Agent Based Models for Quantifying Food Accessibility: Insights for Policy and Decision Making

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1 INTRODUCTION

The UN Sustainable Development Goal "Zero Hunger" (SDG2) aims to end hunger, achieve food security, improve nutrition, and promote sustainable agriculture by 2030 (United Nations, 2024). SDG2 emphasizes equitable food access and security for all, especially vulnerable populations. However, food insecurity is a pressing challenge that impacts millions, even within developed countries like the United States (Feeding America, 2024). Vulnerable communities often lack reliable access to nutritious food, a situation exacerbated by disparities in distribution infrastructure. Despite efforts from numerous NGOs and governmental bodies, food insecurity persists, underscoring the urgent need for effective, data-driven policy tools. This study presents the Food Access Strategy Simulator (FASS), an agent-based model designed to empower policymakers to evaluate the community-level impacts of strategic food distribution placements (*i.e.,* supermarkets, food pantries, farmers markets). FASS models individual and community behaviors, assessing how policy decisions affect food security outcomes in vulnerable areas. By simulating interactions and resource distribution across diverse demographics, FASS provides data-driven insights, promoting equity in food access and supporting informed decision-making for both government and nonprofit stakeholders.

2 METHODOLOGY

The proposed FASS leverages an Agent-Based Modeling (ABM) approach to simulate complex dynamics in food distribution and access. ABM is a simulation modeling technique in which individual entities, or agents, are assigned distinct behaviors and interactions within an environment to simulate complex systems at the micro level (Bonabeau, 2002, Macal & North, 2005). In FASS, the ABM's decentralized approach allows each agent—representing community households and distribution points—to operate based on specific rules and interactions, producing emergent outcomes that reflect real-world complexity. Hence, an ABM is particularly suited to capture diverse consumer behavior and access needs, enabling assessments of distribution scenarios and their effects on food security for vulnerable communities (Railsback & Grimm, 2019).

2.1 ABM MODEL DEVELOPMENT

The agent-based model proposed in this study is the first step in advancing the framework established by previous work, which relied on a proprietary simulation package that limited adaptability (Koh *et al.*, 2019). In contrast, the ABM used in this study is built as a stand-alone python library, thus providing the flexibility to integrate diverse agent behaviors and incorporate additional environmental variables. This independent implementation creates a robust, adaptable simulation environment, enhancing the utility for policymakers and researchers evaluating diverse food access scenarios. Further, the proposed framework incorporates detailed agent attributes to represent food accessibility more accurately. Each household agent is assigned specific characteristics—including income, household size, number of children, employment status, and transportation access—that collectively shape their food access decisions. This granularity captures unique household circumstances often obscured at higher aggregation levels, resulting in a more precise model for food access analysis.

2.2 FOOD ACCESS METRICS

The proposed ABM considers a set of agents $\mathcal{A} = \{1, ..., A\}$, where each agent corresponds to a household. Every agent makes n trips to a food source during the month. In this study, two types of food sources are considered: supermarkets (S) and convenience stores (C). At each trip $i \in \{1, ..., n\}$, agent $a \in \mathcal{A}$ selects a food source $s_{a,i} \in \mathcal{S} = \{S, C\}$, where the probability of selecting a supermarket, denoted by $P_a(S)$, is defined by Equation (1).

$$P_a(S) = \left(\frac{\beta_a}{B} \times w_\beta\right) + (\nu_a \times w_\nu) + \epsilon, \tag{1}$$

where w_β, β_a, B, ν_a, w_ν, and ϵ are the weight associated with the income, agents budget, the population's maximum budget, the number of vehicles available to the agent, weight associated with vehicle access, and a constant to ensure that agents have access to a food source, respectively.

The Monthly Food Access Index (MFAI) of agent $a \in \mathcal{A}$ is then defined as

$$\mathrm{MFAI}(a) = \frac{1}{\gamma_a} \times \frac{1}{n} \sum_{i=1}^{n} \sigma(s_{a,i}), \tag{2}$$

where γ_a is an agent-specific burden factor and $\sigma(s)$ is the nutrition score of food source $s \in \mathcal{S}$. The burden factor $\gamma_a > 1$ if agent a has no vehicle ($\nu_a = 0$) and $\gamma_a = 1$ otherwise. In addition, supermarkets have a higher nutrition score than convenience stores, i.e., $\sigma(S) > \sigma(C)$, reflecting supermarkets' larger selection and higher quality of food items compared to convenience stores.

