Redefining the Food Desert

A Study of Grocery Store Accessibility Within Metropolitan Atlanta

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Abstract: "Food deserts" are areas of an urban environment that are judged to have no accessibility to a nearby grocery store. Traditionally, this accessibility is based on a simple measure of *Euclidean distance*, i.e. a circle of a given radius drawn around the nearest grocery store, thus ignoring the actual road network used to travel to said store. This paper proposes a methodology for constructing *isochrones*, polygons which both incorporate the actual distance travelled to reach a given grocery store, as well as the time it takes to traverse said distance via a variety of different modes. Doing so dramatically reduces the estimated coverage area of a given grocery store, and helps visualize the inequities inherent in using distance-based measures of accessibility without accounting for the mode taken to travel that distance, which particularly harms individuals without access to cars or bikes.

I. Introduction

Background

The consumption of food is one of a handful of essential, recurring tasks undertaken by humanity, along with breathing, drinking, and sleeping. Though many people could survive anywhere from a few days to a couple of weeks without it, realistically most people eat a meal somewhere between one and three times per day. While this food can come from a variety of sources, the overwhelming majority, in the United States at least, are prepared and eaten at home, with 82% of all meals in 2018 falling into this category[1]. With fresh fruits and vegetables lasting, at best, a week in the refrigerator, this in turn necessitates many trips to a grocery store, and indeed over 70% of U.S. consumers report going to the grocery at least once per week, with an average of 8 times per month[2].

However, the trip to the local supermarket can look very different depending on where in the city someone is located: in the densest part of Brooklyn, a grocery store might only be a block or two down the street, while in the suburbs of Phoenix the closest could be many miles away. These differences in the spatial distribution of food stores leads to some areas having a naturally higher burden of accessing quality, fresh ingredients: such areas are commonly referred to as *food deserts*.

While the term *desert* had been used as early as the 1970s to describe areas of a city lacking essential amenities, the first identification of *food* deserts began in the 1990s in the United Kingdom. From there, the term gained popularity with the general public in the United States when former First Lady Michelle Obama made addressing the inequitable distribution of fresh, healthy food a key pillar of the *White House Task Force on Childhood Obesity*[3]. As of the USDA's most recent report in 2019, somewhere between 13% and 28% of census tracts in the United States qualify as food deserts[4].

Research Objective

The USDA definition is, however, an overly simplistic representation of accessibility to grocery stores. While there are several "official" definitions, the ones applying to urban census tracts have three key dimensions[5]:

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[1] Patton, 2018

[2] Rodgers, 2023

[3] Sutton, 2011

[4] *Measuring Access to Food,* 2023

[5] *Measuring Access to Food,* 2023

- *Distance:* At least 33% or 500 people must be located either 0.5-miles (for "medium access") or 1.0-miles (for "low access") from their nearest supermarket.

- *Income:* A given census tract's poverty rate is 20% or greater, or the median family income of the census tract is less than or equal to 80% of the median family income of the wider metropolitan area.

- *Vehicle:* More than 100 housing units in the census tract do not have access to a vehicle, specifically a car.

While it may not be immediately obvious upon first reading, the USDA's definition of food desert has two flaws. First, it overemphasizes access to cars, ignoring those who might take other forms of transportation to do their grocery shopping, such as walking, biking, or public transit. Secondly, it defines access with a purely distance-based measure, and a Euclidean distance ("as the crow flies", i.e., a straight line) at that, ignoring the quixotic realities of a city's road network.

This paper will, therefore, seek to update the definition of *food desert* to address these two points: focusing on the metropolitan area of Atlanta, Georgia, this paper will identify the locations of high-quality food sources, and compare distance-based and time-based measures of travel along the road network against the traditional definition, based on Euclidean distance, with the hypothesis that doing so will reveal new areas that *should* be classified as food deserts, but are currently *not*.

II. Literature Review

Given its sustained prevalence in policy conversations and general importance for public health, food deserts have been the subject of numerous academic inquiries. The studies reviewed for this paper fell into one of three broad categories: *Identification*, *Intervention*, and *Critiques*.

Identification

Many authors have, as with this paper, attempted to re-define the boundaries of a food desert to better approximate the actual conditions of the world: for example, Richards used the road network of rural Appalachia to demonstrate why drive time was a better-suited measure, and was the inspiration for this paper[6]. Hosford, et al. tied this to the newer city planning goal of 15-minute cities, specifically looking at walking and cycling times to grocery stores[7], while both Swayne and Lowery and LeClair and Aksan analyzed grocery store travel times through transit modes (primarily bus), finding that such trips take as much as three times longer than similar trips by car[8], possible increasing the opportunity cost of travelling further for healthy food beyond the

[6] Richards, 2012

[7] Hosford et al., 2022

[8] Swayne and Lowery, 2021

convenience of locally-available and cheap but ultimately unhealthier food from other retailers[9], highlighting the importance of considering non-automobile modes of transportation.

Jiao et al. performed the analysis most closely related to the goals of this paper, looking at travel times across walking, biking, transit, and driving, while also including a dimension for the cost of the grocery store, in order to handicap access measures by what is feasible affordable for an at-risk population[10], though their study was relatively limited in geographic scope. Finally, Widener and Shannon highlight a particularly salient issue by asking "*When* are food deserts?", challenging researchers to consider the temporal component of any food desert analysis, which includes everything the seasonal availability of ingredients at fresh markets, the traffic conditions during evening rush hour, or even the change in location of an individual between home and work, and the path taken between the two[11], and was echoed by Burgoine and Monsivais in their UK-centric study of holistic "foodscapes"[12].

Intervention

Other researchers have instead focused on the most effective ways to *alleviate* the issue of food deserts, which are frequently associated with negative dietary-related health outcomes such as obesity and diabetes, in turn saddling these often lower-income communities with higher healthcare-associated costs in the long-run[13]. Several studies have focused on the impact of the most logical solution: directly increasing supply by introducing a new source of fresh food to a neighborhood previously lacking it, whether it be a full-scale supermarket[14] or smaller-scale sources such as farmers markets[15]. However, this supply-side solution was oftentimes considered insufficient or inefficient, with Ghosh-Dastidar et al. arguing in 2017 that the market supply of fresh and healthy food was naturally self-correcting, making intervention unnecessary, and determining in 2014, as with Larsen and Gililand, that *price* was the most important factor in driving changes in purchasing decisions.

This key finding, on the primary importance of the price of the food instead of the distance to the closest supermarket, agrees with additional research done by Allcott et al., which found that supply conditions only account for 10% of the observed difference in "nutritional inequality", with the other 90% driven by differences in demand[16]. This might be because people rarely travel to their

[9] LeClair and Aksan, 2014

[10] Jiao et al, 2012

[11] Widener and Shannon, 2014

[12] Burgoine and Monisvias, 2013

[13] Cotterill and Franklin, 1995

[14] Ghosh-Dastidar et al., 2014; Ghosh-Dastidar et al., 2017

[15] Larsen and Gilliland, 2009

[16] Allcott et al., 2019

nearest grocery store to do their shopping, instead choosing to go to one further away that has better prices or selection[17], or shopping at multiple stores to optimize the price and selection across all of them[18].

Critiques

These findings tie directly to one of the largest bodies of research on this topic, which questions whether the model of a *food desert* is even a useful one to begin with. At its most basic level, researchers have shown just how sensitive the definition of what areas qualify is to the parameters used in the model. Gripper et al. proved that an overreliance on easy-to-obtain data on food *stores* means that many past papers have missed non-traditional sources of healthy foods from community gardens and urban farms[19], and several researchers studying New Orleans were able to classify anywhere from 17% to 87% of census tracts in the city as food deserts, depending on the exact definition of *food* and *desert* one cared about[20]. This is driven by a number of issues common in cartographic research, including the fallacy of division, the modifiable areal unit problem, boundary effects, and the dynamic nature of population growth and food availability[21].

Still others challenge that the *desert* is the issue. Instead, a growing corpus of literature argues that it is food *swamps* that deserve focus, and have a stronger association with negative health outcomes. These swamps are characterized not by low access to food of any sort, but by particularly high concentrations of *unhealthy* food establishments, lowering the opportunity cost of access to these areas and making it a "sensible" option for those looking to save time and money, and requiring an entirely different set of interventions[22].

Finally, still more object to the framing of a food *desert*, with its inherent association with a natural phenomenon, preferring the stronger language such as food *apartheid*, to draw attention to the intentional choices that have led to this situation[23]. The concentration of food deserts in primarily low-income and minority-dominant neighborhoods is no accident[24], and has been proven to map to historic redlining maps[25]. This framing helps underscore that access to food is not simply a

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[17] Kato and McKinney, 2015; Dubowitz et al., 2015

[18] Gripper et al., 2022

[19] Gripper et al., 2022

[20] Rose et al., 2009

[21] Widener, 2018

[22] Cooksey-Stowers et al., 2017; Rose et al., 2009

[23] Brones, 2018

[24] Walker et al., 2010

[25] Joyner et al., 2022

technical issue to be solved, but inherently tied to topics of equity and justice that go to the root of social structures in the United States.

Response

So, then: if the interventions that work are limited, and the importance of food deserts debatable, why devote time to studying them?

It is important because, regardless of the nuances in the debate, food deserts still represent a real, tangible, cost burden that is inequitably distributed, with lower-income and often more minority-dominant populations facing both less access to cars for personal use *and* fewer full-service grocery stores in their immediate vicinity. Fully quantifying this burden is a worthwhile endeavor if for no other reason than to identify the communities most in need of assistance, whatever form such intervention might take. However, the hope of this paper is to introduce a methodology that is flexible enough to be applied to accessibility deserts in whatever form they might take, be it banking services, daycare services, educational centers, greenspaces, or any other facility that is vital to a sustainable urban life: grocery stores are simply the starting point.

III. Methods

In order to build a picture of food access in metropolitan Atlanta, a three-step process was performed: first, a study area was defined; then, the selection of "grocery stores" was identified; and, finally, a series of *isochrones* were created outwards from the grocery stores for each of the four modes of interest: walking, biking, driving, and transit (considering both rail and bus).

Defining the Study Area

Where is Atlanta?

