Leadership in Sustainable Infrastructure

Leadership en Infrastructures Durables

Vancouver, Canada

May 31 – June 3, 2017/ *Mai 31 – Juin 3, 2017*

MODELING FOOD DESERT DISRUPTORS: AN OBJECT ORIENTED PROGRAMMING APPROACH

Abel, Kelsey C.[1], Faust, Kasey M.[1,2]
[1] The University of Texas at Austin, U.S.A.
[2] faustk@utexas.edu

Abstract: Urban food deserts (FDs) are any bounded geographic area in which over 30% of residents live more than one mile from stores supplying healthy, affordable foods. FDs affect 23.5 million people in the US. Previous FD models primarily focus on determining the extent of FDs based on either temporal food availability (when people access grocery stores) or geographic food availability (radial distance to grocery stores). However, food access also depends on regional mobility, resident behavior, and resident demographics. The study proposes a hybrid agent based model and GIS framework to more holistically capture FDs, coupling temporal and geographic food availability, while incorporating mobility and resident demographics. Data from publically available sources are used to determine demographics specific to residents within the FD (e.g., employment rate and car ownership), existing residential behaviors (e.g., method of transportation for grocery trips), and store locations. This framework is demonstrated through introducing disruptions, such as resident's willingness to walk and placement of new food vendors (e.g. new grocery stores, convenience stores, restaurants) at two different locations, to assess the change in the current level of food access. A FD in Austin, Texas, which is home to approximately 6,500 individuals with a median income of $31,994, is used as the case study. Food access was improved by 0.5% to 39.3% depending on the distance each resident is willing to walk. Results may inform methods that may increase food access through built environment disruptors that shift (and improve) the status quo of food access.

1 INTRODUCTION

Food deserts (FDs) are low-income regions in which there is a dearth of healthy, affordable food (Chung and Myers, 1999; Morland et al., 2002). Formally, this classification is given to any low-income census tract in which either 500 residents or 33% of residents live more than one mile away from a grocery store in an urban area, or more than 10 miles away in a rural area (Rhone et al., 2017; USDA, 2017). Approximately 23.5 million people are estimated to live within these regions across the United States (United States Census Bureau, 2010; USDA, 2017). This expansive issue has led to increased efforts to identify factors that affect food security, and how to mitigate the negative impacts on the residents within these regions (Troy et al., 2011; Chen and Clark, 2013; Hillier et al., 2015; Rhone et al., 2017).

Residents of FDs have higher likelihoods of developing diet-related diseases (e.g. diabetes, heart disease, obesity) compared to residents who do not live in food deserts (Diez-Roux et al., 1999). This is often attributed to the residents' inability to obtain healthy food due to limited capital and mobility, and a lack of healthy food vendors in the region (Baker et al., 2006; Morland et al., 2006; Powell et al., 2007; LeClair and Aksan, 2014). The lack of food access coupled with an inability to readily leave the FD forces these residents to buy their food at corner stores, gas stations, and restaurants (Baker et al., 2006, Block and Kouba, 2006). Such locations primarily offer processed, sugar-dense foods which are known contributors and augmenters of diet-related diseases (James et al., 2001; Bray et al., 2004; Briefel and Johnson, 2004; Gross et al., 2004). Moreover, studies have shown that these negative impacts are diminished when the food environment in these regions is changed, lending credence to the belief that food deserts can indeed be “fixed” (Morland et al., 2002; Morland et al., 2006; Kyureghian et al., 2013).

One area of focus for previous studies is the development of simulation models for known FDs (e.g., Swinburn, 1999; Widener et al., 2013; Hillier et al., 2015). Taking a modeling approach allows multiple courses of action to be tested with limited incurred risk. In so doing, these models eliminate the need to invest massive capital into pilot programs and large-scale experimentation. Previous literature has also focused defining the extent and severity of known food deserts (Neckermanet al., 2009; Wideneret al., 2013; LeClair and Aksan, 2014); assessing temporal availability of food in FDs (Chen and Clark, 2013); and determining how changes in residents’ available resources may change food access (Widener et al., 2012; Widener et al., 2013). While the food desert phenomenon has been widely studied and simulated, no *adaptable* models exist combining temporal and geographic food availability to the authors’ knowledge, nor are the authors aware of models that simulate how food access may be impacted by changes in the built environment.

