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Strategic placement of urban agriculture: A spatial optimization approach

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Abstract
Strategic placement of urban agriculture such as community gardens can expand alternate food supply, support physical activity, and promote social interactions. While social and health benefits are critical priorities when planning new urban agriculture locations, no widely accepted site selection methods have been established. We developed a spatial optimization model to identify new urban agriculture locations in the City of Indianapolis, Marion County, Indiana. Considering block groups with vacant parcels as potential locations, the study uses *p*-median optimization to identify the 25 best locations that would minimize travel from any block group in the city to potential garden locations. We weighted each block group based on food access and prevalence of obesity, where food access was characterized on three dimensions: economic, geographical, and informational. The model was simulated for three policy scenarios with equal, stakeholder-driven, and obesity-driven weights, and the results were compared with randomly selected locations. We found that optimally selected locations were 52% more efficient than randomly chosen locations in terms of the average distance traveled by residents based on the *p*-median solution. However, there was no significant difference in travel distance among the three policy scenarios. The spatial optimization model can help policymakers and practitioners strategically locate urban agriculture sites.

1 | INTRODUCTION

Many U.S. cities are facing challenges with food access, obesity, and vacant lots. For example, in 2015, approximately 74% of Americans lived in urban areas, of which 12% of households without a vehicle had to travel more than 1.6 km for a food store (Rhone et al., 2019). Limited access to food stores can contribute to obesity, affecting 94 million residents in U.S. urban metropolitan areas (Lundeen et al., 2018). Similarly, due to deindustrialization, disinvestment, and suburbanization, vacant and abandoned properties are increasing in U.S. cities (Bonanno & Li, 2015; Newman et al., 2016). Approximately 17% of urban land is considered vacant in the United States, with the highest vacancy rates in Midwestern and Southern cities (Newman et al., 2016).

Cities have developed innovative mechanisms to address these challenges. One of the solutions implemented by many cities is converting vacant parcels into urban agriculture and other forms of green space (Colasanti & Hamm, 2010; Santo et al., 2017; Schilling & Logan, 2008). These policies are

Abbreviations: AHP, analytic hierarchy process; MCPHD, Marion County Public Health Department; NP-hardness, nondeterministic polynomial time hardness; USDA, United States Department of Agriculture.

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informed in part by the emerging research on the potential benefits of community-based urban agriculture, including improved food access, urban environment, and community health (Al-Delaimy & Webb, 2017; Santo et al., 2017).

While food production in urban areas has a long tradition, it has entered the mainstream in developing and developed countries in the last two decades. In several countries, including the United States, Australia, and the United Kingdom, government support for urban agriculture sprang from crises such as the Great Depression and World Wars (Mok et al., 2014). It is promoted to address a systemic problem of structural disparities in food access in impoverished and underserved urban areas (Opitz et al., 2016; Siegner et al., 2018). Currently, there is an increasing trend in urban agriculture in many parts of the world, including the United States, due to the availability of unused lands and innovative policies (Palmer, 2018).

However, urban agriculture is not without tradeoffs. For example, residential gardens typically require single-family homes, and commercial gardeners try to balance the tension between a viable income for urban farmers and food access for low-income consumers (Siegner et al., 2018). Depending on the practices, the gardens can become a source of soil contaminants (Taylor & Ard, 2017). This paper focuses on urban agriculture as an avenue for communities to grow and access fresh produce. We use urban agriculture and gardens interchangeably.

In terms of food access, food security requires that food must not only be accessible and nutritionally adequate, but it must also be culturally acceptable and available through nonemergency sources, including urban agriculture (Larson et al., 2009; Siegner et al., 2018). Lack of food access and security create food deserts that have been defined as "areas of relative exclusion where people experience physical and economic barriers to accessing healthy food" (Shaw, 2006). Food access, food (in)security, and food deserts have been repeatedly correlated with non-White and low-income neighborhoods (Horst et al., 2017; Mok et al., 2014; R. E. Walker et al., 2010).