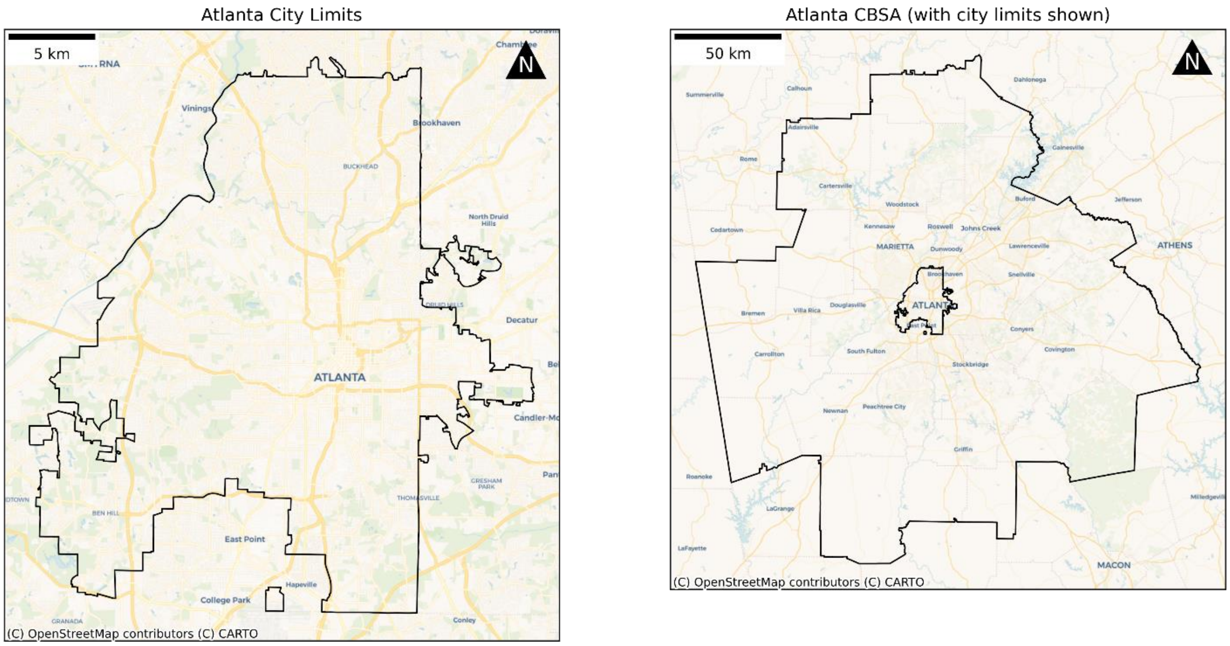
Ask 100 people what, exactly, constitutes the boundary of a city like Atlanta, and one is likely to receive at least 90 unique answers. The most restrictive might be the actual city limits of Atlanta, home to a little less than 500,000 people as of 2022[26], and stretching from the neighborhood of Buckhead in the north nearly (but not quite) to the airport in the south, and extending from beyond the I-285 perimeter highway to the west to just beyond the Fulton-DeKalb county border in the east, before being stopped in its tracks by the city of Decatur. Conversely, the most expansive definition would be the Atlanta core-based statistical area: more than 10 times bigger, with a population of over 6 million, it has a sprawling footprint, encompassing parts or all of 30 counties, and includes cities beyond Atlanta such as Alpharetta, Sandy Springs, Roswell, Peachtree City, and more[27]. In between these two scales, there are a number of other possibilities: it could be the

[26] US Census Bureau QuickFacts: Atlanta City, Georgia, 2022

[27] Resident Population in Atlanta-Sandy Springs-Roswell, GA (MSA), 2022

5 densest, most populated counties (Fulton, DeKalb, Gwinnett, Cobb, and Clayton), or include the additional 6 that make up the Atlanta Regional Commission, the area's regional planning agency.

Figure 01: Comparison of Atlanta administrative boundaries



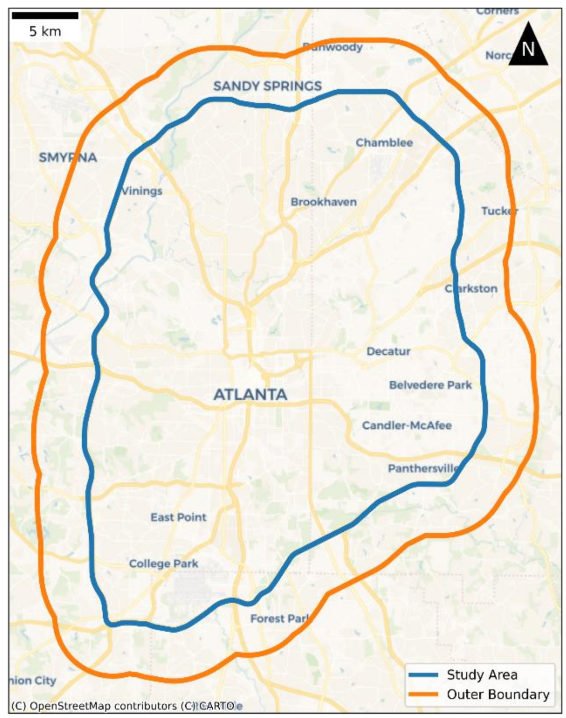
These definitions, however, all have the same flaw: they rely on *administrative* boundaries to define an area. While this does have its usefulness, it rarely aligns with how people outside of government or planning circles view the world. Instead, asking those who grew up in the area what constitutes "Atlanta", in their mind, one might hear the term "ITP" used to refer to Atlanta as being *inside the perimeter*, as opposed to "OTP", or *outside the perimeter*. This colloquial definition uses I-285, a major highway encircling many of the most densely-populated and economically-productive parts of the metropolitan area, as the key boundary: in this way, areas such as Brookhaven, Decatur, and East Point are included, contrary to the "city limits" definition, while secondary centers of activity, such as Sandy Springs and Norcross and beyond, are excluded, recognizing their further distance from the "core" of the city (roughly defined as the Midtown and Downtown neighborhoods). This is the definition selected for the study area of this paper, given its more natural shape, in contrast to the abrupt, irregular edges of county and city boundaries, and its inclusion of both diverse built environments, spanning highly urban to low-density suburban, and diverse populations, including all income brackets and racial demographics.

Extracting the perimeter

With the definition set, the next step was to actually create a workable geometry of the study area. Unfortunately, most common administrative boundaries are not themselves bounded by I-285, and so easy-to-acquire, pre-defined areas such as counties or cities could not be used to create this.

Instead, a road network file from OpenStreetMap was used. OpenStreetMap is an open-source, collaborative, geographic database, which relies on user contributions to fill in geodata, such as the road network or building locations and footprints. Its open-source nature does mean there are drawbacks: it is not always reliable, especially for newer changes to the built environment, and coverage is not equally distributed nationally, but it is sufficiently "correct" to be used in this study, especially in a major city such as Atlanta.

Figure 02: Study Area and Outer Boundary based on I-285



The road network was extracted from OpenStreetMap using the online service BBBike.org[28], which allowed a custom bounding box larger than simply the I-285 perimeter to be set and downloaded as a local PBF (Protocol Buffers Format) file. This file was then processed in Python using the package PyrOSM[29], to filter the road network to *highways* with the name *Perimeter* in them. This returned a series of linestrings, which were then slightly buffered into polygons and dissolved into a single ring with the GeoPandas library[30], from which the exterior line was taken to return just a boundary linestring representing the outer limit of the study area. This boundary was then once again buffered, this time to a distance of 2 miles: this larger area, extending beyond I-285, would be used as the boundary for clipping the road network and searching for grocery stores, to account for *boundary effects*, so as not to exclude, for example, a supermarket directly across the I-285 perimeter, which might serve as the local store for many within it. The final study area can be seen in *Figure 02*, on the previous page.

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[28] *Data Sources*: Schneider

[29] *Software Packages*: PyrOSM

[30] *Software Packages*: GeoPandas

Identifying Grocery Stores

What counts as a grocery store?

As mentioned in the *Literature Review*, the question of which *types* of stores are included within the “foodscape” of an area is integral to understanding the accessibility of said foodscape. Supermarkets and large grocery store chains might be considered the “gold standard”, with their diverse offerings of fresh fruits and vegetables, meats, and dry goods, but are far from the only type of store that might qualify: convenience stores, dollar stores, and pharmacies might also offer one or more of these types of ingredients, while farmers’ markets and urban farms could provide additional access to locally grown foods[31]. Additionally, families might not only shop at a single store, and instead rely on multiple, smaller stores to source the ingredients for a week’s worth of meals, including butcher shops and international or halal stores[32].

However, these considerations were discarded for this paper for two reasons. First, an analysis that fully addressed such complex factors was simply not feasible in the time given for this paper, as significant effort would need to be expended validating the inventory available at many stores, and piecing together which ones could be bundled together to represent a “full” supermarket. Second, making multiple trips to stores represents yet another, additional, time-based cost burden for many, and is usually infeasible for those without access to their own car, unless they are lucky enough to be located very close to complementary stores.

Figure 03: Picture taken of vegetable section at a “Specialized” grocery store

Because of this, this paper will focus solely on stores where a full week’s worth of groceries can be purchased at once, and therefore offers a wide range of fresh fruits and vegetables, meat, and dry goods (meaning intermediate ingredients such as cooking oil, spices, and the like). Such stores will be termed *supermarkets*. Other classifications include *specialized,* for stores that might only offer one or two of these categories, or a single category in small quantities so as to be insufficient for a large number of families to shop there at once (see *Figure 03*), and *limited*, for stores that are not open multiple days of the week (such as many farmer’s markets). Finally, *convenience* stores were discarded entirely, due to their overreliance on the sale of frozen or processed foods.

[31] Ploeg et al., 2009

[32] MacNell et al., 2017

Scraping internet directories for stores

In order to collect store information across all of the study area in a scalable manner, four different internet-based store directory services were iteratively *scraped*: Foursquare, Yelp, Google Maps, and OpenStreetMap. The first three, Foursquare, Yelp, and Google Maps, offer public-facing APIs either completely for free (in the case of Yelp), or for a nominal charge and a generous supply of free monthly credits, which could be queried in Python. In the case of OpenStreetMap, data was downloaded with the assistance of the OSMNx Python package[33].

For all four sources, though, the process followed a similar pattern. First, the study area was divided into a series of hexagons based on the H3 analysis tools developed by Uber[34], using the h3pandas package[35], which, at a resolution level of 7, represents approximately 5 square kilometers per hexagon. Then, the centroid of each hexagon was supplied as the latitude and longitude for a "search" query with each provider's API, along with the categorical, tag, or keyword-based filters to narrowly search for stores matching *grocery* or *convenience*. Then, the resulting list of stores was stripped of duplicates, resulting in a unique list of stores by provider, as shown in *Table 01*.