To fill these identified gaps in literature, this study proposes a hybrid framework, combining agent-based modeling and Geographic Information Systems (GIS) to more holistically model FDs. This model aims to not only simulate the status quo of any FD, but also assess how different kinds of disrupters can impact food access.The proposed framework extends beyond previous models of food deserts in two ways. First, this model combines many factors classically used in FD models, such as temporal and geographic food availability and resident demographics. This allows for the inclusion of unemployment rates, annual income, and car ownership rates/accessibility (data from the United States Census Bureau (2010)). The proposed framework thereby allows for normalization of food access levels with respect to the residents’ true mobility and capital. Secondly, this model simulates how the levels of food access in the FD change in response to built environment disruptors. *Disruptors* are any exogenous or endogenous entity that disrupts the status quo of a system. In the context of this study, disruptors change food access in known FDs. Examples include increases in public transportation, expanded store hours, and new grocery stores. Specific disruptors used to demonstrate the framework in this study are new stores of varying types, and changes to the distance residents are willing to walk to get to a store. Through development of the aforementioned framework, this project aims to better understand what leads to discontinuity within the food system, and to formulate specific, testable disruptors that can be implemented to increase food access and thereby decrease the extent and severity of any food desert.

2 METHODOLOGY

Object oriented programming in AnyLogic is used to develop the proposed framework. The framework is demonstrated using a case study FD, located in Northeast Austin, Texas. This FD is home to approximately 6,500 residents with a median income of $31,994 (United States Census Bureau, 2010). This region has a car ownership rate of approximately 50% and a 30% unemployment rate (United States Census Bureau, 2010). This FD was chosen because of the high number of single-family homes (which implies a semi-uniform population distribution across the region) and its status as a known FD as per the USDA Food Access Atlas (2017).

Quantitative, empirical, and qualitative data are used to define, abstract, implement, and test this model. Numerical data was collected via publicly available sources, such as the US Census Data (United States Census Bureau, 2010) and the USDA Food Atlas (USDA, 2017). Empirical and qualitative data were sourced through journal articles, publically available reports, and semi-structured interviews of subject matter experts (SMEs) whose areas of expertise spanned urban food systems, transportation, and object oriented programming.

2.1 FRAMEWORK

The proposed framework combines Agent-Based Modeling and GIS, detailed below.

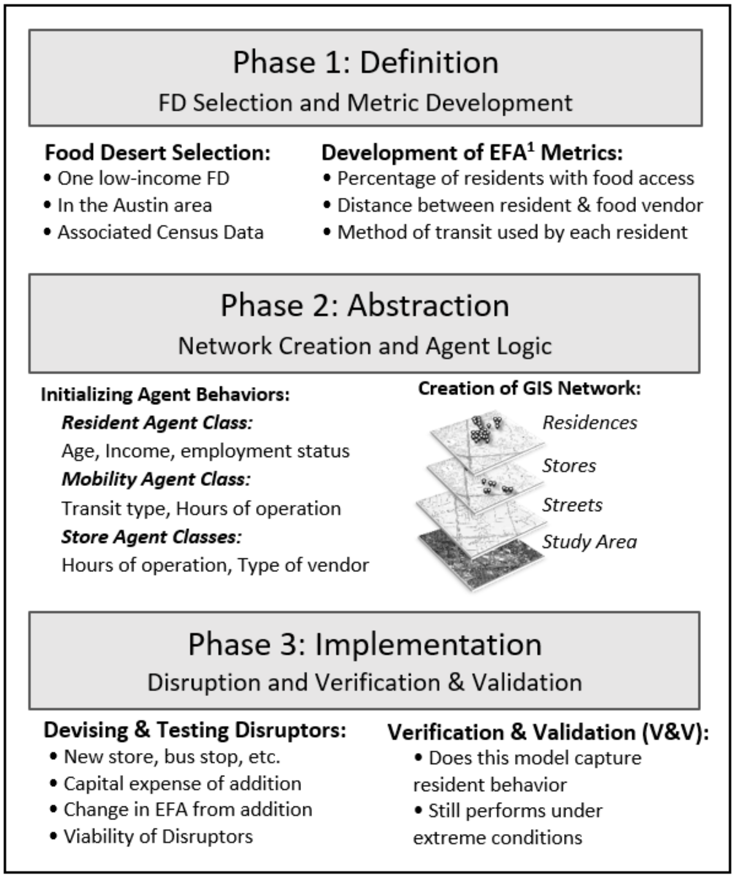
2.1.1 Geographic Information Systems (GIS)

The use of GIS serves two primary functions. First, GIS was used to create the environment in which the agents interact. Specifically, GIS enables the precise placement of physical infrastructure (e.g. stores, residential areas, roads, footpaths) within a given region.

