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Developing a Mobile Produce Distribution System for Low-Income Urban Residents in Food Deserts

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ABSTRACT *Low-income households in the contemporary city often lack adequate access to healthy foods, like fresh produce, due to a variety of social and spatial barriers that result in neighborhoods being underserved by full-service supermarkets. Because of this, residents commonly resort to purchasing food at fast food restaurants or convenience stores with poor selections of produce. Research has shown that maintaining a healthy diet contributes to disease prevention and overall quality of life. This research seeks to increase low-income residents' access to healthy foods by addressing spatial constraints through the characterization of a mobile market distribution system model that serves in-need neighborhoods. The model optimally locates mobile markets based on the geographic distribution of these residents. Using data from the medium-sized city of Buffalo, New York, results show that, with relatively few resources, the model increases these residents' access to healthy foods, helping to create a healthier city.*

KEYWORDS *Access to healthy food, Food deserts, Spatial optimization model, Mobile market, Buffalo, NY*

INTRODUCTION

In the contemporary urban environment, regions where residents lack adequate access to healthy foods are commonly referred to as "food deserts." A number of studies have developed methods for identifying such regions in order to better understand the particular causal mechanisms of their creation[1–13]. As spaces of inaccessibility to fresh produce, food deserts are often associated with low-income areas within a city, as poor residents' food shopping practices are constrained by a number of related geographic, financial, and behavioral factors—including high travel costs to full-service grocery stores, the high price of fresh produce[14], and a preference for convenient, ready to eat meals[15,16].

Many neighborhoods in areas designated as food deserts do have access to fast food restaurants[17] and convenience stores with limited or no selections of produce[15,18]. However, a diet consisting of convenient but highly processed, salt- and sugar-laden food can result in a variety of adverse health outcomes, including cancer, poor oral health, obesity, diabetes, and cardiovascular disease[19–25]. To prevent such adverse health

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outcomes at the community level, steps should be taken toward establishing a system that can efficiently and effectively distribute healthy food to those who lack access.

One way to distribute fresh produce would be to place full-service supermarkets with a wide selection of produce near underserved populations, but market barriers have prevented these stores from operating profitably in low-income neighborhoods, due to their residents' limited ability to pay. Dunkley et al.[26] discuss how fixed costs and space for high-margin items, among other things, result in grocery chains' preference for larger stores, which tend to be located in more affluent neighborhoods. Moreover, Pothukuchi[27] notes that, in addition to higher inner-city operating costs and more demanding regulations, uncertainties associated with depopulating neighborhoods and urban crime keep grocery stores away. As a result, smaller stores with poor selections and high prices serve these areas[12,26,28].

An alternative approach for providing produce in these neighborhoods is to establish a mobile market system that distributes produce as a public good to underserved areas. Such a system would offer a unique service to low-income residents, by removing their often-prohibitive travel costs. In Buffalo, New York, the Massachusetts Avenue Project (MAP), an organization dedicated to sustainable production and distribution of local food, operates a pilot program called Buffalo Grown Mobile Marketplace.* MAP uses a single truck to deliver "organic, locally grown, affordable produce, diverse locally made food products, education and resources to Buffalo's low-income neighborhoods." Acquiring most of their produce from local farms as well as their own urban garden, MAP sends its mobile market to several locations across the city during the summer on different days of the week, with the goal of serving the least healthy food-secure regions across the city.

Expanding MAP's model of a mobile market, this research seeks to characterize a novel distribution system that can be implemented year round. While increasing low-income neighborhoods' access to full-service grocery stores may provide longer-term benefits, the mobile market approach presented here provides households in need with a retail option for produce and can be executed in any urban region relatively quickly and cheaply. A mobile market distribution system is well suited for this task because it can greatly reduce the geographical barriers to access encountered by this population. Ultimately, providing households in need with access to produce is a first step toward improving the diets, and subsequently the health outcomes and quality of life, of low-income urban households.