	Foursquare	**Yelp**	**Google**	**OpenStreetMap**
Access	Paid	Free	Paid	Free
Documentation	See *Data Sources* in *Citations* for links to documentation for each API			
Filter	See *Appendix* for full list of filters and keywords used by provider			
Unique Stores	267	383	210	263

Table 01: Online directories queried

In all 4 datasets	68
In 3 of 4 datasets	56
In 2 of 4 datasets	100
Only in 1 dataset	517
Total Unique Stores	**741**

Table 02: Results of cross-referencing query data

At this point, however, duplicates still existed *across* datasets: certain well-represented chains, such as Publix or Kroger, might have the same store appear in two, three, or all four sources (see *Table 02*). To generate a consistent, unique list of stores across all data providers required an additional two-step cleansing process. First, stores within 500 feet of each other, as judged by their centroid's latitude and longitude, were clustered together. Then, the names of each store were compared using the Python package thefuzz[36], which performs fuzzy string matching,

[33] *Software Packages*: OSMNx

[34] H3Geo.org

[35] *Software Packages*: h3pandas

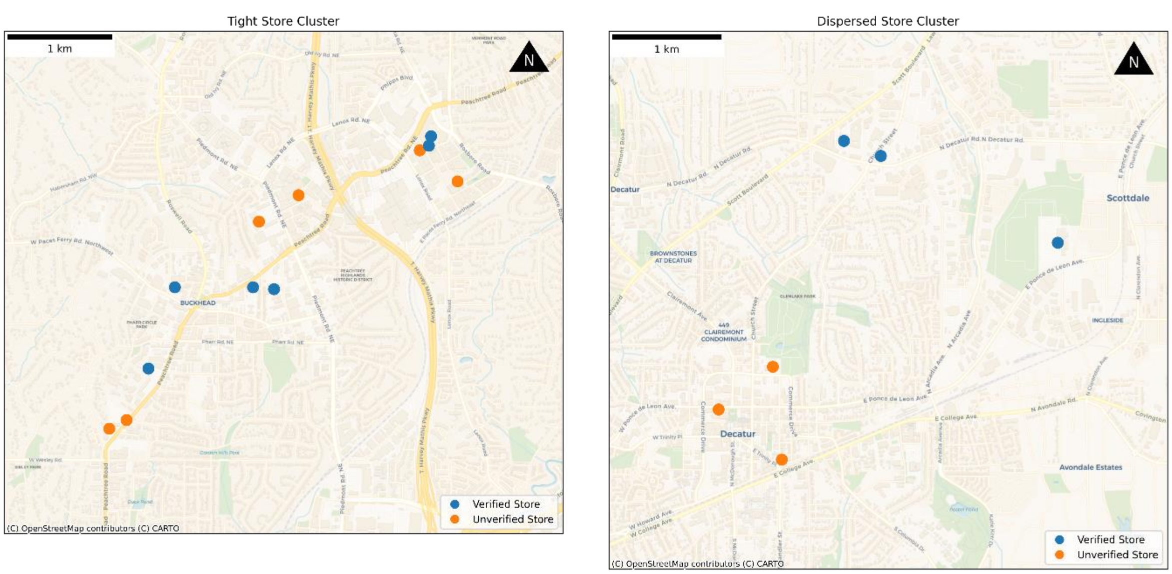
[36] *Software Packages*: thefuzz

and only those with a *similarity score* across their names over 80 were ultimately kept. This would ensure that an *H Mart* store in the Foursquare dataset is correctly matched to both *H Mart Doraville* in the Google Maps dataset and *Super H Mart* in the OpenStreetMap dataset.

Manual validation was then performed, across each match, to ensure it was *accurate*, meaning there hadn't been an erroneous match. In general, quality descended with the number of matches across datasets: a store returning a match across all four was almost always accurate, while those only appearing in a single dataset were much more likely to be not valid. This heuristic was, unfortunately, not strong enough to be automated, and manual verification was still necessary: for example, Target's grocery stores only showed up in Google Maps, while Kroger and Walmart's pharmacy locations routinely appeared in Foursquare, creating false matches with other datasets.

After checking for *accuracy*, each match was then checked for *validity*, meaning whether the store was truly a supermarket or not. Many of these stores were easy to verify: any store of a major grocery chain, such as Kroger, Publix, Walmart, Whole Foods, and the like, could automatically be counted as one, while those from Dollar General, Family Dollar, or a gas station brand could be discarded. However, many more required more intensive research, such as attempting to track down a website listing product selection, looking through Google Maps images from inside the store for vegetables and meats, or finding the address in Google's Street View to confirm the existence of the store in the first place. Stores verified with this additional effort were prioritized based on their relative distance to other, previously confirmed stores, as a food retailer located across the street from a Whole Foods would have less of an impact on accessibility scores than one located several miles from any other grocery stores, as visualized in *Figure 04*.

Figure 04: Comparison of store clustering behaviors



What verification could be accomplished at the computer was not perfect: many stores were both highly prioritized (due to their distance from any other grocery) and had little to no online presence. For these, verification would have to take place in-person.

Visiting stores in-person

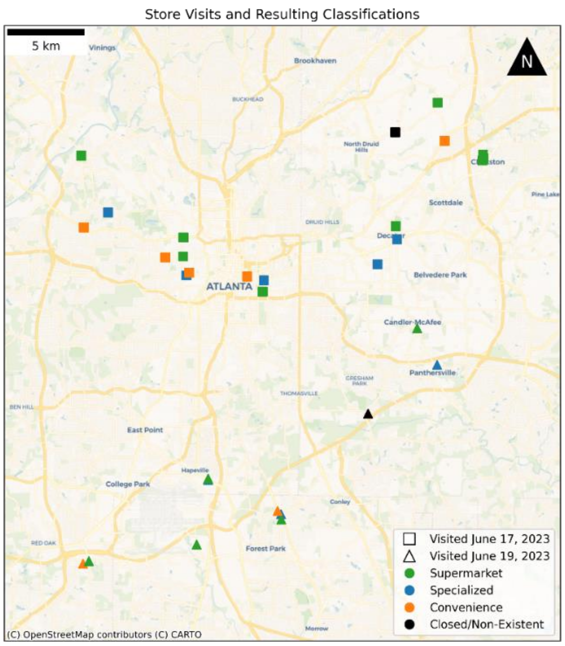
31 stores from the list were selected to be visited, in-person, to confirm their selection of fruits and vegetables, meats, and dry goods, to ultimately categorize them as either a *supermarket* or other, more limited type of grocery store. These establishments ranged from stores from major chains like Kroger and Walmart, which were thought to be potentially permanently closed, to international stores, produce shops, and markets of all types, as well as many suspected convenience stores masquerading as grocery stores in the data.

Categorization was done through visual inspection, mainly by physically entering the store and walking up and down each aisle, taking note of what goods were available. When necessary, retail employees were approached to confirm where items might be located in case they were not immediately obvious. An example form completed for each visit is reproduced below in *Table 03*.

Store Name	Name as appearing on signage Ex: Atlanta Municipal Market
Address	Street address for location Ex: 209 Edgewood Ave SE
Meat?	Are raw/unprocessed meats available? Ex: True, False, Limited
Fruits/Vegetables?	Are fresh fruits/vegetables available? Ex: True, False, Limited
Dry Goods?	Are dry goods/ingredients available? Ex: True, False, Limited
Frozen?	Are frozen foods/prepared meals available? Ex: True, False, Limited
Accept EBT?	Does the store accept EBT/SNAP? Ex: True, False
Notes	Freeform text field for notes Ex: Closed on Sundays
Category	Final categorization Ex: Supermarket, Limited, Convenience

Table 03: Sample form fields and responses

The three store visits were conducted over a two-day period, with 20 stores, mainly in central, north, and west Atlanta, visited on June 17, 2023, and the remaining 11, located to the east and south, visited on June 19, 2023. It is important to note that transportation to and from each store utilized a car, a privilege not afforded to many who are the primary population of concern for this study: it would simply not have been feasible to visit so many sites by biking, walking, or taking public transportation, in the timeline given. A summary result of these visits is displayed below, in *Table 04* and *Figure 05*, and full details can be seen in the appendix.



Total Stores Visited	**31**
Convenience Stores	10
Specialized Stores	7
Permanently Closed	2
Does Not Exist	2
Supermarkets	10

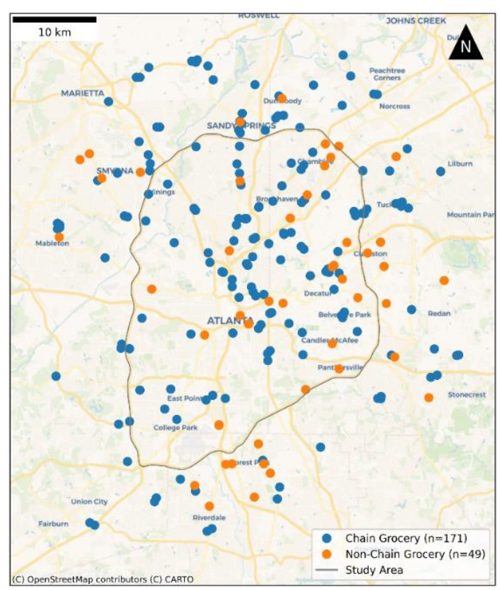
Table 04 (above): Final classifications of stores visited

Figure 05 (left): Map of final classifications and days each store was visited

Final grocery store selection

With all prior steps completed, the final selection of grocery stores included in the analysis consists of the 220 locations shown *Figure 06*. Of these, over 75% were classified as belonging to major national or regional *retail chains*, such as Publix, Whole Foods, or Piggly Wiggly. This might indicate bias in selection, as these chains are more likely to have an online presence, and thus an entry in the directories queried to generate the initial lists, or an easily verifiable picture of goods for sale. However, it could also be caused by the increased monopolization of the food retail space, with the top four chains now accounting for nearly 70% of all spend (though note that two of those four, Costco and Albertsons, are not included

Figure 06: Map of included stores



in this analysis, as they are either not present in the city, or were not included in the online directories used to generate the initial list of stores)[37].

Constructing Modal Isochrones

In geography, an *isochrone map* depicts how far away from a given point one can travel in an amount of time (or distance travelled, though this is a rarer use case). It is similar conceptually to a path-finding algorithm, whereby a computer searches along a system of *ways* and *edges*, such as the intersections and roads of a city, for the path between two points that is usually either the quickest to travel or covers the shortest distance, except that an isochrone is built *outwards* from a single point, in all possible directions simultaneously.

Selecting a routing service

Isochrones are a relatively niche use case: everyday users are not going to popular routing applications such as those provided by Google or Apple and asking to see how far they can travel from their current location in all directions. As such, performing an isochronal analysis required research and testing of multiple lesser-known routing services, run on a local computer.

Valhalla[38], a free and open-source software package originally developed by the start-up *Mapzen*, was ultimately selected for four reasons:

- Valhalla utilizes PBF files from OpenStreetMap, for the road, sidewalk, and bike network, which meant the extract already acquired in *Defining the Study Area* could be re-used,

- Valhalla also supports transit directions by integrating with GTFS, the most widely-used format for providing information on transit services, and the one that MARTA uses,

- It also comes pre-loaded with a variety of "sensible" cost assumptions for how different modes of transportation traverse a network, including default speeds, pauses at intersections, and road prioritization (for a curated list of default settings, see appendix),

- Finally, Valhalla is also highly user-customizable: any of the cost assumptions or input variables could be altered in the request, to make sensitivity analyses across modes feasible.