Food insecurity has multiple causes, such as economic divestment in low-income areas and poor distribution channels, necessitating multifaceted solutions, including urban agriculture (Horst et al., 2017; Siegner et al., 2018). Research has shown that agricultural place-based projects can contribute to overcoming food insecurity and increasing self-reliance in communities (Barthel & Isendahl, 2013; Grewal & Grewal, 2012; Horst et al., 2017; Siegner et al., 2018). Moreover, spatial optimization to select agricultural sites within a city can more efficiently serve disadvantaged communities and individuals living in food deserts (Mack et al., 2017).

Site selection has been extensively studied in location science. The primary goal of location science is to identify the location of one or more facilities that provide some level of coverage (Church & Murray, 2018). In the seminal work of 1964, S. L. Hakimi proposed to locate *p*-facilities, later called *p*-median, to minimize the total weighted distance associated with serving all demand (Church & Murray, 2018). *p*-Median and other spatial optimization models have been leveraged to locate facilities such as schools (Ndiaye et al., 2012), defense buildings (Bell et al., 2011), commercial structures (Dantrakul et al., 2014), and health care facilities (Baray & Cliquet, 2013). These techniques have also been applied in agricultural economics for identifying the optimal location of warehouses (Bornstein & de Castro Villela, 1990), the optimal size of processing plants (von Oppen & Scott, 1976), and the optimal location of vegetable cooling facilities (Chu, 1989).

Core Ideas

- The study uses *p*-median optimization to identify new urban agriculture locations.
- *p*-Median optimization minimizes travel distance while incorporating parameters of food access and obesity.
- Optimally selected locations were 52% more efficient than randomly chosen locations.
- No significant differences were noted in travel distance among the policy scenarios.

Spatial optimization techniques have recently been used in urban agriculture research. Mack et al. (2017) used maximum covering spatial optimization to locate urban gardens for food desert residents. Similarly, Tong et al. (2012) developed a spatial optimization model to locate farmer's markets by incorporating temporal and spatial constraints. Though these papers connect food deserts and urban agriculture, research incorporating stakeholder feedback into urban agriculture-related optimization models is yet to emerge. In addition, there are no widely accepted methods that include social and public health variables into urban agricultural site selection. Doing so can help address food inaccessibility and obesity by leveraging urban agriculture as an intervention strategy. Optimized selection of locations for intervention can help support social and public health goals and provide opportunities to identify vacant areas that can best serve the community needs.

This paper presents a novel approach for identifying new urban agriculture locations using stakeholder priorities within a spatial optimization framework. This research aims to identify optimal locations for establishing new urban agriculture sites that improve access to urban agriculture under different planning scenarios. Using the case of the City of Indianapolis in Marion County, Indiana, we develop a spatial optimization model that incorporates parameters of food access and obesity as weights in the site selection process. We simulate the model for three policy scenarios to understand the location sensitivity to the criteria values. The simulated results from policy scenarios were compared with randomly selected locations.

This paper adds to the existing literature on food access and urban agriculture in at least two ways. First, the study develops a spatial optimization technique for selecting new urban agriculture locations while incorporating stakeholder feedback as scenarios. The scenario-based approach allows policymakers and practitioners to visualize the implications of their choices. Second, the study captures multidimensional aspects of food access by incorporating economic, geographic proximity, and information access factors that are critical facets of food access.

2 | MATERIALS AND METHODS

2.1 | Study area

This study was conducted in the consolidated City of Indianapolis in Marion County, Indiana. Like many cities in the Midwest, Indianapolis faces food accessibility, obesity, and property vacancy challenges. Approximately 22% of Marion County households have limited food access (Andres et al., 2019). The county has an adult obesity rate of 39%, which is higher than the state average of 34.1% (Mantinan et al., 2019). Furthermore, obesity and food access are more prominent among people of color. Approximately 2% of the city's parcels are abandoned and vacant (City of Indianapolis & Marion County, 2019). We found that 257 out of 632 block groups in Marion County had at least one vacant parcel 0.1 hectares or more in size (Figure 1).

Over the last decade, urban agriculture has emerged in Indianapolis due in part to increased consumer interest in locally grown products (Beverage & Toner, 2018). As of 2020, there were more than 160 urban agriculture sites in the city managed by nonprofits, communities, hospitals, and schools (Environment Resilience Institute, 2021; Purdue Extension, 2019). The city has promoted urban agriculture in vacant properties through various incentives; however, site selection is based on individual cases.

