

Planning for Urban Food Security Using a Spatial Multicriteria Decision-Making Approach

by

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Abstract

Discussions related to healthy food access often overlook the social, environmental and regulatory factors that shape it. Within urban environment, these factors intersect with others to create both opportunities and inequities, shaping the geography of who has access to healthy food and who doesn't. To develop a resilient urban food system, we need to consider these multidimensional determinants of an urban foodscape. In this study, a place-based decision-support framework is presented, which moves from the identification of priority neighborhoods for improving food access to the recommendation of viable interventions. Using the Kansas City Metropolitan Area as a case study, I quantified the food access Gap by integrating measures of the retail food environment with mobility-based retail activity patterns into an integrated index Integrated Food Access and Environment Index (IFAEI) at the census block group level. In parallel, I construct a neighborhood vulnerability (Need) index using Principal Component Analysis (PCA) and Analytical Hierarchy Process (AHP), incorporating socioeconomic, health, housing, transportation, and demographic dimensions. Bivariate Local Moran's I is then used to categorize statistically significant local spatial relationships between food accessibility in each Census Block Group (CBG) and vulnerability in neighboring CBGs. I subsequently combine the Vulnerability Index and the IFAEI within each CBG to create a Need-Gap typology, in which high vulnerability indicates high need, and a low IFAEI value indicates a high food-access gap. CBGs where these conditions overlap are classified as High Need-High Gap. To move from diagnosis to action, I examine the highest-priority High Need-High Gap areas using a suitability-screening approach that evaluates local physical, environmental, and regulatory constraints and opportunities for potential food-access interventions.

The intervention strategies align with place-based conditions, emphasizing production-oriented strategies where food production is viable and prioritizing distribution-oriented strategies (e.g., farmers' market sites, pop-up distribution nodes, or candidate locations for healthy retail) in denser areas. Through the suitability screening, I identify candidate sites for project scoping, stakeholder engagement, and future investments. Overall, the study develops a replicable decision support workflow that links equity targeting with feasibility-based siting to generate actionable, locally tailored interventions for building a resilient urban food system.

Keywords: place-based planning; resilience; urban food systems; decision-support system

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List of Abbreviations

ACS	American Community Survey
AHP	Analytical Hierarchy Process
CBG	Census Block Group
GIS	Geographic Information Systems
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
IFAEI	Integrated Food Access and Environment Index
R_FAI	Retail Food Activity Index
mRFEI	Modified Retail Food Environment Index
KCMA	Kansas City Metropolitan Area
DSS	Decision Support Systems
PRISMA	Preferred Reporting for Systematic Reviews and Meta-Analyses
CDC	Centers for Disease Control and Prevention
NAICS	North American Industry Classification System
PCA	Principal Component Analysis
CSA	Community Supported Agriculture
USDA	U.S. Department of Agriculture
TRI	Toxic Release Inventory
SSURGO	Soil Survey Geographic Database
HFAI	Healthy Food Availability Index
FII	Food Insecurity Index
SuRI	Supermarket Redlining Index
FAI	Food Accessibility Index
ESRI	Environmental Systems Research Institute
PFIVI	Place-Based Food Insecurity and Vulnerability Index
RAI	Revealed Accessibility Index
FMI	Food Marketing Index

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Chapter 1 - Introduction

1.1 Background

Access to healthful and nutritious food is a significant challenge in urban planning, particularly for marginalized people from below poverty groups. Inequalities in food security in the Kansas City Metropolitan Area (KCMA) demonstrate wider socioeconomic inequities, severely affecting community well-being and health (Dawood & van Vuuren, 2024; Pérez-Escamilla, 2024). Traditional planning methodologies do not always consider the complex interrelations between spatial, social and economic factors that influence food systems, which makes more advanced and data-driven methodologies necessary to address food vulnerability effectively (Hutton et al., 2022a; Kolak et al., 2018; Shaker et al., 2023).

This research evaluates the factors that influence food accessibility and applies Multi-Criteria Decision Making (MCDM) framework and Geographic Information Systems (GIS) to propose strategies for achieving food security for disadvantaged communities. MCDM offers a methodical and transparent decision-making process for analyzing diverse, and at times, contradictory variables, such as level of economy, level of transit accessibility, level of educational achievement, all of which influence food access patterns (Fazil et al., 2008; Linnemann et al., 2015). The process of merging the GIS with MCDM enhances decision-making in space as it finds the best possible solution while taking into consideration all the competing variables (Bao & Tong, 2017; Haloui et al., 2023). This integration allows planners to create a participatory decision-making process, which can help visualize many aspects that have implications on results and ensure that the opinions of communities are part of policy solutions. This work is aimed at developing an MCDM tool that will enhance participatory planning to strengthen food security. This approach includes identifying socioeconomic factors that

contribute to food insecurity, using multi-criteria decision-making frameworks to identify areas with inadequate access to nutritious food and developing policy interventions. Mapping and geographical analysis may identify food deserts and food swamps which can help in the strategic design of food hubs, urban farms and food distribution networks (Hutton et al., 2022a; Sadler, 2016). The Analytic Hierarchy Process (AHP) helps decision-makers to evaluate a number of criteria, including cost, accessibility, and public health effect (Linnemann et al., 2015).

Critical factors in advancing urban food systems include identifying optimal sites for food hubs considering factors such as population density and transportation facilities, overall socio-economic factors; creating efficient transit routes in line with the need for better accessibility and lower distribution costs; and the integration of regional food systems such as community gardens and food pantries to bolster food security (Haloui et al., 2023; Hutton et al., 2022a; Kharel et al., 2024). Decision Support Systems (DSS) based on Multi-Criteria Decision Making (MCDM) have the potential to offer real-time integration of information, leading to an improved response to changing community needs (Ammar et al., 2024). Promoting urban agriculture may improve the urban food system by facilitating local crop production, hence decreasing reliance on external markets and perhaps increasing resilience to global supply chain shocks (Gunapala et al., 2025).

MCDM have the potential to enhance technical analysis and foster inclusive food planning procedures by integrating community viewpoints. Additionally, the integration of scenario planning with MCDM enables policymakers to foresee future challenges, including climate change and demographic shifts, thereby promoting long-term sustainability (Bizikova & Krcmar, 2015).

This research presents a replicable model for enhancing food security in Kansas City and comparable urban areas by applying advanced decision-making frameworks. The findings will provide practical strategies for improving food system equity, assisting policymakers, planners, and community groups in developing interventions that foster health, equitable resource distribution, and resilience in metropolitan food systems.

1.2 Study Objective

The primary aim of this research is to create a structured planning-focused integrated index that amalgamates food environment, demographic, and socioeconomic data to recognize and give priority to High-Need, High-Gap regions for food access within the Kansas City metropolitan area. Using this integrated framework, the study seeks to assess spatial disparities in food accessibility, support the transition from analytical identification to solution-oriented planning, and inform place-based interventions for more equitable urban food system development.

1.3 Research Questions

The aim of this research is threefold. The research is guided by the following three research questions:

- What socioeconomic and built-environment factors influence food access patterns in urban communities, and
- How can these factors be incorporated into a decision-making tool for the urban food system?
- How can a spatial multicriteria decision-making tool be applied to identify areas with opportunities for healthy food interventions to support urban food systems?

To address these research questions, physical, social, economic, and behavioral data were collected from multiple sources. The IFAEI was developed to capture both the local food environment and observe retail activity patterns. In parallel, neighborhood vulnerability was assessed using theme-based Principal Component Analysis (PCA), with the relative importance of the resulting themes determined through the Analytical Hierarchy Process (AHP). The IFAEI and Vulnerability Index were then combined to identify neighborhoods where limited healthy food access coincided with elevated community need. Finally, a spatial multicriteria decision-making approach was applied to the highest-priority areas to evaluate local suitability conditions and identify feasible locations for healthy food-access interventions.

This research is important since it analyzes food accessibility not only in terms of grocery store availability or physical distance, but also from the perspectives of spatial inequity, community need, travel behavior, and planning interventions. Access to healthy food is shaped not only by the location of food outlets but also by how residents move through the city, the transportation options available to them, and the constraints that influence their daily mobility (Vojnovic et al., 2020). For many households, especially those facing socioeconomic disadvantages, food access is closely connected to travel behavior, including vehicle availability, dependence on transit, walking conditions, and the time and effort required to reach healthy food destinations (Liu et al., 2015; Vojnovic et al., 2020). Existing food-access measures have made important contributions to identifying underserved areas; however, many approaches rely primarily on residential administrative boundaries and measures of retailer proximity, density, or store type. Such measures may not fully represent the places people actually visit for food or their movement beyond neighborhood boundaries (Caspi et al., 2012; Crawford et al., 2014). Retail Food Environment Index-based measures also focus largely on the geographic

distribution and relative composition of food retailers and may not directly incorporate the socioeconomic and mobility factors that shape residents' actual exposure to food environments (Glover et al., 2022). More broadly, the results of composite indices and multicriteria decision-making analyses can be influenced by decisions concerning indicator selection, normalization, weighting, and aggregation; therefore, these methodological choices must be clearly justified and aligned with the decision problem (Cinelli et al., 2020). Furthermore, identifying disadvantaged areas through an index does not, by itself, determine which food-access interventions are feasible under local physical, environmental, and regulatory conditions. These limitations establish the need for an integrated framework that combines food-retail composition, observed food-shopping travel behavior, neighborhood vulnerability, spatial relationships, and site-specific feasibility. Accordingly, this study develops the IFAEI, constructs a PCA- and AHP-based Vulnerability Index, applies bivariate Local Moran's I to identify spatial concentrations and direct overlaps of need and food-access gaps, and uses suitability screening and a decision-support tool to translate the diagnostic findings into context-sensitive intervention options.

The research is notable since it concentrates on the Kansas City metropolitan region, a setting that has both analytical and planning value. Research on food accessibility often prioritizes major metropolitan areas, but mid-sized cities receive comparatively less focused examination despite facing many of the same structural inequalities and planning challenges. Kansas City provides an important case because it reflects the complexities of a mid-sized urban region where food access disparities are present but may not always be visible through frameworks developed primarily for larger cities. By centering Kansas City, this study contributes to a literature that has been less explored and demonstrates the importance of examining food accessibility in metropolitan areas beyond the largest urban centers.

The study's additional relevance is that the Kansas City metropolitan region encompasses two states: Missouri and Kansas. This bi-state structure introduces an added layer of institutional and policy complexity, since planning responses may be shaped differently across jurisdictions. Zoning regulations, land-use policies, development priorities, and implementation mechanisms are not necessarily uniform across the metropolitan area, meaning that the same analytical outcome may carry different practical implications depending on which side of the state boundary a neighborhood is on. This makes the study especially important from a planning perspective, as it highlights how spatial patterns of food accessibility cannot be separated from the governance and regulatory environments in which solutions must be implemented.

The research also highlights the impact of historically developed areas on current food accessibility trends. Decisions about land use, investment, infrastructure, and community development are often grounded in enduring urban histories, and these legacies may continue to affect where food resources are concentrated or lacking. In the Kansas City metropolitan area, legacy neighborhoods may therefore produce distinct and sometimes challenging outcomes in the analysis, revealing that food accessibility is not only a contemporary planning issue but also one connected to historical patterns of urban development and inequality (González-Pérez, 2021; Smirnova et al., 2024). Recognizing these place-based legacies strengthens the study by encouraging a more context-sensitive interpretation of Need-Gap outcomes.

1.4 Chapter outline

This thesis is organized into six chapters that collectively examine food accessibility disparities in the Kansas City metropolitan area and develop a planning-oriented framework for identifying and prioritizing intervention areas. Chapter 2 describes a systematic review of the literature undertaken to identify the theoretical and analytical foundations for this research. The

review synthesizes scholarship on food accessibility, food deserts, spatial inequality, urban food systems, and multicriteria decision-making approaches used in planning and geographic analysis. Chapter 3 outlines the methodological framework, including data preparation, indicator selection, and the Need-Gap identification mechanism developed to identify areas of compounded disadvantage. This chapter also explains how the results of that identification process informed the transition from analytical assessment to the solution-oriented phase of the research. Chapter 4 presents the findings of the Need and Gap analysis and discusses their spatial and planning implications. Chapter 5 applies the framework to the Low-High Clusters considered as High-Need, High-Gap areas through five case-studies, illustrating how different neighborhood contexts may generate distinct place-based intervention scenarios. Chapter 6 concludes the research by discussing the overall implications of the study for urban food system planning, as well as its contributions, limitations, and directions for future research.

Chapter 2 - Literature Review

The increasing significance of equitable access to nutritious food in urban settings has resulted in greater focus on the visualization of food vulnerability and the evaluation of approaches to enhance food equity. This systematic review seeks to provide an overview of the current research on urban food vulnerability mapping and associated planning solutions. As our review shows, integrating spatial and statistical analysis with community involvement and policy changes are some ways researchers have worked out to alleviate food shortages in cities. There are significant changes indicating an upsurge in research from 2020 to 2023, with a noticeable uptick seen in 2021. These findings clearly demonstrate the need for more interdisciplinary research and application of mixed method approaches. Further studies are also needed on policy evaluations and the incorporation of grassroots perspectives to enhance food equity. As urban areas grow, research and data-informed policies are crucial for guaranteeing food access for all inhabitants, especially those most impacted by food insecurity, thus promoting health, social equity, and resilience in urban environments.

2.1 Introduction

The rapid pace of urbanization across the globe has introduced significant challenges to food security, particularly in ensuring equitable access to nutritious food within urban environments. Urban areas, which now house more than half of the global population, have become focal points for addressing food insecurity and the associated socioeconomic disparities (Tacoli, 2017) . As cities expand and evolve, the complexities of urban food systems become increasingly evident, necessitating a deeper understanding of food vulnerability and security. Food systems in urban areas involve intricate supply chains, diverse stakeholders, and significant

disparities in access. Addressing these challenges is critical, as food vulnerability, the risk of insufficient access to nutritious food, directly affects public health and well-being (Feeding America, 2023).

Urban food vulnerability is influenced by a range of spatial, social, and economic factors, rendering it a multidimensional issue that urban planners and policymakers must address. For example, certain urban areas may lack proximity to grocery stores offering healthy food, while others may be economically disadvantaged, limiting residents' ability to purchase nutritious options. The term "food desert," coined in Scotland in the early 1990s, highlights these issues by describing regions with limited access to affordable and nutritious food (Cummins & Macintyre, 2002). Roderick (2020) discusses food deserts and "food apartheid", which hinder access for many low-income communities, resulting in adverse health and economic outcomes.

In summary, tackling urban food insecurity requires a holistic strategy that combines spatial design, socioeconomic evaluation, and public health factors. By comprehending and tackling the fundamental causes of nutritional food lacking, communities may cultivate more equitable food systems, enhancing health outcomes and quality of life for urban inhabitants.

2.2 The dynamics of urban food systems

Urban equity plays a pivotal role in addressing food insecurity, ensuring fair distribution of resources, opportunities, and services so all residents, regardless of socioeconomic or racial background, can access healthy, nutritious food. Without such equity, food insecurity deepens, particularly in low-income and racially diverse neighborhoods where systemic barriers restrict food availability.

The spatial distribution of food resources shapes food access. Food deserts are areas with limited access to affordable, nutritious foods, while food swamps have an abundance of unhealthy options (Walker et al., 2010). Hager et al. (2017) found adolescents in food swamps consumed more unhealthy snacks, while living in food deserts showed no link to fruit and vegetable intake. Thus, food behaviors can also influence food access challenges.

From Figure 2.1, the literature review identified urban food systems are complex, influenced by economic conditions, infrastructure, governance, social networks, and the environment (Battersby, 2017). These systems rely on distant sources and are vulnerable to disruptions from climate change, economic instability, and political conflict (Ericksen, 2008). Inequalities persist, affluent neighborhoods enjoy diverse food options, while low-income areas face scarcity. Research links food deserts and swamps to poverty and unemployment (Beaulac et al., 2009; Cooksey-Stowers et al., 2017), emphasizing the need for integrated strategies in urban policy.