Building modal isochrones

Valhalla was run in a local environment utilizing a Docker container image. Network set-up happened automatically when run for the first time, as the PBF and GTFS files were ingested and

[37] Food and Water Watch, 2021

[38] *Software Packages*: Valhalla

processed[39], and elevation tiles downloaded and mapped to network edges. From there, isochrones were built from each grocery store's latitude and longitude in turn, sending requests to the local instance's *isochrone* endpoint using Python, and optionally iterating across a dictionary of different cost and input options, if any sensitivity analysis was being performed on the mode. A summary of the analysis variants is displayed in *Table 05* – note that a *contour* refers to the cutoff time or distance at which an isochrone's edges are defined (so a 15-minute cutoff means that the outer edge of an isochrone can be reached in 15 minutes, and anything inside can be reached in less).

Table 05: Isochrone analyses performed for each mode

Mode:	**Auto**	**Pedestrian**	**Bicycle**	**Transit**
Time Contours	5, 10, 15 min.	15, 30, 60 min.	15, 30, 60 min.	15, 30, 60 min.
Dist. Contours	All modes except ***Transit*** were analyzed with 0.5, 1.0, and 2.0-mile cutoffs			
Sensitivity Analyses	None	Slower walking speeds	None	Different departure times

To allow for comparison with the current definition of food desert, 0.5 and 1.0-mile radii were also drawn around each grocery store. Unlike the isochrones, these do not follow the road network itself, and instead are simple circles.

IV. Results

Comparing Distance-Based Contours

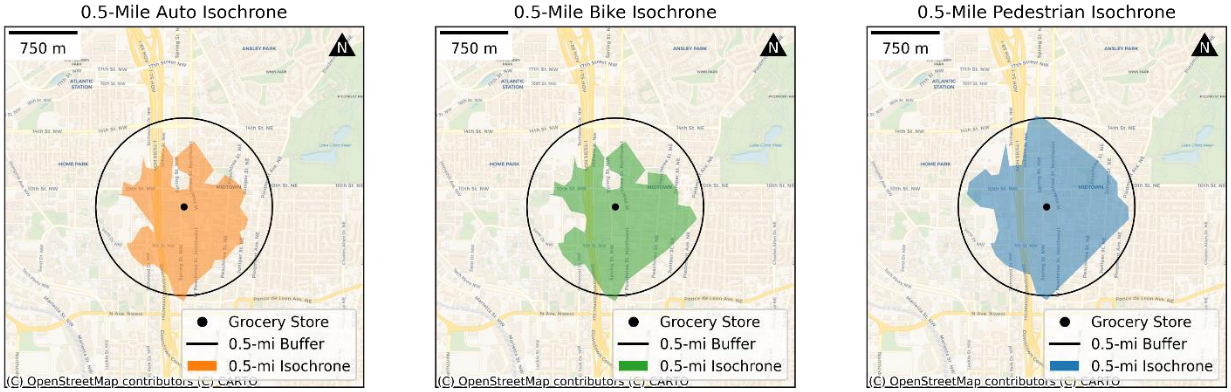
Although traditionally isochrones are time-based measures (the suffix *chrone* derived from the Greek *chronus,* meaning "time"), most food desert definitions are instead based on distance. Therefore, the first set of results generated focused on "isodistances" which, for simplicity, will continue to be referred to as isochrones.

The most commonly used definition of food desert within the United States draws a circular buffer of either 0.5 miles or 1.0 mile around a grocery store, whereas distance-based isochrones follow the road network to a similar distance, and thus account for turns, one-way or no-access streets, and the like. (Note that, due to limitations with the routing engine selected for this assignment, no distance-based isochrones are available for the *transit* mode.)

[39] A special thank you to @nilsnolde on GitHub, who helped me troubleshoot several steps of the set-up process

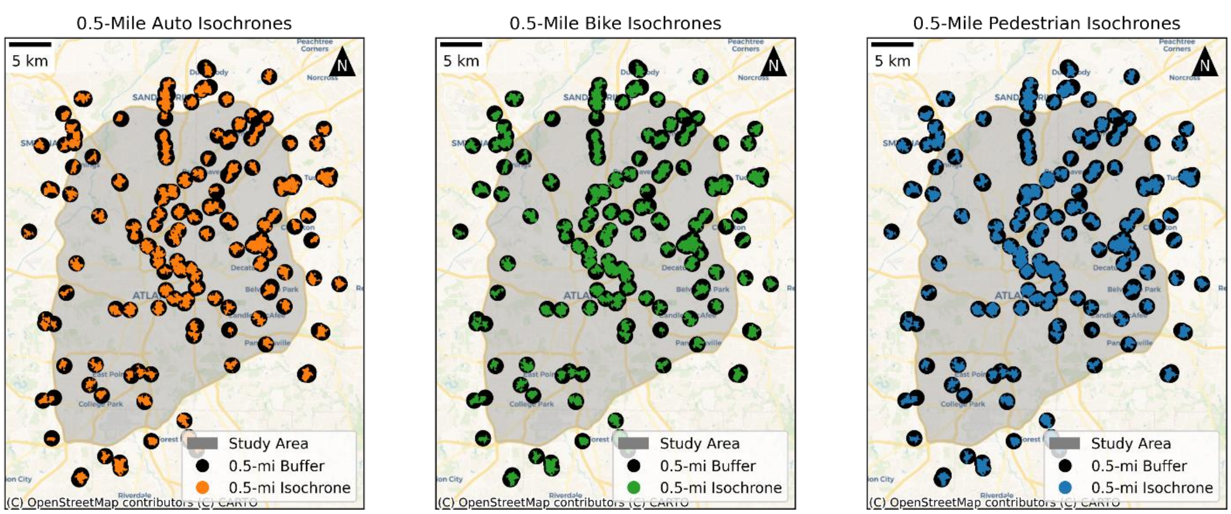
0.5-Mile Distance

Figure 07: 0.5-mile isochrones around a single store



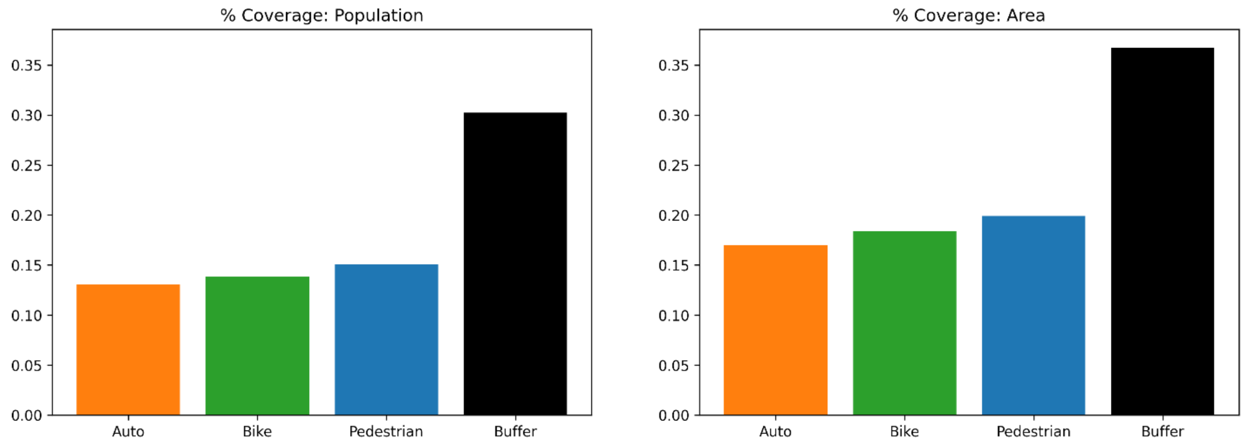
When the isochrone about a single store is shown, as in *Figure 07*, two observations immediately stand out. The first is that all three modes share a roughly similar shape: instead of a simple circle, jagged points appear as the road network is traversed, with "points" appearing in the directions where the fewest turns are required to reach. More notable, however, is the *size*: regardless of which mode of transportation is taken, a distance-based isochrone is *always* smaller than the radius about a point used under the traditional definition. This is sensible: without a road network, an isochrone would *exactly* match the circle, but each turn taken to follow said network shortens the total distance that could be travelled. Thus, an isochrone limited by distance would be expected to reach *at most* as far as the circle, which can be seen at the southern intersection of isochrone and circle, where each mode of transportation can take Spring St directly south, with no turns required.

Figure 08: 0.5-mile isochrones around all stores



This trend is seen to repeat itself across all modes and all store locations (*Figure 08*), regardless of where in the road network they are found: distance-based isochrones are *always* smaller than the current, simplified definition of food desert.

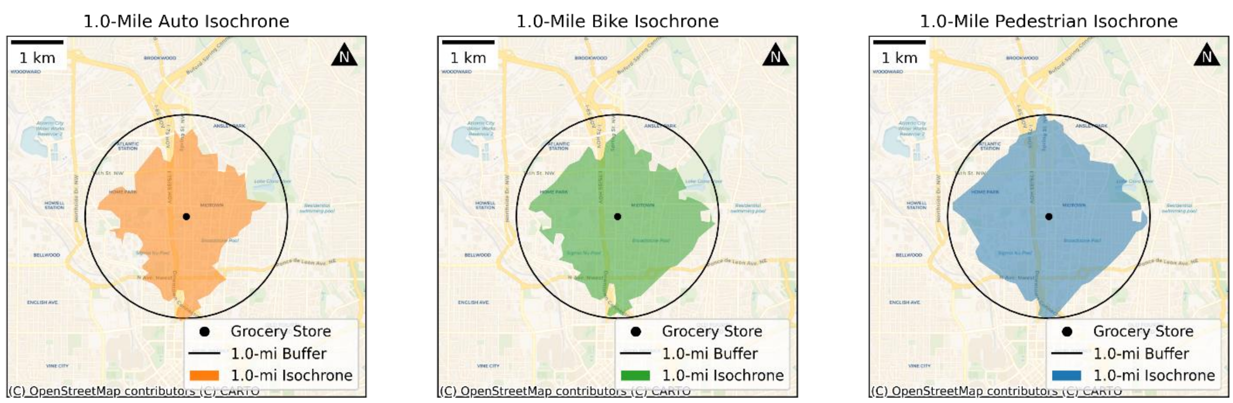
Figure 09: Coverage of 0.5-mile isochrones by mode



The impact of this is seen when *coverage* is aggregated, like in *Figure 09*. Here, each mode's isochrones were overlain on the census blocks[40] located within the study area; those blocks with more than 50% of their area included in an isochrone are considered "covered", and thus serviceable by a grocery store. While the buffer-based definition estimates coverage between 25% and 35%, distance-based isochrones are *significantly* smaller: only between 10% and 20%.