2.2 | Data preparation

The data preparation mainly involved estimating the weights for the spatial model; that is, parameters of food access and obesity weighted by population (Table 1). Following McEntee and Agyeman (2010), we defined food access on three dimensions—economic, information, and geographic access. Economic access was defined as financial barriers that impact one's ability to purchase food, whereas information access encompassed educational, cultural, and social constraints that influence how and why people choose to eat certain foods. Geographic access evaluates individuals' proximity to grocery stores and their ability to travel to the store. U.S. Census Bureau block groups, which generally contain 600 to 3,000 people, were used as the unit of analysis (U.S. Census Bureau, 2019, September 16).

2.2.1 | Economic and information access

Economic access was estimated using the percentage of households below the poverty line in the past 12 mo. Similarly, information access was estimated as the percentage of the population 25 yr and over who had no high school diploma or higher degrees. These information were compiled from the American Community Survey (ACS) 2017 (U.S. Census Bureau, 2017). All the socioeconomic data were converted into percentages for comparability.

2.2.2 | Geographic access

Geographic access was measured using two variables–distance to the food store and vehicle ownership. Geocoded locations of food stores in Marion County were derived from the Polis Center (Polis Center, 2018) and the USDA. The Polis Center provided information on the store name, address, and type (i.e., supermarket, grocery stores, etc.); the data was originally received from Marion County Department of Public Health. We included supermarkets, grocery stores, convenience stores, and fruit and vegetable markets for the study. The geocoded locations of farmers' markets were derived from USDA Supplemental Nutrition Assistance Program. To calculate the distance to stores, we created block group centroids for 632 block groups of Marion County in ESRI ArcMap 10.7. The Caliper Corporation's TransCAD software was used to calculate the minimum travel distance on the road network from block group centroid to the nearest food store using the in-built road network data. To control for edge effect (i.e., to allow people to travel to nearby stores around the county's edge), we included grocery stores within 3.2 km of the county border.

2.2.3 | Obesity

We defined obesity as the percent of the population who were obese or overweight based on the 2005 Obesity Survey conducted by the Marion County Public Health Department (MCPHD). The data were aggregated at the health township level, which are groupings of census tracts delineated by the MCPHD. We assigned the health township-level data to their respective block group based on the spatial boundary.