Rising living costs, limited jobs, and inflation worsen food insecurity, forcing households to choose between food and essentials like housing or healthcare (Wight et al., 2014). Low-income areas often see higher prices for healthy foods, fewer fresh options, and more fast-food outlets, increasing diet-related health risks. Kharel et al. (2024) highlight pricing as a key factor in food access equity, while USDA documented limited supermarket access in low-income communities. Marginalized groups, racial minorities, immigrants, and low-income households, are disproportionately affected (Dutko et al., 2012; Morales et al., 2021; U.S. Department of Agriculture, Economic Research Service, n.d.).

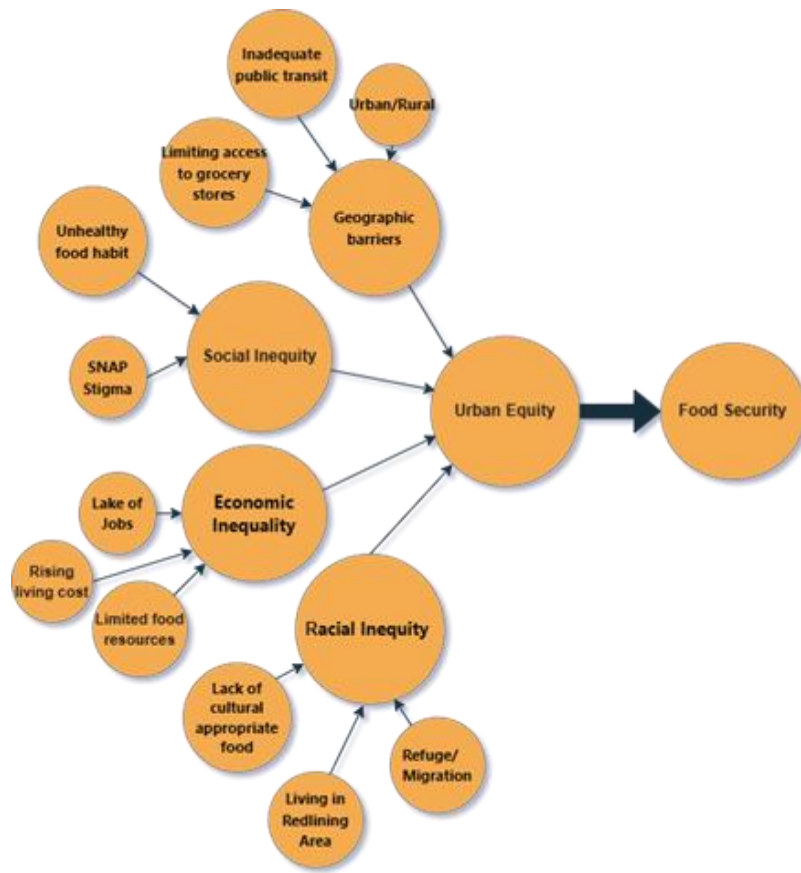
Historical practices like redlining exacerbate inequities, discouraging investment in food infrastructure and contributing to obesity and chronic disease (Alwitt & Donley, 1997;

Rothstein, 2017; Shaker et al., 2023). Cultural food access is also critical, absence of culturally appropriate options can harm mental well-being and nutrition (Wright et al., 2021). Immigrant-heavy neighborhoods often lack stores selling traditional foods, making cultural food equity essential (Murrell et al., 2022; Park et al., 2011). Buffalo's refugee-focused food equity programs illustrate targeted approaches (Judelsohn et al., 2021).

Transportation access strongly influences food security. Ethnic grocery stores may be closer than restaurants, but without reliable transport, access remains limited (Rybarczyk et al., 2020). Rising urban living costs further strain food budgets (Gundersen & Ziliak, 2015). Urban residents often face lower access costs than rural residents, but inequities persist (Losada-Rojas et al., 2021).

Overall, urban equity affects food access through transportation systems, food retail location, economic opportunity, and cultural inclusivity. Tackling structural barriers, such as transit gaps, affordability, and stigma toward assistance programs, is essential for equitable, culturally appropriate, and nutritious food access for all.

Figure 2.1. Relationship between different dynamics of urban equity and food security



2.3 Systematic Analysis

A systematic review was conducted to evaluate the mapping of the food accessibility issues and how applications of GIS have evolved in the last 10 years of research. The selection of articles for systematic was reported in accordance with the Preferred Reporting for Systematic Reviews and Meta-Analyses (PRISMA) statement. To support the research questions, a systematic literature review is conducted to analyze different aspects of the subject. Peer-reviewed journal articles were identified through database searches and screened according to relevance to food accessibility, food environments, and planning frameworks. After applying inclusion and exclusion criteria, the final set of studies was subjected to manual review.

Relevant articles were identified through search strings applied to the Web of Science and Scopus databases. The search string combined terms related to the study, as presented in

Table 2.1. The review covered publications from January 1, 2015, through July 11, 2024, the date on which the database search was completed. The starting year of 2015 was selected because it immediately followed the Agricultural Act of 2014, which formally authorized the Healthy Food Financing Initiative (HFFI) as a stand-alone program within the U.S. Department of Agriculture (Benson, 2022). The initiative established a federal framework for providing loans, grants, and technical assistance to healthy food retailers and related enterprises seeking to improve food access in underserved communities (Benson, 2022; U.S. Department of Agriculture, n.d.). The formal authorization and subsequent implementation of HFFI created a relevant policy context that may have encouraged greater attention among public agencies, community organizations, financial institutions, food-system practitioners, and researchers to healthy food access and place-based intervention strategies. Accordingly, the 2015-2024 period was selected to capture a decade of contemporary scholarship following this federal policy development while also encompassing the program's subsequent implementation, reauthorization, and expansion (Benson, 2022; Spade, 2018; U.S. Department of Agriculture, n.d.). Although this study does not test whether the 2014 Farm Bill directly caused changes in publication activity, the authorization of USDA's HFFI provides a relevant policy milestone for defining the beginning of the review period.

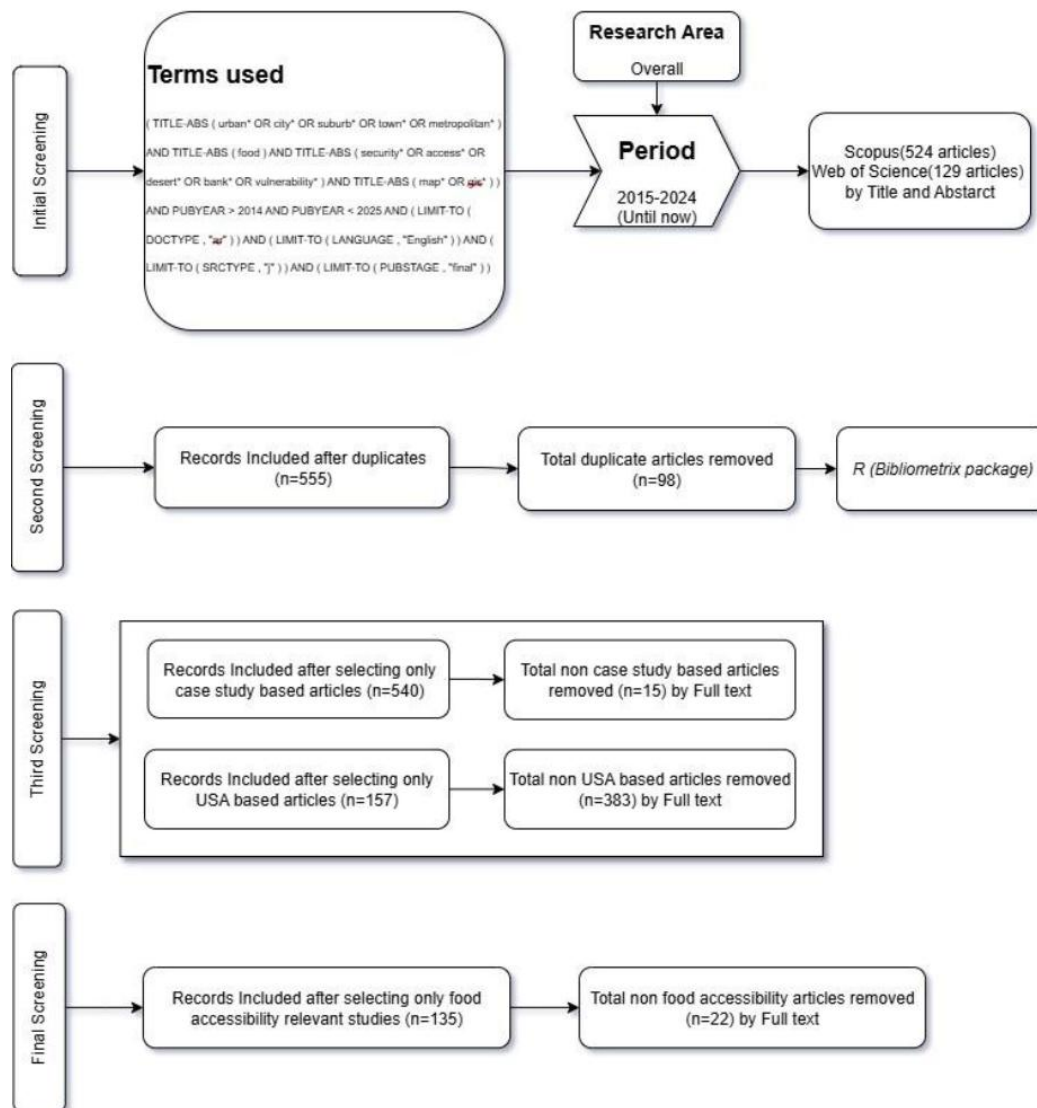
Initially, a broad search on the “Web of Science” and “Scopus” databases returned 129 and 524 papers through the first screening of the titles and abstract. Using *R (Bibliometrix package)*, 555 papers were combined without any duplicity and identified as relevant to the research. In the Third Stage of screening, the main inclusion criteria were applied, whether those papers that have at least one case study and have analyzed the food relevant studies in their case study and identified 540 articles by screening the full text of the articles. After screening the full

text of these papers, 15 papers were found irrelevant. Another screening has been done to identify the United States based articles which consider the food relevant studies as their major factor in their research, and this helped to narrow down to 157 articles, and 383 articles were eliminated as irrelevant. In the final stage of the study, the full texts of 86 papers were reviewed again to identify the 135-food accessibility relevant studies and eliminate non-food relevant studies. Among non-relevant studies, many types of study have been taken place such as agriculture, production, physical health, animal health, land use change, identification of next gardening locations, etc. These 135 papers were completely aligned with our review objectives. For the analysis, I developed a Microsoft Excel sheet and extracted information related to each parameter and across different scales. The data collected was later synthesized to report the results presented in the next section.

Table 2.1. Search criteria used in WoS and Scopus.

Scopus & WoS search criteria
(TITLE-ABS (urban* OR city* OR suburb* OR town* OR metropolitan*) AND TITLE-ABS (food) AND TITLE-ABS (security* OR access* OR desert* OR bank* OR vulnerability*) AND TITLE-ABS (map* OR gis*)) AND PUBYEAR > 2014 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final"))

Figure 2.2. PRISMA diagram summarizing the search and selection process



In Figure 2.2, the process of selecting journals is obtained from the use of PRISMA approach, which provides a structured framework designed to standardize and improve the reporting of systematic reviews (Moher et al., 2010).

Each study was then classified by methodological orientation, distinguishing among quantitative, qualitative, and mixed-method approaches. To capture methodological diversity, attention was given to the specific analytical tools employed, including regression models, spatial-statistical techniques, participatory approaches, and GIS-based multicriteria methods.

In addition, the review identified and documented the indices and frameworks used to measure food accessibility and vulnerability. These included established metrics such as the Food Marketing Index (FMI), Supermarket Redlining Index (SuRI), Healthy Food Availability Index (HFAI), Food Insecurity Index (FII), mRFEI, Multicriteria Food Index (MCM), and others, reflecting both spatial and socio-environmental dimensions.

In the first stage of analysis, articles are categorized by the methods used and the different indices employed to measure food accessibility, as determined by a thorough review of the research's full text. Table 2.2 shows a methodological emphasis on quantitative approaches in studying food accessibility and related planning issues. Of 135 studies, 97 (71.9 percent) adopted quantitative methods, 24 (17.8 percent) used qualitative approaches, and 14 (10.4 percent) employed mixed-method designs. This pattern highlights the prevalence of statistical and spatially explicit analyses, although qualitative and integrative frameworks are gaining recognition.

Quantitative methods feature diverse regression techniques, including linear, logistic, Poisson, multinomial, and geographically weighted regression (GWR). Spatial and statistical tools such as network and suitability analysis, cost-distance modeling, Euclidean distance, spatial autoregression (SAR), Getis-Ord Gi statistic, and GIS-based multicriteria modeling are also prevalent. These approaches allow researchers to detect disparities, model accessibility, and link food environments with socioeconomic indicators. In contrast, qualitative methods are less common but provide critical insights into community experiences and perceptions through participatory approaches and stakeholder engagement. These emphasize cultural and social factors that quantitative models often overlook. Mixed-method approaches combine statistical rigor with participatory and spatial techniques. Examples include overlay and network analysis,

Euclidean and cost-distance measures, spatial proximity analysis, PGIS, and AHP. By merging empirical modeling with community-driven perspectives, mixed-method studies create richer, context-sensitive assessments that support equitable and participatory planning outcomes.

Table 2.2. Methods and analytical techniques identified in the reviewed literature

Methodological category	Methods and analytical techniques
Participatory and qualitative methods	Participatory methods; participatory GIS
Spatial accessibility and proximity analysis	Network analysis; Euclidean distance; cost-distance analysis; spatial proximity analysis
Spatial overlay and pattern analysis	Overlay analysis; Cluster and Outlier Analysis; Getis-Ord (Gi*) statistic
Suitability and decision-support methods	Suitability analysis; GIS-based multicriteria modelling; Analytic Hierarchy Process (AHP); sensitivity analysis
Conventional statistical analysis	Linear regression; binomial logistic regression; multinomial logistic regression; Poisson regression; longitudinal and multivariable regression; multivariate ordinary least squares regression
Spatial statistical analysis Reliability assessment	Geographically weighted regression; spatial autoregression Cronbach's alpha
Mixed-method approaches	Integration of participatory or qualitative data with GIS, spatial accessibility, overlay, suitability, or statistical analysis

2.3.1 Food Access and Equity Indices

Food security has been addressed through various research studies in multiple ways. Among those, using different indexes to ensure food accessibility is one of them. The assessment of food accessibility and its broader implications on public food habits and urban Planning relies on various indices tailored to measure specific aspects of the food environment. These indices integrate metrics that evaluate food availability, quality, and affordability in different geographical and socioeconomic contexts. The FMI, applied by Taylor et al. (2023), establishes standardized criteria for categorizing grocery stores and assessing their stock

levels. It enables a structured evaluation of food outlets within food accessibility studies (Taylor et al., 2023). Complementing this, the Supermarket Redlining Index (SuRI) of Zhang and Ghosh (2016) that evaluates the dynamics of supermarket closures or relocations to suburban areas. It incorporates criteria such as sales volume, employee count, SNAP and WIC acceptance, service area size, and population density, providing insights into systemic inequalities in food access (Zhang & Ghosh, 2016). Another essential tool is the HFAI, developed by Hager et al. (2017b), Francis et al. (2022), and Hutton et al. (2022a), which scores the availability of healthy versus unhealthy food options in retail environments. It integrates factors like affordability, public transportation access, and walkability, offering a nuanced understanding of regional disparities (Francis et al., 2022; Hager et al., 2017b; Hutton et al., 2022b).