1.0-Mile Distance

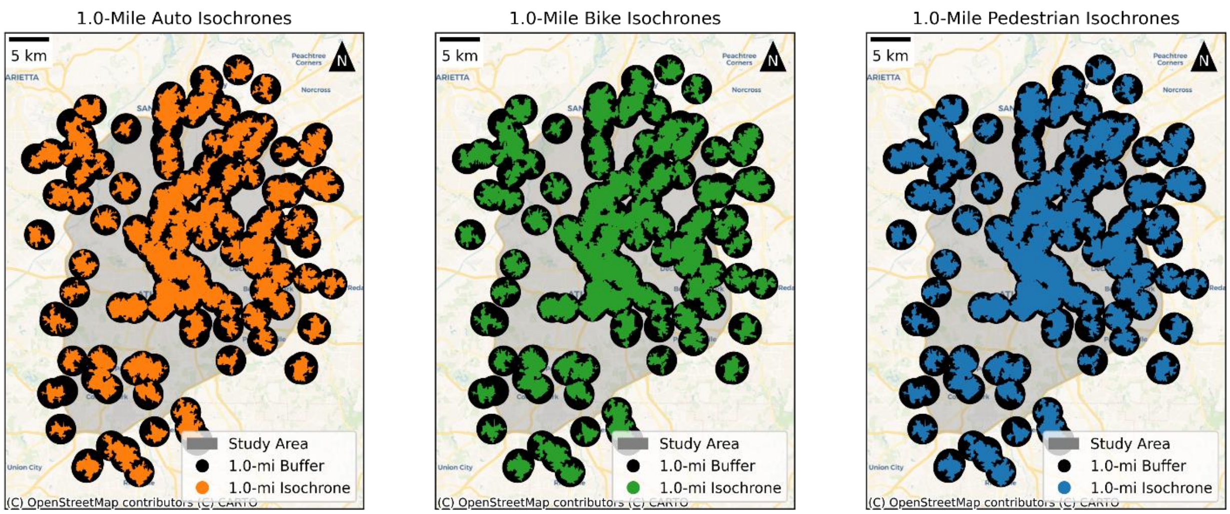
Figure 09: 1.0-mile isochrones around a single store



[40] Census *blocks* were used instead of the more common *tracts* or *block groups* due to their smaller size; Tracts and blockgroups are often wide enough across that the time it takes to walk across one becomes non-negligible.

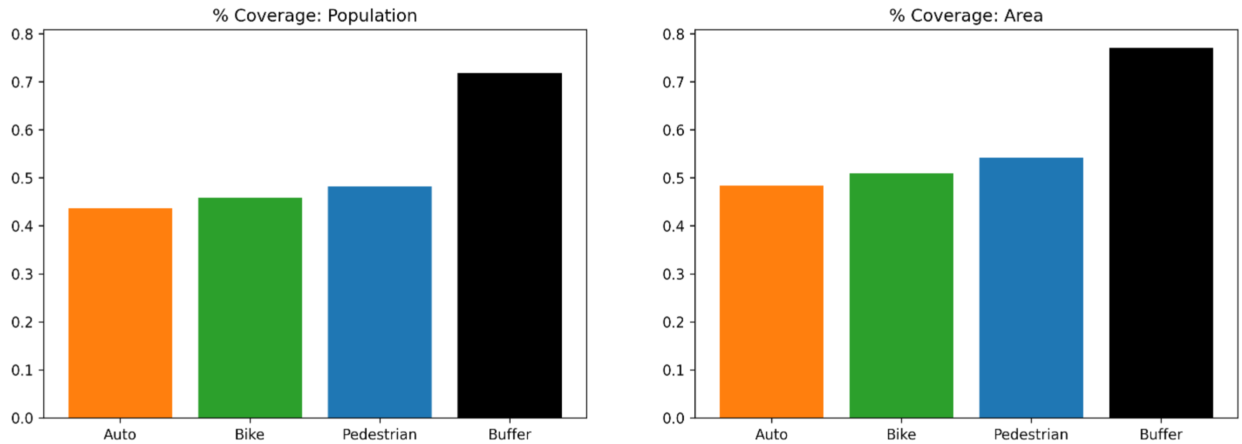
Findings are broadly similar at the more expansive definition, which uses a 1.0-mile cutoff. In *Figure 09*, the diamond shape of the isochrone is much more visible, as the grid network of Midtown (where this grocery store is located) allows significant distance to be travelled without turns. Interestingly, the *Auto* network is once again the smallest – this might be due primarily to its prioritization of high-throughput roads such as highways and arterials over the smaller side streets that *Bike* and *Pedestrian* modes prioritize. It should be remembered, however, that the *Auto* mode traverses this distance significantly faster than the other two modes, which will become important once *time-based* contours are analyzed (see next section).

Figure 10: 1.0-mile isochrones around all stores



When *all* stores are taken into account (*Figure 10*), there begins to be a noticeable amount of overlap at a 1.0-mile distance, especially in the densest areas along the I-75/85 "spine" of Atlanta, running from Downtown through Midtown towards Buckhead. These areas might be considered the *opposite* of food deserts, with residents given multiple stores to choose from within their "travel-shed", but, for the purposes of this study, no additional weighting is given to any census block that can reach more than one grocery store.

Figure 11: Coverage of 1.0-mile isochrones by mode



In *Figure 11*, again, the drop-off in coverage across definitions at a 1.0-mile distance is considerable. While the traditional definition estimates coverage between approximately 65% and almost 80%, no mode goes higher than 55%, and goes as low as 30%.

Comparing Time-Based Contours

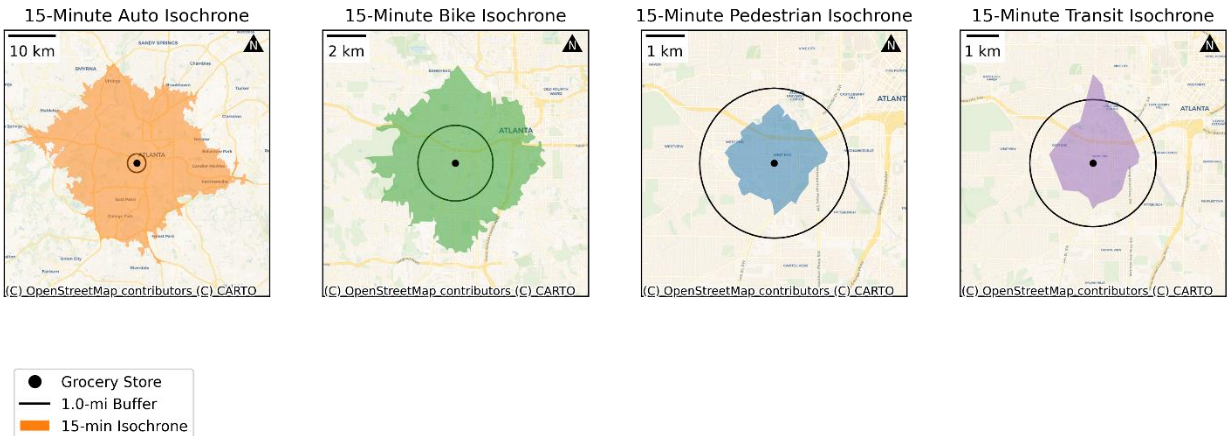
The other glaring issue with the traditional definition of food desert is that people rarely think of travel in terms of *distance*, and instead consider *time*. That the nearest grocery store is one or five miles away means less than *the time it would take to traverse that distance*.

Some research has already been done by the USDA that demonstrates a correlation between distance-based and time-based measures of accessibility. Travel time varies somewhat widely, but on average those in low-access metropolitan areas travel almost a third longer than those in high-access areas, or around 20 minutes (one-way) versus only 15[41], though this data was not provided by-mode. As such, a cutoff of 15 minutes was used for each isochrone in this analysis.

When viewed through a time-based lens, the isochrones of different transportation modes start to take on radically different shapes and sizes (*Figure 12*). The *Auto* mode is truly enormous, as a 15-minute isochrone is enough to cover over two-thirds of the metro area from just a single grocery store, while the *Bike* mode is also quite significant, easily extending beyond the 1.0-mile buffer used in the traditional definition. The *Pedestrian* mode, on the other hand, is the most handicapped, covering barely half of the traditional buffer. This might seem unintuitive, as, at a walking speed of 3.1 miles per hour, people would be expected to travel a full mile in around 20 minutes, but that is under *idealized conditions*, ignoring the realities of making turns, crossing streets, and waiting at intersections, all of which consume precious seconds for each action, shortening the isochrone.