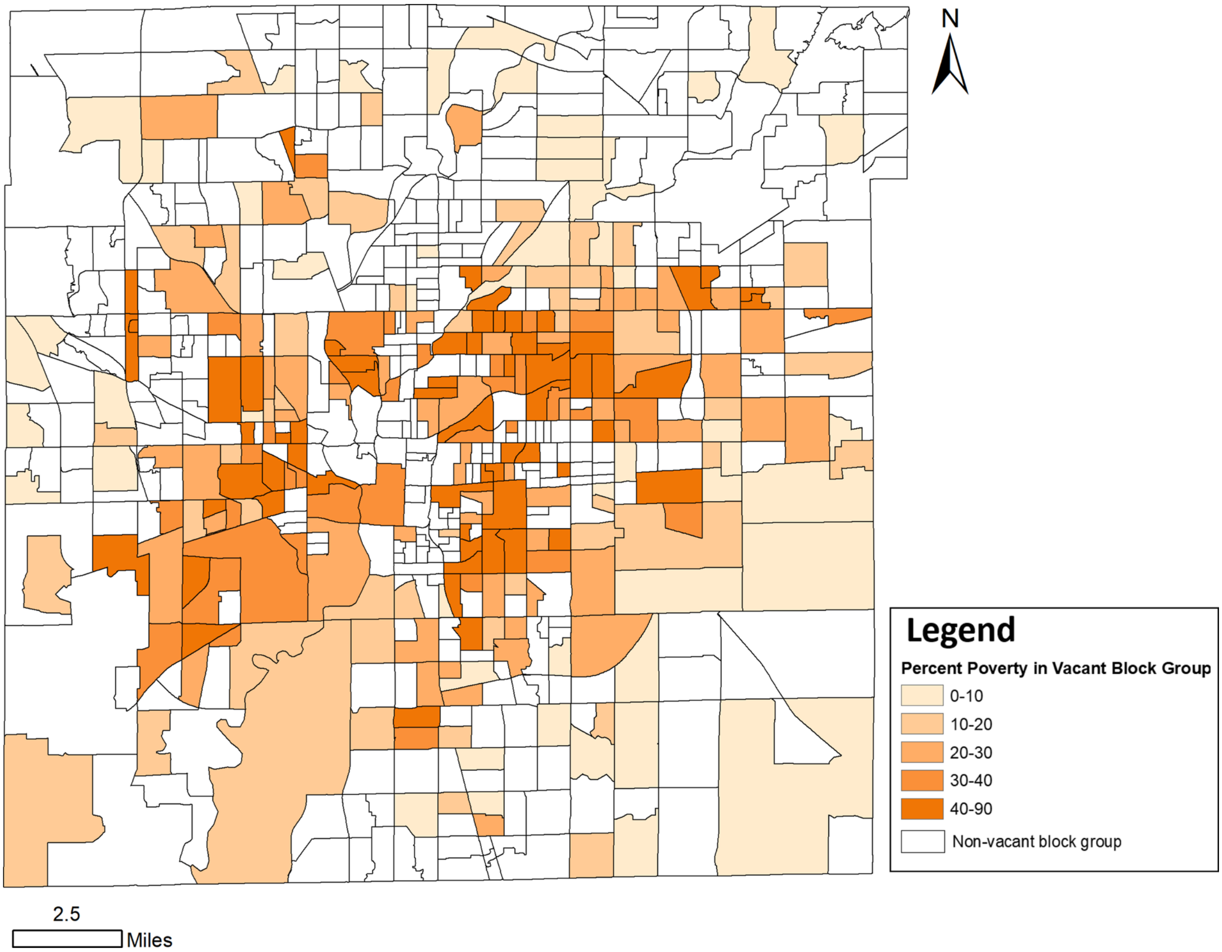

FIGURE 1 Percent poverty in block groups with the vacant parcel(s). The poverty rate in nonvacant parcels is not displayed

TABLE 1 Criteria variables for the weights

Variables	Description	Unit	Sources
Economic access			
Household poverty in percentage	Percent of household below poverty line in the past 12 months	Percent	ACS 2017
Geographic access			
Tenure with no vehicles in percentage	Percent of tenure (owner occupied and renter occupied housing units) with no vehicles	Percent	ACS 2017
Distance to store	Minimum travel distance of block group centroid to the nearest food store	Miles	Polis Center 2017
Information access			
Population with no high school diploma or higher	Percent of population 25 years and over who have no high school diploma (includes equivalency) or higher	Percent	ACS 2017
Other variables			
Obesity rate	Percent of population who are obese or overweight	Percent	MCPHD 2005
Total population	Total population of residents in a block group	Count	ACS 2017

Note. ACS, American Community Survey, MCPHD, Marion County Public Health Department.

TABLE 2 Weights for three scenarios

Variables	Stakeholder-driven	Equally weighted	Obesity-focused
Poverty	0.434	0.20	0.125
Distance to store	0.245	0.20	0.125
No vehicles	0.197	0.20	0.125
Educational attainment	0.078	0.20	0.125
Obesity	0.045	0.20	0.50

2.2.4 | Potential urban agriculture sites

The vacant parcels in the city were considered as potential area for new urban agriculture sites. Block groups with one or more abandoned or vacant housing parcels with at least 0.1 hectares in size were identified as potential block groups for new urban agriculture. The vacant parcel data were obtained from the City of Indianapolis (City of Indianapolis & Marion County, 2019).

The five criteria variables (Table 1) were processed using the following steps to generate the weights: (a) normalization of the criteria variables, (b) stakeholder-driven weights generation using pairwise comparison, (c) development of scenario weights, and (d) final weighted score.