Table 2.3. Index Used in the reviewed literature

Index	Remarks	Indicators	Source
Food Marketing Index (FMI)	Grocery shops are categorized, and standards are standardized with the FMI. It's applied to determine which food outlets are required for the food accessibility analysis.	Stocking of Food store	(Taylor et al., 2023)
Supermarket Redlining Index (SuRI)	The Supermarket Redlining Index (SuRI) is a ranking system that employs specific criteria to evaluate chain supermarkets.	Sales volume (\$), number of employees (count), whether the store accepts SNAP and/or WIC coupons, size of the service area, and population density of the service area closed or relocated to the suburbs	(Zhang & Ghosh, 2016)
Healthy Food Availability Index	HFAI score used to show how wholesome the food options are in shops. HFAI indicators to independently classify foods as healthy or harmful depending on their interactions with each retailer. Depending on the	Limited affordability and availability of healthy foods, public transportation, safe walkways.	(Francis et al., 2022; Hager et al., 2017b; Hutton et al., 2022a)

desired result, different indices use different sets of components, which can be weighted to show the relative importance of every variable in each region.

Food insecurity index (FII)	The percentage of people who may be food insecure in a census tract is represented by FII.	poverty, unemployment, and the percentage of households that are occupied by renters	(Bacon & Baker, 2017a)
Gini index	The Gini index illustrates income distribution disparity at the tract level. The purpose of the Gini index is to serve as a proxy for gentrification in North American cities by showing a positive correlation with gentrification.	Income and Poverty	(Shaker et al., 2023)
Revealed Accessibility Index (RAI)	This index is for model Comparison. RAI values in each city were found to exhibit spatial autocorrelation, or clustering, using the global Moran's I index, which was calculated using the ESDA approach.	Food access for each restaurant and grocery in our active travel neighborhoods, food outlet usage (as indicated by reported revenue), square footage, quantity of other competing food outlets, and travel cost (i.e., distance decay within each neighborhood)	(Rybarczyk et al., 2019)
Place-Based Food Insecurity and Vulnerability Index	PFIVI is the application of a mixed-methods GIS technique to a standard raster overlay analysis.	Location of food access	(Meenar, 2017)
Food Access Index	FAI is the calculation of street Food access index network distances to the closest supermarket, and the mean street network distance for each census tract.	Street, food store location, land use, census tracts	(Kolak et al., 2018)
Modified Retail Food Environment Index (mRFEI)	The mRFEI combines data for areas classified as Food Swamps, regions with high relative concentrations of energy-dense snack foods with	supermarkets, large grocery stores, super-centers, and produce stores within census tracts or miles from the tract boundary.	(Boskovic et al., 2026; M. Li & Yuan, 2022; Salari et al., 2023)

	data used to calculate FD. Every census tract is given a number by the mRFEI, which indicates how many retailers out of 100 are likely to provide healthy food alternatives. A score of 15 or less is considered "low-access," while a score of 30 or more is considered "high-access."		(Rangarajan, 2023)
Social Vulnerability Index (SVI)	During public health emergencies, SVI is a method that may be used to identify and quantify the social requirements of vulnerable groups at the county level in every state.	poverty, lack of vehicle access, and crowded housing	(Barboza-Salerno, 2020)
Diversity Index	Racial and cultural variety in a region is summed up by the index, a metric created by the Environmental Science Research Institute (ESRI).	Race, cultural diversity	(Barboza-Salerno, 2020)
Accessibility index	The target statistical region is calculated using the accessibility index. This stage looks for any stores that are situated within a certain distance from the unit area's centroid.	Access to stores	(Chen, 2019)
Multicriteria Food Index	The goal of MCM is to create a weighted composite index that represents the quality of the food environment for each CBG in a chosen neighborhood by combining many different variable indicators of food access.	Proximity to Food Stores Proximity to Farmers Markets, Proximity to Community Gardens, Proximity to Food Pantries Coverage Food Availability, Food Cost	(Pettygrove & Ghose, 2016)

From Table 2.3, the indices commonly employed in food environment studies, two indices have been utilized more frequently than others which are mRFEI and the HFAI. These indices have been applied three times in the context of analyzing food environments.

The mRFEI measures the proportion of healthy food outlets relative to less healthy food outlets within a given geographic area, offering insights into the distribution of food retailers that provide healthy food options (Salari et al., 2023). This index is widely used to evaluate how the availability of nutritious foods can impact dietary behaviors and health outcomes in various populations. Similarly, the HFAI assesses the accessibility and availability of healthy foods within retail outlets (Francis et al., 2022). By quantifying the presence of fruits, vegetables, and other nutritious items in grocery stores, supermarkets, and convenience stores, the HFAI is a critical tool in understanding food environments and their influence on public health, particularly in regions characterized by food deserts or food insecurity (Hutton et al., 2022a). The frequent use of these indices in research underscores their importance in capturing the complexities of food access and the broader relationship between food environments and health outcomes. Their consistent application highlights their reliability and validity in assessing food availability and its implications for diet-related health disparities.

Similarly, the FII from Bacon & Baker (2017) quantifies the prevalence of food insecurity within census tracts, correlating it with indicators like poverty, unemployment, and rental housing prevalence (Bacon & Baker, 2017). Indices like the Gini index by Shaker et al. (2023) and RAI by Rybarczyk et al. (2019) provide broader socioeconomic and spatial analyses. While the Gini Index serves as a proxy for income disparity and potential gentrification, and using this index helps to analyze equity outcomes across different demographic groups, highlighting disparities faced by low-income households, carless individuals, and racial minorities (Kharel et al., 2024; Shaker et al., 2023). Conversely, RAI leverages spatial autocorrelation to compare food access and usage in active travel neighborhoods (Rybarczyk et al., 2019). The Place-Based Food Insecurity and Vulnerability

Index (PFIVI) adds a geospatial layer to food access analysis using mixed-methods GIS techniques (Meenar, 2017). The Food Access Index (FAI) and the mRFEI delve deeper into geographical accessibility. FAI calculates network distances to supermarkets and evaluates street-level access (Kolak et al., 2018), whereas mRFEI classifies regions based on the density of retailers providing healthy food options, identifying low-access areas prone to food swamps (Boskovic et al., 2026; M. Li & Yuan, 2022; Salari et al., 2023). mRFEI evaluates the ratio of healthy to unhealthy food retailers within a defined geographic area, such as census tracts or a 1,000-meter buffer. Healthy retailers include supermarkets, large grocery stores, fruit and vegetable markets, and warehouse clubs, while unhealthy options comprise convenience stores, small grocers with three or fewer employees, and limited-service restaurants according to Centers for Disease Control and Prevention (CDC) (CDC, 2012; Ferdinands et al., 2023). Recent updates incorporate diverse outlets, including food banks, delis, and sushi bars, to better reflect food environments (Glover et al., 2022; R. Xu et al., 2023). This measure supports public health initiatives by identifying food accessibility disparities. Social metrics are also critical, as illustrated by the Social Vulnerability Index (SVI), which quantifies the needs of vulnerable groups during emergencies (Barboza-Salerno, 2020). The Diversity Index, developed by the ESRI, measures racial and cultural diversity, highlighting its intersection with food access issues (Barboza-Salerno, 2020). Lastly, integrative approaches like the Accessibility Index and the Multicriteria Food Index (MCM) offer comprehensive frameworks by evaluating proximity to various food sources and creating composite scores to represent food environment quality (Chen, 2019; Pettygrove & Ghose, 2016). These indices collectively underscore the multifaceted nature of food access challenges and provide robust methodologies for addressing inequities.

mRFEI was selected as the primary indicator of food accessibility for this study because it was the most used index across the reviewed literature for quantifying food access disparities. Its emphasis on healthy vs. unhealthy food outlets makes it ideal for identifying food access issues.

2.3.2 Research trends

As per the scientific output of the Food Vulnerability Mapping of 2015 to 2024 (Figure 2.3), the number of studies in the past decade has increased fast and has a more pronounced upward trend. The trend indicates that research on Food Vulnerability Mapping has gained more interest over the last couple of years, as the rate of growth per year is 14.93.

Figure 2.3. Scientific Growth in Sources

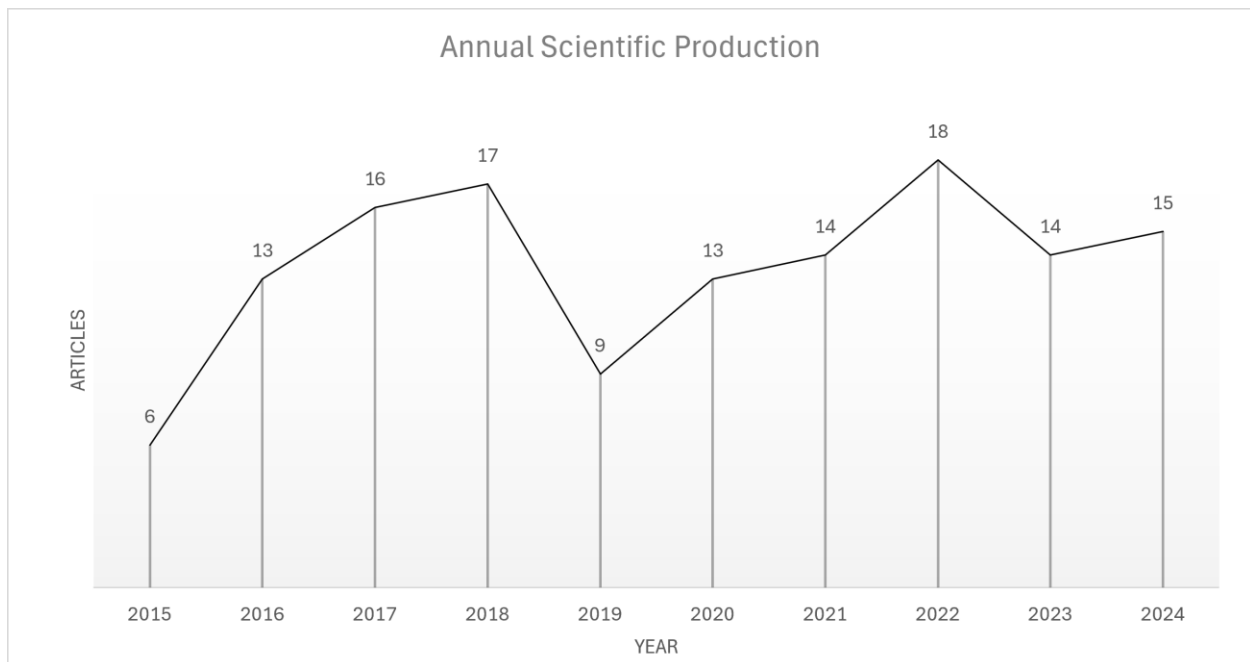


Figure 2.3 shows the trend of annual scientific production over the years. From the figure, scientific production saw a significant rise from 2015 to 2017, indicating a period of increased research activity or output. There was a sharp decline in 2018, suggesting a drop in research output during that year. Production recovered after 2018, showing a steady increase

until it peaked in 2021. The gap of article production might be influenced by COVID-19 outbreak and left a large portion of people in dark era of food accessibility. US based food relevant research reflected a gradual improvement before the COVID-19 pandemic (U.S. Department of Agriculture, Economic Research Service, n.d.). After 2021, there was a noticeable increase in 2022, followed by a slight downward in 2023. However, the pandemic years brought sudden disruptions in employment, supply chains, and affordability, altering household food access in ways not seen since the Great Recession (U.S. Department of Agriculture, Economic Research Service, n.d.). The post-COVID years (2021 onward) reveal that inflation and structural inequities have sustained or even worsened food insecurity, despite economic recovery efforts (U.S. Department of Agriculture, Economic Research Service, n.d.). While there are fluctuations, the general trend shows resilience, with production bouncing back after declines.

2.3.3 Opportunities for addressing food security

While the challenges of food vulnerability in urban areas are significant, there are also numerous opportunities to address these issues through innovative approaches and partnerships. One promising avenue is the development of local food systems that prioritize sustainability, resilience, and security (Clancy, 2004). Local food systems, characterized by shorter supply chains and closer connections between producers and consumers, can enhance food security by reducing dependence on distant food sources and increasing the availability of fresh, locally grown produce.

Community-based initiatives are also crucial in addressing food vulnerability and promoting food security. These initiatives often involve partnerships between local governments, non-profit organizations, and community groups to develop solutions tailored to urban residents'

specific needs (Alkon & Agyeman, 2011). For instance, food cooperatives, farmers' markets, and community-supported agriculture (CSA) programs can provide affordable, healthy food options to underserved communities while supporting local farmers and strengthening local economies (Brown & Miller, 2008). Moreover, education and outreach programs that promote healthy eating habits and food literacy are essential to improving food security (Caraher & Coveney, 2004).

Moreover, the role of urban Planning and policy in shaping food environments has gained increasing attention in recent years. Urban planners and policymakers play a crucial role in determining the location of food retailers, the availability of public transportation, and the design of infrastructure that supports healthy food access (Pothukuchi & Kaufman, 2000). By incorporating food access considerations into urban planning processes, cities can create more equitable food environments that support the health and well-being of all residents (Raja et al., 2008). This includes promoting mixed-use development, encouraging the establishment of grocery stores in underserved areas, and supporting community-based food initiatives, such as farmers' markets and urban gardens (Brace et al., 2020).

In addition to these structural interventions, there is a growing recognition of the importance of community-led initiatives in addressing food vulnerability and promoting food security. Community-based organizations, local food cooperatives, and grassroots movements have been instrumental in advocating for better food access and creating innovative solutions to food insecurity (Allen, 2010). These initiatives often focus on empowering residents to actively shape their food environments, whether through organizing community gardens, establishing food co-ops, or advocating for policy changes that support local food

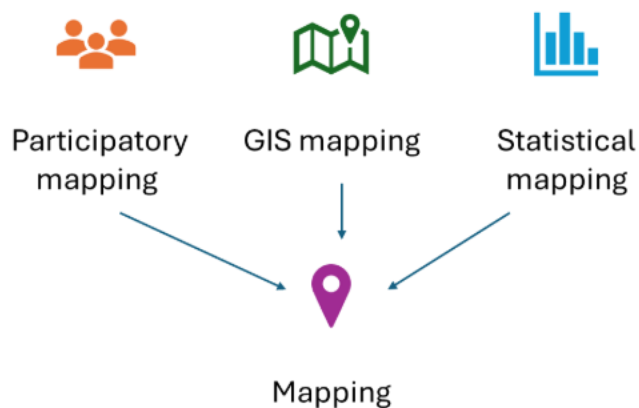
systems (Block et al., 2012). By fostering community engagement and participation, these efforts create more inclusive and resilient urban food systems.

Significant challenges still need to be addressed despite the progress made in understanding food vulnerability and promoting food security. One of the key obstacles is the need for more comprehensive data on food access and food insecurity at the local level (Walker et al., 2010). While national surveys provide valuable insights into overall trends, they often need to capture the nuances of food vulnerability within specific urban neighborhoods. This limitation underscores the need for more localized research that considers urban residents' diverse experiences and needs. Additionally, there is a need for more interdisciplinary approaches that bring together insights from geography, sociology, public health, and urban Planning to develop holistic strategies for addressing food vulnerability and promoting security (Shannon et al., 2021).

2.3.4 Mapping food vulnerability: a spatial approach

Mapping food vulnerability can help identify areas lacking healthy food access and formulate actionable policies to improve food access. Food vulnerability or food desert maps can be produced through different approaches. Figure 2.4 illustrates a conceptual framework for food accessibility mapping, integrating three key elements: participatory mapping, GIS mapping, data and statistical mapping.