This paper develops a model for a mobile food market distribution system for a medium-sized city. In this model we analyze the geographical availability of healthy food and the spatial distribution of the population in need. We then analyze and optimize the utility of food distribution locations. The "Material and Methods" section presents the methods used in this paper, beginning with the "The Constructing an Inaccessibility Measure and Selecting Demand Locations" section provides a technique for locating residents who lack access to fruits and vegetables. Next, the "Designing a Spatial Optimization Model" section describes an approach to spatial optimization that selects appropriate locations given the geographic distribution of those with limited access. The "Results" section reports the results and examines how the food distribution model affects accessibility to healthy foods. Finally, the "Discussion" section discusses the implications of the results, the model's potential limitations, and identifies areas for future research.

*For more on this initiative see: http://www.mass-ave.org/MobileMarket.htm

MATERIALS AND METHODS

We demonstrate the utility of our food distribution model by applying it to Buffalo, New York. Once a prosperous industrial city, Buffalo is presently one of the poorest cities in the USA, resulting from depopulation and unemployment as the USA transitioned to a post-industrial economy[29]. The confluence of both people and jobs leaving the city has resulted in an economically segregated urban landscape, with large numbers of vacant lots pockmarking east- and west-side neighborhoods. The following section describes how spatial data are used to identify the location of households without access to healthy foods and then goes on to derive population estimates to inform the placement of mobile markets using the spatial optimization model.

Constructing an Inaccessibility Measure and Selecting Demand Locations

The initial step in developing a mobile market distribution system is to identify which households are most in need of improved access to produce. Locating this population is an input to the spatial optimization model, which specifies where the mobile markets are to be placed. As previously mentioned, a number of researchers have developed methods for detecting the location of food deserts. Raja et al. and Lee and Lim[8,12] have both considered Buffalo as a study area. Lee and Lim 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[30], Lee and Lim find that a number of areas with poor access to healthy food exist in Buffalo. Raja et al. show that restaurants and niche food stores serve areas that are not served by supermarkets. Rather than 'food 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 full-service grocery stores, they are served by smaller convenient stores. Therefore, these households' ability to purchase nutritious foods is largely dependent upon the stock of healthy foods in smaller stores.

In this paper, we describe a spatial inaccessibility measure to identify the residents who stand to benefit most from a visit by the mobile market. Non-spatial barriers to healthy food access (time constraints, family structure) may still exist, but are beyond the scope of this research. Moreover, other impediments, like consumer preference for unhealthier foods, cannot be addressed if there is no readily accessible alternative present.

Boundary, demographic, and road data from the 200 US Census are mapped, in addition to the point locations of full-service grocery stores in and around the city, derived from geocoding addresses found using Google Maps' directory and cross checked with the phone directory. Only full-service grocery stores are considered for reasons related to their ample supplies of produce, relative to smaller convenience stores. The measure is calculated using block group data, with the population abstracted to households because it is assumed that food purchases are coordinated at this level.

It is assumed that limited accessibility to produce due to high time and travel costs arises for households without access to a vehicle and beyond walking distance to the closest full-service grocery store. The inaccessibility measure, N_i is the estimated sum of distances traveled by households in a particular block group to reach their closest full-service grocery store. For a Census block group i, the measure is calculated as follows:

$$N_i = r_i d_i \tag{1}$$

Where:
N_i – The inaccessibility measure;
r_i – The number of households without a vehicle;
d_i – The network distance from the centroid of the ith block group to the closest full-service grocery store

Figure 1 shows how the measure varies across Buffalo. By capturing the location of both large populations with poor access to full-service grocery stores and smaller populations with very poor access the measure illustrates the locations of households with the most need.

These scores are used to inform the selection of two different target populations. The first set consists of the population of households within the 77 block groups with an inaccessibility measure above the 50th percentile and a centroid network distance of more than 1 mile to the closest full-service grocery store. The second set includes households within the 52 block groups that have an inaccessibility measure above the 75th percentile and a centroid network distance of more than 1 mile to the closest full-service grocery stores. These block groups are seen in Figure 2.