2.2.5 | Normalization of criteria variables

For each demand point (i.e., block group centroid), we used five criteria—four measures of access (i.e., poverty, distance to store, household without vehicles, and educational attainment) and obesity rate (Table 2). Since the five criteria variables had different minimum and maximum values, we used min-max scaling to shift to the range of 0 to 1 to facilitate comparability across the variables.

$$x_{\text{normalized}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

2.2.6 | Stakeholder driven weights generation using pairwise comparison

The normalized values were assigned stakeholder-derived weights to resemble their relative importance using pairwise comparison. Pairwise comparison is a popular method initially proposed by Saaty (1980) as a part of the analytic hierarchy process (AHP). AHP is a method for developing a hierarchy of multiple decision factors and determining their relative importance. One of the key steps of AHP is developing weights through pairwise comparison (Chen et al., 2013). The weight generation involved the following steps. First, we conducted an online Qualtrics survey among stakeholders ($n = 11$), mainly comprised of researchers, urban growers, and municipal planners. The survey asked respondents to rank their preference (e.g., poverty vs. obesity) for each pair of criteria on a scale of 1 to 9 (1 = equal preference and 9 = high preference). The survey had 10 unique pairs of criteria to choose from: poverty vs. distance to store (distance), poverty vs. no vehicle, poverty vs. educational attainment (education), poverty vs. obesity, distance vs. no vehicle, distance vs. education, distance vs. obesity, no vehicle vs. education, no vehicle vs. obesity, and education vs. obesity. Following Saaty (1980), matrix algebra was performed on the responses to generate final weights for the five criteria (Table 2).

2.2.7 | Development of scenario weights

Besides the weights generated from stakeholder input, we also developed weights based on some hypothetical scenarios. We designed two additional scenarios with different weight values to understand how new agriculture locations might change under these scenarios. The equally weighted scenario gave equal weights of 0.2 to five variables, whereas 0.50 was assigned to the obesity rate for the obesity-focused scenario.

2.2.8 | Final weighted score

A final weighted score was generated at the block group level for each scenario (Table 2). We multiplied the normalized criteria variables with their respective weights and summed them across each block group to generate the final weighted score. The summed value was rescaled so that the total of all weights was equal to 632 (total number of block group). The rescaled weight was multiplied by 10% of the total population in each block group to get the final weighted score under an assumption that 10 percent of the population would utilize urban agriculture.

2.3 | Model

The p-median spatial optimization model was used to identify the optimal location for establishing new urban agriculture sites so that the total travel distance between each block group in the county and block group with the potential new garden site was minimized. In other words, the model aimed to distribute the gardens to different parts of the county so that residents need to travel less to access gardens. Since travel distance was weighted by five criteria variables (i.e., poverty, vehicle ownership, educational attainment, and obesity rate), block groups with high criteria values received higher preferences.

p-Median optimization uses integer programming, a special case of mathematical programming that relies on linear and nonlinear algebra to solve the optimization calculation. The problem is challenging to solve due to nondeterministic polynomial time hardness (NP-hardness). Brute force solutions to the NP-hardness problem become impossible even with the latest computer processing power, speed, and memory density. However, with proper heuristic algorithms, *p*-median problems can be solved robustly.

p-Median locates *p*-facilities that minimize the total distance associated with serving all of the demand. We followed the methodological parameters: (a) each block group with a vacant parcel(s) was a potential site for new agriculture and had the capability of handling the demand coming from all the block groups; (b) new urban agriculture site was assigned to their closest vacant block group; and (c) the garden site could be located anywhere on the block group with vacant parcels (Church & Murray, 2018).

We built the network model in TransCAD using the following steps. The polygon shapefile containing all block groups in Marion County was converted into centroids in ArcMap and imported into TransCAD as demand nodes in the network. Similarly, the block groups with vacant parcels were converted into centroids and imported into TransCAD as supply nodes (i.e., potential new agricultural site locations). The final weighted scores were processed in Excel and R programming language and joined with the block group centroid. The road network in-built in TrasnCAD was used to calculate the shortest travel distance to generate a distance matrix. The block group centroids were assigned to the nearest road network node segments in TransCAD.