Figure 2.4. How mapping is being used in recent research



Participatory mapping is a collaborative cartographic process in which community members and stakeholders actively engage in creating maps that integrate local knowledge, experiences, and priorities with spatial data (Chambers, 2006). It is designed to empower participants by ensuring that the resulting spatial representations reflect both the tangible and intangible aspects of a place, including cultural, social, and economic values (Brown & Kyttä, 2014). For example, a participatory mapping approach in Flint, Michigan, identified optimal sites for healthy food retail interventions using expert input, the analytic hierarchy process, and key variables like food access and socioeconomic distress (Sadler, 2016). Results pinpointed the northwestern quadrant, aligning high-suitability areas with underserved neighborhoods, supporting community-driven efforts to improve healthy food access. Another study, participatory mapping in Southeastern Virginia identified gaps in food security data, revealing missing non-traditional food sources like pantries and gardens, and over 24 km² of unmet need outside USDA-designated areas (Hutton et al., 2022a). Authors engaged experts across food distribution, nutrition, and human services in mapping sessions to address 6 percent of food source absence deficiencies in existing national datasets (Hutton et al., 2022a). From the study of

Bao and Tong (2017), they investigated the impact of geographical scale on food availability assessments, specifically in identifying food deserts. Using Tucson as a case study, they found that analyses based on larger spatial units may misrepresent true access levels, often underestimating access for lower-income populations (Bao & Tong, 2017). Block group-level studies are more appreciated than county-level studies. Many have different opinions regarding this situation. The geographical scale of food availability assessments is an important aspect of incorporating the maximum population in the study. However, major food-related studies, such as the USDA Food Desert and the CDC's mRFEI, rely on census tract-level analysis (CDC, 2012; U.S. Department of Agriculture, n.d.). This raises concerns about the accuracy and reliability of these analyses for informing the public. The findings suggest aggregated data at larger spatial scales may misrepresent actual food availability, especially for low-income populations in densely populated urban areas (Bao & Tong, 2017). While GIS mapping is not universally advantageous, its value lies in using it strategically and efficiently when the situation demands it.

In terms of GIS mapping, Widener et al. (2015) utilized spatial analysis to map food deserts, focusing on the geographic distribution of food retailers and their proximity to residential areas using suitability analysis. This approach highlights areas where residents face significant challenges in accessing fresh, healthy foods. One key methodology in studying food vulnerability in urban areas is spatial analysis, particularly using GIS. GIS allows researchers to map and analyze the spatial distribution of food access, identifying areas most at risk of food insecurity (Widener et al., 2015). Through spatial analysis, it is possible to visualize the relationship between food outlets, transportation networks, and socioeconomic variables, providing valuable insights into the factors contributing to food vulnerability

(Apparicio et al., 2007). In their study, Benez-Secanho et al. (2021) conducted a spatial analysis to investigate fresh food accessibility in Georgia, indicating that 15.3 percent of the population travels more than 10 minutes to get fresh food. GIS mapping uses the network analyst tool to identify the affordable food sources within driving or walking distance.

Critical determinants such as race, financial status, job status, and education affect accessibility, with urban regions doing more favorably than rural counterparts. Mapping food vulnerability using GIS has proven effective in identifying food deserts and areas of high food insecurity. For example, a study by Larsen and Gilliland (2008) in London, Ontario, used GIS to identify neighborhoods with limited access to supermarkets and fresh produce. The study found that low-income and minority populations were disproportionately affected by these food deserts, highlighting the spatial dimensions of food insecurity. Houston-Galveston metropolitan area uses GIS to explore how transportation modes and socioeconomic factors influence access to affordable food (Kharel et al., 2024).

Shannon et al. (2018) utilized GIS mapping to explore food access in Atlanta, Georgia, revealing significant disparities in food availability across different socioeconomic groups, especially for the previously designated redlining areas. Living in redlined districts profoundly affects food accessibility owing to past disinvestment and economic disparities. These studies demonstrate the power of spatial analysis in uncovering the geographic patterns of food vulnerability, which are essential for informing targeted interventions. Bacon and Baker (2017) demonstrated how spatial analysis can identify high-need areas and inform the strategic deployment of interventions to maximize impact. GIS mapping has emerged as a powerful tool for mapping and analyzing spatial patterns of food access and vulnerability (Shannon et al.,

2021). GIS integrates spatial data with socioeconomic indicators to provide a nuanced understanding of the distribution of food deserts and food swamps across urban landscapes. Moreover, GIS can pinpoint neighborhoods with high levels of food insecurity and limited access to fresh produce, thereby identifying areas most needing interventions to improve food security (Bader et al., 2010). These insights are crucial for informing policy decisions and allocating resources to address food inequities in urban areas. In a case study from Santa Clara County, California, researchers used GIS to evaluate how effectively served food assistance distribution sites (i.e. food banks, soup kitchens, free food distribution sites) align with areas of high need and most urban areas are adequately served, except certain rural and urban locations (Bacon & Baker, 2017).

Food security goes beyond simply ensuring access to food; it encompasses the fair distribution of food resources and the ability of all individuals to obtain nutritious food that meets their dietary needs and cultural preferences (Gibson, 2012). Achieving food security in urban areas involves addressing the root causes of food insecurity, such as poverty, unemployment, and systemic discrimination, and promoting sustainable and resilient food systems (Alkon & Agyeman, 2011). This includes supporting local food production, enhancing distribution networks, and fostering community engagement in food-related decision-making processes. Efforts to promote food security must also consider the unique challenges different communities face within urban areas, recognizing that a one-size-fits-all approach is unlikely to be effective (Agyeman & McEntee, 2014). However, there is growing recognition of the need to incorporate food systems into urban Planning to ensure that cities are resilient and equitable (Pothukuchi & Kaufman, 2000).

Policies to improve food security must address the root causes of food vulnerability, including income inequality, inadequate transportation infrastructure, and the lack of affordable housing (Raja et al., 2008). For example, improving public transportation systems can enhance access to supermarkets and farmers' markets for residents in underserved areas, reducing food deserts and improving dietary outcomes (Brace et al., 2020). Kostopoulou et al. (2024) examine food accessibility in Massachusetts using spatial analysis and machine learning to quantify disparities across transportation modes, and food access is significantly more equitable for individuals with cars, whereas walking and public transit present challenges for lower-income households. Urban agriculture initiatives, such as community gardens and rooftop farms, can also increase access to fresh produce while fostering community engagement and social cohesion (Corrigan, 2011). These initiatives highlight the potential for urban Planning to play a transformative role in addressing food vulnerability and promoting food security.

2.4 Mult-Criteria Decision Making Approach

Food accessibility remains a significant challenge, particularly in underserved urban communities where socioeconomic disparities and infrastructure gaps limit access to nutritious food. Addressing this requires a comprehensive approach integrating multiple factors, from geographic barriers to policy interventions. Multi-criteria decision-making (MCDM) tools provide a structured framework to analyze these complexities, combining qualitative and quantitative data for better planning. This review explores the role of MCDM in improving urban food systems, focusing on participatory planning, policy development, and data-driven decision-making.

2.4.1 MCDM

MCDM encompasses methods designed to help decision-makers evaluate choices involving multiple, often conflicting, criteria. These tools allow for systematic comparisons of alternatives, balancing quantitative metrics like cost with qualitative factors such as community preferences (Pohekar & Ramachandran, 2004; Velasquez & Hester, 2013). MCDM approaches fall into compensatory and non-compensatory categories. Compensatory methods, like the Weighted Sum Model (WSM) and Multi-Attribute Utility Theory (MAUT), permit trade-offs between criteria (Fazil et al., 2008; Ruzante et al., 2017). Non-compensatory methods, like Elimination by Aspects (EBA), require minimum thresholds for critical criteria (Pohekar & Ramachandran, 2004).

MCDM's versatility is reflected in applications from food security to supply chain management (Frej et al., 2017). When integrated with Geographic Information Systems (GIS), MCDM becomes a powerful tool for spatial decision-making, essential in urban planning and agricultural site selection (Haloui et al., 2023). In short, MCDM supports informed, transparent decision-making by evaluating multiple dimensions at once (Velasquez & Hester, 2013).

2.4.2 Integrated Food Access and Environment Index (IFAEI)

While numerous indices have been developed to measure food environments, most emphasize either structural availability or behavioral interaction, seldom both. To address this methodological limitation, this study introduces the IFAEI, a novel composite metric that merges the mRFEI and the Retail Food Activity Index (R_FAI).

The mRFEI, developed by the Centers for Disease Control and Prevention (CDC), measures the ratio of healthy to less healthy food retailers within a geographic unit using NAICS codes. It is widely used in public health and planning research to quantify structural access to

nutritious food (CDC, 2012; Y. Liu & Chen, 2023). However, it does not capture consumer behavior or mobility patterns.

By contrast, the R_FAI reflects the proportion of visits to healthy food retailers out of all food-related visits, incorporating actual behavioral data derived from mobility patterns (Xu et al., 2023). This index captures dynamic, real-world interactions with the food environment and addresses limitations of proximity-based or static indicators.

The IFAEI integrates both dimensions, retail structure and behavioral use, into a unified spatial index. To date, no known studies have combined mRFEI and R_FAI within a GIS-based MCDM framework. This integrative approach enables a more realistic assessment of food access by accounting for both the presence of resources and the community's engagement with them. The IFAEI serves as the foundation for this study's AHP-MCDA spatial decision model and supports the identification of underserved communities with greater precision.

2.4.3 Different MCDM Methods

Various MCDM methods address complex decision problems. The Weighted Sum Model (WSM) is simple yet effective when criteria are uniformly measured (Fazil et al., 2008). The Analytic Hierarchy Process (AHP) breaks decisions into hierarchical structures, allowing for subjective input and stakeholder involvement (Linnemann et al., 2015).

Flexible and Interactive Tradeoff (FITradeoff) accommodates incomplete preference data, ideal for complex supplier selections in food systems (Frej et al., 2017). Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives based on proximity to a perfect solution, practical in scenarios like restaurant selection (Shu et al., 2024; Yılmaz & Günal, 2023).

MAUT supports regulatory decisions by assigning utility scores to attributes, balancing food safety with public health outcomes (Chisholm et al., 2022; Ruzante et al., 2017). Scenario Planning with MCDA evaluates decisions under different future conditions, supporting long-term policymaking (Bizikova & Krcmar, 2015).

GIS-based MCDA integrates spatial data, helping policymakers effectively target interventions like urban farm locations (Haloui et al., 2023). Selecting the right MCDM method ensures solutions are well-suited to the decision's complexity and context.

2.4.4 Decision Support System to Fight Food Inaccessibility

Decision Support Systems (DSS) have been widely utilized to address a range of complex urban challenges, including transportation planning, environmental management, and infrastructure investment prioritization (Geertman & Stillwell, 2003; Malczewski, 2006a). In recent years, researchers have increasingly applied DSS frameworks to tackle issues of food inaccessibility by integrating spatial data, stakeholder input, and multicriteria decision-making to identify underserved areas and inform equitable policy interventions (Ramaswami et al., 2016). Decision Support Systems (DSS) integrate data, analytical tools, and MCDM methods to address food inaccessibility (Gillespie & Smith, 2008). These systems enable stakeholders to evaluate trade-offs between economic, environmental, and social goals (Pérez-Escamilla, 2024). By integrating real-time data, DSS empowers communities to respond proactively to food accessibility challenges, ensuring equitable distribution and fostering resilience (Velasquez & Hester, 2013). A GIS-based Multi-Criteria Decision Analysis (MCDA) integrated within a Decision Support System (DSS) serves as a powerful tool for mapping food deserts and guiding targeted interventions, such as the placement of food hubs or mobile markets (Haloui et al., 2023). By combining spatial analysis with weighted decision-making criteria, the DSS evaluates

key factors like population density, transportation access, income levels, and proximity to food retailers (Dawood & van Vuuren, 2024). This approach enables planners and policymakers to visualize disparities, compare alternative strategies, and prioritize areas most in need of improved food access, thereby enhancing the effectiveness of food system planning. Techniques like AHP and FI Tradeoffs improve supply chain efficiency, reducing waste and enhancing resilience against disruptions (Clapp et al., 2022; Frej et al., 2017; Linnemann et al., 2015). MAUT further supports regulatory decisions by balancing food safety with affordability (Chisholm et al., 2022; Fazil et al., 2008). By integrating real-time data, DSS empowers communities to respond proactively to food accessibility challenges, ensuring equitable distribution and fostering resilience (Velasquez & Hester, 2013).

This study advances DSS design by introducing the IFAEI as the foundation for its GIS-based model. By combining the mRFEI and the R_FAI, IFAEI provides a dual perspective on structural and behavioral access. The study also incorporates an interactive web-based mapping platform, enabling stakeholders to explore spatial outputs, adjust decision criteria, and provide feedback, offering a participatory, adaptive tool for urban food planning.

2.4.5 Socioeconomic Factors Influencing Food Access Patterns

Socioeconomic factors such as income, education, employment, and transportation deeply influence food access. Low-income households often rely on cheaper, less nutritious food and face barriers accessing fresh produce (Pérez-Escamilla, 2024; Velasquez & Hester, 2013).

Higher education levels improve nutrition awareness and access to assistance programs, while lower levels limit these opportunities (Clapp et al., 2022; Sharareh & Wallace, 2022). Employment stability is crucial, as precarious work limits consistent access to healthy food

(Ammar et al., 2024). Transportation gaps exacerbate food insecurity, particularly in areas far from food retailers (Ruzante et al., 2017). Using MCDM and GIS tools, policymakers can integrate these socioeconomic factors into their strategies, designing equitable, targeted interventions (Haloui et al., 2023; Linnemann et al., 2015).

2.4.6 Identifying Underserved Communities Using MCDM

MCDM methods are essential for identifying underserved communities, enabling evaluation of criteria such as income, transportation, and service access. Prior studies have used GIS-based MCDM approach to map these factors, which highlight areas needing attention (Dawood & van Vuuren, 2024; Haloui et al., 2023).

MAUT compares alternatives based on attributes like affordability and healthcare access (Ruzante et al., 2017). Scenario planning anticipates future demographic or climate impacts, supporting sustainable planning (Bizikova & Krcmar, 2015). These tools ensure interventions are targeted and data-driven, improving food security and overall community well-being (Velasquez & Hester, 2013). Among these tools, the Analytic Hierarchy Process (AHP) is especially well-suited for weighing community-specific indicators. AHP enables researchers and stakeholders to prioritize variables through pairwise comparisons and translate subjective preferences into measurable criteria (Linnemann et al., 2015). While existing studies have successfully used AHP in urban planning and food environment assessments, few apply it at the block-group level using localized data inputs or within mid-sized urban regions (Wątróbski et al., 2022).

2.4.7 MCDM and Decision Framework Access to Policy-Driven Decision-Making

MCDM framework can be used to support policy-driven decisions by balancing economic, social, and environmental goals (Erdoğan et al., 2016). GIS-based MCDM can help pinpoint areas for resource allocation, such as food hubs (Dawood & van Vuuren, 2024;

Haloui et al., 2023). However, the literature reveals a gap in food accessibility studies that integrate participatory GIS with weighted decision-support models. Most existing tools offer static visualizations or lack input mechanisms for stakeholders to influence spatial criteria (Ahmed et al., 2019). This study aims to address this limitation by deploying an interactive web mapping platform that allows users to explore results from the AHP-weighted MCDA model and submit feedback. This participatory approach enhances the model's responsiveness to community needs and supports more equitable food system planning.

Studies have used AHP to evaluate complex supply chain decisions in the food system (Linnemann et al., 2015). MAUT has been applied to balance considerations of food safety and economic impacts (Chisholm et al., 2022; Ruzante et al., 2017). FITradeoff has incorporated diverse stakeholder perspectives in food policy decisions (Frej et al., 2017). Scenario planning methods have also been employed to help policymakers prepare for uncertainties and build more resilient food systems (Bizikova & Krcmar, 2015). These frameworks enable data-driven, transparent, and adaptable strategies, ensuring well-informed, equitable policies that meet community needs. One of the studies incorporates scenario design techniques to explore plausible future food system conditions and develops a decision support system that identifies key drivers and evaluates context-specific interventions (Agyemang et al., 2022). By enabling the co-creation of locally relevant planning scenarios, the tool empowers stakeholders to anticipate potential shocks and make strategic, pre-emptive decisions that enhance food system resilience and equity.