Designing a Spatial Optimization Model

Now that the source of demand is established as a subset of block group centroids, selected in the previous section using the inaccessibility measure, a spatial optimization model can be utilized to determine efficient and equitable locations to set up the mobile markets. This research will use a derivation of the p-median model, which places p number of facilities on a network so that the average travel cost for the population with demand is minimized. This model is useful in scenarios where goods need to be placed in optimal positions on a road network so residents may efficiently access them. Researchers have used variations of the p-median problem on topics ranging from the placement of relief facilities after a hurricane[31–33] to locating appropriate sites for retail stores[34]. The spatial optimization model used in this paper is an extension of the capacitated-median model, which extends the simpler p-median model by adding minimum and maximum capacity constraints and removing the constraint dictating that a fixed number of facilities be used to serve those with demand. While not as common in the literature as the p-median model, versions of the capacitated-median model have been used to locate facilities where the number of people a facility can serve is important, e.g., pharmacies[35], schools[36], and preventative healthcare centers[37]. A variety of algorithms have been developed to obtain solutions to median problems both optimally and heuristically[38,39]. Further description of the p-median and other median models is provided by Daskin[38].

A version of the capacitated-median model is ideal for this project because it allows planners to locate sites for mobile markets that minimize the average network travel cost for residents in need, while minding the limited cargo holds

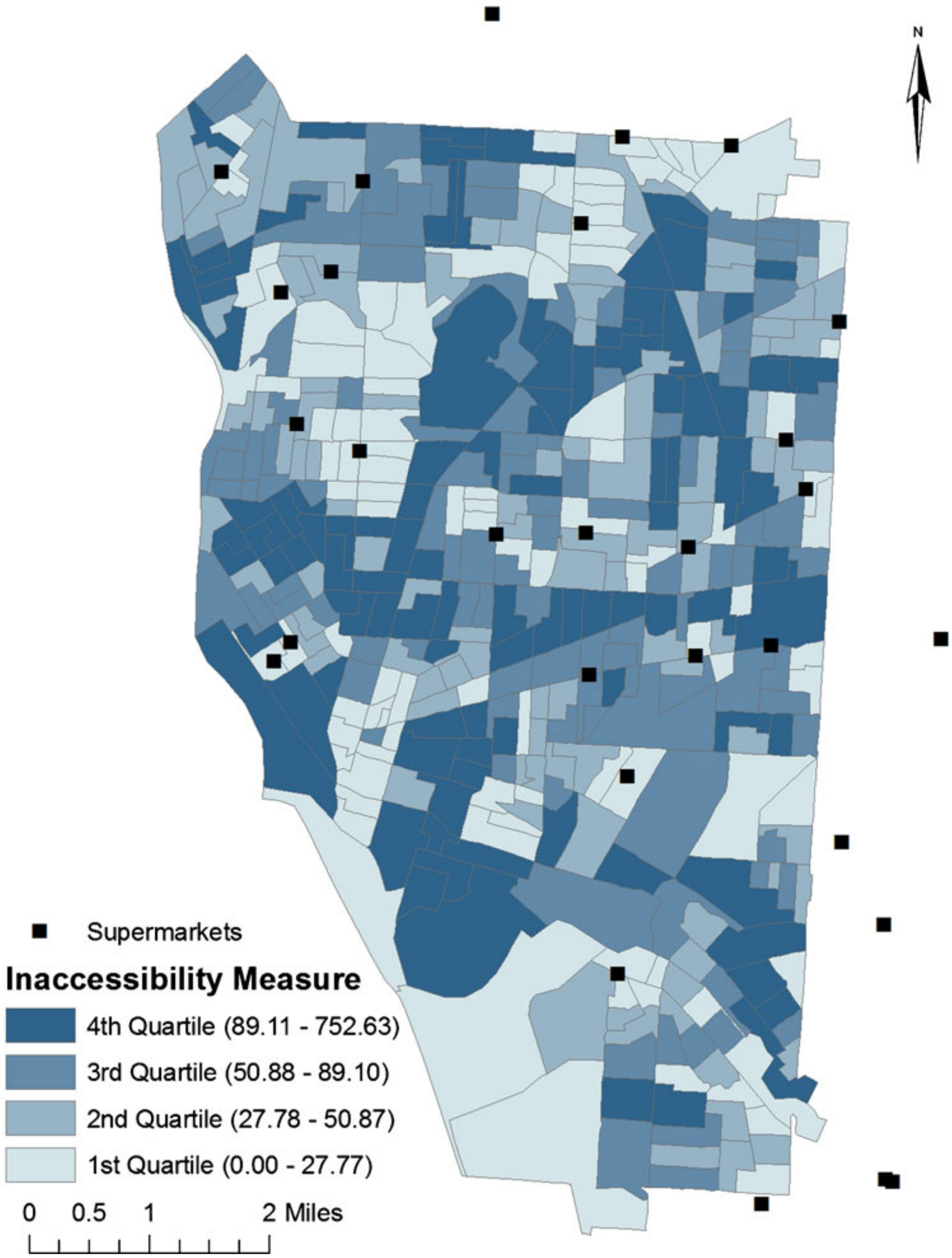

FIGURE 1. Map of the level of access to healthy food in the city of Buffalo, NY, capturing the existence of inaccessible areas, or "food deserts".