The *p*-median model notations are

$$z_{ij} = \begin{Bmatrix} 1, \text{if demand } i \text{isassignedtofacility} j \\ 0, \text{otherwise} \end{Bmatrix}$$

$$z_{jj} = \begin{Bmatrix} \text{if node } j \text{hasbeenselectedforafacilityandassignedtoitself} \\ 0, \text{otherwise} \end{Bmatrix}$$

p-median:

$$\text{Minimize} \sum_i \sum_j a_i d_i z_{ij} \tag{1}$$

Subject to

$$a_i = q_i \sum_{k=1}^{5} w_k t_{ik} \tag{2}$$

$$\sum_j z_{ij} = 1 \forall i \tag{3}$$

$$\sum_j z_{ij} = p \tag{4}$$

$$z_{ij} \le z_{jj} \forall i, j \& i \neq j \tag{5}$$

$$z_{ij} \in \{0, 1\} \, \forall i, j \tag{6}$$

The objective function minimizes the total weighted distance of demand assignment (i.e., block group) given constraints (Equation 1). The value a_i for the demand point is the population (q_i) at demand *i* multiplied by the sum of five weighted criteria t_{ik} (Equation 2). Each demand *i* was assigned to a facility in constraints (Equation 3). Constraint established that exactly *p* facilities located within the vacant block group were to be sited (Equation 4). The constraint in Equation 5 ensured that demand *i* couldn't be assigned to facility *j* (i.e., $z_{ij} = 1$) unless a facility at *j* had been sited (i.e., $z_{ij} = 1$). Integer restrictions were imposed in constraints (Equation 6) (Church & Murray, 2018). We used *p*-median optimization to simulate 25 optimum block groups (i.e., $p = 25$) for three scenario weights: equal, obesity-focused, and stakeholder-determined weights.

3 | RESULTS

The goal of the *p*-median optimization applied in this study was to minimize the total travel distance by all residents. Visual interpretation of the *p*-median simulation results showed that obesity and equally weighted scores located the optimal block groups in proximity, whereas stakeholder-weighted results identified block groups in the northern and southern parts of the city (Figure 2). The variation could be due to differential weights of poverty and obesity. While obesity received a high score in the obesity-weighted scenario, poverty received a high score in the stakeholder-driven scenario.

The result from the *p*-median simulation also showed no significant difference in the average travel distance per resident among the three scenarios. The average travel distance was 3 km per resident for stakeholder-weighted loca-

