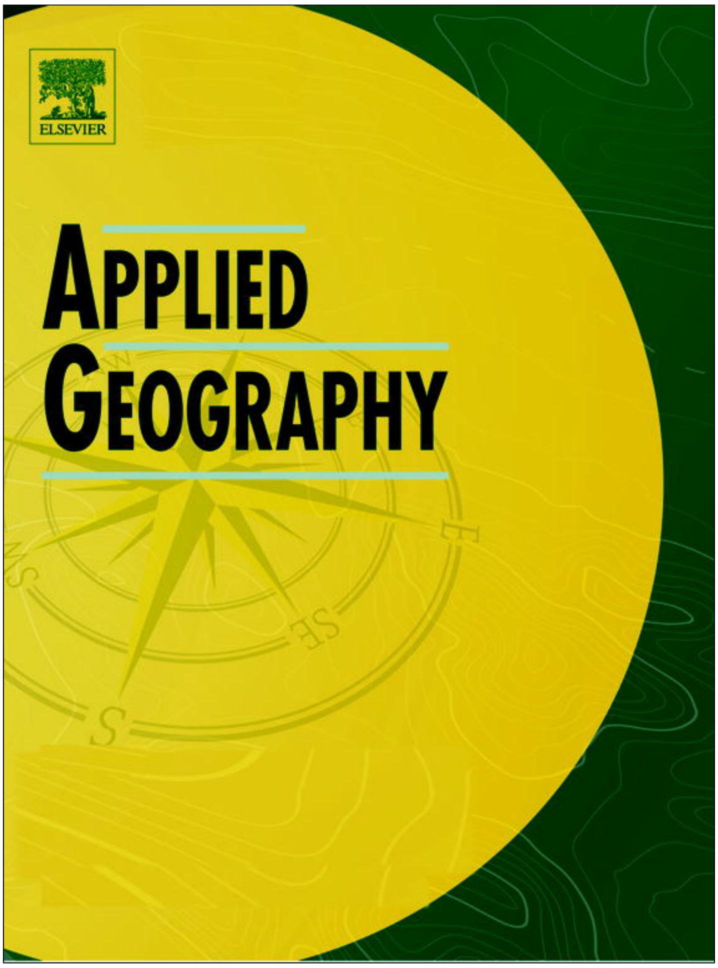
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Agent-based modeling of policies to improve urban food access for low-income populations

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A B S T R A C T

Despite advances in medical technology and public health practices over the past few decades, there has been a steady increase in the prevalence of chronic diseases like type 2 diabetes among low-income urban residents in the US. For this population, maintaining a diet consisting of nutritious foods is complicated by a number of physical and social barriers. In cities, a coalescence of social, spatial, and economic factors influence the availability of healthy food in any given place. The urban food environment contextualizes the structural and individual-level norms that drive daily decision-making about what to eat. Understanding and acting on the processes that reduce these residents' access to healthy foods will make for a healthier urban landscape. This paper advances the discussion of food deserts by using an agent-based model to simulate the impact of various policy interventions on low-income households' consumption of fresh fruits and vegetables. Using a simulated population of low-income households in Buffalo, NY, initialized with demographic and geographic data from the US Census and the City of Buffalo, a baseline scenario is established. Four different scenarios are explored in contrast to the baseline, including increasing the frequency that households shop for groceries, increasing the probability convenience stores stock fresh produce, and implementing a mobile market distribution system. The paper concludes by analyzing the effectiveness of the varying strategies, and discussing policy implications.

Introduction

The concept of urban food deserts is well established (McKinnon, Reedy, Morrissette, Lytle, & Yaroch, 2009). Urban residents lacking spatial and economic access to healthy foods, such as fresh fruits and vegetables (F&Vs), are at risk of having diets with poor nutrition, which in turn puts them at risk of chronic diseases like obesity, cardiovascular disease, and type 2 diabetes (Ebbeling, Pawlak, & Ludwig, 2002; He et al., 2004; Higdon, Delage, Williams, & Dashwood, 2007; Joshipura et al., 2001; Mokdad et al., 2001; Smith-Warner et al., 2001; Sorensen, Linnan, & Hunt, 2004; Vainio & Weiderpass, 2006). However, the underlying processes that hinder access, and therefore increase poor health outcomes, are largely conflated.

This paper contributes to the current discourse on food deserts by presenting an agent-based model (ABM) that tests a number of spatial and aspatial interventions in the city of Buffalo, NY. An ABM provides a dynamic platform where individual-level actors can independently react to hypothetical changes to different aspects of the urban food system, such as spatial or temporal constraints. These changes are presented as hypothetical policies aimed at eliminating food deserts from the urban landscape. Doing this provides insights into both which policies are most effective, as well as what processes may be hindering access to healthy foods.

The next section reviews previous research on food deserts, noting that measuring access to healthy food in western urban centers is not easily generalizable. Section Model formulation and population initialization goes on to describe the model's scope and formulation, while Section Parameter initialization details the initialization of the ABM's parameters. This is followed by the presentation of results in Section Policy simulations. Finally, Section Discussion offers a discussion of model results, limitations, and directions for future research.

Review of food desert literature

A number of studies, from the US and elsewhere, have closely examined the urban food desert phenomenon. At a basic level, the common goal of this work involves identifying and parsing through variables that matter when it comes to healthy food consumption.

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These variables include, but are not limited to, distance, mobility, economic and social capital, and behavioral factors (e.g. preference for convenient foods).

In their article on measuring access to healthy foods in a British city, Donkin, Dowler, Stevenson, and Turner (1999) approach the problem by thinking about how social and geographic aspects come together. They compile a list of foods compatible with an "ethnic" diet, identify vendors, and calculate network buffers to show which areas have access. The authors note that this is not a complete picture of the problem, but rather a "first indication." They do note that the use of network buffers and GIS afford them a look at how far people are from sources of healthy food, but their analysis does not adequately account for the mobility of the population in question. For example, the travel cost of a one-mile journey on public transportation is generally higher than that of a journey by automobile.