2.5 Research Gap

Despite growing interest in food accessibility research, several critical gaps remain unaddressed, particularly in the context of mid-sized urban regions. Existing

studies predominantly focus on large metropolitan areas, often overlooking the spatial and socioeconomic complexities of cities such as the Kansas City Metropolitan Area (KCMA). This geographic bias limits the availability of fine-grained, localized analyses capable of informing block-group-level interventions tailored to community-specific needs.

Moreover, most spatial models in the literature focus on either structural indicator, such as proximity to healthy food outlets, or behavioral metrics, without integrating both dimensions. The combined use of the mRFEI and the R_FAI in a unified framework is largely absent. This omission reduces the explanatory power of existing tools and weakens their relevance for real-world planning applications. Additionally, existing research has given limited attention to how spatial analyses of food accessibility can be translated into place-based planning solutions tailored to the specific characteristics of high-priority neighborhoods. While many studies are effective in identifying areas of disadvantage, fewer extend this analysis toward understanding how localized social, economic, and spatial conditions influence the suitability of different intervention strategies. Consequently, literature still lacks sufficient attention to approaches that integrate spatial prioritization with context-sensitive, place-based intervention planning in urban food systems.

In conclusion, tackling food deserts and promoting food security requires a comprehensive strategy that incorporates GIS mapping, specific legislation, and community-oriented solutions. GIS and spatial analytics provide essential insights into the intricate interactions of transportation, socioeconomic variables, and land use in influencing food accessibility. Effective interventions must address both the physical and social aspects of food availability, allowing urban planners and politicians to design more inclusive and sustainable solutions. Boosting access to grocery stores, enhancing transportation infrastructure, and

engaging communities are essential for developing resilient food systems. Ultimately, addressing disparities in food availability is crucial for alleviating food security and fostering healthier, more inclusive communities.

Chapter 3 - Study Method

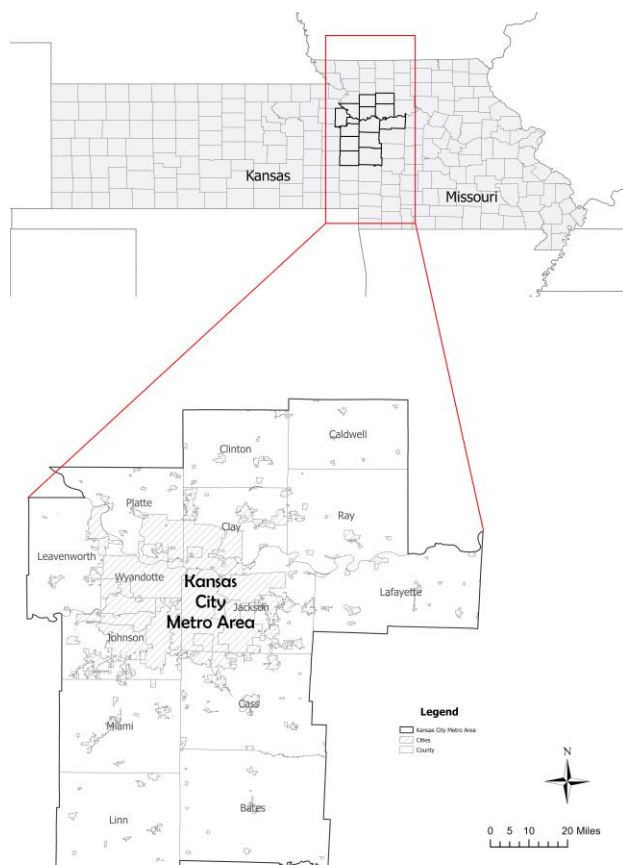
This study employs a quantitative methodological framework, using statistical and spatial analytical approaches to assess and evaluate parameters related to food accessibility at the local level. The significant parameters influencing food accessibility, combined with other physical and environmental factors, were used to develop a spatial MCDA framework to enhance food security in underprivileged urban neighborhoods. The KCMA is taken as a case study for this research. A rigorous, data-driven technique is applied to systematically evaluate food security challenges in underprivileged neighborhoods within KCMA. This research is motivated by the urgent need to address ongoing food insecurity and limited access to food in underserved urban communities (Heyda, 2023). Communities in food deserts face considerable socioeconomic inequalities and geographical obstacles that collectively undermine community health and welfare. This study employs a GIS-based MCDA methodology to ensure a transparent, objective, and replicable decision-making process. (Haloui et al., 2023). The combined use of literature-based methodological selections with practical geographical analysis might augment community engagement. It enables the creation of focused, efficient strategies to enhance food accessibility in the Kansas City Metro Area.

3.1 Study Area

The Kansas City Metropolitan Area (KCMA) is the study area for this research shown in Figure 3.1. This metro region, characterized by its bistate zoning regulations, unique urban structure, history, and socio-economic disparities, offers a unique setting for investigating the food accessibility issues that urban communities encounter. The Kansas City metropolitan area is a cross-border urban agglomeration centered in Kansas City, Missouri, and includes 14 counties spanning Missouri (nine) and Kansas (five). It encompasses approximately 8,472

square miles (21,940 km²) and has a population of over 2.2 million. It is the biggest metropolitan region in Kansas, while Wichita is the largest metro area entirely inside the state. The bi-state structure of the KCMA poses unique challenges for governance, planning, and policy coordination while also providing opportunities for cross-jurisdictional collaboration to tackle regional issues such as transportation, economic development, and equitable access to resources. The research focuses on block group level within the metropolitan region, offering a fine spatial resolution suitable for comprehensive community-level analysis. Improving food availability in this region greatly benefits public health, community development, and bolsters community resilience.

Figure 3.1. Study Area, Kansas City Metro Area



3.2 Data Collection

The study focused on the KCMA, and all indicators were harmonized to a consistent census geography. The data collection process for this research integrates spatial, socioeconomic, behavioral, and food environment datasets to evaluate food accessibility across the Kansas City Metropolitan Area. Geographic boundaries were defined at the CBG level using Census TIGER/Line shapefiles. Core variables were sourced from the American Community Survey (ACS) 5-Year Estimates (2020-2025), CDC PLACES Project, Data Axle, Safe Graph, and U.S. Environmental Protection Agency Smart Location Database. A single master dataset was created in which each row corresponds to a census unit and each column corresponds to an indicator. This master file became the sole input to both PCA and AHP-based scoring, ensuring that all transformations and score computations operate on a shared, traceable data structure.

A key component in this study is the construction of IFAEI, combining the mRFEI and the R_FAI (CDC, 2012; Ferdinands et al., 2023; R. Xu et al., 2023). mRFEI scores calculated using spatial distribution data of food stores. At the same time, R_FAI was computed using mobility data reflecting visits to healthy vs. unhealthy food retailers. The data collected for this study are shown in Table 3.1. Descriptive statistics for all selected variables are provided in Appendix B. These statistics offer an overview of the distribution and variability of socioeconomic, transportation, health, and housing indicators used in the analysis.

Table 3.1. Data variables to be used in this study

Category	Variable		Year	Data Source
Demographic &	poverty_rate_pct	Poverty rate (percent of residents below poverty line)	2023	U.S. Census Bureau, ACS

Socioeconomic (SOC)				5-year estimates
	cash_or_snap_pct	SNAP or cash assistance (percent of households)	2023	
	unemployment_rate_pct	Unemployment rate (percent of labor force)	2023	
	age65plus_pct	Older adults (65+) (percent of residents)	2023	
	black_pct	Black population (percent of residents)	2023	
	hispanic_pct	Hispanic population (percent of residents)	2023	
	hh_with_children_pct	Households with children (percent of households)	2023	
Transportation / Built Environment (TRN)	no_vehicle_pct	No-vehicle households (percent of households)	2023	
	mean_commute_time_min	Mean commute time (minutes)	2023	
	stop_density_sqkm	Transit stops density (stops per km ²)	2025	Initial Data from Kansas City Area Transportation Authority. Prepared in ArcGIS (GTFS/transit stops layer) U.S. Environmental Protection Agency Smart Location Database
	walk_nat_index	Walkability (national index score)	2025	
Health Vulnerability (HLT)	DISABILITY_CrudePrev	Disability prevalence (percent of adults)	2023	CDC PLACES Project

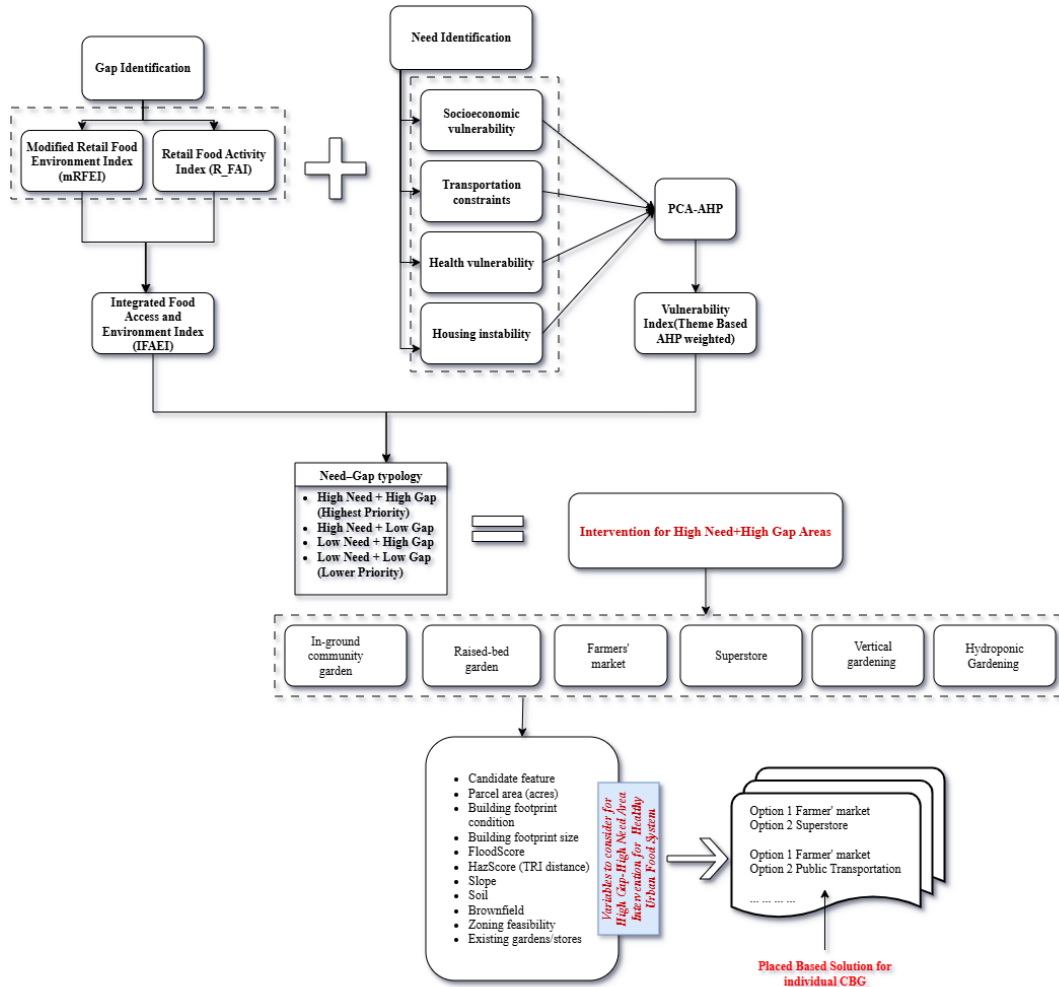
	OBESITY_CrudePrev	Obesity prevalence (percent of adults)	2023	
	DIABETES_CrudePrev	Prevalence of diabetes (percent of adults)	2023	
	BPHIGH_CrudePrev	High blood pressure prevalence (percent of adults)	2023	
	CHD_CrudePrev	Coronary heart disease prevalence (percent of adults)	2023	
Housing Instability (HOU)	renters_pct	Renter-occupied housing (percent of households)	2023	U.S. Census Bureau, ACS 5-year estimates
	vacancy_rate_pct	Housing vacancy rate (percent of units)	2023	
	overcrowding_pct	Overcrowding (percent of households; >1 person/room)	2023	
Food Environment (Structural)	mRFEI (Modified Retail Food Environment Index)		2024	Data Axle (Prepared through ArcGIS)
Food Activity (Behavioral / Mobility)	R_FAI (Retail Food Activity Index)		2024	SafeGraph (Prepared through ArcGIS)
Integrated Food Access Metric	Integrated index (mRFEI + R_FAI) / IFAEI (Gap-side measure)		2025	Computed by the author in Python/ArcGIS from mRFEI and R_FAI

3.3 Study Method

The study was conducted in three phases, addressing the three research questions. In the first step, complete socioeconomic and geospatial datasets were gathered from sources that were open to the public, such as the U.S. Census Bureau, CDC PLACES, and Data Axle-Safe graph.

These datasets went through necessary data cleaning, consistency checks, and normalization in ArcGIS. As shown in Figure 3.2, the whole study method was divided into three phases: Phase One (Gap Identification), Phase Two (Need Identification) and Phase Three (Intervention of High Need-High Gap Areas)

Figure 3.2. Flow chart of the Study method



3.3.1 Phase One

In this first phase of the study, we evaluated food accessibility at the block group level. To develop a multidimensional measure of food accessibility, this study introduces the

IFAEI, which combines the structural characteristics of the food environment with patterns of food retail activity. The IFAEI integrates two primary indices: the mRFEI and the R_FAI.

Table 3.2 shows the healthy and unhealthy or less healthy food source categories used in calculating the mRFEI and R_FAI calculations in this study. This classification was modified according to the availability of data and the change in the North American Industry Classification System (NAICS) shown in Table 3.2. In order to achieve consistency between the two indices, the identical NAICS codes were employed in selection of stores through the CDC method, in addition to factoring in the availability of store-level data and travel behavior data to recognize the pertinent food store visits. The NAICS codes employed in this study are mostly related to the NAICS system of 2017, which is consistent with the CDC mRFEI methodology. Even though more recent revisions (e.g., 2022 NAICS) changed the structure of retail classifications, the chosen codes were kept maintaining the consistency with available datasets and already existing food environment metrics.

Table 3.2. NAICS Code Classification of Food store Used in mRFEI and R_FAI Indices

Retail Food Store types	NACIS Code - mRFEI 2024 and R_FAI
Healthy food sources	452311 – Warehouse Clubs and Supercenters 445230 – Fruit and Vegetable Markets 445120 – Convenience Stores 624210 – Community Food Services (<i>e.g., food banks, meal programs</i>) 445110 – Supermarkets and Other Grocery (except Convenience) Stores (Small grocers with greater than 3 employees)
Unhealthy/Less food sources	447110 – Gasoline Stations with Convenience Stores 722513 – Limited-Service Restaurants (<i>fast food, takeout</i>) 722511 – Full-Service Restaurants 445110 – Supermarkets and Other Grocery (except Convenience) Stores (Small grocers with 3 or less employees)

The mRFEI, developed by the Centers for Disease Control and Prevention (CDC), evaluates the ratio of healthy to unhealthy food retailers within a defined geographic area, such as census tracts or a 0.5-mile buffer. The equation is:

$$mRFEI = \left(\frac{\text{Number of Healthy Food Retailers}}{\text{Number of Healthy Food Retailers} + \text{Number of Unhealthy Food Retailers}} \right) \times 100 \quad (1)$$

Or,

$$mRFEI = \left(\frac{\text{Number of Healthy Food Retailers}}{\text{Number of Total Food Retailers}} \right) \times 100 \quad (2)$$

Here,

$$\text{Total Food Retailers} = \text{Healthy Food Retailers} + \text{Unhealthy Food Retailers} \quad (3)$$

Healthy retailers include supermarkets, large grocery stores, fruit and vegetable markets, and warehouse clubs, while unhealthy options comprise convenience stores, small grocers with three or fewer employees, and limited-service restaurants. The value of mRFEI ranges from 0 to 100, with higher values indicating a greater availability of healthy food options (CDC, 2012; Ferdinands et al., 2023). Complementing this, the R_FAI is a behavior-based index that quantifies the proportion of actual consumer visits made to healthy food outlets. It is defined as:

$$R_{FAI} = \frac{\text{Visits to healthy food retailers}}{\text{Visits to healthy food retailers} + \text{Visits to less healthy food retailers}} \quad (4)$$

Where,

Visits to healthy food retailers represents the total number of observed visits originating from CBG to healthy food retailers, and

Visits to less healthy food retailers represents the total number of observed visits from the

same CBG to less healthy food retailers. The R_FAI produces a value between 0 and 1, with higher scores indicating a larger share of visits to healthy food outlets.