The second function of GIS is as a route provider for the resident agents. These distance calculations enabled via the GIS map environment allow each agent to determine the shortest distance between themselves and a store along both roads and footpaths (walking vs. driving).

2.1.2 Agent Based Modeling (ABM)

Agent-based modeling (ABM) is used to capture the actions and interactions of autonomous entities (i.e., agents). The individual-centric aspect of this methodology allows for capturing the agents' logic and behaviors during interactions within an environment. Through these interactions, emergent behaviors may be observed and identified (Bonabeau, 2002).



1. Effective Food Access (EFA) is the percentage of residents that lack food access.

Figure 1: Methodology of this project divided into three distinct phases

2.2 Model Logic

Table 1 summarizes the object classes modeled. Parameters and Data were collected from the USDA food atlas (2017), the United States Census Bureau, (2010), Google Maps (2017), and subject-matter experts. The object class, *Residents,* contains the demographic information (e.g., household size, car ownership (United States Census Bureau, 2010)) and behavioral rules (e.g., decision to move to store, store selection) of the resident agents in all regions of the FD.

This data was incorporated into the resident agents, as well as the agent statechart, shown in Figure 2. Statecharts are comprised of states and transitions, each of which can have built-in code that establishes rules and actions for an agent in that particular state or transition. At the beginning of the simulation, agents are added into a specified state (indicated in Figure 2) and transition to another state when they are triggered, or when they meet the criteria to enter the transition. Certain aspects about the agent (e.g. food level, probability of needing groceries, current location) change in real time based on information or events within the environment. As an example, when an agent's food level decreases, the likelihood that the agent will need to go to a Vendor Class Agent (i.e., a store) increases. Once a low food level triggers the agent to obtain more food, the agent selects and then travels to a store within the food desert. Store selection is based on a weighted sum of the distance to a store and the likelihood that the store will provide healthy, affordable food (see Eqn. 1).

Table 1: List of agent classes and the parameters, variables, and rules associated with each agent class

Object Classes	**Function**	**Parameters and variables**	**Examples of decision rules and formulas**
Residents	Individual resident movement and decisions	• Speed • Food Level (FL) • Home Location • Population size	• Move to *Store* based on FL • Select *Mode of Transit* • Determines which *Store* to go to based on: 1. Proximity to store 2. Likelihood of finding healthy food
Food Vendors	Provides food to the resident of the region	• Location • Likelihood of carrying healthy food options • Hours of operation • Type of store	• Increases the FL of visiting agents • Does not allow agents to enter and purchase food outside of *Store* hours
Mobility Agent Class	Represents agent movement through the FD	• Speed • Transit capacity • Cost of use • Availability to resident	• Used to move linearly through the network • Picks up/drops off passengers at stores • Cannot hold more passengers than given capacity

Equation 1 is built on assumptions validated by SMEs; specifically, agents prefer to travel the shortest distance to a store, and go to stores with the highest likelihood of selling affordable, healthy food.

$$[1]\ \mathrm{Max}\left(\frac{1}{\mathrm{D}}\cdot \mathrm{W_d} + \mathrm{P}\cdot \mathrm{W_p}\right)$$

, where D is the distance (through the network) between a given agent and the store being considered, P is the probability that the store provides healthy, affordable food, W_d is the weighted importance of distance on a resident's store selection, and W_p is the weighted importance of finding healthy food on a resident's store selection.

Post store selection, the agent enters a selected *Mode of Transit* state, and either drives, walks by choice, or walks by necessity. These options are included in the base/status quo model as these are the modes of transit used in the USDA's definition of a food desert (2017). If the resident owns a car, the agent is assumed to drive. If the agent does not own a car, but lives within one mile of a store, then the agent will choose to walk to the store. This method of transit is referred to as walking by choice, and the one mile distance (USDA, 2017) is called the resident's *Willingness to Walk.*