Other studies have examined accessibility by looking at the makeup of different types of food stores alongside the demographic makeup of various urban regions. Morland, Wing, Diez Roux, and Poole (2002) find that wealthy, non-minority neighborhoods are more likely to have supermarkets with lower priced healthy foods than poorer, minority neighborhoods. Similarly, Larsen and Gilliland (2008) show food deserts exist in London, Ontario, and neighborhoods of low socio-economic status have poor spatial access to supermarkets with large selections of fruits and vegetables. In Detroit, Michigan, a study has shown that impoverished African American neighborhoods are significantly further from supermarkets than other low-income populations (Zenk et al., 2005). Lee and Lim (2009) use a spatial statistics test to identify food desert regions in the city of Buffalo, NY. The authors develop an index that identifies Census block groups where demand for groceries is not fully met. By analyzing the spatial distribution of this index using the G-statistic (Getis & Ord, 1992), Lee and Lim find that a number of areas with poor access exist in Buffalo.

Despite all of these findings, there exists other research that suggests the problem of food deserts is not always so straightforward. For example, Raja, Ma, and Yadav (2008) show that food deserts are not present in Buffalo, NY, if restaurants and niche food stores are considered. Rather than "deserts" per se, Raja et al. focus on the large disparity between predominately white and non-white neighborhoods' access to supermarkets. The authors conclude that, while many non-white neighborhoods have poor access to supermarkets, they are well served by smaller convenience stores. Therefore, these households' ability to purchase nutritious foods depends largely upon the stock of healthy foods in smaller stores. The influence of the geography of healthy food stores is further complicated by studies that find no relationship between spatial access and obesity, socioeconomic class, and diet (An & Sturm, 2012; Bertrand, Thérien, & Cloutier, 2008; Lee, 2012).

With all of this conflicting evidence, the validity of a generalizable food desert phenomenon becomes uncertain. Different studies make convincing arguments about whether the spatial factors affect urban residents' diets. However, the magnitude of the diet related health problems facing socioeconomically disadvantaged populations and the presence of some evidence that spatial factors play a role warrant further inspection. The examination of healthy food access put forth in this paper is novel because it is not attempting to classify certain urban spaces as food deserts. Rather, through the dynamic modeling of hypothetical interventions, it explores how changes to the spatial and economic makeup of the urban food environment result in population-wide increases in healthy food consumption.

Thus far, policy measures have failed to eliminate food deserts from urban regions. This is partly due to the complex and dynamic nature of the urban food landscape, which consists of disaggregate grocery shoppers with varied tastes and budgets, and food vendors with equally diverse inventories and business models. Because of this landscape's complexity, it is useful to conceptualize it as an interconnected system where residents' food purchasing habits are influenced by a dynamic local environment (Metcalf & Widener, 2012).

This system conceptualization has several unique advantages over considering each of the components by themselves. First, there are modeling tools, which allow researchers to simulate an interconnected system over time. One such method is the previously discussed agent-based modeling where components of the system, existing at multiple scales, can be disaggregated and explicitly represented. In previous research, ABMs have been used to understand numerous social and environmental systems (Gimblett, 2002). Another advantage is that feedback between components can be explicitly represented.

To this point ABMs have been sparingly employed to explore urban food systems. A noteworthy exception uses a self-described simple agent-based model to demonstrate how segregation, price, and preference affect the number of healthy diets (Auchincloss, Riolo, Brown, Cook, & Diez Roux, 2011). The paper constructs a highly abstract region with low- and high-income residents, along with food stores that could sell healthy or unhealthy food. The model is then used to conduct a number of experiments with various levels of income segregation and healthy food store placements to understand how these affect the shopping patterns of residents. The results from these virtual experiments suggest that the income differential in diet can be addressed by lowering the price of healthy food and cultivating preferences for healthy food among low-income residents.

This paper develops a spatially explicit ABM that explores the food purchasing behavior of low-income residents in Buffalo, NY. It expands on the work done in the Auchincloss et al.'s model by integrating empirical spatial data and explicitly modeling policy interventions. Contextualizing a model like this in a particular urban environment such as Buffalo is an important step toward place-specific characterizations of food deserts.

Model formulation and population initialization

An ABM is constructed to explore policy scenarios relevant to the urban food landscape in Buffalo. Subsection Problem definition and model scope explicitly defines the research question being used to guide model development. This is followed by a description of how the simulated population of low-income households is generated in Subsection Model formulation. Finally, Subsection Agent-level behavior explains the model's agent-level behavior.

Problem definition and model scope

As discussed in the previous section, evidence suggests that socioeconomically disadvantaged urban residents are at a higher risk for a variety of chronic diseases, because their diets often lack the critical nutrients gained through consuming healthy foods. With this in mind, a reasonable question to ask is: given present urban landscapes, what strategies can be implemented to help increase the nutrition of low-income households' diets?

For this research, Buffalo, NY is modeled. A city of approximately 300,000 people, Buffalo is in many ways representative of other Rust Belt cities. The city has become one of the poorest in the country since deindustrialization, and has suffered from racial segregation, political corruption and ineptitude, planning decisions that have prioritized private vehicle transportation, and massive outmigration that has resulted in a large number of vacant and abandoned properties (Cope & Latcham, 2009; Goldman, 2007). In addition, past research has pointed to Buffalo as a city with areas that are without access to healthy foods, which manifest because of some of the aforementioned factors (Lee & Lim, 2009; Metcalf & Widener, 2012; Raja et al., 2008; Widener, Metcalf, & Bar-Yam, 2011).

Having bounded the spatial extent of the model, the question can now be further refined to ask: given the urban landscape of Buffalo, NY, where there is a high proportion of low-income residents without access to healthy foods, what strategies can be implemented to help increase the nutrition of low-income households' diets? For this research, "low-income households" are defined as households living at or below the poverty level as defined by the US Census. Additionally, because there is a body of medical research that links eating fresh F&Vs with positive health outcomes (Algert, Agrawal, & Lewis, 2006; Hung et al., 2004) the model will concentrate on modeling low-income households' purchases of fresh F&Vs. For the purpose of the model, our research question is:

Given an urban landscape like that of Buffalo, NY, where there is a high proportion of low-income residents without access to healthy foods, what strategies can be implemented to help increase the rate households in poverty purchase fresh F&Vs?

Model formulation

Given the model scope defined by the above research question, key components to be programmed into the model are the population of households in poverty within the city limits of Buffalo and food vendors that sell F&Vs. Because of the role distance plays in overall access, the geography of these components is relevant. A GIS is used to manage the data and conduct the necessary data preparation required for model initialization.