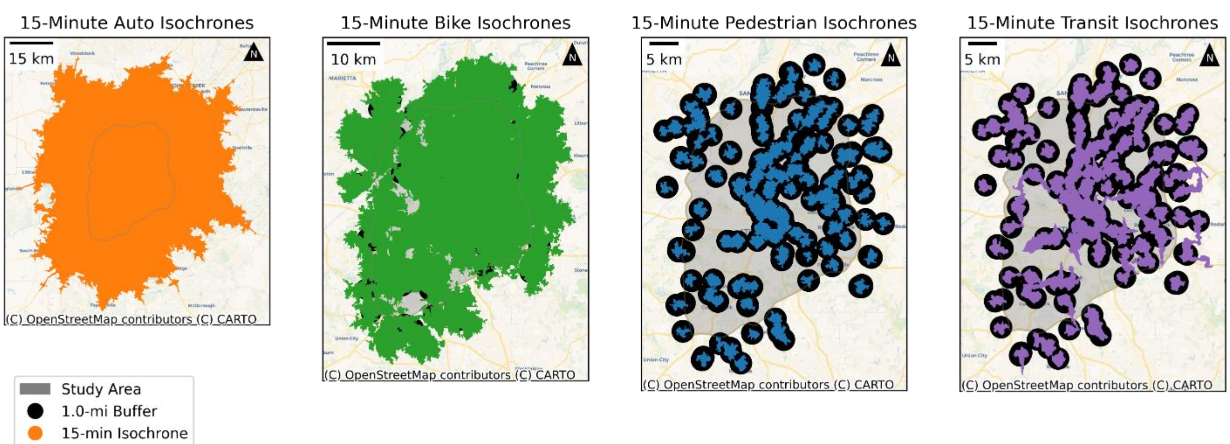
[41] Ploeg et al., 2009

Figure 12: 15-minute isochrones around a single store



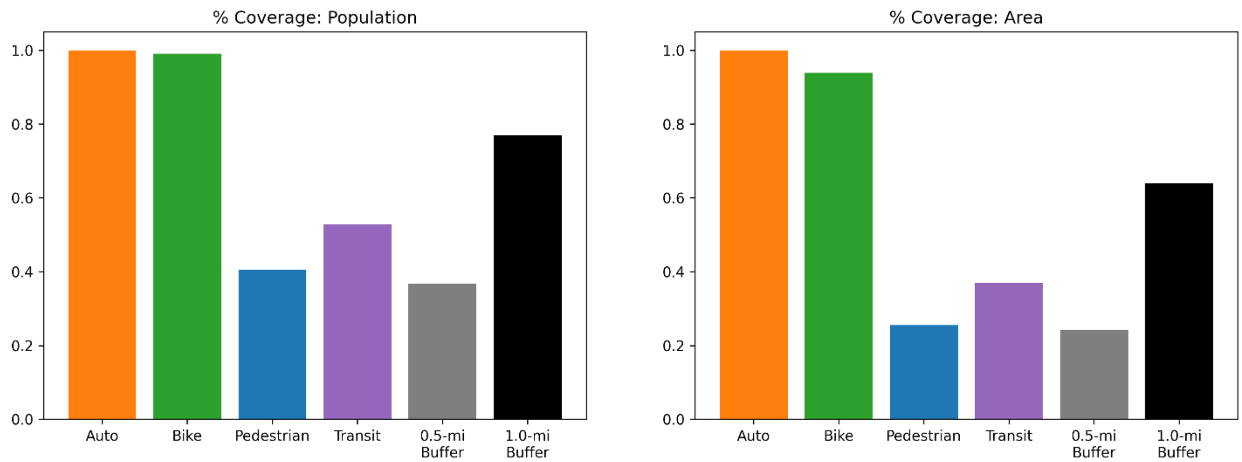
Most interesting, however, is the *Transit* isochrone. To the west, south, and east of the example above, its radius extends no further than the *Pedestrian* mode – but to the north, it juts beyond the edge of the buffer circle, like a compass point. This is due to the grocery store's proximity to a transit stop, which extends the isochrone's reach along its route. This key feature of the *Transit* mode demonstrates the importance of transit in accessibility measures, and the limitations of the traditional food desert definition in not being able to account for this.

Figure 13: 15-minute isochrones around all stores



The differences between modes are even more stark when the full isochrone map is revealed, as shown above in *Figure 13*. Here, the study area is no longer visible in the *Auto* mode map, and only barely visible in the *Bike* mode map, clearly illuminating the power of car and bike access in a city. Conversely, both the *Pedestrian* and *Transit* mode maps show a significant amount of black (where coverage is achieved under the traditional buffered measure but not under the time-based contours). At the same time, many "spurs" are visible on the *Transit* mode's isochrones, following transit (mainly bus) paths out into the extended reaches of the map.

Figure 14: Coverage of 15-minute isochrones by mode



This conclusion is clearly evident when total coverage is tabulated (*Figure 14*). The *Auto* and *Bike* modes either approach or achieve 100% coverage, besting even the generous 1.0-mile buffered definition, while the *Pedestrian* mode does only slightly better than the restrictive 0.5-mile definition. The *Transit* mode does strictly better than the *Pedestrian* mode, as expected: if no transit lines were nearby, the *worst* that could be achieved would be identical to the *Pedestrian* mode. However, the benefit from transit access is limited, and the *Transit* mode does not approach the coverage offered under the 1.0-mile buffer definition.

Pedestrian: Sensitivity to Walking Speed

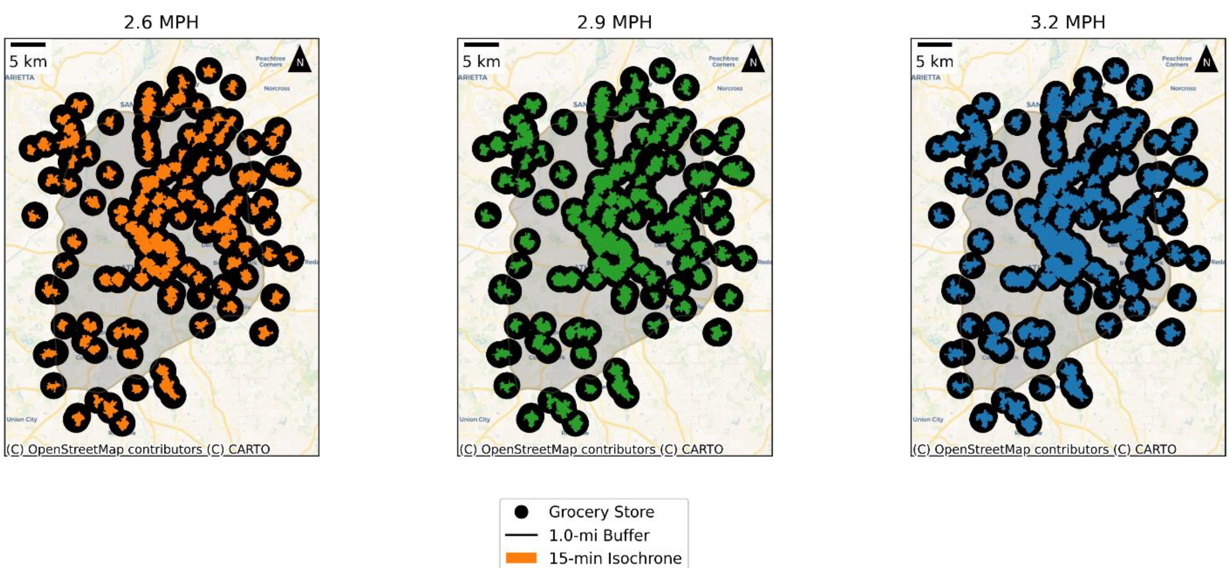
Due to the short distances involved, the *Pedestrian* mode is the most sensitive to the assumption of *speed* used when computing a time-based isochrone. Though the default walking speed in Valhalla of approximately 3.2 miles per hour aligns favorably with research done on average population walking speed[42], the actual walking speed of an *individual* might vary for any number of reasons: their age, the weather, the presence of children, any infirmaries or disabilities, the condition (or absence) of sidewalks, or simply the burden of carrying groceries over distance. Therefore, two alternate sets of *Pedestrian* isochrones were built to simulate the impact of these various issues on coverage statistics: a "heavily burdened" scenario using a 2.6 miles per hour walking speed, and a middle-ground speed of 2.9 miles per hour, the average for older populations.

[42] Bohannon, 1998

Figure 15: 15-minute isochrones around a single store at various walking speeds

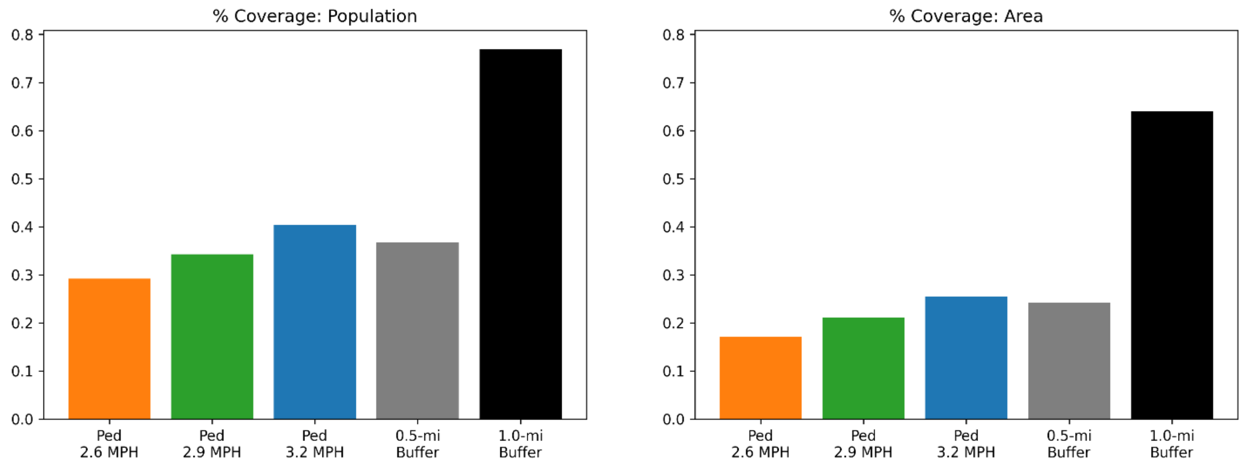
When viewed around a single store (*Figure 15*), the differences are relatively marginal, more so than expected: though the slowest speed is around 20% slower than the fastest, it is difficult to see in the maps above. This might be due to the visual difficulty of comparing areal planes, where increase in size is proportional to, roughly, the *square root* of the difference in speed, or it could suggest that walking speed is less important than the other time-based cost assumptions in this analysis, such as time spent waiting at each intersection.

Figure 16: 15-minute isochrones around all stores at various walking speeds



Similarly, very few differences are visually noticeable in the full isochrone map (*Figure 16*), outside of the core of Downtown and Midtown core, where many more of the isochrones overlap in the fastest speed assumption relative to the slowest.