3 PRELIMINARY EXPERIMENTS AND RESULTS

The FASS was tested on an instance from Franklin County, Columbus, Ohio, United States. Franklin County was chosen for its socioeconomic diversity, encompassing both high-income areas and a significant number of households below the poverty line, making it an ideal site to analyze food insecurity dynamics.

To accurately represent the demographic and socioeconomic diversity, a multi-step process was used to assign agent attributes. First, Census tracts, each covering between 1,200 to 8,000 individuals, were selected due to their granularity in socioeconomic data, obtained from the American Community Survey (ACS) (US Census Bureau, 2024). Second, income distribution for each census tract was calculated by income buckets as defined by ACS, allowing agents to be randomly assigned an income level within these proportions. For example, if 20% of a tract's population falls within the $25,000 to $30,000 income range, 20% of agents receive an income within this range. Finally, household sizes were randomly assigned from one to four members based on census data, while vehicle availability and the number of workers per household were determined using ACS variables such as "Household Size by Vehicles Available" and "Number of Workers by Vehicles". This approach reflects realistic distributions and provides detail in understanding access disparities.

Food store data was obtained via the Open Street Maps API, filtered by relevant keywords, including "supermarket", "convenience store", "butcher", and "grocery". Each store was then mapped to a specific geographic location within Franklin County, categorized by type to facilitate analysis of food variability and access. Furthermore, the classification of food stores was divided into two primary categories: supermarkets (S), which generally offer a wider variety of healthy food options, and convenience stores (C), which often lack diverse food selections. This classification enables FASS to differentiate access levels based on store type, aligning with literature on the nutritional disparities between store categories.

3.1 EXPERIMENTAL RESULTS

The experiment was conducted on a total of 1454 agents and four food sources, $S = 1$ and $C = 3$, with agents making a total of seven trips ($i = 7$). Additionally, for Equations (1) and (2), the parameters included a maximum income of the population $B = 200,000$, weight of the budget $w_\beta = 10$, weight of the vehicle $w_\nu = 5$, and the access constant $\epsilon = 60$. In this experiment the MFAI reflects the likelihood of households opting for supermarkets over convenience stores. It also shows fluctuations across time steps, driven by the probability of each agent selecting a supermarket or convenience store during simulated trips. On average, the MFAI score was at 84.22 across households (see Figure 1).