and number of available mobile markets. By establishing these optimal locations, mobile markets will be able to depart from a warehouse, where they can be stocked with food from any number of sources (from conventional suppliers to locally grown produce from urban farms), and set up in areas where they can be easily accessed by residents in the targeted Census block

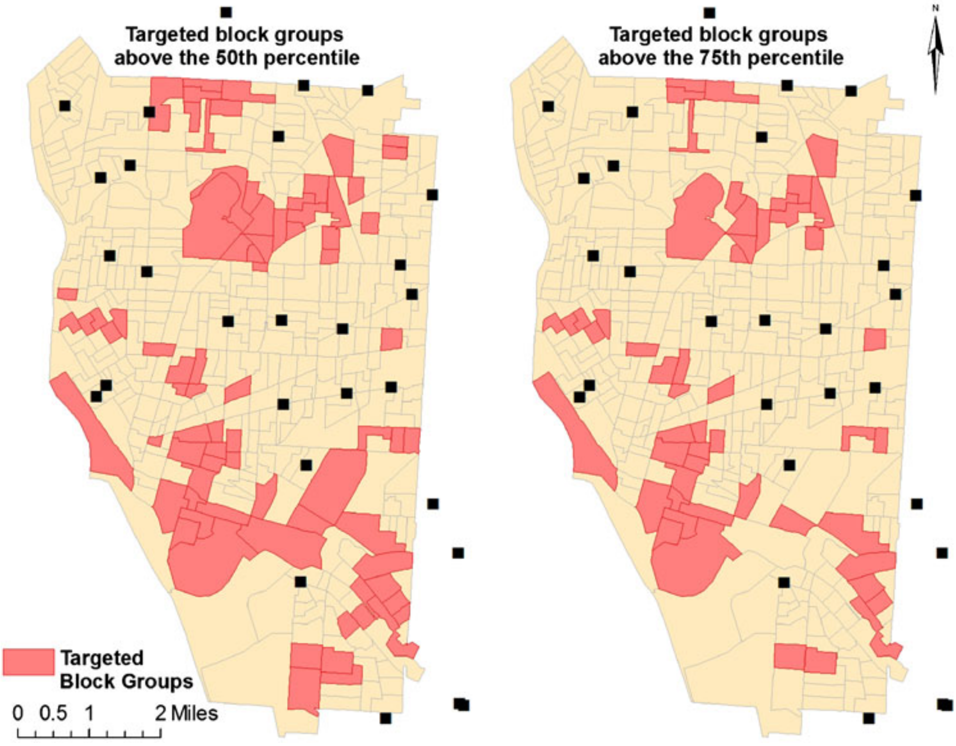

FIGURE 2. The selected block groups have an inaccessibility measure above either the 50**th** percentile (*left*) or 75**th** percentile (*right*) and are more than one mile from the closest full-service grocery store.

groups. The modified capacitated-median model for fresh produce distribution is constructed as follows:

Minimize:

$$\sum_i \sum_j h_i d_{ij} Y_{ij} \tag{2}$$

Subject to:

$$\sum_j Y_{ij} = 1 \forall i \in I, \tag{3}$$

$$Y_{ij} \leq X_j \forall i \in I, j \in J, \tag{4}$$

$$\sum_j h_i Y_{ij} \geq b_j X_j \forall i \in I, \tag{5}$$

$$\sum_j h_i Y_{ij} \leq B_j X_j \forall i \in I, \tag{6}$$

$$\sum_{k \in J | d_{ik} \leq d_{ij}} Y_{ik} - X_j 0 \forall i \in I, j \in J, \tag{7}$$