To do this, the data are first compiled from reliable sources. For this research, food vendors are defined as supermarkets, convenience stores, farmers' markets, and mobile grocery markets. The locations of supermarkets and convenience stores are compiled using Hoover's business directory and crosschecked with Google Map's directory (Hoover's Inc., 2010), while the farmers' market locations are collected from a website maintained by the State of New York (2011). While the aforementioned sources provide a good representation of the food vendor environment in the city, it may not be perfect because the openings or closings of stores could be left out of the latest database update.

Here, the definition of a supermarket is considered to be large to very large grocery stores with a wide selection of affordable healthy foods, and include local, regional, and national chains like Dash's Markets, Wegmans, Tops Friendly Markets, and Price Rite. Convenience stores on the other hand range from local corner stores, to chain drug stores, to small specialty food vendors. While imperfect, classifying a diverse range of food vendors as either supermarkets or convenience stores provides a reasonable starting point for implementing the model. A more nuanced discussion of food store classification is available in Powell et al. (2011), where the authors elaborate on complications like the widespread availability of affordable, unhealthy foods at supermarkets.

Potential locations of mobile grocery markets are included to explore alternative food access scenarios. All food vendor addresses are geocoded using an address locater tool within GIS software, and a spatial data file of points is generated. A map of food vendor locations is shown in Fig. 1. Finally, a file containing the latitudes, longitudes, and type for each food vendor is constructed, providing a means for programmatically loading this data into the ABM.

Because household-level behavior is of interest, a spatially disaggregate representation of low-income households is constructed in our ABM. Before dynamic household agent-level behavior is simulated, an agent population is generated that replicates the observed number and spatial distribution of low-income households across the city. To accomplish this, 2010 parcel data from the City of Buffalo are used to calculate an exact longitude and latitude value for each residential location. Then, data on the proportion of households in poverty from the US Census is used to assign each parcel a probability of being low-income. This generally replicates the spatial distribution of low-income households in the city.

While there are limitations to creating a simulated population in this manner, involving issues like the modifiable areal unit problem (Openshaw, 1984), this method generates approximately 17,171 low-income households (Fig. 1). Assuming an average household size of 4, this accounts for 68,684 residents, or approximately 91 percent of the Buffalo residents in poverty in 2009. Many of these households are also placed in neighborhoods in the east- and west-side of the city, which have higher proportions of minority residents. Ultimately, this simulated population of low-income households in Buffalo provides a useful analog, allowing for scenarios to be explored that factor in a realistic spatial distribution of the population at risk of not having consistent access to fresh F&Vs.

Agent-level behavior

Once the population of agents is established, the dynamic behavior of each agent is defined. Returning to the research question and model scope discussed in Section Problem definition and model scope, the behavior to be modeled is that of purchasing fresh F&Vs at local food vendors. The household agent decision-making process may be broken into discrete steps.

First it is assumed that each household agent will keep a certain amount of food within the house. When this stock of food is depleted, the agent will make a trip to a food vendor to purchase more food. It is presumed that each household has one person that completes all grocery shopping. In this model, different populations will stock different amounts of food to last them a week, two weeks, or a month. This induces variation in shopping frequency, as an agent must make a shopping trip when the food stock is depleted. However, the model assumes that the total amount of food purchased by agents is the same, no matter their shopping frequency. For example, a monthly grocery shopping agent may spend 100 dollars per trip, where a biweekly shopper would spend 50, and a weekly shopper would spend 25.

In consideration of the research question, an agent's shopping frequency has an effect on how often it has fresh F&Vs available in its food stock. It is assumed that produce remains edible for one week, at which point the agent will no longer have any in stock. Therefore, agents that shop more frequently will be more likely to have a constant supply of produce in their pantries. The depletion of fresh F&Vs alone does not trigger a shopping trip, but is tracked to analyze what policies result in produce being more widely available in homes.

When an agent shops for food, it has a choice between going to a supermarket or a convenience store. For this model, farmers' markets and mobile markets are also classified as supermarkets, because it assumes that they carry a large variety of mostly healthy food. In scenarios where these temporary food stores are available, agents can only visit them when they are designated as open.

During simulation, the model keeps track of the closest supermarket and convenience store to every agent, as it is assumed they will choose the nearest option for each store type. Through the course of a simulation run, an agent has a probability of choosing a supermarket assigned using a lookup table function resembling an inverse sigmoid (Fig. 2), with Equation (1) as an input:

$$\frac{d_s/\alpha}{d_c} \tag{1}$$

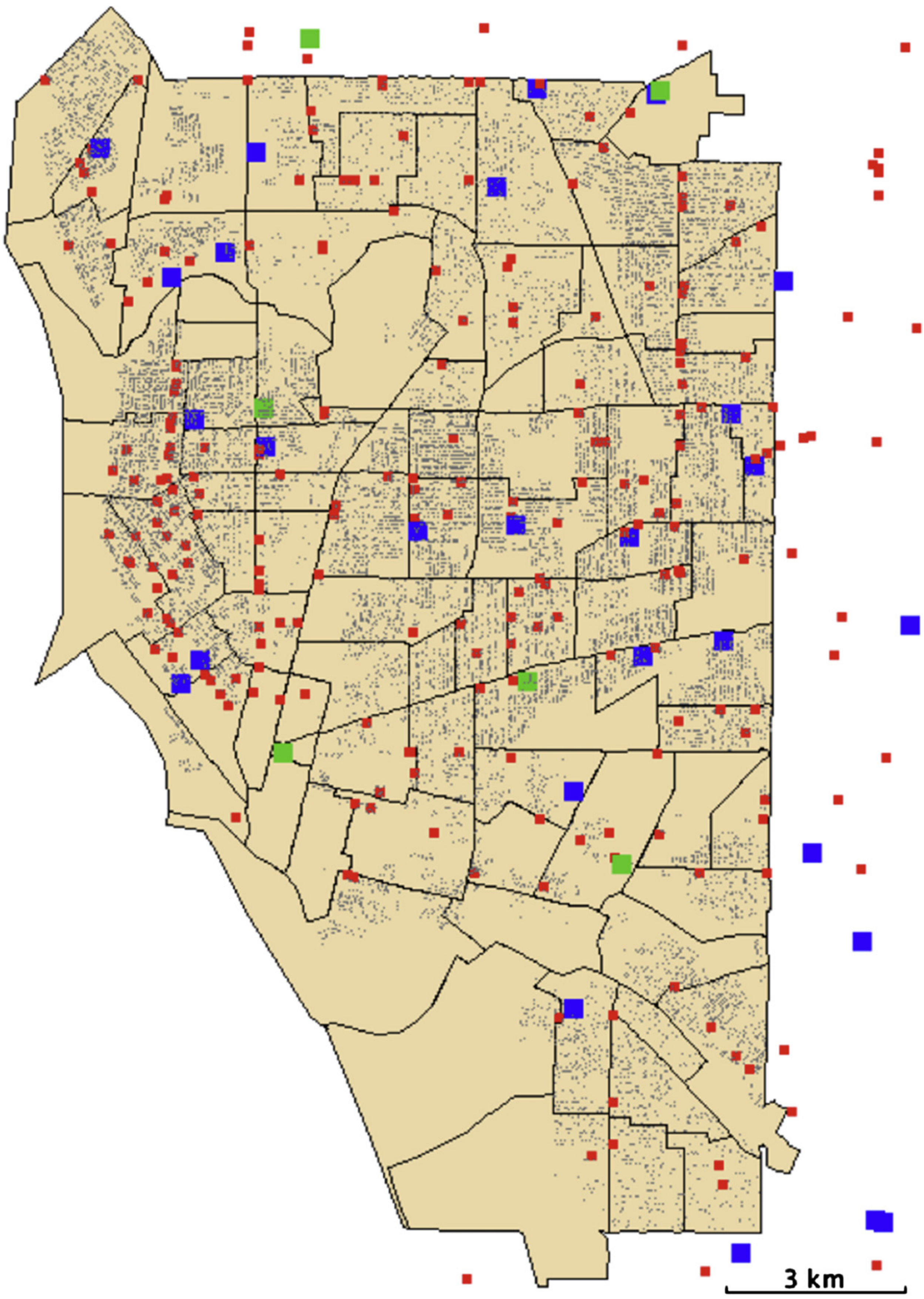

Fig. 1. Gray squares indicate the location of the simulated population of low-income households in Buffalo, large blue squares are the actual locations of supermarkets, large green squares show the locations of farmers' markets, and small red squares are convenience or specialty food stores with limited selections. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

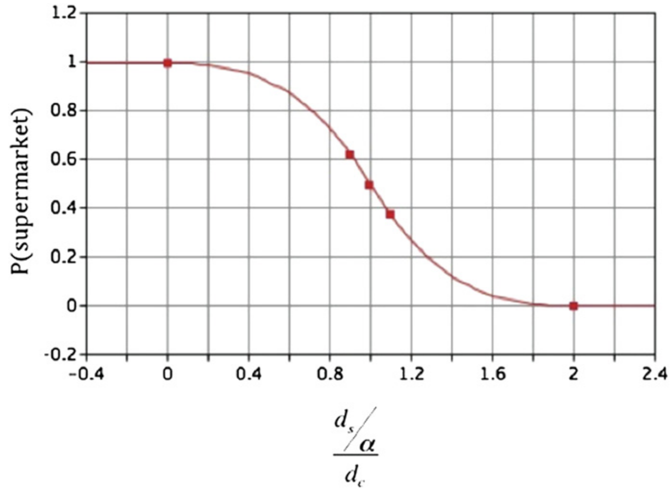

Fig. 2. The lookup function used to determine the probability of shopping at a supermarket. The *x*-axis is the weighted ratio of distances described in Equation (1). The *y*-axis is the probability of shopping at a supermarket.

where d_s is the straight line distance to the nearest supermarket, d_c is the straight line distance to the nearest convenience store, and α is a constant, where large values of α result in a higher probability of shopping at a supermarket. The distances d_s and d_c are updated whenever there is a change in the locations of food stores. Agents' constant monitoring of store distances also creates a feedback dynamic, where changes in the food store environment result in changes in where agents shop. The lookup table, generated within the ABM software, provides a continuous function using a spline interpolation, and returns a value of zero for instances where $(d_s/\alpha) > 2d_c$ (Fig. 2). When α equals 1, and $d_s = d_c$, there is an equal chance that an agent will choose the supermarket or the convenience store. The use of the constant α is meant to emphasize the draw of supermarkets due to their larger selections and store sizes.

Effectively, this process generates a store preference for an agent by comparing the weighted distances to the nearest supermarket and convenience store. The weighting constant α reduces the magnitude of the distance for supermarkets, thereby accounting for the more desirable aspects of these stores. The actual value of α is chosen during the model's initialization, in the next section. With the mechanism for initializing the probability of shopping at the closest supermarket set, the initial probability of shopping at the closest convenience store is set to 1 − (*probability of shopping at a supermarket*).

Agents decide where to shop based on the previously discussed probabilities. Once an agent knows where it will shop, there are two more considerations that must be made before it purchases fresh F&Vs. First is the probability that the food store visited sells fresh F&Vs. All supermarkets are assumed to sell fresh F&Vs, so the probability of their availability is equal to 1.0. In contrast, one third of convenience stores are assumed to stock fresh F&Vs, making the probability of availability equal to 0.33. The second consideration is whether an agent will actually purchase F&Vs when they are available. An agent who shops at a convenience store that does not sell fresh F&Vs has a zero probability of purchasing F&Vs because there is no option. However, if the agent shops at a supermarket or a convenience store that sells fresh produce, then each agent has a non-zero probability of purchasing F&Vs. The values of these probabilities are assigned during model initialization to reflect observed rates, which are discussed in depth in the following section.

Parameter initialization

With the model's structure established, its parameters are initialized to values that result in simulation outputs that match empirical observations as closely as possible. Parameters are set to corresponding values recorded in empirical studies, when available. A number of these studies have documented values that correspond to parameters internal to the model presented in this research. These include:

- The percentage of households participating in SNAP that shop for food less than once every two weeks is approximately 30% (USDA, 2006, 2009). This is a reliable sample for the agent population, as households in poverty are eligible for SNAP benefits. Given this information, one third of agents are randomly assigned as monthly shoppers, one third are randomly assigned as biweekly shoppers, and one third are randomly assigned as weekly shoppers.
- The probability of purchasing fresh F&Vs at a supermarket is estimated to be in between 80% and 86% (USDA, 2009). Therefore, when shopping at a supermarket, the probability that agents purchase fresh F&Vs is set to the more conservative value of 0.80.
- The percentage of people purchasing fresh F&Vs when grocery shopping at a convenience store is reported as approximately 78% (USDA, 2009). However, other research suggests that the availability of fresh produce in the "inner city" is less than in other locations (Chung & Myers, 1999). Therefore, agents that shop at a convenience store are assigned a more conservative probability of 0.75 of purchasing fresh F&Vs.

