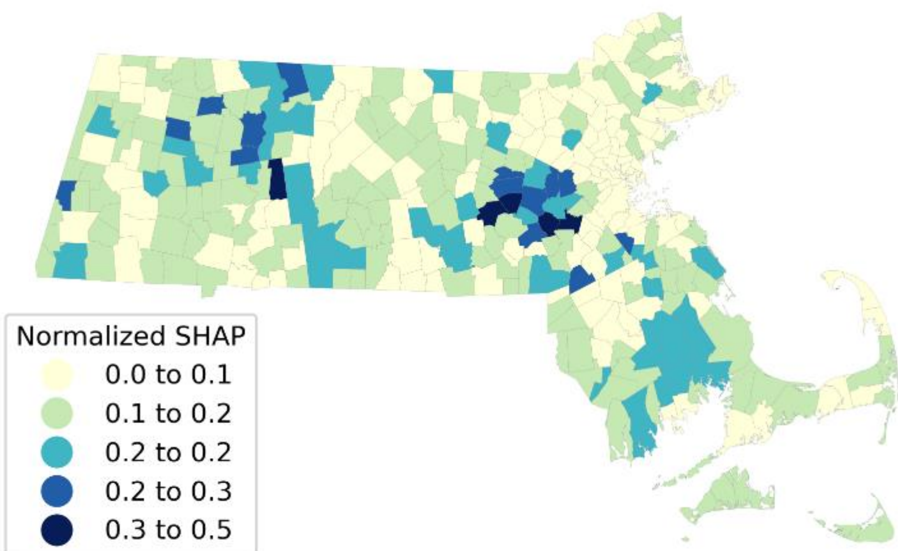

Figure D.22 Normalized SHAP value college and technical schools access – Obesity

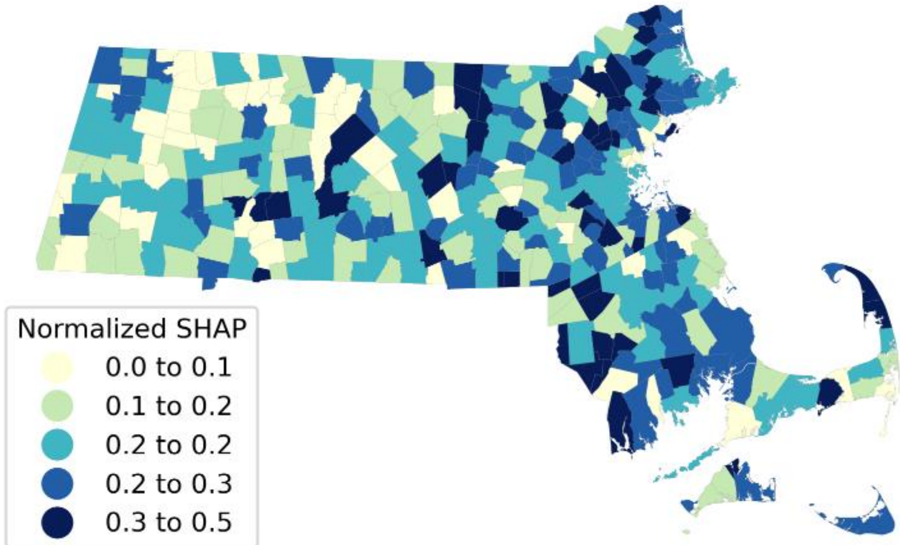

Figure D.23 Normalized SHAP value park access – Obesity

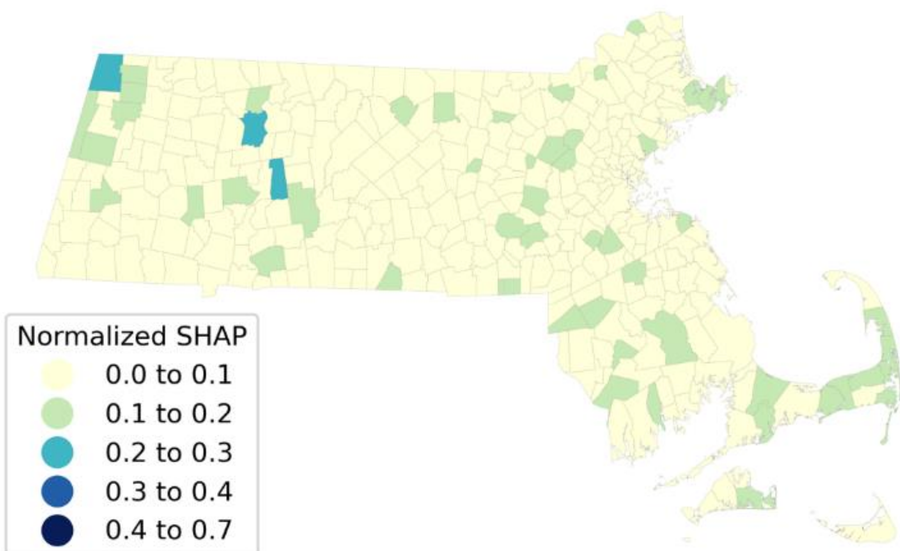

Figure D.24 Normalized SHAP value walk access – Obesity