$$p \leq p_{\max}, \tag{8}$$

$$X_j = \{0,1\} \forall j \in J, \tag{9}$$

$$Y_{ij} = \{0,1\} \forall i \in I, j \in J. \tag{10}$$

Where:
i – Index of demand nodes;
j – Index of nodes for potential mobile markets;
h_i – Demand at node i;
b_j – Minimum capacity of mobile market at site j;
B_j – Maximum capacity of mobile market at site j;
d_{ij} – Shortest network distance between node i and node j;
p – Number of mobile markets located;
$p_{\max}$ – Maximum number of mobile markets available;
X_j – {1,0}, where 1 implies a potential mobile market is located at site j and 0 implies no mobile market is located at site j;
Y_{ij} – {1,0}, where 1 implies site i is served by a mobile market at site j and 0 implies site i is not served by a mobile market at site j

The objective function (2) seeks to minimize the travel costs. Constraint (3) assures that each node i is served by one mobile market. Constraint (4) guarantees that a node i can only be served by an open mobile market. Constraints (5) and (6) represent the minimum and maximum capacities of the mobile markets in J. The maximum capacity constraint accounts for the finiteness of supplies at each mobile market and the minimum capacity constraint eliminates the possibility of opening up a mobile market for some minimum number b_j residents. Constraint (7) forces assignments to a node's closest facility, so residents are not assigned a mobile market that is not the closest open one. Constraint (8) limits the number of mobile markets that can be used, e.g., $p_{\max}$ will equal 20 if there are only 20 mobile markets available. Constraints (9) and (10) define the binary decision variables X and Y.

To gauge how the model behaves, a number of its inputs are parameterized. The model is tested with two different sets of demand nodes (I), discussed in Section "Constructing an Inaccessibility Measure and Selecting Demand Locations". In both cases, the set of candidate locations for mobile markets (J) is the same as the set of demand nodes. This means that mobile market locations are restricted to being set up in the block groups targeted for service. It is possible that using the entire set of block group centroids as the set of candidate locations would provide better solutions. However, explaining why a mobile market service is not intended for residents of the particular block group where it is sited may prove to be problematic. With the sets I and J determined, two road network travel cost matrices are constructed using Census road data.

In addition to running the model with two different populations of demand, the maximum capacity of a mobile market (B_j) and maximum number of mobile markets available ($p_{\max}$) are varied. This is done to examine under what conditions the mobile market distribution model works best. The maximum capacity represents the upper limit of households that can be served by a single mobile market. It is important to note that the lower limit of the sum of maximum capacities is approximately equal to:

$$\frac{\text{number of households with demand}}{\text{number of mobile markets}}.$$

A value lower than this results in the solution being infeasible because every household will not be able to receive the service. The minimum capacity b_j is held constant at 25 households, meaning a mobile market will only be placed at a block group's centroids if it is expected to serve 25 households or more at that location. This is done to prevent a mobile market from being located in an area where it is only expected to serve a small number of households. In this situation, the mobile market may not be the ideal way of addressing these households' inaccessibility, and a more targeted approach should be devised.

Finally, the demand variable h_i for a block group i is also constant and set equal to the ceiling function of the proportion of households at or below the poverty line multiplied by the total number of households. This results in demand values of 7,091 and 5,495 households, for the 50th and 75th percentile scenarios, respectively. While the original inaccessibility metric is based on the number of carless households in a block group, the number of households below the poverty threshold is used as the demand because the goal of this distribution system is to serve those who lack both spatial immobility and the financial means to purchase produce. There may be other block groups with a high number of households below the poverty line, but our selection criteria assures us that they have spatial access to produce because they either likely have a vehicle available or live less than a mile from a full-service grocery store.

With the demands for the two scenarios known, the lowest maximum capacities that can satisfy these populations are 473 households per mobile market for the 50th percentile scenario and 367 households per mobile market for the 75th percentile scenario. Despite this, the maximum capacities are set to vary from 600 to 800 households per mobile market in increments of 25, because other constraints may make the problem unsolvable if the smallest maximum capacities are used. In more pragmatic terms, assuming each household purchases produce once a week, a mobile market that serves 600 households can be thought to provide produce for 120 households a day during the 5-day workweek. The number of mobile markets available is varied from 15 to 30 in increments of 5. This range of simulated parameter values was specified to demonstrate how deploying different numbers of mobile markets can influence the overall effectiveness of the distribution system.