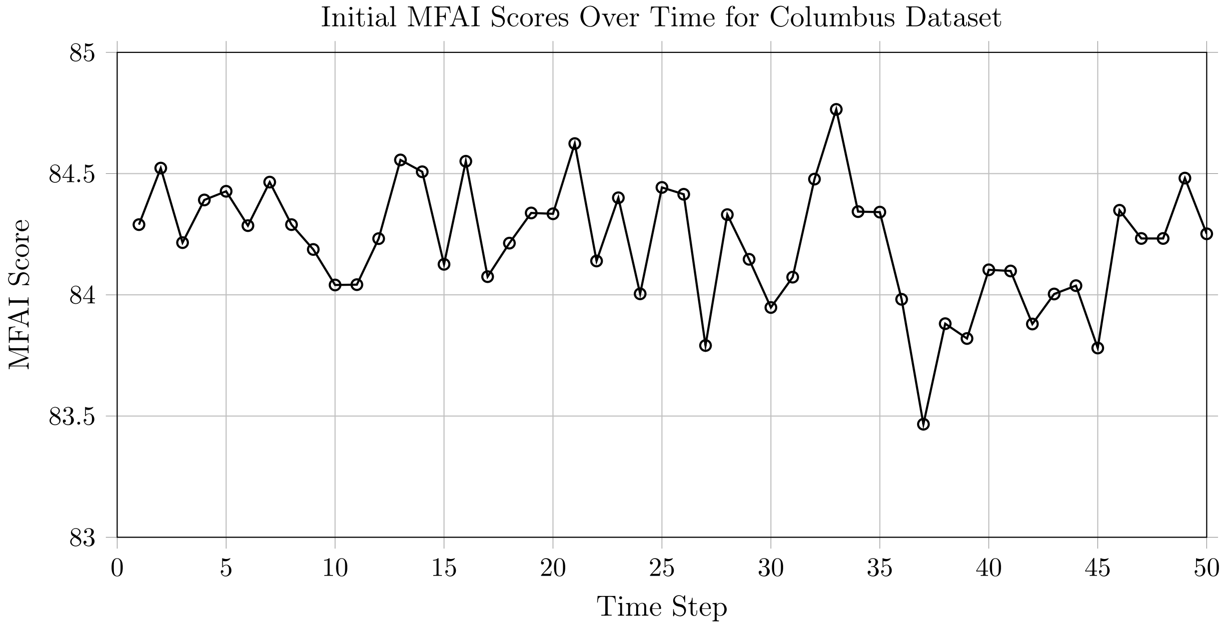

Figure 1 – *Graph of initial MFAI scores over time for Columbus dataset*

3.1.1 IMPACT OF STORE TYPE REMOVAL

A sensitivity analysis was conducted by altering the availability of the supermarket to assess its influence on the MFAI score. Unsurprisingly, removing the supermarket in the dataset caused a substantial drop in the average MFAI to 49.26, indicating a significant reduction in food access quality when households rely exclusively on convenience stores. This underscores the critical role that a supermarket plays in maintaining higher levels of food access (See Figures 2 and 3). We also observed that MFAI scores stabilize at a lower level when households select convenience stores due to the absence of a supermarket option. This highlights the value of supermarkets in reducing food deserts and improving overall food accessibility within vulnerable communities.

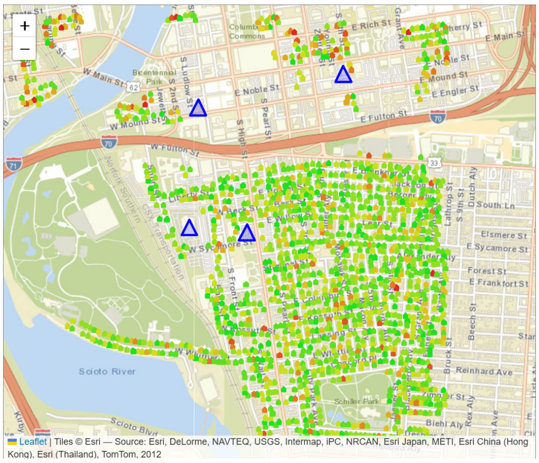

Figure 2 – *Four Stores*

average MFAI score of 84.22

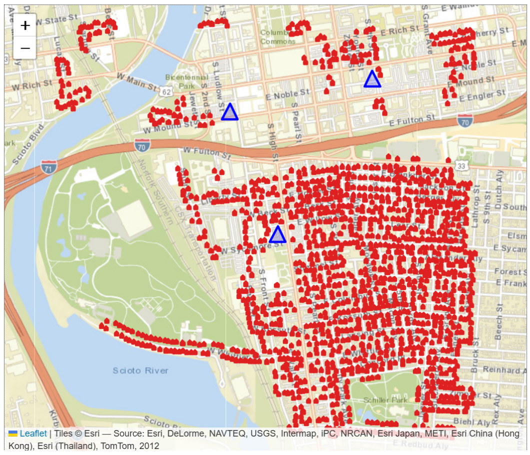

Figure 3 – *Three Stores*

average MFAI score of 49.26

4 FUTURE WORK

This study is part of an ongoing research collaboration between academics and practitioners. Future work is aimed at refining and expanding the model's capabilities. While the current version provides a framework for assessing food accessibility, limitations exist. Currently, the MFAI does not account for the distance between households and stores, an important factor in real-world food accessibility. Incorporating distance will improve the model's accuracy and reflect the travel burdens faced by households in accessing food. Future iterations will also integrate additional factors, such as weather conditions and transportation infrastructure, to capture dynamic influences on food access. Long-term plans for FASS include expanding the model to more geographic regions and incorporating more complex household dynamics. By addressing these areas, FASS will serve as an adaptable tool for guiding effective policies to reduce food insecurity. Additional results obtained by the time of the conference will be included in the presentation.

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