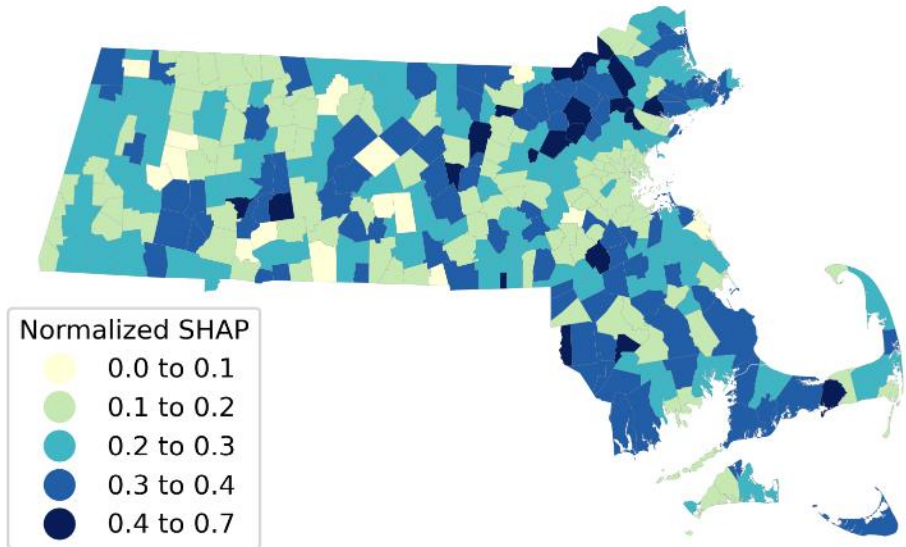

Figure D.25 Normalized SHAP value bike access – Obesity

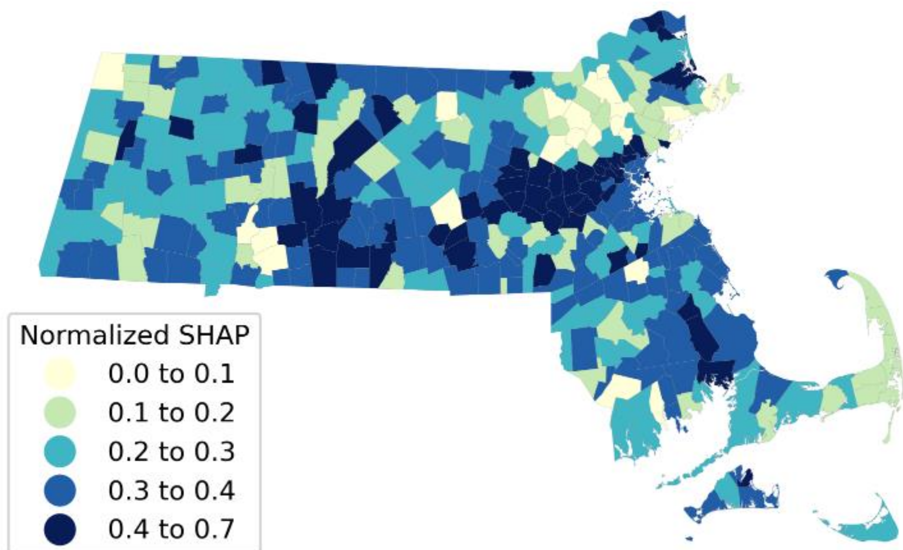

Figure D.26 Normalized SHAP value transit access – Obesity

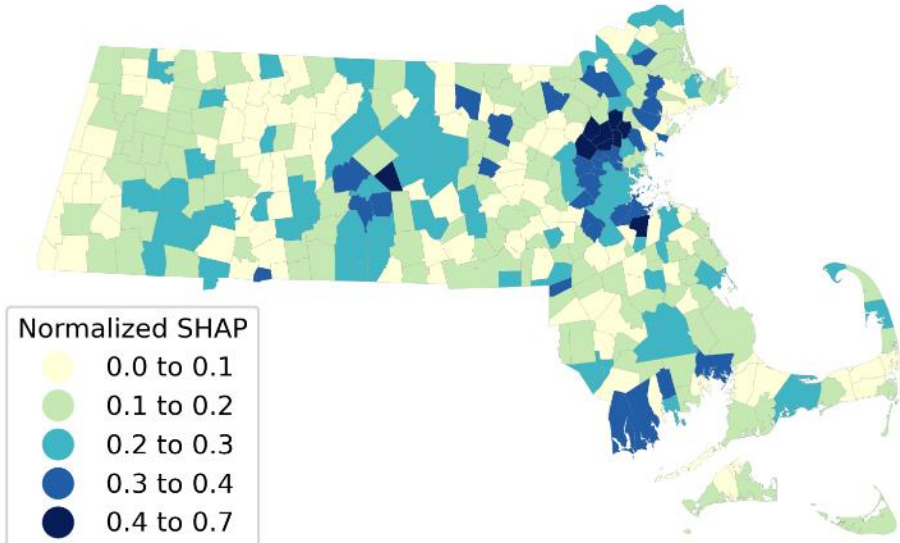

Figure D.27 Normalized SHAP value car access – Obesity