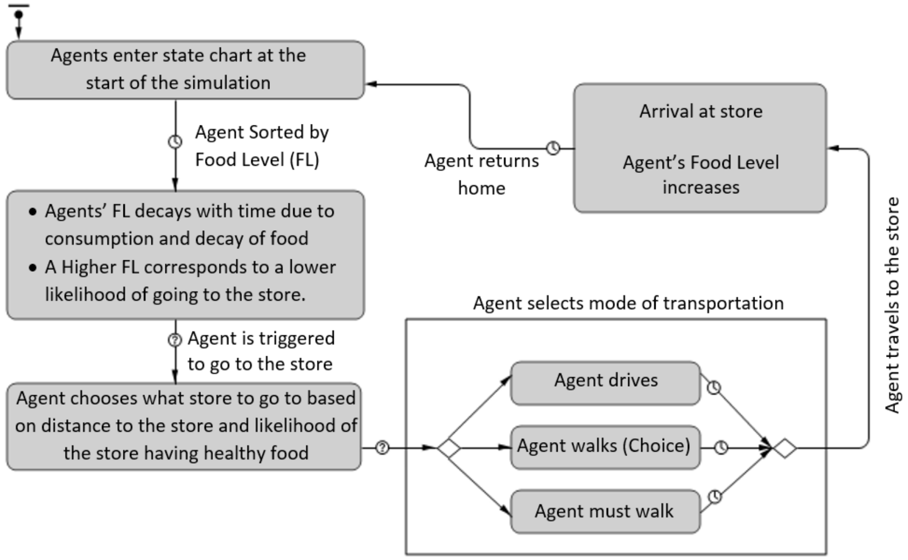


Figure 2: ABM Statechart (comprised of states and transitions)

The distance that the residents are willing to walk can be reduced to represent true resident willingness to walk as defined by SMEs. If an agent cannot drive or walk by choice, then the agent must walk to the store as a last resort. *The percentage of residents who walk as a last resort acts as the metric for the percentage of people who lack food access within this region.*

The number of residents in the region was divided by the average family size in Austin, Texas, determined by the 2010 US Census. With an average household size of 2.37 people per household, the region's population of approximately 6,500 residents equates to approximately 2,800 households (United States Census Bureau, 2010). Household representation more accurately represents how food is purchased as food is more often purchased at the family level than the individual level. The model was calibrated to reflect the observed, average number of household trips per week in 2015 (1.6 trips per week) (FMI, 2016).

2.3 Metrics

Disruptors were introduced to the model to evaluate the changes in food access. The metric used to measure food access is the percentage of residents who had to walk by necessity. Walking by necessity is determined by individuals who had to travel a longer distance (by walking) than his/her willingness to walk. The baseline value for willingness to walk is one mile, as determined by the USDA's (2017) definition of a food desert. As stated previously, lack of access is defined as living more than one mile (as the crow flies) to a grocery store. It should be noted that within this model, distance between the residents and stores is measured along a path rather than radially. The route distance is used because radial distances have been proven inaccurate determinations of proximity to a location and therefore, access (Jones et al., 2010). However, the model allows for distance measurements to be radial for more accurate comparisons when verifying and validating the model.

2.4 Introduction of Disruptors

Specific disruptors were introduced to the model to demonstrate the framework. The implemented disruptors are (1) changes in the residents' willingness to walk, (2) the introduction of two stores at different locations (with one store being added at a time), and (3) changes to the type of store at the selected locations. As disruptors are added to the model, the resulting change in food access is measured against the baseline/status quo food access levels. The model was simulated for four weeks to allow ample time for aggregation of the different resident behaviors.

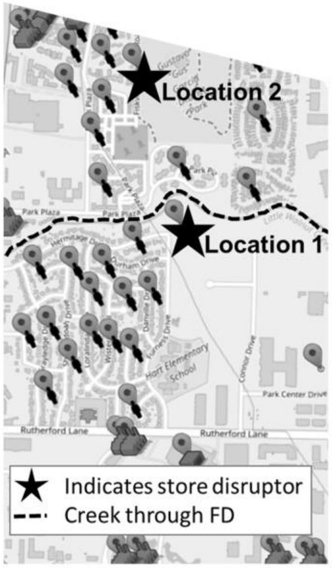


Figure 3: Store disruptor locations

2.4.1 Agent's Willingness to Walk by Choice

While the USDA (2017) defines food access by 1-mile (radial) distances, discussion with SMEs indicated that the 90th percentile of people in the US are not willing to walk more than 0.25 miles to a store. In order to account for this discrepancy, the *Willingness to Walk* disruptor was incorporated into the model, allowing for user-defined values (via a slider on the model's user-interface) between 0 to 1.25 miles, in 0.25 mile increments (i.e., 0 m to 2000 m, in 400 m increments.) The three values assessed and discussed in Section 3, are 0.25 miles, 0.5 miles, and 1 mile (i.e., 400m, 800m, and 1600m).

2.4.2 Location and type of Additional Stores

A new store was introduced in two different locations within the FD, selected based on land use data and strategic judgement. These locations are vacant lots with a footprint in which a store could be constructed. These locations are indicated in Figure 3. At each location, three different categories of stores were implemented, specifically, a convenience store, a restaurant, and a grocery store.