RESULTS

The average network distances from the centroids of targeted block groups to a mobile market are presented in Tables 1 and 2. In all cases, the model deploys

TABLE 1 Results from the scenario where households in block groups in the 50th percentile are used as the demand set. Table elements are the average distance in miles

	Number of available mobile markets			
Maximum capacity (households)	15	20	25	30
600	0.48	0.34	0.25	0.20
625	0.48	0.33	0.25	0.20
650	0.47	0.33	0.25	0.20
675	0.46	0.33	0.25	0.20
700	0.44	0.33	0.25	0.20
725	0.44	0.33	0.25	0.20
750	0.44	0.33	0.25	0.20
775	0.43	0.33	0.25	0.20
800	0.43	0.33	0.25	0.20

TABLE 2 Results from the scenario where households in block groups in the 75th percentile are used as the demand set

Maximum capacity (households)	Number of available mobile markets			
	15	20	25	30
600	0.36	0.24	0.17	0.11
625	0.35	0.24	0.17	0.11
650	0.34	0.24	0.17	0.11
675	0.34	0.24	0.17	0.11
700	0.34	0.24	0.17	0.11
725	0.34	0.24	0.17	0.11
750	0.34	0.24	0.17	0.11
775	0.34	0.24	0.17	0.11
800	0.34	0.24	0.17	0.11

mobile markets to locations that reduce the average distance to produce to less than half of a mile, which is a significant improvement considering all of these block groups' centroids are at least 1 mile away from their nearest full-service grocery store. In both the 50th percentile and 75th percentile scenarios, as more mobile markets are made available the average distances decrease. This is expected, as more markets mean there are more points of distribution spread throughout the city. Conversely, increasing the maximum capacity of households served has little effect on decreasing the average distance. This is because, in most cases, the maximum capacity is sufficiently large and does not keep the model from finding a lower objective function.

Figures 3 and 4 show the locations the model selects for the 50th and 75th percentile scenarios with the maximum capacity of a mobile market set at 600 households. Only these solutions are mapped because the largest difference in distance when markets have a maximum capacity of 600 and 800 is 1/20th of a mile for the 50th percentile scenario and 1/100th of a mile for the 75th percentile scenario. Here, it is visually apparent that these mobile markets are being located in areas where there are few full-service grocery stores.

Overall, the distribution system is able to increase in need households' spatial accessibility to produce. By simply making fruits and vegetables available, this model provides the first step toward providing households in food deserts with the ability to maintain healthy diets. Additionally, there are relatively few resources required to provide this mobile market distribution system. In this exploratory study, only 15 to 30 trucks with the ability to hold enough fruits and vegetables for 120 to 160 households per day, and workers are needed to greatly increase accessibility to produce in food deserts. Using the 50th percentile scenario's average of 2.30 people per household, 15 mobile markets, and an average consumption of 2.0 lbs of fruit and vegetables per person per day[40], this amounts to approximately 3,800 lbs of produce per day per truck. This load is well within the capabilities of a typical tractor-trailer.*

*Gross vehicle weight ratings in the state of New York are well over 30,000 lbs (http://www.troopers.state.ny.us/faqs/traffic_safety/commercial_vehicles/)