This evidence provides useful heuristics for initializing the agent probabilities. The final assignment is the probability an agent will choose to go to the supermarket or convenience store for food shopping. Empirical data provide details on the store choice patterns of SNAP recipients, however there is no information on the role spatial proximity in store choice plays. This research follows the assumption, pointed to in previous research, that geography influences where people shop for groceries.

With α set equal to 5, multiple high-level shopping patterns documented in the USDA's reports are replicated in the initialized model. These patterns include the number of households' grocery trips to supermarkets and convenience stores, the proportion of households primarily shopping at supermarkets, and the proportion of households primarily shopping at convenience stores. Because of this, $\alpha = 5$ will be the parameter's value during most of the next section's experiments.

Policy simulations

The previous section has outlined the structure and initial conditions of the agent-based model. With this template, a number of policy interventions are simulated to test their effectiveness in increasing the number of low-income households that stock fresh F&Vs. All simulation experiments are run for a time period equivalent to four years to show the seasonal and long-term dynamics of the tested policies.

The key outcome of these simulation runs is the number of households that have fresh F&Vs in stock at a point in time. This differs from the number of households that purchase F&Vs, but provides a clearer picture of which household agents have F&Vs on hand and are therefore able to consume these healthy foods. While the number of households purchasing fresh F&Vs per grocery trip may be relatively high, as discussed in the previous section, the consumption of these foods will be lower. Consider a monthly grocery shopper. It is assumed that even if this shopper buys fresh F&Vs every time they shop, they will not have any on hand after a week's time due to the assumed expiration rate. This leaves them with approximately three weeks out of four without these foods. For this reason, measuring the number of households with fresh F&Vs in stock is deemed a more informative metric.

Scenario 1: Farmer's markets

The first scenario introduces the impermanent farmers' market vendors into the system. This is done for two reasons. First, it is meant to demonstrate how changes in the availability of fresh F&Vs can result in fluctuations in their consumption by residents with limited access. Generally, previous research has excluded impermanent food vendors from their studies (Widener et al., 2011). Second, farmers' markets are a part of the urban foodscape and are therefore included in all subsequent scenarios. Within the model, household agents treat farmers' markets the same as supermarkets. The farmers' markets' locations and open dates are obtained from the State of New York. Within the agent-based model, farmers' markets are placed at their proper coordinates, and open or close as they would in real life. Every time a market opens or closes, the population of household agents reevaluates the current state of the food vendor environment. For example, if a farmers' market has opened nearer to a household agent than the closest supermarket, that agent will now consider the farmers' market to be its preferred alternative to the convenience store, in place of the supermarket.

Fig. 3 shows how integrating farmers' markets into the system produces an oscillatory effect, where the number of households with fresh F&Vs in stock increases during the summer months. For reference, the figure also shows the number of households with fresh F&Vs in stock without farmers' markets in the food vendor environment. In the case without farmers' markets, the number remains fairly stable over time. Note that there are slightly fewer household agents with F&Vs in stock when there are no farmers' markets than in the trough of the case when the simulation includes farmers' markets. This is due to the fact that one farmers' market is open all year, increasing the accessibility of fresh F&Vs in a new area of the city.

As expected, introducing farmers' markets to the food environment increases the number of households with fresh F&Vs in stock, as there are now more food vendors where household agents may purchase these foods. The troughs of the oscillation correspond to a number of households with fresh F&Vs in stock seen in the simulation run without any farmers' markets. However, during the summer days the number increases by in between 100 and 200 households.

These simulation results provide a dynamic context to the many metrics used to identify food deserts that only consider permanent vendors. There is a clear and regular pattern in simulated low-income households' stocking of fresh F&Vs driven by the opening and closing of farmers' markets. Further more, evidence demonstrates that diets are influenced by habit (Johansson, Thelle, Solvoll, Bjørneboe, & Drevon, 1999; King, Mainous, Carnemolla, & Everett, 2009). Residents with only irregular access to fresh F&Vs face difficulties in habitually incorporating these foods into their meals. Because of this, interventions aimed at creating a more constant and greater level of consumption by those households at risk of having variable access to fresh F&Vs should be prioritized.

Scenario 2: shopping frequency

The second scenario will introduce the first intervention strategy aimed at increasing the number of low-income household agents with fresh F&Vs in stock. One of the biggest obstacles low-income household agents face in stocking healthy foods is the limited time fresh F&Vs have before they expire. In a perfect system, all agents would shop for groceries and fresh produce at a rate that precludes them from having to deal with expired F&Vs. However, as discussed in Section Agent-level behavior, a larger percentage of households shop for groceries once every two weeks or monthly. Given the model's assumption that two thirds of the agents shop, on average, at a biweekly or monthly rate and that fresh F&Vs expire after one week, there are a large number of household agents that will spend at least half of the time without fresh produce in stock.

Scenario 2 explores how the number of household agents with fresh fruit and vegetables changes by implementing a hypothetical program that switches some proportion of biweekly and monthly shoppers to weekly grocery shopping rates. Such a program could be achieved by identifying households that shop for groceries less frequently, and then providing a ride service to their food vendor of choice. The agent-based model is run with 0, 10, 25, and 50 percent of the approximately 11,500 biweekly and monthly grocery shopping