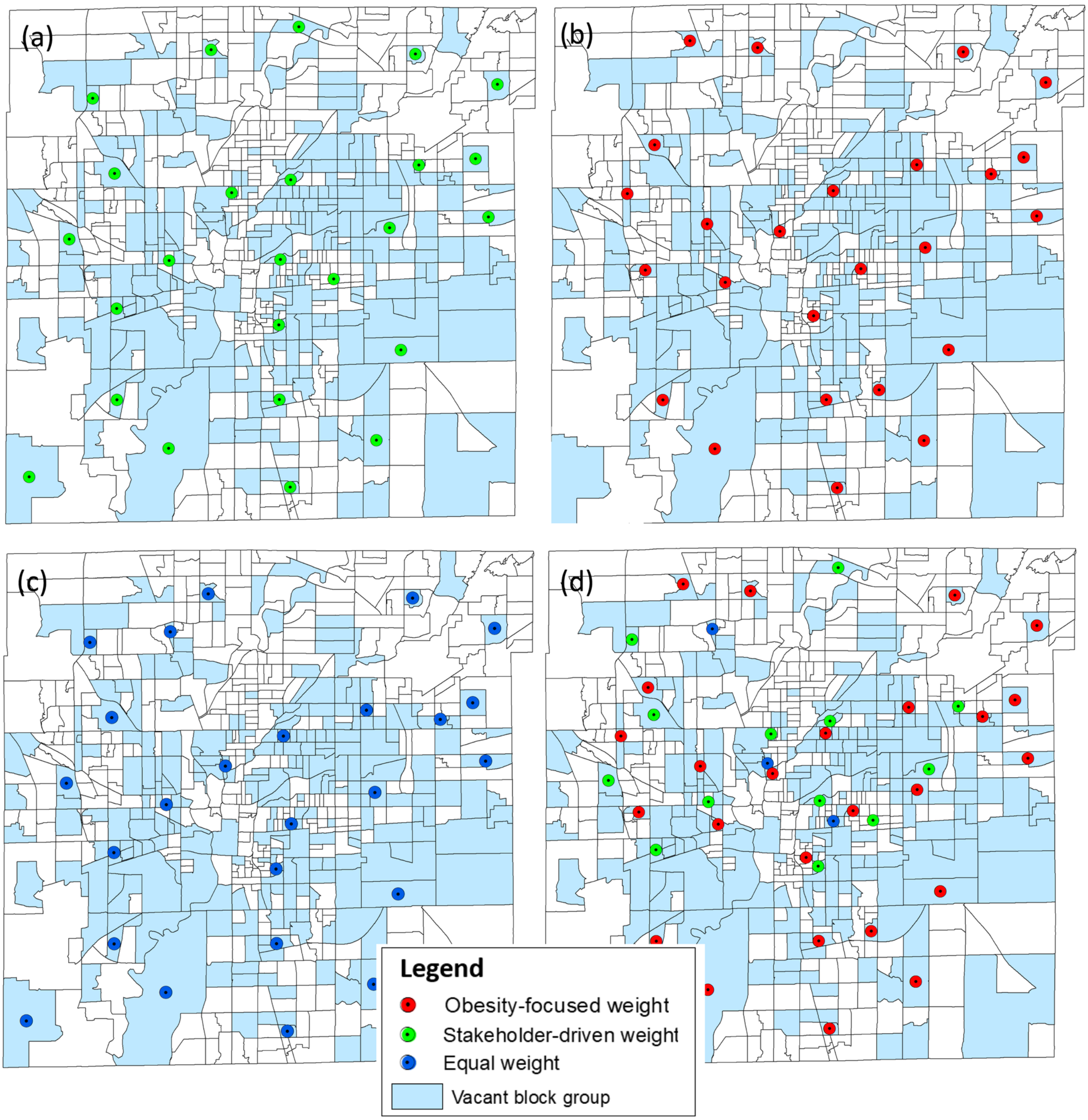

FIGURE 2 Optimal locations of 25 potential urban agriculture sites using (a) stakeholder-driven, (b) obesity-focused, (c) equal weights, and (d) all weights overlayed

tions, 2.9 km for obesity-weighted locations, and 3 km for equally weighted locations. If we located the urban agriculture in the block group using weights derived from stakeholder input, a resident of Marion county will only gain around 3% efficiency in average travel distance compared to locations derived using other weights. However, the total travel distance saved is significant if we scale this up to the total population. For example, assuming that only 10% of block group residents will visit the garden, the allocation would save around 1,609 km in a given time if we choose stakeholder-driven locations over obesity-weighted locations.

To understand if optimally generated locations were more efficient than randomly selected locations, we identified 25 random sites and estimated the average travel distance. Like the three stakeholder-driven scenarios, the randomly selected sites were limited to block groups with vacant parcels. The result of the randomly identified locations was compared with the obesity-driven weighted locations because it had the lowest average travel distance. We found that location derived from the optimization method had an average travel distance of 1.87, whereas that from random selection had a distance of 2.85. Therefore, the optimally selected locations reduced the average travel distance per resident by 52% compared with random selection and hence would be more efficient in improving residents' accessibility to new agriculture locations.

4 | DISCUSSION

The strategic placement of urban agriculture has the potential to address multiple issues. Our primary research goal was to illustrate how spatial techniques can be applied for establishing new urban agriculture sites while incorporating different policy priorities. We used a spatial optimization approach that included critical parameters on food access and obesity as weights. The optimization model was evaluated for three policy priorities represented by scenario weights: equal, stakeholder-driven, and obesity-focused weights. We found that the spatial optimization technique generated more efficient locations than the random selection method. Compared with randomly selected sites, the residents would travel less miles to reach the urban agriculture sites selected by the spatial optimization approach. Though policymakers are very unlikely to distribute the resources randomly in practice, a science-based selection criterion is likely to identify targeted areas for intervention. The weighted travel-distance-based approach is valuable in addressing food accessibility because the geographical proximity of fresh food sources is one of the main determinants of food access (Luan et al., 2015; Rhone et al., 2019).