2.5 Limitations

As with any study, limitations exist. Public transit is not included in the model. This is done for two reasons. 1) *All public transit options are located outside of the geographic boundary of the food desert*. Public transit is physically outside of the scope of this project, and it was therefore not considered in this model. 2) *The USDA's current definition of a food desert does not take into account public transportation.* Status as a food desert is determined by radial distance to the nearest grocery store. This radial distance can take on one of two values—either one mile when a resident does not own or have access to a private vehicle, and five miles when the resident owns their own vehicle or has access to a private vehicle (USDA, 2017). The division between distances is determined by private car ownership, not public transit accessibility. This definition is quite limited. However, using this definition ensures that the levels of food access determined by the model match those collected by the USDA and allows for the validation of the model.

Another limitation of this model is the incorporation of hours of operation for grocery stores and the impacts this has on limiting temporal access to food. However, two of the three grocery stores in the region are open 24 hours, and therefore this model still yields an approximate idea of the food access within this FD. In calibrating the model, it was assumed that all residents are part of a household rather than single people living alone.

2.6 Verification and Validation

Verification and validation is an iterative process which occurs alongside the development of a given model. Discrete classifications of this process were detailed by Sargent et al. (2004) and include: conceptual model validation, computerized model verification, operational validation, and data validity. The first step in the validation and verification process occurred by conducting semi-structured interviews with SMEs to validate assumptions about agent behavior. Conceptual model validation occurred as the agent logic was constructed from data sources, ensuring that the agent logic and corresponding behaviors were reasonable and accurately represented the population behaviors. After completing the model logic, computerized verification was done by observing the method and destination of agent movements through their environment. Continued conversations with SMEs ensured the ongoing accuracy of assumptions made in the model, and reaffirmed the potential usefulness of the model to decision makers.

3 RESULTS AND DISCUSSION

Table 2 summarizes the changes in food access resulting from changes in the *Willingness to Walk* parameter. For each trial, the model was run for approximately 4 weeks, in which approximately 17000 trips to the store were made.

Table 2: Changes in food access at different values of the **Willingness to Walk** parameter

Willingness to Walk (by choice) mile	Number of total trips	Drove % (trips)	Walk by **choice** % (trips)	Walk as a **last resort** % (trips)	**Change in Access** %
1.00 (Baseline)	17131	50.4% (8619)	43.5% (7442)	6.2% (1057)	-
0.50	16975	50.3% (8542)	8.3% (1409)	41.3% (7015)	35.1% (5958)
0.25	17115	50.4% (8612)	0.8% (145)	48.8% (8344)	42.6% (7287)

Table 3 details the change in food access resulting from the addition of stores within the FD. Percent Change in access were recorded in two ways. First, percent change in access resulting from different store types were recorded while holding Willingness to Walk constant. Second, the percentage of people who with food access were compared to the baseline, or status quo, case using current USDA metrics (Willingness to Walk = 1 mile or 1600 m).

Table 3: Changes in food access due the **introduction of new stores** at different locations and with different values of the **Willingness to Walk** parameter

Disruptor	Number of total trips	Drove % (trips)	Walk by **choice** % (trips)	Walk as a **last resort** % (trips)	**Change in Access due to store addition** %	**Change in Access from USDA / 1-mile Estimate** %
WILLINGNESS TO WALK (BY CHOICE) =1.0 MILE (1600 M)						
Baseline	17131	50.4% (8619)	43.7% (7442)	6.0% (1057)	-	-
Store, Location 1						
Convenience Store	16774	50.7% (8493)	43.9% (7353)	5.5% (917)	0.5%	0.5%
Restaurant	16861	50.7% (8530)	43.9% (7394)	5.5% (919)	0.5 %	0.5 %
Grocery Store	16905	50.7% (8562)	43.8% (7404)	5.5% (933)	0.5%	0.5%
Store, Location 2						
Convenience Store	16581	50.6 % (8439)	43.9 % (7311)	5.5 % (912)	0.5 %	0.5 %
Restaurant	16581	50.7 % (8908)	43.8 % (7266)	5.5% (907)	0.5 %	0.5 %
Grocery Store	17101	50.5 % (8625)	49.5 % (8462)	0.00% (0)	6.0%	6.0%
WILLINGNESS TO WALK (BY CHOICE) =0.5 MILE (800 M)						
Baseline	16975	50.3% (8542)	8.3% (1409)	41.3% (7015)	-	35.3%
Store, Location 1						
Convenience Store	17101	50.6% (8639)	8.2 % (1398)	41.3% (7054)	0.0%	35.3%
Restaurant	16749	50.6 % (8463)	8.2 % (1369)	41.3 % (6907)	0.0 %	35.3%
Grocery Store	16835	50.2% (8440)	20.4 % (3431)	29.5% (4995)	11.8 %	23.5%
Store, Location 2						
Convenience Store	17065	50.6 % (8624)	8.2 % (1394)	41.2 % (7033)	0.1 %	35.2%
Restaurant	16926	50.6 % (8553)	8.2 % (1386)	41.3 % (6980)	0.0 %	35.3%
Grocery Store	16983	50.5 % (8570)	11.3 % (1920)	38.2 % (6479)	3.1 %	32.2%
WILLINGNESS TO WALK (BY CHOICE) =0.25 MILE (400 M)						
Baseline	17115	50.4% (8612)	0.8% (145)	48.8% (8344)	-	42.8%
Store, Location 1						
Convenience Store	16837	50.6% (8510)	0.9 % (156)	48.5% (8164)	0.3%	42.5%
Restaurant	17056	50.6 % (8620)	0.9 % (157)	48.5 % (8267)	0.3%	42.5%
Grocery Store	16907	50.2% (8477)	2.4% (399)	47.5% (8024)	1.3 %	41.5%
Store, Location 2						
Convenience Store	16921	50.7 % (8551)	1.0 % (156)	48.3 % (8208)	0.5%	42.3%
Restaurant	16838	50.6 % (8510)	0.9 % (156)	48.5 % (8166)	0.3 %	32.5%
Grocery Store	17076	50.5% (8614)	4.2 % (714)	45.3 % (7738)	3.5 %	39.3%