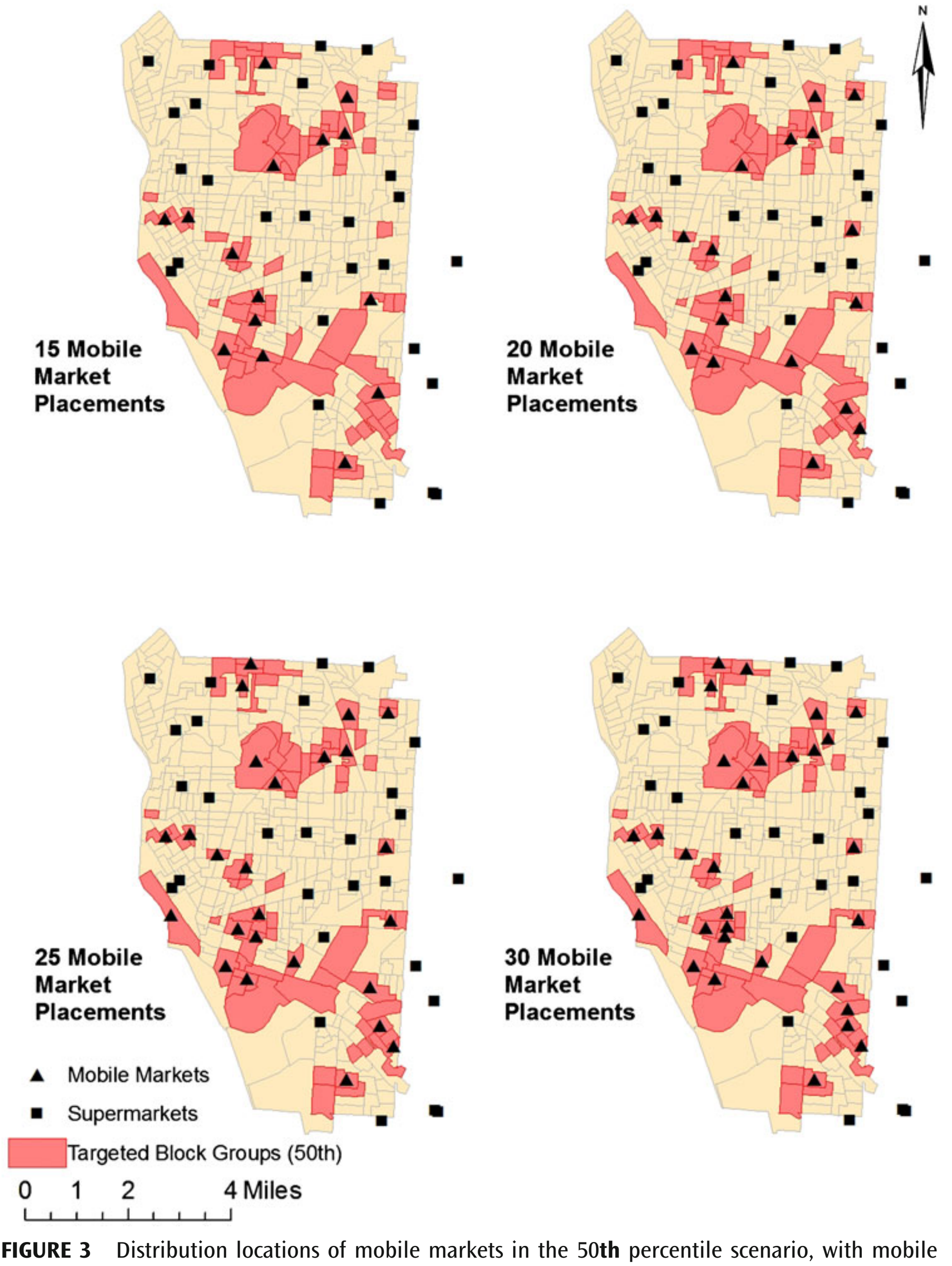

FIGURE 3 Distribution locations of mobile markets in the 50**th** percentile scenario, with mobile markets that have a weekly capacity of 600 households.

DISCUSSION

This research demonstrates that it is possible to increase residents' access to produce in food deserts by deploying mobile markets to locations where the target populations' travel costs are minimized. The results show that such a system helps relieve food insecurity by decreasing the average network distance to healthy foods from over 1 mile to less than half of a mile. From a policy perspective, the strategy of