Figure 17: Coverage of 15-minute isochrones at various walking speeds



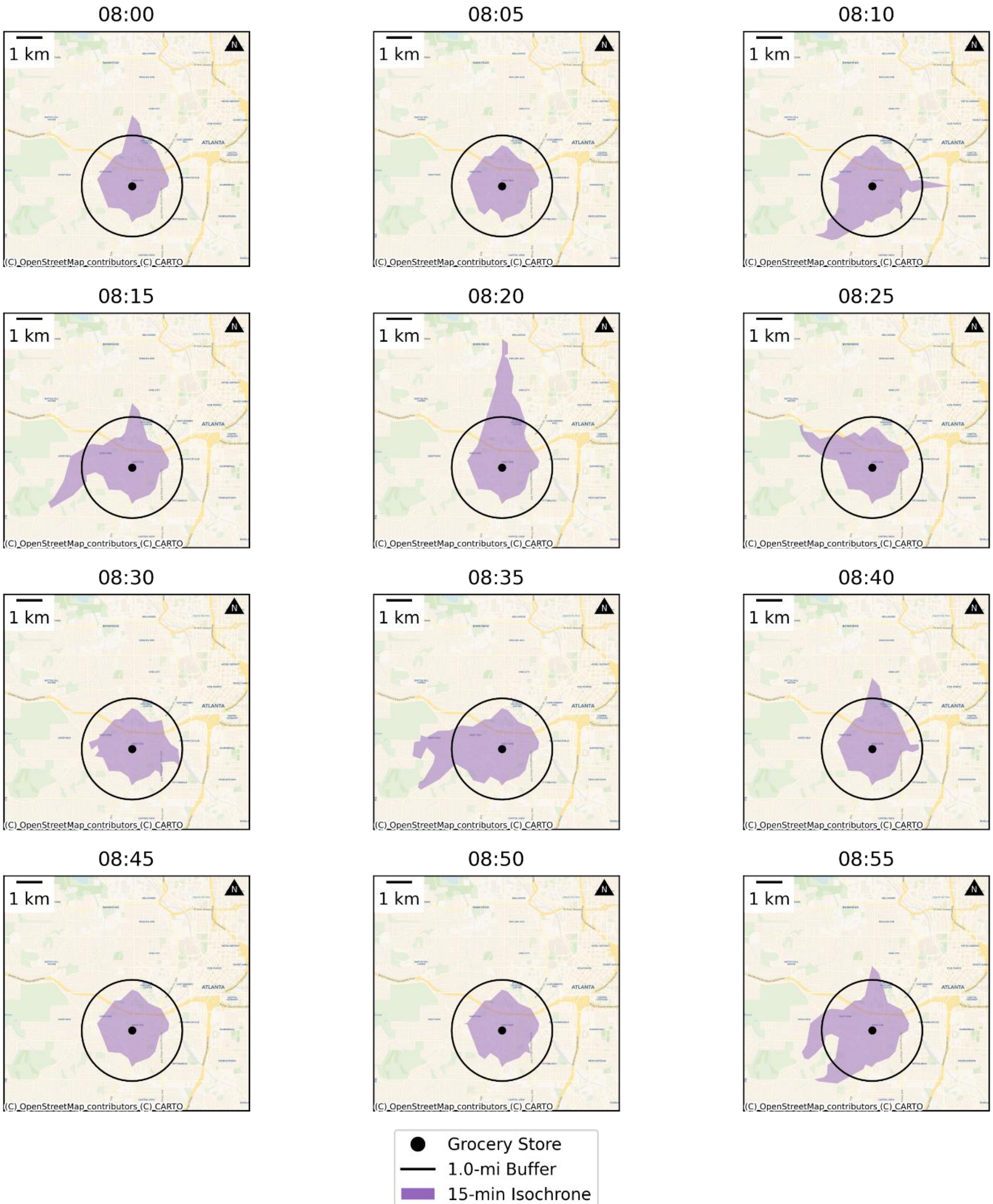
The coverage charts in *Figure 17*, however, reveal the importance of these assumptions: the gap from 2.6 miles per hour to 3.2 miles per hour is around 10%, and is enough to bring coverage from the *Pedestrian* mode above the 0.5-mile buffer definition of food desert. Additionally, the ratio implied by a 10% change in coverage for a 20% change in speed suggests the need for more study into the other assumptions used by the Valhalla routing engine in the *Pedestrian* mode, to further fine-tune the model and arrive at a more accurate coverage map.

Transit: Sensitivity to Departure Time

In contrast to the *Pedestrian* mode, the key sensitivity in the *Transit* mode is not the *speed* variable, but instead *departure time*. Those taking transit are dependent upon the schedule of the bus and rail lines operating from their nearest stops and, to be maximally accurate, time-based isochrones need to account for *time spent waiting at a given stop*. This can have wide-ranging impacts in a city like Atlanta: most transit coverage is driven by bus lines that run "infrequently", with many stops only seeing service every thirty minutes *or more*.

In the prior examples shown, a fixed departure time of 08:00 on a hypothetical Sunday was used, which would be expected to produce high coverage in some areas with departures near that time, and low coverage in others. For this sensitivity analysis, this departure time as modulated, generating isochrones based on 12 different departure times, each five minutes apart, ranging from 08:00 to 08:55, on the same Sunday. As no bus in MARTA's network has a periodicity of over one hour, this produces a wide range of coverage estimates for each store, as shown below.

Figure 18: 15-minute isochrones around a single store at various departure times



For the single store analyzed in *Figure 18*, each five-minute interval reveals a different possible collection of routes that could be taken. Sometimes, such as at 08:05, no routes are available, and the isochrone is similar to that of the *Pedestrian* mode. However, other times, like 08:55 instead make multiple routes in different directions available.

This view can also view the periodicity or service level of certain bus routes. Isochrones generated at 08:15, 08:35, and 08:55 all display the same spur extending to the southwest corner of the map. This is due to bus route #71, whose westward route leaves West End Station at 08:20, 08:40, and 09:00 on Sundays, passing by the grocery store a few minutes later, before heading onwards along Cascade Avenue SW past the Greenwood Cemetery. Conversely, the northern spurs are *either* route #68, which terminates at Ashby and is visible in the maps for 08:00 and 08:40, or route #1, which continues much further northward. Indeed, route #1 most clearly illuminates the topic of *waiting time*: both isochrones at 08:15 and 08:20 take this same route, but the earlier time necessitates an additional five minutes of waiting time for the bus, which dramatically shortens the distance travelled northwards, compared to the later time.

Calculating coverage at each departure time wouldn't make sense for this analysis: some stops will have their "peak" coverage at a given time, while others have the opposite. Instead, for each set of isochrones at a stop, the *maximum isochrone* and *minimum isochrone*, judged by total area, were taken, which articulates the theoretical maximum and minimum transit coverage that can be expected from a stop.

Figure 19: Minimum and maximum 15-minute isochrones around all stores for transit

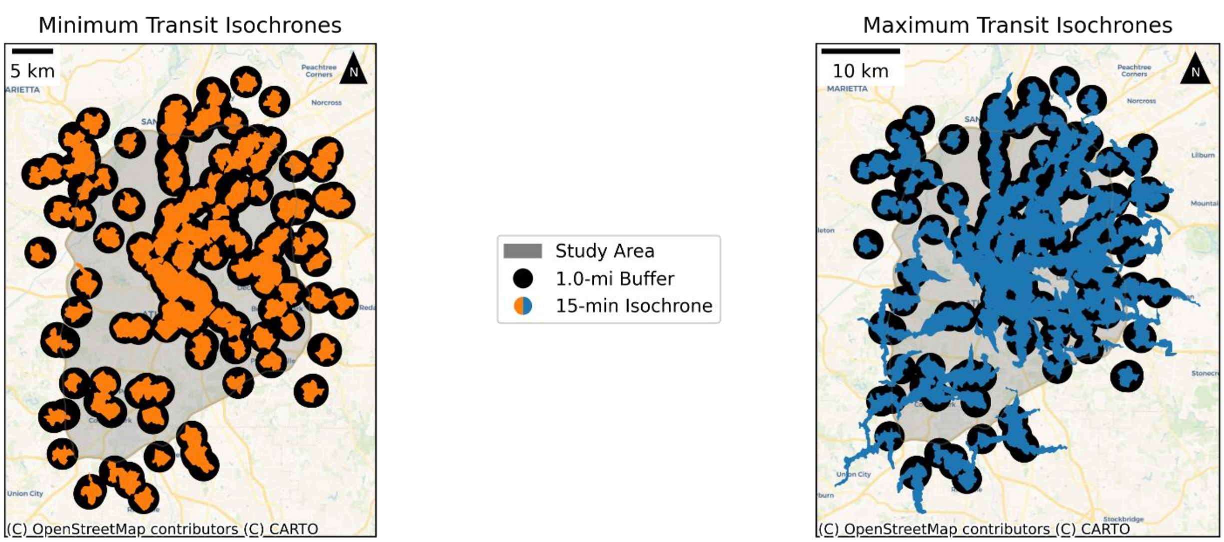
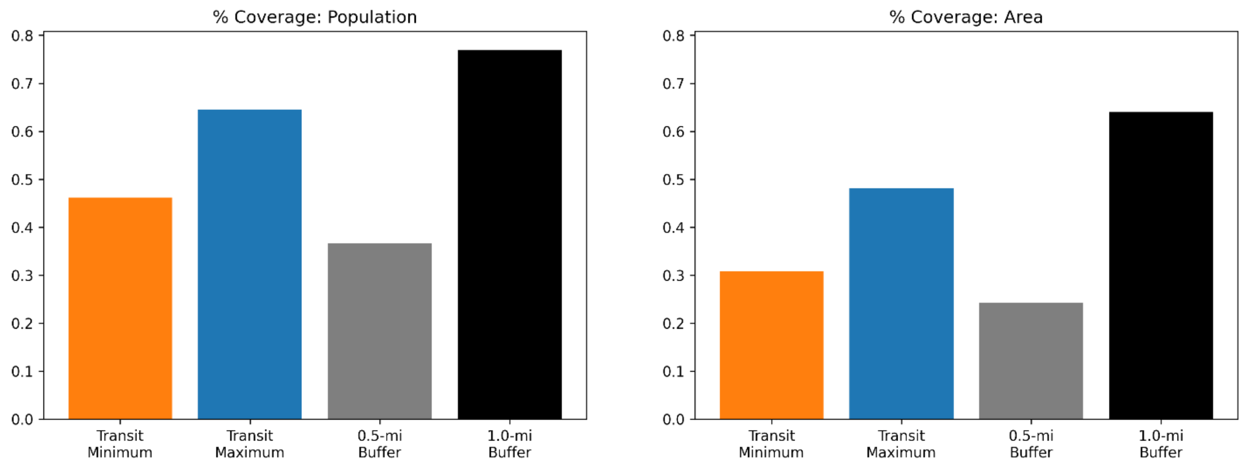


Figure 19 displays these isochrones. The *minimum* map is, as expected, strikingly similar to the *Pedestrian* mode map: very few spurs are visible, especially for those areas with service intervals longer than 15 minutes (which is most of the city), and accessibility is no greater than the distance

one could walk. However, the *maximum* map is much more complex, with multiple sets of spurs connecting to form accessibility *corridors* along certain bus routes.

Figure 20: Coverage of minimum and maximum 15-minute isochrones for transit



This nuance does make a difference in coverage, as the graph above demonstrates. With only the *minimum* isochrones taken into account, coverage is barely above that of the 0.5-mile buffer definition (though still above the default *Pedestrian* mode, probably due to those stores located along rail lines). The *maximum* isochrones are, however, significantly larger, showing around 20% more coverage of both population and area, underscoring the importance of short, regular service intervals for transit-dependent populations in accessibility.

V. Discussion

Though this paper attempted to provide the most accurate look at grocery store accessibility in the Atlanta area, some shortcomings could not be fully addressed, many of which relate to the data collection and analysis process. The most consequential of these is almost certainly the definition of which retail locations should or should not be included as a "grocery store". Though much time was spent in the *Methods* section detailing how the final set of grocery stores was selected, it was by no means perfect, as much of the initial selection was dependent on internet directories of stores such as Yelp and Foursquare, which are themselves incomplete. Additionally, the focus on *supermarkets* for this paper ignores the complicated reality of foodscapes in the current urban environment, which, as highlighted in the *Literature Review*, might involve shopping at multiple stores to complete a full weeks' shopping, or the presence of alternative sources of food, such as urban farms and food banks. Finally, the final curation process, which involved visiting stores in-person, was ultimately a subjective one, and could have been influenced by the biases of the observer making the visit. Many of these issues might be overcome if such an analysis was paired with a survey-based method of identifying grocery stores, using responses from actual residents to understand when and where they shop throughout the month. As it stands now, though, any attempt to generalize the methods utilized in this paper to other cities should be undertaken cautiously, as on-the-ground efforts are *required* to properly validate grocery stores.