*Interestingly, as people's willingness to walk increases, the impact per store decreases***.** This implication is that if people are willing to go farther, then they will have access to more stores, and therefore the impact of an individual store will not be readily apparent. Measuring the average distance traveled by the residents who walk (by choice or last resort) may provide more accurate insight of the individual impact of a store in a region.

Table 3 shows that food accessibility decreases by 42.6% when the distance a resident is willing to walk changes from 1 mile (1600 m) (in accordance with the USDA's definition of a food desert) to 0.25 miles (400 m) (the distance the 90th percentile of US citizens are willing to walk based on conversations with subject matter experts). *These results demonstrate how the definition of food deserts may not represent true food access in a given region.*

The type of store introduced to the region has a substantial effect on food access. As expected, the introduction of a grocery stores create the largest increases in food access. Conversely, convenience stores and restaurants generate nominal increases in food access. The location of the disruptor impacts the effectiveness of increasing food access. Placing a grocery store in the center of the FD had a greater effect on increasing food access than the same store placed in the northern location area of the FD, regardless of what distance the residents were willing to walk.

The disruptor which showed the greatest percentage increase in food access was the addition of the grocery store in Location 1 with a *Willingness to Walk* of 0.5 miles or 800 m. Figure 4 shows the comparison of this datum and baseline data.

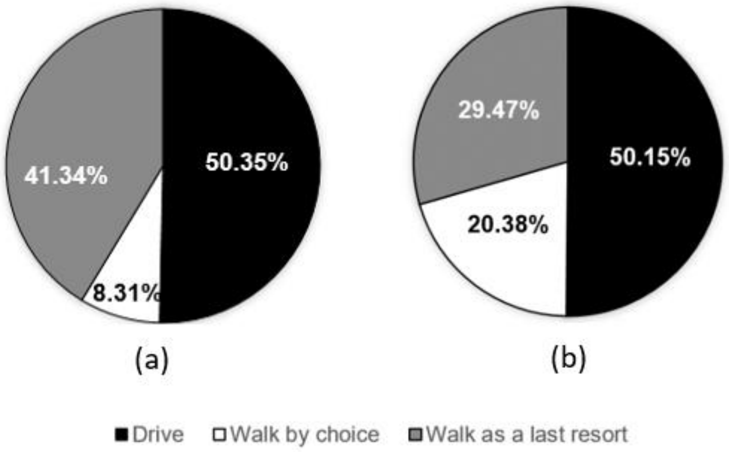


Figure 4: Breakdown of residents' selected mode of transit (Willingness to Walk = 0.5 miles or 800 m): (a) status quo, (b) supermarket disruptor placed in Location 1

Also of note is the simulation which resulted in the complete elimination of the food desert, or where 0% of residents walked as a last resort. This result occurred when a grocery store was placed at Location 1 and the *Willingness to Walk* was 1 mile, or 1600 m.