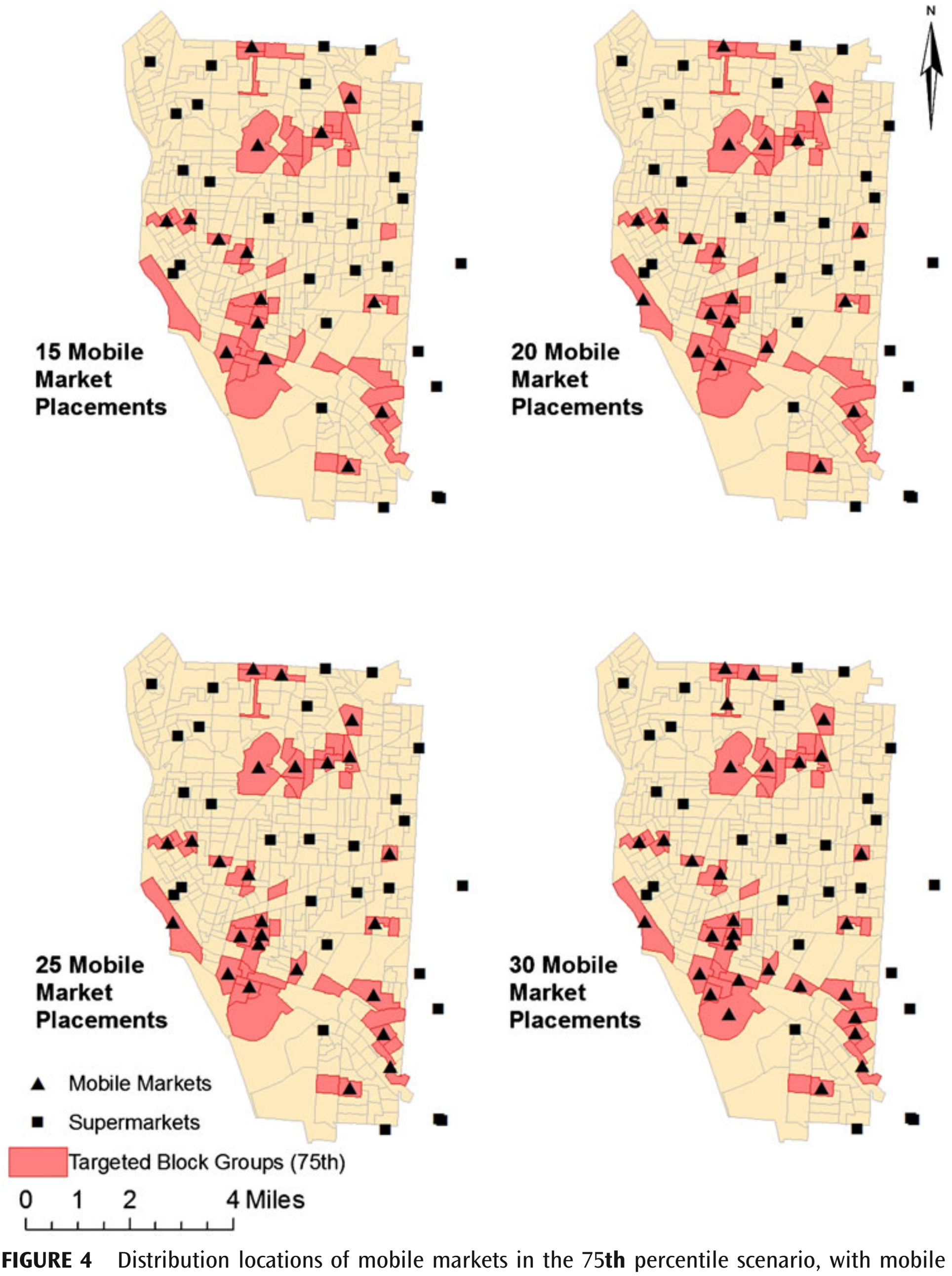

FIGURE 4 Distribution locations of mobile markets in the 75**th** percentile scenario, with mobile markets that have a weekly capacity of 600 households.

using a spatial optimization model to locate mobile markets in areas with need is straightforward and requires few resources.

The distribution system model is an initial step toward providing low-income residents the ability to maintain a healthy diet. Barriers other than spatial accessibility are not solved by this approach. For example, if low-income residents are required to purchase fruits and vegetables at full price, these foods may still be inaccessible. Additionally, preferences for convenience in the form of familiar "quick and easy" meals might impede or at least delay acceptance of mobile markets as an option for regular food purchases. A more complete approach to resolving food insecurity should address underlying consumer preferences toward fruits and vegetables.

Using the methods presented here, urban policy makers have the ability to address the spatial accessibility of healthy food as a contributor to public health risks. Once issues of spatial inaccessibility are resolved, more steps can be taken to eradicate food insecurity from the contemporary urban landscape.

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