R_FAI was constructed using SafeGraph mobility data, particularly the VISITOR_HOME_CBGS field. For each food-retail point of interest, this field provides aggregated information on the inferred home CBGs of visiting mobile devices and the number of visits associated with each origin CBG. Food-retail locations were first classified as healthy or less healthy using the retailer-classification criteria established for this study. The visit counts associated with each origin CBG were then extracted and summed separately for healthy and less healthy retailers. This process produced CBG-level totals of observed healthy and less healthy food-retailer visits, which were used to calculate the R_FAI. Additionally, each location contains its own CBG and 0.5 mile buffer from its CBG. The buffer allowed nearby retailers located immediately outside a CBG to be included in the analysis, recognizing that residents are not necessarily limited to food outlets located within the formal boundary of their home CBG. This approach is particularly important in small geographic units, where a nearby supermarket may be excluded from a boundary-based measure despite being accessible to residents. The use of SafeGraph data added a mobility-based dimension to the analysis by linking observed food-retailer destinations to visitors' inferred home CBGs. Unlike conventional place-based measures, which assume that residents are primarily influenced by retailers located near their homes, the R_FAI reflects observed cross-boundary food-travel patterns. Residents may visit food retailers outside their neighborhoods because of employment locations, transportation availability, food prices, store preferences, product availability, or other daily travel routines. The use of R_FAI is a new in urban food planning research field where GPS mobile phone location data used to monitor or capture food travel based movement (Hossain, 2025; R. Xu et al., 2023). For this

research, it was developed to represent mobility-based food access patterns and was aggregated at the CBG level to support spatial analysis across neighborhoods.

To ensure consistency in scale between the two indices used in this study, the behavior-based mRFEI index, originally ranging from 0 to 100, was changed to a 0 to 1 scale. This was necessary to align it with the R_FAI, which is measured on a 0-1 scale. The transformation facilitates direct comparison and combination of both indicators in subsequent spatial analysis. Although either indicator could have been rescaled, mRFEI was transformed to preserve the established interpretation and scale of R_FAI and to facilitate their subsequent equal-weight combination. Without this adjustment, the larger numerical range of mRFEI would have disproportionately influenced the integrated index. Transformation Equation:

$$\text{Transformed } mRFEI (tmRFEI) = mRFEI/100 \quad (5)$$

where tmRFEI represents the transformed availability-based food-access score for CBG. This linear transformation changes only the numerical scale of mRFEI and does not alter its relative distribution, ranking, or substantive interpretation.

$$\frac{(tmRFEI + R_FAI)}{2} = \text{Integrated Food Access and Environment Index (IFAEI)} \quad (6)$$

Higher IFAEI values indicate comparatively more favorable healthy-food-access conditions, while lower values indicate a greater food-access gap. This integrated index captures both the built environment and actual food access patterns, addressing limitations of traditional geographic indicators. As demonstrated in prior research (Xu et al., 2023) behavior-informed indices are better suited to revealing food access disparities affecting low-income and marginalized communities.

3.3.2 Phase Two

This study adopts a GIS-based Multi-Criteria Decision Analysis (MCDA) approach to assess food accessibility disparities across CBGs in the Kansas City metropolitan area. Following the IFAEI analysis, a spatial MCDA framework was developed that integrates various socio-economic and built-environment factors to identify optimal locations for healthy food solutions. This approach integrates GIS for the management, analysis, and visualization of spatial data with MCDA as a structured framework for combining multiple criteria into a unified assessment.(Malczewski, 2006b). This approach helps establish a framework for urban food system planning, applicable to various healthy food solutions and adaptable for additional food production or accessibility initiatives. This study operationalized the MCDA process using theme-based Principal Component Analysis (PCA) to provide composite scores within key thematic dimensions, and the Analytical Hierarchy Process (AHP) to allocate relative weights among those dimensions (Xie & Meng, 2023). The components were subsequently incorporated into a GIS framework to generate spatially explicit indices and priority classifications for action. This framework provides a systematic and policy-relevant basis for evaluating food access inequities in a spatial decision-making context. This research employed a survey-based pairwise comparison procedure based on the AHP to calculate the weight of each of the themes derived through PCA in a structured questionnaire format and sent to faculty members and graduate students involved in the GRIP Urban Food Systems team and asking their opinion of pairwise themes towards influencing food accessibility vulnerability. These pair-wise comparisons allowed the participants to rate one theme in comparison to another in terms of their knowledge, research experience and knowledge of urban food systems. Their input guides the pairwise comparison process through structured online forms. The analysis was

conducted using a combination of Python and ArcGIS Pro. The resulting judgment matrix was normalized to produce criterion weights, which were applied to geospatial data layers in ArcGIS Pro.

3.3.2.1 Thematic indicator framework

To operationalize population-side vulnerability (Need), the study first structured candidate indicators into four conceptually distinct dimensions: socioeconomic vulnerability, transportation constraints, health vulnerability, and housing instability. This thematic framework was adopted to preserve interpretability and to ensure that the final index reflects multiple mechanisms through which residents may experience barriers to obtaining healthy food. Grouping indicators by theme also supports a modular index design, allowing each dimension to contribute as a distinct component rather than allowing any single cluster of highly correlated variables to dominate the overall measure simply because more indicators are available for that topic.

3.3.2.2. Directional alignment of indicators

Prior to Principal Component Analysis (PCA), all indicators were transformed to ensure a consistent directional meaning: higher values indicate higher vulnerability. Indicators that represent advantage or reduced constraint were inverted so that increases correspond to greater vulnerability. For example, variables such as income and built-environment accessibility proxies (e.g., walkability or transit stop density) were coded so that higher values reflect greater constraint rather than improved access. This step is important for interpretability because PCA solutions can produce loadings with arbitrary signs; aligning indicators beforehand ensures that the resulting component scores can be interpreted consistently across themes as increasing vulnerability.

3.3.2.3. Theme-specific PCA and component extraction

PCA was conducted separately for each theme rather than across the full indicator pool. For a given theme, only the indicators assigned to that dimension were included, and each indicator was standardized (z-scored) to account for differences in units and variance. PCA was then applied to summarize the shared variation among correlated indicators within the theme. Each principal component (PC) was retained as the theme-level vulnerability score because it captures the dominant common pattern across the indicators and provides a parsimonious representation of that dimension. This procedure produced one theme score per block group for each dimension.

To support interpretability and to prepare for theme-based PCA, indicators were grouped into conceptual domains. The final set of themes was designed to be both statistically coherent (variables within a theme are plausibly correlated) and substantively meaningful to planning. A representative theme structure includes: (i) Socioeconomic Vulnerability (SocIndex), (ii) Transportation and Mobility Constraints (TrnIndex), (iii) Housing and Neighborhood Stability (HouIndex), and (iv) Health Vulnerability (HltIndex).

Table 3.3. Thematic Structure for Variables.

Theme	Short form	Indicators (block group level)	Desired direction	Recoding rule before PCA
Socioeconomic vulnerability	SocIndex	poverty_rate_pct; cash_or_snap_pct; unemployment_rate_pct; age65plus_pct; black_pct,hispanic_pct, hh_with_children_pct	Higher = more vulnerable	Keep as is higher means worse
Transportation constraints	TrnIndex	no_vehicle_pct; mean_commute_time_min; stop_density_sqkm; walk_nat_index	Higher = more constrained	Keep: no_vehicle_pct (+), commute time (+). Flip “better access” variables:

				stop_density_sqkm ($\times -1$), walk_nat_index ($\times -1$)
Health vulnerability	HltIndex	DISABILITY_CrudePrev; OBESITY_CrudePrev; DIABETES_CrudePrev; BPHIGH_CrudePrev; CHD_CrudePrev	Higher = more vulnerable	Typically keep as- is (higher prevalence = worse)
Housing instability	HouIndex	renters_pct; vacancy_rate_pct; overcrowding_pct	Higher = more vulnerable	Typically keep as- is (higher instability = worse)

3.3.2.4. Rescaling of theme scores

Because PCA component scores are not inherently bounded and may differ in magnitude across themes, each theme score was rescaled to a 0–1 range to facilitate comparability. Under this transformation, values closer to 0 indicate comparatively lower vulnerability within that theme, while values closer to 1 indicate comparatively higher vulnerability. Rescaling ensures that differences do not influence subsequent integration of theme indices in score ranges produced by PCA but instead reflects substantive differences and the chosen weighting scheme.

Standardization (z-score)

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (7)$$

where:

- i = block group (spatial unit), $i = 1, 2, \dots, N$
- j = indicator/variable, $j = 1, 2, \dots, K$
- x_{ij} = observed value of indicator j in block group i
- μ_j = mean of indicator j across all block groups

- σ_j = standard deviation of indicator j across all block groups
- z_{ij} = standardized (unitless) value of x_{ij}

After standardization, PCA will be less likely to be dominated by indicators with larger numeric scales.

3.3.2.5. AHP survey processing and derivation of theme weights

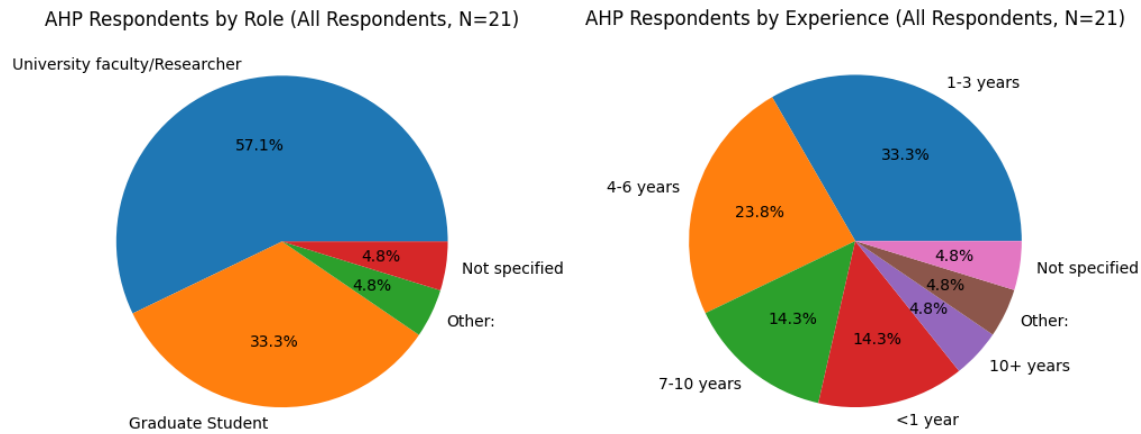
An Analytical Hierarchy Process (AHP) survey was used to determine the relative importance of the four dimensions included in the neighborhood Vulnerability Index: socioeconomic vulnerability, transportation constraints, housing instability, and health vulnerability. Participants were purposively selected based on their academic, professional, or research experience in areas relevant to food accessibility, food security, urban and regional planning, public health, community development, and spatial analysis. The participant panel included faculty members, researchers, professionals, and graduate students whose education, research, or employment involved food-system or community-vulnerability issues. This purposive selection approach was intended to obtain informed judgments from participants with relevant subject-matter knowledge rather than from a convenience sample of the general population.

The questionnaire was distributed among the selected participants, and the completed responses were compiled for analysis. The full AHP questionnaire is provided in Appendix A. In addition to the pairwise-comparison questions, respondents were asked to report their professional role and years of relevant experience.

A total of 22 responses were received. Of these, 21 were complete and one was incomplete. As shown in Figure 3.3, university faculty members and researchers represented 57.1 percent of the complete respondents, while graduate students represented 33.3 percent. The

remaining respondents selected “Other” or did not report their role. Regarding relevant experience, 33.3 percent reported one to three years, 23.8 percent reported four to six years, 14.3 percent reported seven to ten years, and 14.3 percent reported less than one year. Smaller shares reported more than ten years of experience, selected “Other,” or did not report their experience.

Figure 3.3. Characteristics of AHP respondents by professional role and relevant experience (n=21) (AHP survey responses)



Pairwise-comparison matrix

Respondents completed six pairwise-comparison questions, representing all unique comparisons among the four vulnerability themes. For each comparison, participants indicated the relative importance of one theme compared with another. A simplified Saaty-type scale of 1, 3, 6, and 9, together with the corresponding reciprocal values, was used to facilitate consistent and intuitive responses. A value of 1 indicated equal importance, while values of 3, 6, and 9 indicated progressively stronger levels of importance. Reciprocal values indicated that the second theme was considered more important than the first (Saaty, 2008).

For each respondent, the AHP survey responses were converted into a pairwise comparison matrix. $A = [a_{ij}]$ of size $n \times n$ (here, $n = 4$ themes). Each entry a_{ij} represents the

stated relative importance of the criterion i over criterion j on a ratio scale (Saaty, 2008). The AHP matrix satisfies two standard properties:

$$a_{ii} = 1, a_{ij} = \frac{1}{a_{ji}} \quad (8)$$

where $a_{ii} = 1$ indicates that any criterion is equally important to itself, and the reciprocal condition ensures internal consistency of the matrix structure (i.e., if i is judged more important than j by a factor of a_{ij} , then j must be less important than i by $1/a_{ij}$) (Saaty, 2008).

Because multiple respondents completed the AHP survey, individual judgments were combined to obtain a single set of group-level theme weights. In AHP, there are two commonly accepted aggregation approaches for group decision-making:

Aggregation of Individual Priorities (AIP): compute a weight vector for each respondent first, and then aggregate the resulting weight vectors across respondents (e.g., by averaging or geometric mean of weights) (Saaty, 2008).

$$Aw = \lambda_{\max} w \quad (9)$$

Here,

A = pairwise comparison matrix. Each entry a_{ij} is how much more important a criterion i is the criterion j .

w = the priority vector (weights, i.e., $w_{Soc}, w_{Trn}, w_{Hlt}, w_{Hou}$), scaled so the weights sum to 1.

$\lambda_{\max}$ = the largest eigenvalue of A (called "lambda max").

The resulting priority vector was normalized so that the four theme weights summed to 1. Thus, each complete response produced an individual set of weights representing the respondent's assessment of the relative importance of the four vulnerability dimensions.

Consistency assessment

The internal consistency of each respondent's pairwise judgments were evaluated using the Consistency Index (CI) and Consistency Ratio (CR).

Consistency Index (CI):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (10)$$

Consistency Ratio (CR):

$$CR = \frac{CI}{RI} \quad (11)$$

where $n = 4$ and RI is Saaty's Random Index for size n ($RI = 0.90$ for $n = 4$). The resulting group weights were then used to combine the four PCA-derived theme indices into the final vulnerability (Need) index. Following group-AHP practice, respondent-level priority vectors were aggregated to obtain group theme weights using the median, which is a recognized alternative to geometric-mean aggregation and provides robustness to extreme individual judgments (Kryvobokov, 2005).

A Consistency Ratio (CR) was calculated for each respondent to evaluate internal consistency of judgments (Schmidt et al., 2015). The dataset contained 22 total responses, 21 of which were complete and 1 was incomplete. Two weight sets were prepared: a full set using all complete responses and a filtered set excluding responses above the selected consistency threshold ($CR \leq 0.20$) (Pauer et al., 2016; Rizzardo et al., 2019). The median CR was 0.1965, indicating moderate overall consistency across respondents, with 11 respondents meeting the $CR \leq 0.20$ threshold. This procedure allows the study to document weighting choices transparently and assesses the impact of consistency filtering on the final index.