Through this simulation, an interesting result was revealed. When a grocery store was placed in Location 2, and the willingness to walk was set to 1 mile, zero percent of the residents lacked access to food. This implies a complete elimination of the food desert. To understand this result, the position of Location 2 was moved to different places in the food desert that were north of the creek (indicated in Figure 3). These locations yielded the same result (0% walking as a last resort), which indicates that this creek acts as a physical barrier, dividing the FD into two distinct parts. Investigating further, it was discovered that only one footpath exists linking the two segmented regions within the boundaries of the FD. This finding demonstrates that establishing foot traffic across this creek may have a profound impact on agent mobility within this region and therefore on regional food access. *This finding also demonstrates the importance of unique disruptors that are tailored to the food desert itself.* In this case, providing a footpath might be an inexpensive way to increase the food access within the region.

4 SUMMARY AND CONCLUSIONS

Food deserts are an expansive problem affecting 23.5 million US citizens, and have cascading impacts on the health of the residents of these regions. Modeling how disruptors are implemented in food deserts provides a method to explore alternatives to improve food access. Previous models attempt to better understand the problem, but do not offer an adaptable framework with which to test how a given disruptor will impact food access within a given FD. This model aims to fill this gap in the literature by designing a framework that allows for the visualization of food selection, while measuring how known food access changes when disruptors are added in the region.

The results yielded from this framework demonstrate the capability of the model to measure changes in food access resulting from disruptors. The first disruptor modeled was the distance that a resident was willing to walk to get to a store. Changing this distance to reflect the current definition of a food desert (one mile) to what the 90th percentile of US citizens are willing to walk decreased food access by 42.6%. The addition of store disruptors in one of two locations had varying degrees of impact on food access based on location, the residents' willingness to walk, and the type of store disruptor implemented. The percentage of food access increase obtained through these experiments ranged from 0.5% to 41.5% when compared to the baseline/status quo simulation (6.0% lack of access). The greatest single impact on baseline food access was an 11.8% reduction in those who walked as a last resort, and was the result of adding of a supermarket in Location 1 when willingness to walk was 0.5 miles, or 800 m. The most significant effect on the total level of food access in the region was in the complete elimination of a food desert (with 0.0% walking as a last resort) which resulted from the placement of a grocery store at Location 2 when willingness to walk was 1 mile, or 1600 m.

The adaptability of this model and its demonstrated ability to pick out emergent behaviors affirm that this model may be useful in further studies of this region. Future iterations of the model aim to include hours of operation of all stores, public bus routes surrounding the FD, and other forms of public transit. An alternative way to place disruptors that will be incorporated into future models is the random placement of stores using a parameter variation model. Optimizing the placement of store disruptors may follow methods such as k-means clustering. Future work may also assess non-traditional disruptors within FDs, including mobile food vendors, regular farmer's markets, etc. Through development of the aforementioned framework, this study aids in understanding what leads to discontinuity within the food system, and models specific, testable disruptors to increase food access and mitigate the negative effects of food deserts.

5 REFERENCES

Apparicio, P., Abdelmajid, M., Riva, M., and Shearmur, R. (2008). Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues. *International Journal of Health Geographics*, *7*(1), . doi:10.1186/1476-072x-7-7

Baker, E. A., Schootman, M., Barnidge, E., and Kelly, C. (2006). The role of race and poverty in access to foods that enable individuals to adhere to dietary guidelines. *Preventing Chronic Disease*, *3*(3), 1–11. Retrieved from https://www.cdc.gov/pcd/issueS/2006/jul/pdf/05_0217.pdf

Block, D., and Kouba, J. (2006). A comparison of the availability and affordability of a market basket in two communities in the chicago area. *Public Health Nutrition*, *9*(07), 837–845. doi:10.1017/phn2005924

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Science of the United States.* 99(suppl 3). 7280–7287.

Bray, G. A., Nielsen, S. J., and Popkin, B. M. (2004). Consumption of high-fructose corn syrup in beverages may play a role in the epidemic of obesity. *The American Journal of Clinical Nutrition*, *79*(4), 537–543. Retrieved from http://ajcn.nutrition.org/content/79/4/537.short

Briefel, R. R., and Johnson, C. L. (2004). SECULAR TRENDS IN DIETARY INTAKE IN THE UNITED STATES*. *Annual Review of Nutrition*, *24*(1), 401–431. doi:10.1146/annurev.nutr.23.011702.073349

Chen, X., and Clark, J. (2013). Interactive three-dimensional geovisualization of space–time access to food. *Applied Geography*, *43*, 81–86. doi:10.1016/j.apgeog.2013.05.012