However, the location of sites was influenced by the input weights. Because obesity rates are prevalent around the western, eastern, and southern parts of the city, the optimal locations are more concentrated in those areas. The stakeholder-weighted optimization had greater weights for poverty and identified high-poverty areas in the northeastern parts of the city as priority locations for new agriculture sites. Therefore, the technique can be adapted to produce different results based on the stakeholder priorities.

The goal of optimization is to minimize the total distance traveled by all demand points. The *p*-median solution among the three scenarios evaluated in this study showed no significant difference in average travel distance, indicating that sites can be efficiently selected to meet multiple planning objectives.

Site location is a multifaceted decision-making process. This study attempted to capture the complex dimension of food access and obesity into the site selection process. Although many studies on food access have primarily focused on geographical proximity, this study included poverty, educational attainment, and vehicle ownership as critical variables for food access.

Spatial optimization techniques have important policy implications, particularly in the context of social and health equity. The goal of global optimization methods applied in this study was to minimize the total travel distance to new agriculture locations. The *p*-median approach tends to be the most effective in reducing the total travel distance and can contribute to food accessibility and other environmental benefits through reduced travel distance.

In addition, the methodology incorporated critical social parameters, including obesity, poverty, and food accessibility. The model will likely locate more agricultural sites in population clusters with high obesity and low accessibility. Therefore, the spatial optimization technique can be used for strategic prioritization to achieve specific social goals, such as obesity reduction and improving equity.

While the study incorporated multiple criteria, it had some limitations. Site selection is a complex problem that needs to consider multiple factors. Though food access and obesity were incorporated in optimization, factors such as community readiness for urban agriculture, public transit accessibility, and food affordability are other variables that can influence food access (Krikser et al., 2016; Walker, 2016). We also had difficulty combing heterogeneous datasets with different temporal and spatial scales. For example, our study used obesity data from a 2005 survey, while the census data was for 2017. However, Marion County as a whole did not have significant changes in obesity rates between 2005 and 2018 based on a model simulation done by "500 Cities Project" of the Center for Disease Control and Prevention (CDC, 2021).

Future work can expand current research by including additional variables on travel time and traffic patterns. We can also compare optimization results with other decision support tools such as multicriteria analysis (Malczewski & Rinner, 2015). A survey of urban growers could shed insight on nuances of food access. Similarly, the demand and supply-side analysis of urban agriculture, such as crop seasonality, could enrich our understanding of the linkages between supply and demand.

5 | CONCLUSION

This study identified potential locations for urban agriculture using spatial optimization. The technique incorporated critical parameters on food access and obesity as weights. We also evaluated the optimization under three different scenarios to assess the impact of weight choice on site selection. We found that optimally selected locations were 53% more efficient than randomly chosen locations in terms of the average travel distance based on the *p*-median solution. However, there was no significant difference in average travel distance among the three policy scenarios. The spatial locations of garden sites differed based on the weights used in the optimization.

The *p*-median optimization technique has an important implication on social equity. The optimization identifies potential garden areas so that it reduces the average travel distance of the residents. Since the study includes obesity and accessibility as the weights, the model locates sites closer to neighborhoods with high obesity and high inaccessibility. The strategic and systematic approach to site selection can improve social outcomes by improving food accessibility and potentially altering air quality through reduced travel miles.

We developed a methodology that incorporates biophysical and social parameters, including stakeholders' critical feedback for sustainable planning. A systematic process to strategically locate urban agriculture using spatial techniques such as spatial optimization can help address food inaccessibility, obesity, and property vacancy. However, we acknowledge that site selection alone will not help address food access and obesity challenges. A comprehensive program that promotes nutrition education (Rose, 2010), economic revitalization (Bitler & Haider, 2011), and collective civic actions (Pourias et al., 2016; Svendsen et al., 2016) are promising strategies to address obesity and food accessibility.

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AUTHOR CONTRIBUTIONS

Bhuwan Thapa: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. Aniruddha Banerjee: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Resources; Software; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. Jeffrey S. Wilson: Conceptualization; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Writing-original draft; Writing-review & editing. Samantha Hamlin: Conceptualization; Formal analysis; Methodology; Resources; Writing-original draft; Writing-review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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