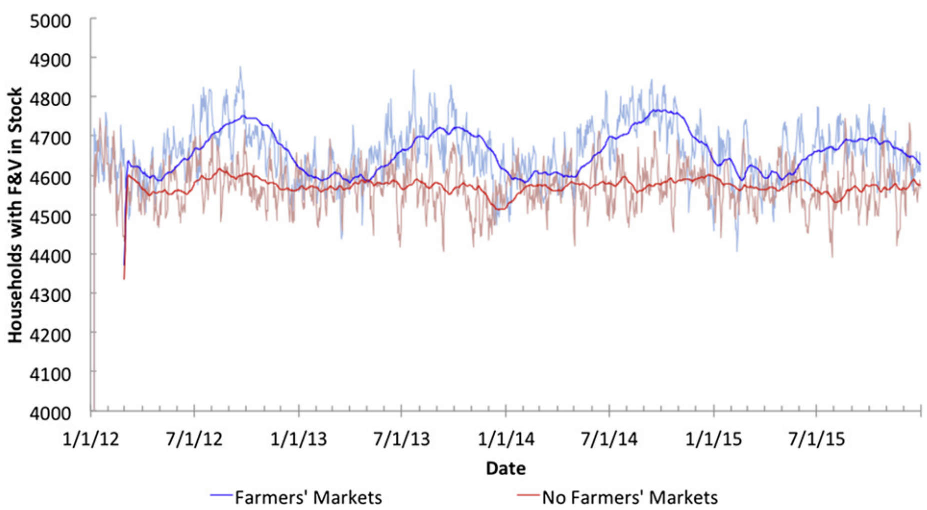

Fig. 3. The noisy light blue line represents the number of households with fresh F&Vs in stock when farmer's markets are incorporated into the food environment. The dark blue line is a 60-day simple moving average. The noisy light red and dark red correspond respectively to the same metrics, but in an environment without farmers' markets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

agents changing to weekly grocery shopping agents after the first year of simulation. It is important to note that this intervention does not attempt to shift the probability of an agent shopping at a supermarket/farmers' market or convenience store.

The model's output is displayed in Fig. 4. It is evident that this intervention can impact the number of low-income households with fresh F&Vs in stock. A program where only 25 percent of households that normally grocery shop biweekly or monthly are switched to shopping weekly results in approximately 600 more households with fresh produce in stock than the base case. When 50 percent of biweekly and monthly grocery shopping households are switched to shopping weekly, approximately 1400 more households stock fresh fruits and vegetables over time.

Scenario 2 demonstrates that by only increasing the frequency of households' grocery shopping trips, without adjusting shopping preferences, the number of households stocking fresh F&Vs, and implicitly the consumption of these healthy foods, greatly increases. This is important because as previously discussed, shifting a person's preference for certain foods can be difficult. However the results from this scenario suggest that through encouraging a more logistical and less taste driven transformation in the population, the goal of bettering low-income household diets can be achieved.

Scenario 3: healthy convenience stores

The next intervention explored involves increasing the percentage of convenience stores that sell fresh F&Vs from 33 percent to 100 percent. Subsection parameter initialization explained that a household agent deciding to shop at a convenience store only has a probability of 0.33 of finding fresh produce. If an agent does not find fresh produce then there is a zero percent chance that they will stock these foods. However, if the agent shops at a convenience store with fresh produce, they have a probability of 0.75 of purchasing fresh F&Vs.

This policy intervention would require incentives for convenience stores to dedicate shelf space to fresh produce, and an expansion of the produce distribution network to include these food vendors. As previous research notes, low-income households have generally good access to convenience stores (Raja et al., 2008). Additionally, Scenario 3 offers the added advantage that many households already shop at convenience stores for their groceries, thereby reducing the need to adjust shopping patterns.

Fig. 5 shows the results of this scenario, with probabilities a convenience store has fresh produce of 0.33, 0.50, 0.66, 0.83, and 1.00. Increasing the probability of having fresh produce at a convenience store results in a linear increase in the number of household agents with fresh F&Vs in stock. There is an increase of approximately 1000 households stocking fresh produce when the probability increases from 0.33 to 1.00.

These simulations suggest that utilizing convenience stores as a distribution point for fresh F&Vs would provide a promising way to increase the number of households stocking fresh produce. By increasing the probability that an agent will shop at a convenience store with produce in stock, there is subsequently a relatively good chance that households will purchase, and then consume this food.

Despite this, the economics of enacting the strategy tested in Scenario 3 may not make sense from the standpoint of the store. Convenience stores by their very nature are smaller, and have less shelf space to store products with a limited shelf life. Therefore, an alternative means for distributing these healthy foods to households without spatial access to a supermarket or farmers' market that bypasses convenience stores is explored in the following section.

Scenario 4: mobile markets

The final scenario presented implements a version of a mobile market distribution system originally developed using a spatial optimization model (Widener, Metcalf, & Bar-Yam, 2012). A spatial optimization model considers where food-insecure households are, and then places distribution vehicles or facilities so as to best serve this population. Using mobile market vehicles is an opportune way to improve access to fresh produce and other foods throughout an urban region. A number of cities have successfully implemented mobile market programs, including Buffalo's Massachusetts Avenue Project's Mobile Market, Real Food Farm's Mobile Market in Baltimore, New York's Green Cart program, and Chicago's Fresh Moves program. While the logistics and size of these programs vary, they are all designed to improve the availability of healthy foods in neighborhoods with poor access. As opposed to coordinating with a large number of convenience store owners,

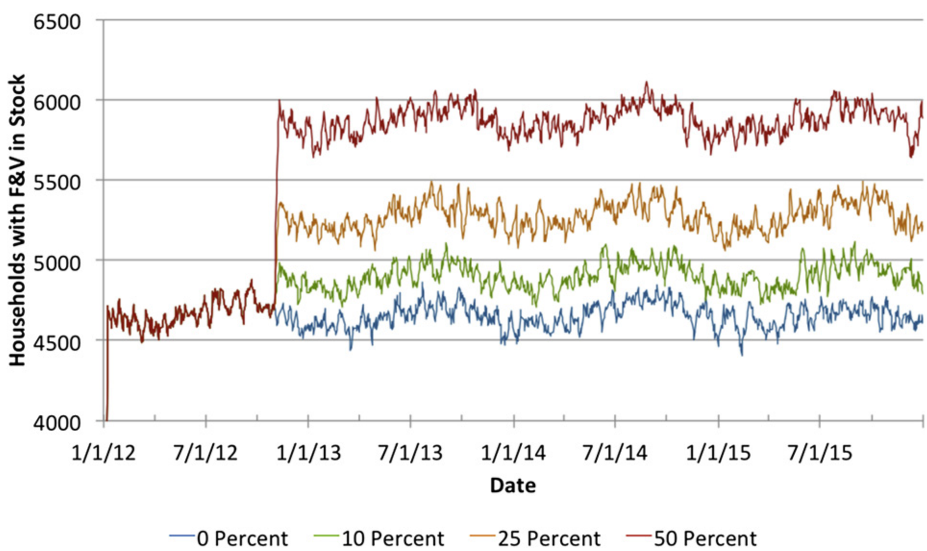

Fig. 4. An intervention that increases the rate of grocery shopping of some percentage of infrequent shoppers can greatly increase the number of households with fresh produce in stock.