Chung, C., and Myers, S. L. (1999). Do the poor pay more for food? An analysis of grocery store availability and food price disparities — Experts@Minnesota. *Journal of Consumer Affairs*, *33*(2), 276–296. Retrieved from https://experts.umn.edu/en/publications/do-the-poor-pay-more-for-food-an-analysis-of-grocery-store-availa

Diez-Roux, A., Nieto, F., Caulfield, L., Tyroler, H., Watson, R., and Szklo, M. (1999). Neighbourhood differences in diet: The Atherosclerosis risk in communities (ARIC) study. *Journal of epidemiology and community health.*, *53*(1), 55–63. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/10326055

FMI. "Consumers' Weekly Grocery Shopping Trips in The United States from 2006 to 2016 (Average Weekly Trips per Household)." *Statista - The Statistics Portal*. Statista. August 2016. Web. 22 Feb 2017.

Google Maps. (2017). Retrieved from https://www.google.com/maps/@30.3451623,-97.6855965,14.73z

Gross, L. S., Li, L., Ford, E. S., and Liu, S. (2004). Increased consumption of refined carbohydrates and the epidemic of type 2 diabetes in the United States: An ecologic assessment. *The American Journal of Clinical Nutrition*, *79*(5), 774–779. Retrieved from http://ajcn.nutrition.org/content/79/5/774.short

Hillier, A., Smith, T., Cannuscio, C. C., Karpyn, A., and Glanz, K. (2015). A discrete choice approach to modeling food store access. *Environment and Planning B: Planning and Design*, *42*(2), 263–278. doi:10.1068/b39136

Horner, M. W., and Wood, B. S. (2014). Capturing individuals' food environments using flexible space-time accessibility measures. *Applied Geography*, *51*, 99–107. doi:10.1016/j.apgeog.2014.03.007

James, P. T., Leach, R., Kalamara, E., and Shayeghi, M. (2001). The worldwide obesity epidemic. *Obesity Research*, *9*(S11), 228S–233S. doi:10.1038/oby.2001.123

Kyureghian, G., Nayga, R. M., and Bhattacharya, S. (2013). The effect of food store access and income on household purchases of fruits and vegetables: A mixed effects analysis. *Applied Economic Perspectives and Policy*, *35*(1), 69–88. doi:10.1093/aepp/pps043

LeClair, M. S., and Aksan, A.-M. (2014). Redefining the food desert: Combining GIS with direct observation to measure food access. *Agriculture and Human Values*, *31*(4), 537–547. doi:10.1007/s10460-014-9501-y

Leete, L., Bania, N., and Sparks-Ibanga, A. (2012). Congruence and coverage. *Journal of Planning Education and Research*, *32*(2), 204–218. doi:10.1177/0739456x11427145

Morland, K., Roux, D., and Wing, S. (2006). Supermarkets, other food stores, and obesity: The atherosclerosis risk in communities study. *American journal of preventive medicine.*, *30*(4), 333–339. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/16530621

Morland, K., Wing, S., and Roux, A. D. (2002). The Contextual effect of the local food environment on residents' diets: The Atherosclerosis risk in communities study. *American journal of preventive medicine.*, *92*(11), 1761–1768. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1447325/

Neckerman, K. M., Bader, M., Purciel, M., and Yousefzadeh, P. (2009). *Measuring Food Access in Urban Areas*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.189.2233

Powell, L., Chaloupka, F., and Bao, Y. (2007). The availability of fast-food and full-service restaurants in the United States: Associations with neighborhood characteristics. *American journal of preventive medicine.*, *33*, 240–245. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/17884571

Sargent, R.G. (2004). Verification and Validation of Simulation Models. Syracuse, NY.

USDA. (2017). Food Access Research Atlas [Demographic map]. Retrieved from https://www.ers.usda.gov/data-products/food-access-research-atlas/go-to-the-atlas.aspx

Widener, M. J., Farber, S., Neutens, T., and Horner, M. W. (2013). Using urban commuting data to calculate a spatiotemporal accessibility measure for food environment studies. *Health and Place*, *21*, 1–9. doi:10.1016/j.healthplace.2013.01.004

Widener, M. J., Metcalf, S. S., and Bar-Yam, Y. (2012). Developing a mobile produce distribution system for low-income urban residents in food deserts. *Journal of Urban Health*, *89*(5), 733–745. doi:10.1007/s11524-012-9677-7

Widener, M. J., Metcalf, S. S., and Bar-Yam, Y. (2013). Agent-based modeling of policies to improve urban food access for low-income populations. *Applied Geography*, *40*, 1–10. doi:10.1016/j.apgeog.2013.01.003