Aggregation of Individual Judgments (AIJ): combine respondents' pairwise comparison values for each matrix entry and then compute weights from the resulting group matrix. The standard AIJ rule uses the geometric mean:

$$a_{ij}^{group} = \left(\prod_{r=1}^R a_{ij}^{(r)} \right)^{1/R} \quad (12)$$

where $a_{ij}^{(r)}$ is respondent's r 's judgment comparing criterion i to j , and R is the number of respondents included (Saaty, 2008). The second approach is the Aggregation of Individual Priorities, in which a priority vector is first calculated separately for each respondent and the resulting individual weights are then combined. In this study, respondent-level priority vectors were aggregated using the median. The median was selected to reduce the influence of unusually high or low individual weights and to provide a robust estimate of the group-level priorities (Kryvobokov, 2005).

The final group weights were based on the 11 respondents who met the selected consistency threshold of $CR \leq 0.20$. Table 3.4 presents the group pairwise-comparison matrix for the consistent respondent group.

Table 3.4.. Group AHP pairwise matrix (ONLY consistent respondents, using $CR < 0.20$)

	SocIndex	TrnIndex	HouIndex	HltIndex
SocIndex	1.0000	2.1324	2.2206	1.2973
TrnIndex	0.4690	1.0000	0.8706	0.5842
HouIndex	0.4503	1.1487	1.0000	0.6988
HltIndex	0.7708	1.7118	1.4310	1.0000

The resulting group-level weights were subsequently used to combine the four PCA-derived theme indices into the final neighborhood Vulnerability Index. This process incorporated informed judgments regarding the relative importance of the four vulnerability dimensions rather than assigning equal weights to all themes.

3.3.2.6. Integration of PCA theme indices and AHP weights

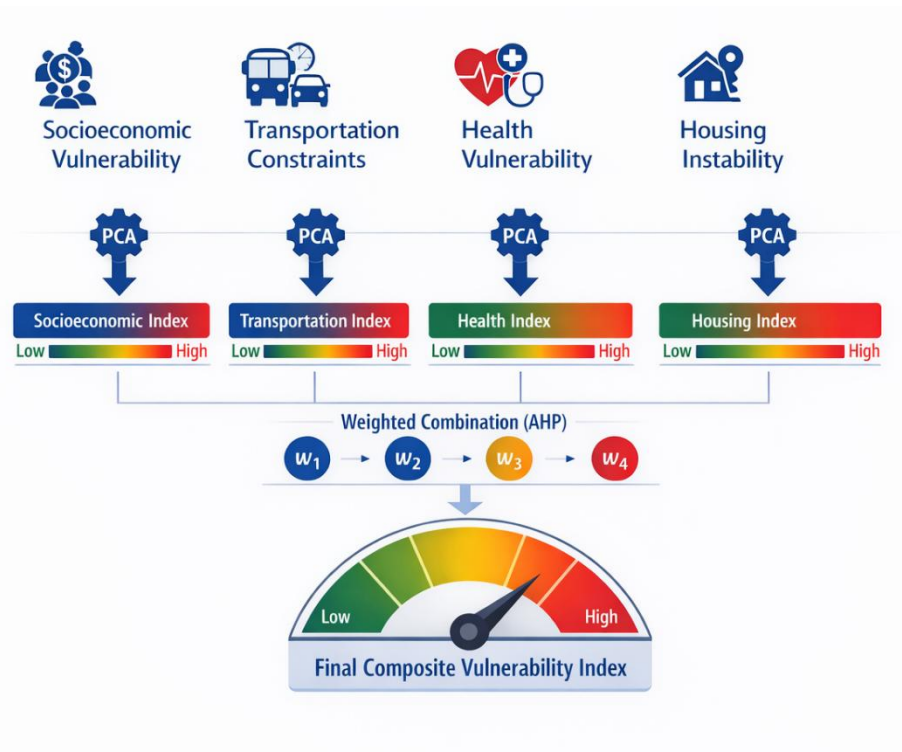
As shown in Figure 3.4, the final composite vulnerability index (Need) was calculated by combining the normalized PCA-based theme indices with the AHP-derived theme weights.

SocIndex, TrnIndex, HltIndex, and HouIndex denote the 0–1 rescaled PC1 scores for the four themes, and w_{Soc} , w_{Trn} , w_{Hlt} , and w_{Hou} denote the corresponding AHP weights. The block-group-level vulnerability index was computed as:

$$VI = w_{Soc} \cdot SocIndex + w_{Trn} \cdot TrnIndex + w_{Hlt} \cdot HltIndex + w_{Hou} \cdot HouIndex \quad (13)$$

This approach integrates vulnerability patterns within each theme (PCA) with (ii) decision-relevant emphasis across themes (AHP). The resulting file provides the Need metric used in subsequent Need-Gap typology mapping and in the identification of priority geographies for feasibility screening and intervention planning.

Figure 3.4. A composite Vulnerability Index Scoring



3.3.2.7. Need-Gap Typology using Bivariate Local Moran's I Analysis

This study frames food accessibility as a multidimensional condition shaped by both population-side vulnerability and environment-side food access conditions. In practice, a neighborhood may have food outlets nearby yet remain functionally underserved due to socioeconomic barriers, limited mobility resources, or health constraints. Conversely, a neighborhood may have comparatively lower vulnerability but still face weak access conditions due to limited availability of healthy food options. To capture these distinct mechanisms, the analysis separates food access disadvantage into two complementary dimensions Need and Gap and uses their intersection to define equity-relevant priority geographies.

A bivariate Local Moran's I analysis was conducted to examine the localized spatial relationship between food-access conditions and neighborhood vulnerability across the Kansas City Metropolitan Area. Local indicators of spatial association identify statistically significant local clusters and spatial outliers that may not be apparent from an area-wide statistic (Anselin, 1995). CBGs were used as the geographic unit of analysis, and the analysis was performed in GeoDa. The IFAEI (Gap) was entered as the first variable, representing the food-access condition of each focal block group. The composite Vulnerability Index (Need) was entered as the second variable, representing socioeconomic and demographic vulnerability in neighboring block groups. GeoDa supports exploratory spatial data analysis, spatial-weights construction, and global and local measures of spatial association (Anselin et al., 2006).

Bivariate Local Moran's I differ from a direct correlation or quadrant comparison between two variables measured within the same geographic unit. The statistic compares the standardized value of one variable at a focal location with the spatially lagged values of a second variable in neighboring locations. The local statistics were expressed as:

$$I_i^{BV} = z_{x,i} \sum_j w_{ij} z_{y,j} \quad (14)$$

Where, $z_{x,i}$ represents the standardized IFAEI value for focal block group i , $z_{y,j}$ represents the standardized Vulnerability Index value for neighboring block group j , and w_{ij} represents the spatial relationship between the focal and neighboring block groups.

Accordingly, the analysis evaluated whether block groups with relatively low or high IFAEI values were spatially associated with surrounding block groups characterized by relatively low or high vulnerability. Spatial relationships were defined using a first-order Queen-contiguity spatial-weights matrix. Under Queen contiguity, two block groups were considered neighbors when they shared either a common boundary or a common vertex. The weights matrix used GEOID as the unique identifier and included all 1,819 block groups in the study area. The matrix was symmetric, meaning that when one block group was identified as a neighbor of another, the relationship also applied in the opposite direction. The number of neighbors ranged from one to 17, with a mean of 6.51 and a median of six neighbors.

GeoDa standardized the IFAEI and Vulnerability Index values relative to their respective study-area means before calculating the statistics. Therefore, the terms “Low” and “High” indicate relative positions below or above the metropolitan-area average rather than externally established thresholds. The mean IFAEI across the 1,819 block groups was 0.2493, with a standard deviation of approximately 0.0912. Block groups with IFAEI values below 0.2493 were positioned on the Low side of the Moran scatterplot, while those with values above 0.2493 were positioned on the High side. Thus, Low IFAEI refers to below-average food-access conditions within the study area and should not be interpreted as an absolute regulatory or public-health threshold for inadequate access.

Statistical significance was evaluated using 999 random permutations and the GeoDa significance cut-off of 0.05. Statistically significant local associations were classified into four categories in Table 3.5: High-High, High-Low, Low-High, and Low-Low and one additional not significant category. In this analysis, the first term refers to the IFAEI value of the focal block group, while the second term refers to the spatial lag of vulnerability among neighboring block groups. Because low IFAEI represents poorer food access and high vulnerability represents greater need, the Low-High category was identified as the principal pattern of policy interest. The four categories were interpreted as follows:

Table 3.5. Cluster categories

Cluster category	Interpretation
High-High	High IFAEI with high vulnerability in neighboring block groups
High-Low	High IFAEI with low vulnerability in neighboring block groups
Low-High	Low IFAEI with high vulnerability in neighboring block groups
Low-Low	Low IFAEI with low vulnerability in neighboring block groups
Not significant	There is no statistically significant spatial association between IFAEI and vulnerability.

To translate the bivariate Local Moran's, I result into a planning-oriented classification, Low-High clusters were further evaluated as potential High Need-High Gap areas. A Low-High cluster identifies a focal block group with a low IFAEI value surrounded by neighboring block groups with high vulnerability. The low IFAEI represents a food-access gap, while high surrounding vulnerability indicates greater socioeconomic need. However, this spatial classification does not necessarily confirm that the focal block group itself is highly vulnerable. Therefore, the Vulnerability Index of each focal Low-High block group was compared with the KCMA mean of 0.4950. Low-High block groups with Vulnerability Index values above this mean were designated as High Need-High Gap areas because they combined below-average food access with above-average vulnerability within the same geographic unit. These areas were

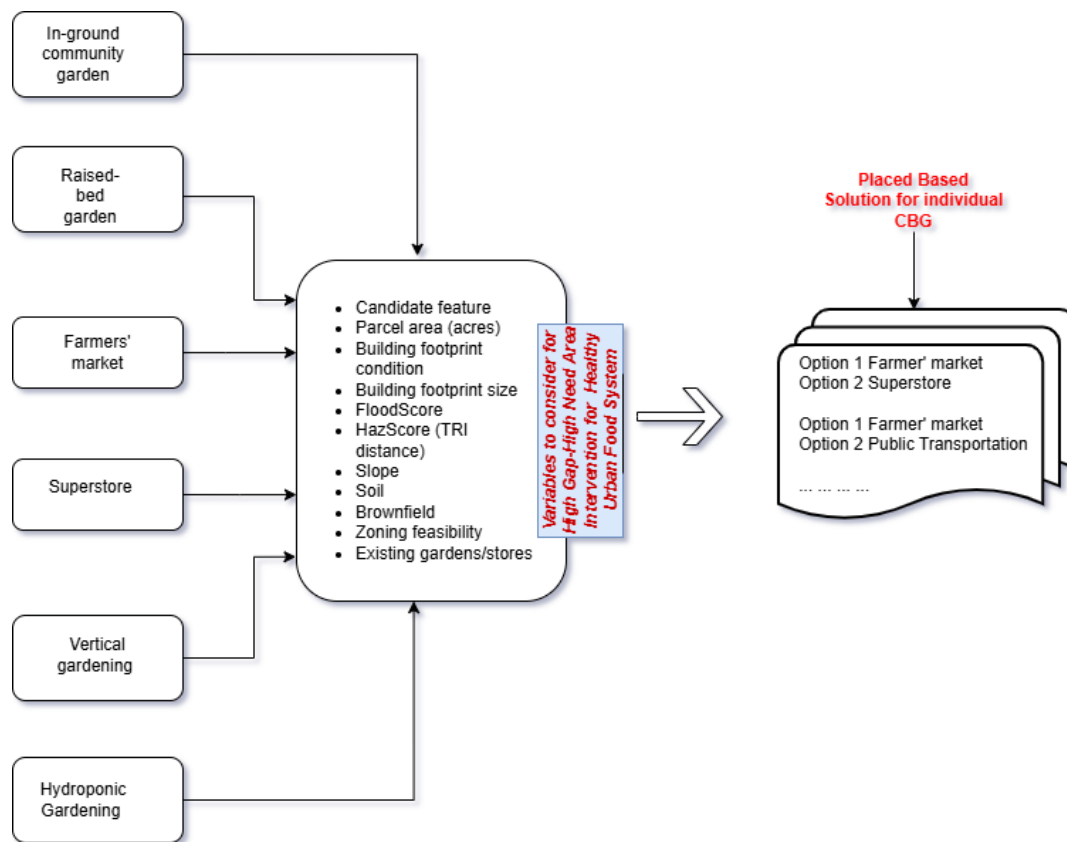
considered extremely high-priority areas for planning and intervention because they experienced both substantial food-access limitations and elevated socioeconomic vulnerability. This supplementary designation did not alter the original Local Moran's I classification but provided a clearer basis for prioritizing resources and targeted food-access strategies.

3.3 Phase three

To operationalize the MCDA framework discussed in the previous section, the study produces four maps corresponding to the four Need-Gap categories. These maps visualize how vulnerability and access conditions intersect across the study area and establish the geographic basis for implementation-focused planning.

The primary focus is the High Need-High Gap category, where vulnerable populations coincide with comparatively weak accessibility conditions. From Figure 3.5, it is clearly identified that these priority block groups and their variables are to select place-based intervention planning options. The study selects a subset as case study areas for place-based intervention planning. In the final stage, each case study area is evaluated using an intervention-oriented feasibility workflow (e.g., land and environmental feasibility and land-use/regulatory context) to generate candidate sites and area-specific improvement recommendations. Because feasibility and neighborhood context differ across locations, recommended strategies are not fixed; instead, intervention options are tailored to each case study area using a consistent decision logic that links equity targeting to implementable opportunities.

Figure 3.5. Selection of feasible intervention for High Need-High Gap Areas



Following typology mapping, the study selects a subset of 10 percent High Need-High Gap block groups as case study areas for intervention-oriented analysis. Case study selection is designed to support place-based planning by focusing on neighborhoods where the equity need is most pronounced and where local context can meaningfully shape the intervention pathway. Selection is guided by the magnitude of disadvantage indicated by the underlying Need and integrated accessibility measures within the High Need-High Gap set (i.e., block groups that remain among the most vulnerable and exhibit the weakest integrated access conditions), while also considering geographic distribution across the metropolitan area to avoid concentrating all case studies in one subregion.

In the next stage, these priorities and case-study geographies are evaluated using an intervention-oriented feasibility workflow. This stage uses location-specific constraints and opportunities to support implementable recommendations and candidate locations, allowing intervention options to vary by neighborhood context rather than applying a single strategy uniformly across the region.