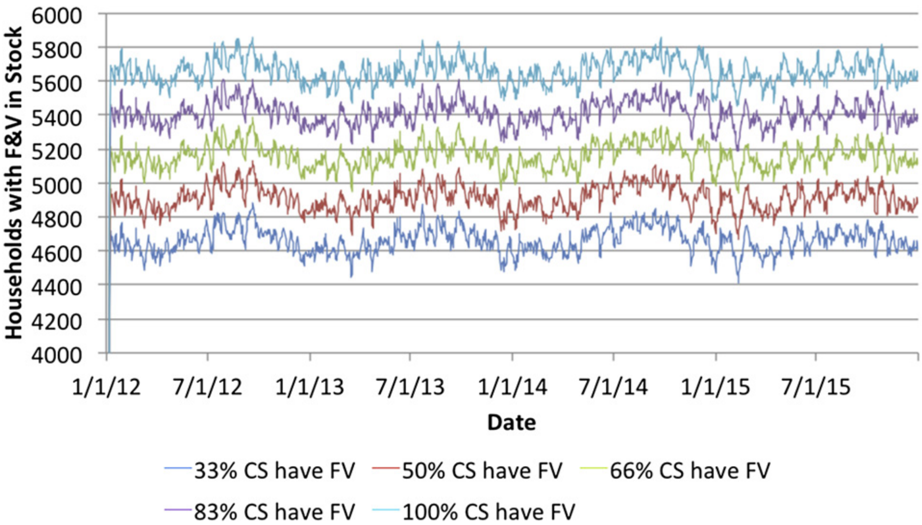

Fig. 5. Changes in the number of household agents with fresh F&Vs in stock given different probabilities that convenience stores will sell fresh produce.

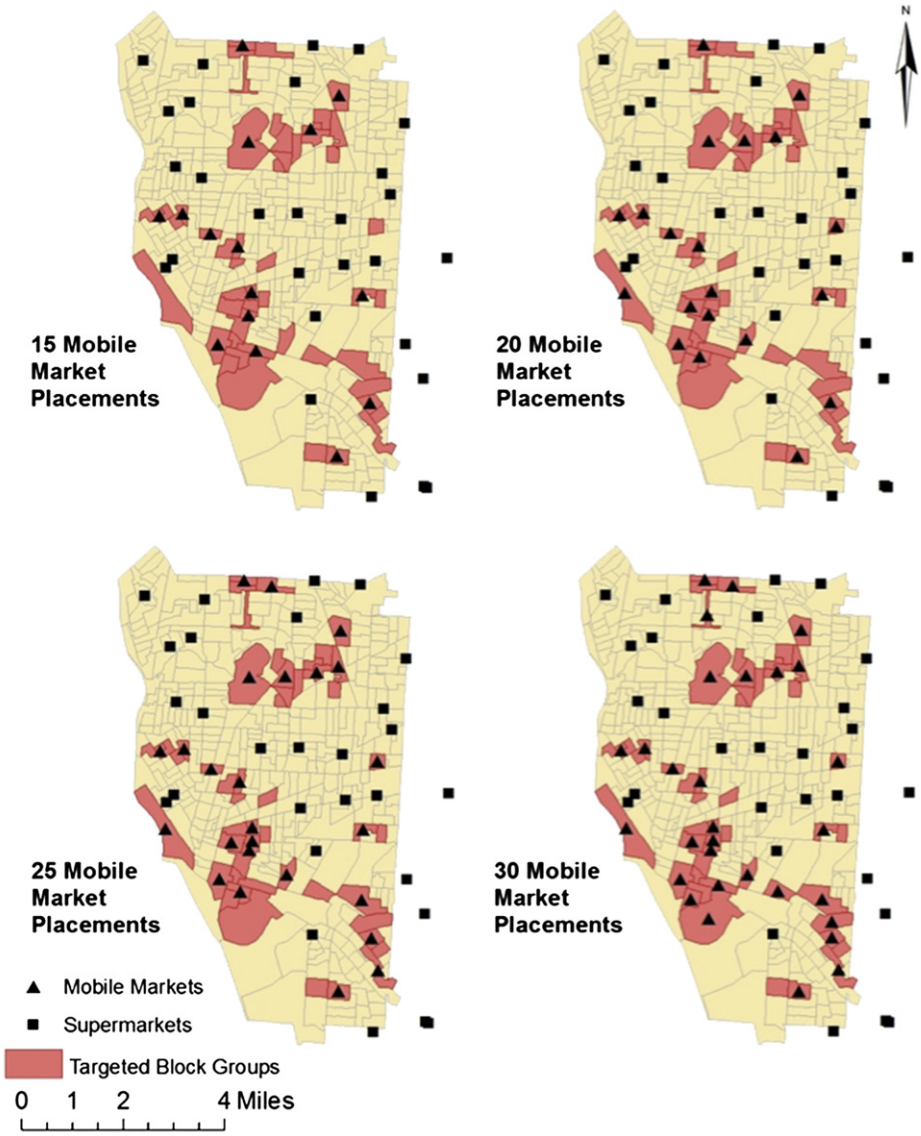

Fig. 6. Optimal placement locations of mobile markets, given supermarket locations (Maps courtesy Widener et al., 2012).

developing a new produce distribution network, and potentially subsidizing produce sales at convenience stores, a strategy could be devised where mobile markets are loaded at a single warehouse and then located in regions without access to supermarkets.

The simulations run for this scenario use the mobile market placements proposed in Widener et al. (2012). The spatial optimization model locates 15, 20, 25, and 30 mobile markets throughout regions designated as food deserts in Buffalo (Fig. 6). These mobile market locations are imported into the model, and household agents treat them as if they are supermarkets. As with farmers' markets, this is a simplifying assumption. The results are displayed in Fig. 7.

The increase in the number of household agents with fresh F&Vs in stock is relatively small between the different mobile market distribution plans. However, when compared to the approximately 4,600 households with fresh F&Vs in stock in the baseline scenario without any mobile markets (see Fig. 3), all mobile market distribution plans, no matter the number (15, 20, 25, or 30), result in a substantial increase of around 500 households stocking fresh F&Vs.