The isochrone analysis itself, however, also had its own limitations. One of note is that the routing engine is, in many ways, an *idealized* way of traveling throughout a city. Though some assumptions do try to account for the real-world time penalties inherent in, say, driving, including time spent at intersections and the like, a more realistic analysis would incorporate more data which was simply not available at the time. This could include anything from *traffic speeds*, which would handicap the speed of cars throughout the city, to *elevation profiles*, which would suitably slow the bicycle and pedestrian modes, or *bus timeliness statistics*, which would incorporate the inherent unreliable nature of transit that often results in buses arriving at each stop later than scheduled. Similarly, the sensitivity analysis for the transit mode could be expanded to find the optimal departure time on a minute-level interval, across *all* days of the week, instead of the current five-minute interval on a single Sunday. Finally, the sensitivity analysis for the pedestrian mode could have gone further in modeling the real-world carrying capacity of people, to appropriately consider the distance a single person can carry a week's worth of groceries, especially if they are carrying those groceries for multiple individuals in a household, and whether or not multiple trips are needed.

VI. Conclusion

The goal of this paper was to demonstrate the inherent deficiencies in the current definition of *food deserts*. Under the traditional measure, accessibility is determined based on a simple circle, with a radius of either 0.5-miles or 1.0-miles, drawn about the grocery stores in an area. If, however, the actual path travelled over the road network is considered instead, this area of coverage shrinks dramatically, often to almost half as much as previously estimated. Furthermore, changing the metric from one based on a set distance to one based on *travel time* better encapsulates the way people think about moving through the built environment, and illuminates the difference in accessibility achievable under different modes of transportation.

Two clear paths might be undertaken next based on this work. First, this analysis has thus far completely ignored any demographic data, even though *poverty* and *vehicle access* are two key components in the generally accepted definition of "food desert". Though usually only available at the resolution of a block group or a census tract, as opposed to the census blocks as used in this paper, finding a way to incorporate this data could help granularly identify the areas of most concern within Atlanta, and quantify the number of people currently at-risk. Second, attention should be turned towards which solutions matter most to alleviate the issues of food deserts. Though already a sizeable area of research, as shown in the *Literature Review*, this paper has hopefully shown a light on other possible methods of intervention that could have a larger impact than those methods previously tried, from app-enabled grocery delivery to increased public transit service or the proliferation of more community-centric, small-scale food establishments.

The concept of a *food desert* certainly has its flaws, but, so long as it continues to be used as a framework for identifying and allocating resources to underserved areas, it deserves to be appropriately defined and studied. The current literature has thus far used overly simplistic methods in its studies of this, which can be corrected for with a fairly trivial amount of additional effort, using freely available and open-source software. Doing so will not only improve the accuracy with which these areas are uncovered, helping to bring attention to potentially hundreds of thousands of more people currently at-risk; it might also help expand this concept beyond access to grocery stores, and to the other amenities that are so important for life in an urban environment, such as educational institutions, community centers, greenspaces, and more.

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Data Sources

Grocery Store Search APIs

Foursquare, *Place Search*, Places API, https://location.foursquare.com/developer/reference/place-search

Google Maps, *Place Search*, Places API, https://developers.google.com/maps/documentation/places/web-service/search

Yelp, *Search Businesses*, Fusion API v3, https://docs.developer.yelp.com/reference/v3_business_search

Road Network Data

OpenStreetMap contributors (as of May 20, 2023), https://www.openstreetmap.org/

Schneider, Wolfram, *BBBike Extract Service*, https://extract.bbbike.org/

Other

H3Geo, *Tables of Cell Statistics Across Resolutions | H3*. https://h3geo.org/docs/core-library/restable/. Accessed 16 July 2023.

US Census Bureau (2020), *US Administrative Boundaries: TIGER/Line Shapefiles*, https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2020.html

Software Packages

	Name	Category	Version	Link
1	Contextily	Geographic	1.3.0	https://github.com/geopandas/contextily
2	Fiona	Geographic	1.8.21	https://github.com/Toblerity/Fiona
3	GeoPandas	Geographic	0.12.1	https://github.com/geopandas/geopandas
4	H3Pandas	Geographic	0.2.4	https://github.com/DahnJ/H3-Pandas
5	Matplotlib	Visualization	3.5.2	https://github.com/matplotlib/matplotlib
6	Numpy	Analytic	1.23.5	https://github.com/numpy/numpy
7	OSMNx	Data Acquisition	1.3.0	https://github.com/gboeing/osmnx
8	Pandas	Analytic	1.5.2	https://github.com/pandas-dev/pandas
9	Pygris	Data Acquisition	0.1.5	https://github.com/walkerke/pygris
10	PyrOSM	Data Acquisition	0.6.1	https://github.com/HTenkanen/pyrosm
11	Shapely	Geographic	2.0.1	https://github.com/shapely/shapely
12	thefuzz	Analytic	0.19.0	https://github.com/seatgeek/thefuzz
13	tqdm	Misc.	4.64.0	https://github.com/tqdm/tqdm
14	Valhalla	Routing	3.4.0	https://github.com/valhalla/valhalla

Table 06: Software packages used during analysis

VIII. Appendix

Grocery Stores Query Parameters

	Foursquare	Yelp	Google	OpenStreetMap
Endpoint	places/search	businesses/search	nearbysearch/	N/A
Filter Type	categories	categories	type	tag
Filter List	17065, 17067, 17069, 17070, 17071, 17073, 17077, 17142, 17144	ethicgrocery, ethnicgrocery, farmersmarket, grocery, intlgrocery, organic_stores	supermarket	Key: shop Tags: grocery, supermarket, covenience, greengrocer, deli, food, farm
Documentation	Link	Link	Link	Link

Table 07: Parameters and endpoints for querying different online directories

Selected Store Visit Survey Results

ID	Store Name	Date Visited	Category	Rationale
1	Atlanta Municipal Market	2023-06-17	Supermarket	
2	O4W Town Pantry	2023-06-17	Specialized	Limited vegetables, meats
3	Grant Park Market	2023-06-17	Supermarket	
4	Oakhurst Market	2023-06-17	Specialized	Limited fruits, vegetables
5	Kelly's Market	2023-06-17	Specialized	Limited fruits, vegetables
6	Kroger	2023-06-17	Closed	
7	Thriftown	2023-06-17	Supermarket	
8	International City Market	2023-06-17	N/A	Does not exist
9	International Grocery	2023-06-17	Specialized	Limited meats, vegetables
10	Talar's Market	2023-06-17	Supermarket	
11	David's Produce Store	2023-06-17	Specialized	Only vegetables
12	Oak Grove Market	2023-06-17	Specialized	Limited everything
13	In Towne Market	2023-06-17	Convenience	
14	Walmart	2023-06-17	Closed	
15	Troy Supermarket	2023-06-17	Convenience	
16	Neighborhood Discount	2023-06-17	Convenience	
17	Lowery Food Mart	2023-06-17	Convenience	
18	Buy Low Super Market	2023-06-17	Supermarket	
19	Mh Super Market	2023-06-17	Convenience	
20	Busy Bee Groc Store	2023-06-17	Convenience	
21	Food Value	2023-06-19	Supermarket	
22	Syde Foods	2023-06-19	Convenience	
23	Food Town Market	2023-06-19	Supermarket	
24	Tienda Santacruz	2023-06-19	Supermarket	
25	City Market	2023-06-19	Supermarket	
26	Convenient Food Mart	2023-06-19	Convenience	
27	La Unica	2023-06-19	Supermarket	
28	Carniceria Garcia	2023-06-19	Specialized	Butcher shop
29	Short Stop Grocery	2023-06-19	Convenience	
30	Convenient Food Mart	2023-06-19	Convenience	
31	Kansato Enterprise	2023-06-19	N/A	Does not exist

Table 08: Synthesized results of in-person store visits

Valhalla Default Cost Parameters

Auto	Explanation	Default
manuever_penalty	Time added switching between roads	5 sec
gate_cost	Time added for undefined or private gates	30 sec
gate_penalty	Time added for gates with no access	300 sec
use_highways	Willingness to take highways, between 0 and 1	1.0
use_tolls	Willingness to pay for tolls, between 0 and 1	0.5
use_living_streets	Willingness to take "living streets", between 0 and 1	0.1
top_speed	The maximum speed the car can travel	140 kph
ignore_closure	If set to true, ignores all "closed" roads	false

Table 09: Default Valhalla settings for auto *mode*

Bike	Explanation	Default
manuever_penalty	Time added switching between roads	5 sec
gate_cost	Time added for undefined or private gates	30 sec
gate_penalty	Time added for gates with no access	300 sec
bicycle_type	Can be one of *Road*, *Hybrid*, *Cross*, or *Mountain*, and will change a few options en-masse (speed, hills)	Hybrid
cycling_speed	Average travel speed on smooth, flat roads; different for each type of bike	18 kph
use_roads	Willingness to take roads, between 0 and 1	0.5
use_hills	Willingness to climb hills, between 0 and 1	0.5
use_living_streets	Willingness to take "living streets", between 0 and 1	0.5
avoid_bad_surfaces	Need to avoid roads with poor surfaces "relative to the bicycle type being used"	0.25

Table 10: Default Valhalla settings for bike *mode*

Pedestrian	Explanation	Default
walking_speed	Assumption on how fast someone will walk	5.1 kph
walkway_factor	Factor to multiply the cost when encountering a footway	1.0
sidewalk_factor	Factor to multiply the cost when encountering a sidewalk	1.0
step_penalty	Penalty for transitions to steps or stairs in path	0
use_tolls	Willingness to pay for tolls, between 0 and 1	0.5
use_hills	Willingness to climb hills, between 0 and 1	0.5
use_living_streets	Willingness to take “living streets”, between 0 and 1	0.6
max_hiking_difficulty	Limit on the max sac_scale value allowable on a route	1

Table 11: Default Valhalla settings for pedestrian *mode*

Transit	Explanation	Default
use_bus	Desire to use buses, between 0 and 1	Unsure
use_rail	Desire to use rail/subway/metro, between 0 and 1	Unsure
use_transfers	Desire to favor transfers, between 0 and 1	Unsure

Table 12: Default Valhalla settings for transit *mode*