These simulations suggest that Buffalo only needs a smaller number of mobile market vehicles deployed to significantly improve the food security of its residents. Given the geography of permanent food vendors and farmers' markets, at a point the benefits seen from more mobile markets begin to diminish, considering the costs associated with deploying these vehicles. However, these simulations show that a mobile market distribution system boost the number of low-income households stocking fresh produce.

Discussion

Summary of results

Results from the scenarios presented in the previous section illustrate a number of strategies to increase the number of low-income households with fresh fruits and vegetables in stock. Achieving such an increase is important because having fresh produce available in the home is a first step toward increasing the consumption of these foods. As mentioned previously, increased consumption of fresh fruits and vegetables provides long-term health benefits, including reducing the chance of obesity, stroke, and cardiovascular disease. Below, Scenario 1 will not be discussed in depth, as it is designed to demonstrate the model's baseline output and does not map to an exact policy intervention.

Given the assumptions of the agent-based model, the intervention most effective at increasing the number of agents stocking fresh produce is from Scenario 2. Here, 50 percent of the approximately 11,500 biweekly and monthly grocery-shopping households were switched to weekly grocery shopping. The number of total household agents stocking fresh fruits and vegetables jumps to approximately 6000 households, suggesting that a large factor in improving these residents' diets involves more frequent grocery shopping.

Although, Scenario 2 produced the largest gains in household agents stocking fresh F&Vs, it did not explicitly address the spatial distribution of food vendors in Buffalo. While the frequency at which households shop for groceries is not completely independent of geography (e.g. being closer to a supermarket may result in more trips due to convenience), this experiment suggests that, in Buffalo, programs which help low-income households find the time to shop for food on a weekly basis is an important component of policy interventions. Such programs should mind households' alternate responsibilities, like multiple jobs or childcare. It is also important to note that distaste for fresh fruits and vegetables could lead a grocery shopper to visit food vendors at a less frequent rate. Despite this, there is still an opportunity to promote more frequent grocery shopping through transportation programs, or perhaps providing SNAP benefits at a weekly rate instead of the current monthly distribution model.

The two spatially explicit policy interventions presented in Scenarios 3 and 4 also successfully increase the number of low-income household agents with fresh fruits and vegetables in stock, but to a lesser extent than the shopping frequency experiments of Scenario 2. However, they directly address the spatial problem by moving fresh fruits and vegetables to regions that currently do not have access. Both Scenarios 3 and 4 show that expanding the geographic prevalence of places where healthy food can be obtained increases the stocking of fresh produce. However, given the complexity of intervening in the convenience store

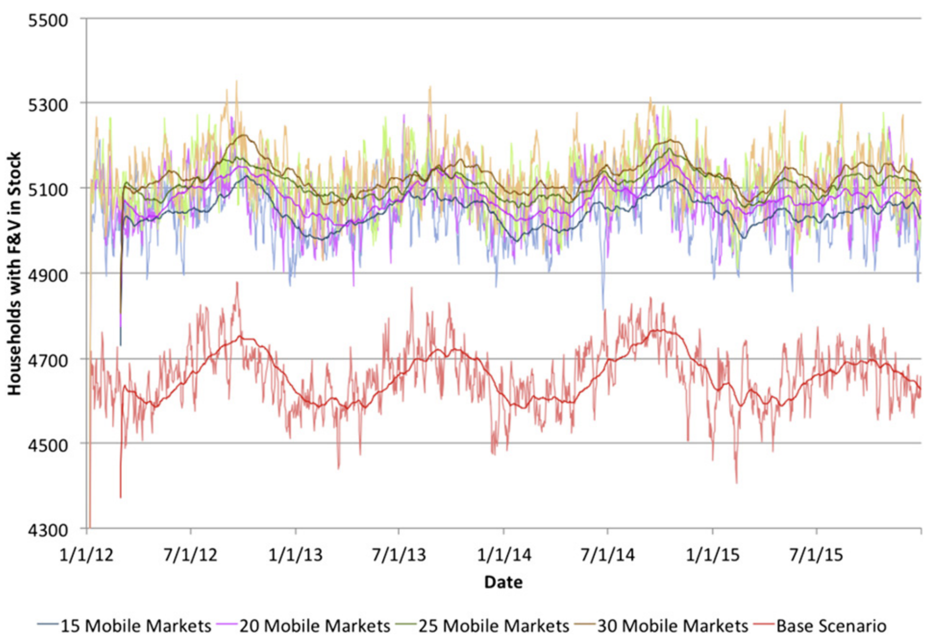

Fig. 7. Number of households with fresh F&Vs in stock given different mobile market distribution plans.

industry (Scenario 3) and the comparable outcomes seen in the simulations with mobile markets, it may be easier to implement a mobile market distribution system with a number of vehicles appropriate for the urban region at hand (Scenario 4).

Study limitations

While these outcomes are promising, it is important to note that there are a number of limitations to this research. First, the model treats the purchasing of groceries by low-income households at a very abstract level. Particularly, there is a simplifying assumption that food prices are the same across all stores made necessary because of a lack of higher resolution pricing data. Related to this point, and as mentioned in Section Agent-level behavior, the cumulative cost of groceries consumed per month is assumed to be equal, regardless of the frequency of shopping trips.

A second limitation to consider is that the grocery shopping behavior of low-income grocery shoppers, and grocery shoppers in general, are not so easily reduced to one, two, or four trips to a supermarket or convenience store. In fact, a study by Yoo et al. (2006) describes an intercept survey of shoppers in Houston, TX and found there is a large amount of variability in the frequency of grocery shopping. This variability includes weekly, biweekly, and monthly grocery shopping trips to various types of food vendors, with and without small trips in between. As this type of data was not available for the study area, and the low-income population in particular, the assumptions described to initialize parameters in Section Parameter initialization are used so as to keep the model as transparent as possible. However, while adjustments to the proportion of monthly, biweekly, or weekly shoppers may result in some changes in the models' results, the overall trends should remain constant. Despite this, future studies should strive to incorporate more detailed data specific to the geographic region in question.

Conclusion

Ultimately, there are a number of interventions that will achieve the desired goal of increasing the consumption of fresh produce by low-income households in Buffalo, NY. Given the wide array of research on identifying regions as being with or without access to healthy foods, it is important that geographers consider the spatial and aspatial strategies work best for improving diets among socioeconomically disadvantaged populations in various urban environments. Decoupling spatial effects from behavioral and economic factors will better allow for the development of context-dependent solutions.

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