3.3.3.1 Selection of Feasibility Criteria

Table 3.6. Feasibility Criteria

Feasibility criterion	Variable/indicator	What it measures	Why it matters for intervention selection	Most supportive of
Regulatory feasibility	Zoning	Whether food retail stores or urban agriculture-related land uses are legally allowed	Determines if gardens, markets, or indoor production can be implemented without major regulatory barriers	All options, depending on the district
Land suitability	Soil conditions / SoilScore	Agricultural quality or limitations of the soil	Helps decide whether in-ground growing is feasible or whether raised beds / indoor systems are safer	Community garden, raised-bed garden
Terrain suitability	Slope / SlopeScore	Physical steepness of parcels	Flatter land is easier and cheaper to cultivate, set up markets, and prepare for site work.	Gardens, farmers' market
Environmental risk	Flood risk / FloodScore	Exposure to flood-prone conditions	High flood risk reduces the suitability for permanent food infrastructure and cultivation.	Markets in lower-risk areas; indoor options if outdoor risk is high
Site contamination constraint	Brownfield presence / BrownfieldScore	Potential contamination or redevelopment complexity	Brownfields may restrict in-ground cultivation and push intervention choice toward safer non-soil options	Raised beds, indoor hydroponics, vertical agriculture

Land opportunity	Vacant land availability	Presence and amount of unused or underused parcels	Indicates whether outdoor, parcel-based interventions can be introduced in the neighborhood	Community garden, raised-bed garden, farmers market
Development scale capacity	Parcel size/acreage	Amount of usable land available	Larger parcels allow more intensive or multifunctional food interventions	Farmers market, larger garden, possible food hub
Built-form opportunity	Building footprint size	Size of existing building structures	Identifies whether existing buildings can support indoor growing or food hub functions	Indoor hydroponics, vertical agriculture

Floodway

FEMA Resilience Analysis and Planning Tool were the sources used for collecting flood data. Flood hazard classes were converted to an ordinal suitability score and applied as an intervention-specific constraint, with regulatory floodway excluded, the 1 percent annual chance flood hazard and future-conditions 1 percent hazard strongly penalized, levee-protected areas treated as conditional due to residual risk, and the 0.2 percent annual chance hazard given a minor penalty; this structure is consistent with evidence on flood-related contaminant transport and produce contamination risks, residual risk behind levees, and long-term commercial building flood losses.(Ciszewski & Grygar, 2016; Pinter et al., 2016; Porter et al., 2022; Shiraz et al., 2020)

Toxic Release Inventory (TRI)

This layer of data is collected from Toxic Release Inventory (TRI) website. Proximity to TRI facilities was operationalized using multi-ring buffers (100 m, 250 m, 500 m, 1000 m) to

represent distance-decay in potential exposure and to support sensitivity across near-to-local spatial scales. Similar proximity buffer approaches have been used in TRI-based environmental equity analyses (e.g., ~500-yard and ~1000-yard buffers) and in broader proximity-to-hazard studies, where multiple buffer distances are common and often fall between ~250 m and 1000 m. The resulting distance bands were converted to an ordinal hazard proximity score (HazScore), with higher values indicating greater separation from TRI facilities." (Baden et al., 2007; Brender et al., 2011; Zhou et al., 2025)

Soil

Soil Survey Geographic Database (SSURGO) soil order was converted to a 0–5 SoilScore representing native-soil suitability for in-ground cultivation. Higher scores were assigned to Mollisols and Alfisols due to their generally higher organic matter/base status and native fertility, moderate scores to Inceptisols, and lower scores to Entisols and Vertisols due to limited development or management constraints; water/no-soil areas were excluded. SoilScore was applied as a strict feasibility threshold for in-ground gardens, consistent with urban agriculture suitability studies that use biophysical criteria to represent cultivation feasibility. For raised-bed gardens, soil requirements were relaxed because raised beds with imported soil and barriers are widely adopted mitigation practices in urban gardening. SoilScore was not applied to farmers markets or building-based systems (vertical/hydroponics) because markets are not cultivation-dependent and ZFarming/hydroponics are designed to operate without reliance on ground soil. (Bonanno et al., 2017; Kessler, 2013; Li, 2023; Scheffe et al., n.d.; Thomaier et al., 2015)

Slope

Digital Elevation Model (DEM) was downloaded from USGS Earth Explorer and slope was derived from the DEM as percent rise and reclassified into ordinal suitability classes,

consistent with land-suitability studies that operationalize slope using percent-based categories and penalize steeper terrain (Al-Ghorayeb et al., 2023; Preeti et al., 2022). A hydrologic siting study in explicitly reclassified slope percentage into flat (0–5 percent), mild (5–10 percent), moderate (10–15 percent), steep (15–30 percent), mountainous (>30 percent), and used that reclassified slope layer in a GIS suitability workflow (Preeti et al., 2022), Similar studies had been used to treat 0–5 percent as the highest suitability, followed by 5–10 percent , 10–15 percent , and then lower suitability as the slope increases for land suitability(Al-Ghorayeb et al., 2023). Many GIS-MCDA land-suitability studies followed the same approach: compute slope from a DEM, reclassify it into suitability classes, and combine it with other criteria in weighted overlay models. (Wubalem, 2023)

Building footprint

Building footprint spatial data collected from Wyandotte County Geospatial and the Kansas City, Missouri, Parcel Viewer. Land is already covered by the building footprints in dense urban areas, considering a great way to estimate the potential of urban agriculture for the remaining vacant lands (Saha & Eckelman, 2017). Research on mapping/identifying vacant land explicitly treats derelict structures/built-up fabric as flagging parcels that intersect building footprints as “not open land” (S. Xu & Ehlers, 2022).

Peer-reviewed literature on Zero-Acreage Farming (ZFarming) defines building-based agriculture as food production in/on buildings and explicitly emphasizes the "non-use of land/acreage,” which supports treating *building presence* as desirable for vertical/hydroponic options. (Thomaier et al., 2015). GIS-MCDA commonly standardizes different criteria onto a common scale for overlay/selection (Malczewski, 2006c).

Brownfield

Brownfield are coming from post-industrial usage of a piece of land, which is not viable for urban agriculture development, as it damages the soil's favorable structure for growing (Ahmad et al., 2018). The data had been collected from United States Environmental Protection Agency. It is considered as a constraint for some interventions. For in-ground edible gardens, using a strict constraint is supported because urban garden soils can contain contaminants (including lead), and exposure reduction strategies are recommended when contamination is possible. (Kessler, 2013). For raised-bed gardens, studies show that raised beds and clean soil are commonly used mitigation strategies to reduce exposure from contaminated soils. (Egendorf et al., 2018). Moreover, it's also defensible to not automatically exclude brownfields for non-soil-contact or redevelopment-oriented uses (like a superstore or indoor hydroponics), because brownfield planning research often evaluates brownfields as *candidate redevelopment sites* using decision-support/MCDA frameworks rather than treating them as automatic "no." (Hammond et al., 2023, 2024; Morio et al., 2013)

Zoning

KCMA, as a bi-state region, experiences planning and implementation conditions influenced by varying policy and zoning frameworks among jurisdictions shown in Table 3.7. Regulatory requirements differ between Kansas and Missouri, complicating the evaluation and comparison of intervention feasibility. The availability and consistency of regulatory information are constrained, especially when rules have undergone numerous changes over time. Consequently, certain intervention alternatives may be more easily implemented in one jurisdiction but encounter more stringent procedural or regulatory obstacles in another. The inconsistent policy environment adds a significant layer of uncertainty to the feasibility

evaluation, as the appropriateness of a specific intervention is affected by both local spatial conditions and variations in governance, zoning flexibility, and implementation requirements across jurisdictions. The information had been collected by reviewing the City of Kansas City, Missouri, and the City of Kansas City, Kansas (City of Kansas City, Missouri, 2025; Unified Government of Wyandotte County and Kansas City, Kansas, n.d.).

Table 3.7. Zoning regulations for different interventions.

Intervention	MO	KS
In-ground Garden	Allow/evaluate under urban agriculture or garden rules. KCMO's Chapter 88 explicitly lists Agriculture, Urban with Home Garden and Community Garden, so this should be coded from those use permissions by district. (City of Kansas City, Missouri, 2025).	Allow/evaluate under agricultural-use logic where clearly supported. The KCK code includes an agricultural use definition, so this is the most defensible Kansas-side anchor for in-ground growing (Unified Government of Wyandotte County and Kansas City, Kansas, n.d.).
Raised-bed Garden	Same as an in-ground garden. KCMO's urban agriculture framework is the relevant anchor; raised beds fit within that broader garden logic (City of Kansas City, Missouri, 2025).	Treat the same as garden/agricultural use unless a district table says otherwise. There is no separate raised-bed category in KCK, so this should follow the agricultural-use pathway rather than be treated as prohibited. (Unified Government of Wyandotte County and Kansas City, Kansas, n.d.).
Farmers Market	Use the retail/temporary sales pathway instead; KCMO's use tables include Food and Beverage Retail Sales, which is a better anchor for market-type activity than garden provisions (City of Kansas City, Missouri, 2025).	Explicitly recognized. KCK's code includes a Farmers' market definition, so this should be treated as its own intervention-specific use and coded from the applicable district or permit pathway (Unified Government of Wyandotte County and Kansas City, Kansas, n.d.).

Superstore (New)	It is only allowed where food retail is allowed, with added caution for large-format review. KCMO’s code includes Food and Beverage Retail Sales, and the 2025–2026 amendment created Large Format Uses standards, so large grocery/superstore should be cross-walked through both. (City of Kansas City, Missouri, 2025).	There is no separate “superstore” use term in the KCK, so use the commercial district framework remain unresolved. The ordinance does show commercial and industrial district structures and special-use content. (Unified Government of Wyandotte County and Kansas City, Kansas, n.d.).
Vertical Gardening (Building)	KCMO’s recent amendment adds a Green Roofs definition, but that is not the same as vertical gardening. (City of Kansas City, Missouri, 2025).	There is a lack of verification of “vertical gardening” as an explicit KCK use for Kansas City KS.
Hydroponics (Indoor)	There is no mention of “hydroponics” Zoning regulation documents (City of Kansas City, Missouri, 2025).	There is no mention of "hydroponics" in the Zoning regulation documents (Unified Government of Wyandotte County and Kansas City, Kansas, n.d.).

Table 3.8 presents the screening criteria used to guide the selection of urban food system intervention options based on physical site conditions, environmental constraints, and zoning feasibility. The table compares the minimum suitability requirements for six intervention types: in-ground gardens, raised-bed gardens, farmers markets, new superstores, vertical gardening, and indoor hydroponics. Each option is evaluated using parcel characteristics, building footprint conditions, flood risk, hazardous exposure, slope, soil suitability, brownfield status, and zoning compatibility. Together, these criteria provide a practical framework for identifying which intervention is most appropriate for a given site.

Table 3.8. Selection Criteria of Variables

Variable	In-ground Garden	Raised-bed Garden	Farmers Market	Superstore (New)	Vertical Gardening (Building)	Hydroponics (Indoor)
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Candidate feature	Vacant parcel	Vacant parcel	Vacant/event parcel	Large vacant parcel/asse mblage	Building footprint s	Building footprints
Parcel area (acres)	≥ 0.25	≥ 0.20	≥ 0.10 (<i>small</i>)	≥ 10	N/A	N/A
Building footprint condition	NoFootScore = 5	NoFootScore = 5	Optional	NoFootScore = 5	Building exists (Footprint area threshold below)	Building exists (Footprint area threshold below)
Building footprint size	N/A	N/A	N/A	N/A	$\geq 20,000$ sq ft (<i>recommended</i>)	$\geq 5,000$ sq ft (<i>small</i>)
FloodScore	≥ 4 (<i>0.2 percent + or best</i>)	≥ 3 (<i>levee+</i>)	≥ 3 (<i>levee+; 2 only if "conditional"</i>)	= 4 preferred (<i>or ≥ 4 if needed</i>)	≥ 3	≥ 3
HazScore (TRI distance)	= 5 (<i>>1000m</i>)	≥ 3 (<i>$\geq 500m$</i>)	≥ 2 (<i>$\geq 250m$</i>)	≥ 3 (<i>$\geq 500m$</i>)	≥ 2	≥ 2
SlopeScore	≥ 3 (<i>≤ 15 percent) (conservative: ≥ 4)</i>	≥ 4 (<i>≤ 10 percent)</i>	≥ 4 (<i>≤ 10 percent) (strict: =5)</i>	≥ 4 (<i>≤ 10 percent)</i>	Optional (<i>≥ 3</i>)	Optional (<i>≥ 3</i>)
SoilScore (SSURGO order)	≥ 4 (<i>Alfisols/ Mollisols</i>)	≥ 2 (<i>Entisols +; raised beds reduce dependence</i>)	Not used	Not used	Not used	Not used

Brownfield	BrownFlag = 0 (don't pick)	Allowed (BrownFlag can be 1; then "raised beds required")	Allowed (flag if BrownFlag = 1)	Allowed (flag if BrownFlag = 1)	Allowed (flag)	Allowed (flag)
Zoning feasibility	Permitted/Conditional (not prohibited)	Permitted/Conditional (not prohibited)	Permitted/Conditional (temporary/outdoor allowed)	Large retail permitted/conditional (not prohibited)	Allowed as building alteration / not prohibited	Allowed (often industrial/commercial) / not prohibited

3.3.3.2 Prioritization of intervention options

As shown in Table 3.9, feasibility flags are summarized to the block-group level (count of feasible sites within block group) to support the selection of Option 1 and Option 2 interventions for each High Need-High Gap area. The final output per block group is the selection of Option 1 (the highest-priority feasible intervention) and Option 2 (the next feasible intervention), based on preference ordering (e.g., superstore first, where feasible, then garden options, then markets, then building-based strategies). Land-based interventions require a minimum parcel size, open-land availability (no building footprints), acceptable flood risk, sufficient separation from TRI hazards, manageable slope, and, when relevant, favorable native soil order. Building-based interventions require adequate building footprints, acceptable flood risk, sufficient hazard separation, and zoning approval for indoor or building-integrated food production.

Table 3.9. Rules of selecting feasible Interventions

Step	Rule
Option 1	highest-priority feasible intervention for that BG. Superstore → In-ground Garden → Raised-bed Garden → Farmers Market → Vertical → Hydroponics
Option 2 Tie-breaker (if multiple feasible sites)	Next feasible intervention from the same list Choose the candidate with: best FloodScore, then best HazScore, then largest area (parcels) or largest footprint (buildings).
If no feasible	Mark as “No feasible site” and document why (floodway / hazard proximity / no land / no buildings).

This chapter presented the methodological framework used to analyze healthy food accessibility in the Kansas City Metropolitan Area and to identify feasible intervention opportunities in priority neighborhoods. The study combined GIS-based spatial analysis with multi-criteria decision-making techniques to move from identifying food access inequities to evaluating practical planning responses. The IFAEI was developed by combining mRFEI and R_FAI to capture both the retail food environment and food-related activity patterns, while a Neighborhood Vulnerability Index was constructed to represent relative community need across key social and built-environment dimensions. These two components were integrated through the Need-Gap framework to identify block groups where high vulnerability and low food access overlap. From this broader pattern, five case study areas were selected for detailed examinations to demonstrate how the framework can be applied in different local contexts. Overall, this methodology established a structured, place-based, and replicable foundation for the results and planning implications presented in the following chapter.

Chapter 4 - Results and Discussion

The chapter provides an inclusive result of food accessibility at neighborhood level, incorporating various analytical elements. It starts with the spatial analysis of mRFEI and R_FAI that measures the structural quality of the food environment and the intensity of retail food activity. These elements are combined to produce the Gap index, which indicates regions with poor access to food. Simultaneously, a multidimensional Vulnerability (Need) index is created based on a PCA-AHP framework on the socioeconomic, transportation, health, and housing dimensions. Need and Gap integration leads to a typology that determines the areas of priority, especially the High Need-High Gap neighborhoods, which gives a data-based basis of targeted planning interventions.

4.1 Spatial Patterns of Food Access Indicators in KCMA

The spatial distribution of food access indicators in the Kansas City Metropolitan Area shows that there is a certain geographical difference between the urban center and the suburban and rural locations. The mapped mRFEI values represent the proportion of healthy food retailers relative to the total number of healthy and less healthy food retailers within each CBG and its associated study area. Values range from 0 to 1, where higher values indicate a healthier relative retail-food environment. The light-yellow category (0.0000–0.1500) represents CBGs in which approximately 0 percent–15 percent of identified food retailers were classified as healthy. The green category (0.1501–0.2000) represents approximately 15 percent–20 percent healthy retailers, while the turquoise category (0.2001–0.2600) represents approximately 20 percent–26 percent. The dark-blue category (0.2601–1.0000) represents CBGs in which more than approximately 26 percent of food retailers were healthy, with possible values extending to 100 percent. Thus, lighter colors indicate a lower relative presence of healthy food retailers, whereas

dark colors indicate a higher relative presence. However, because the highest category covers a broad range, dark blue does not necessarily mean that all retailers in a CBG were healthy.

Figure 4.1. mRFEI

Modified Retail Food Environment Index (mRFEI) for KCMA

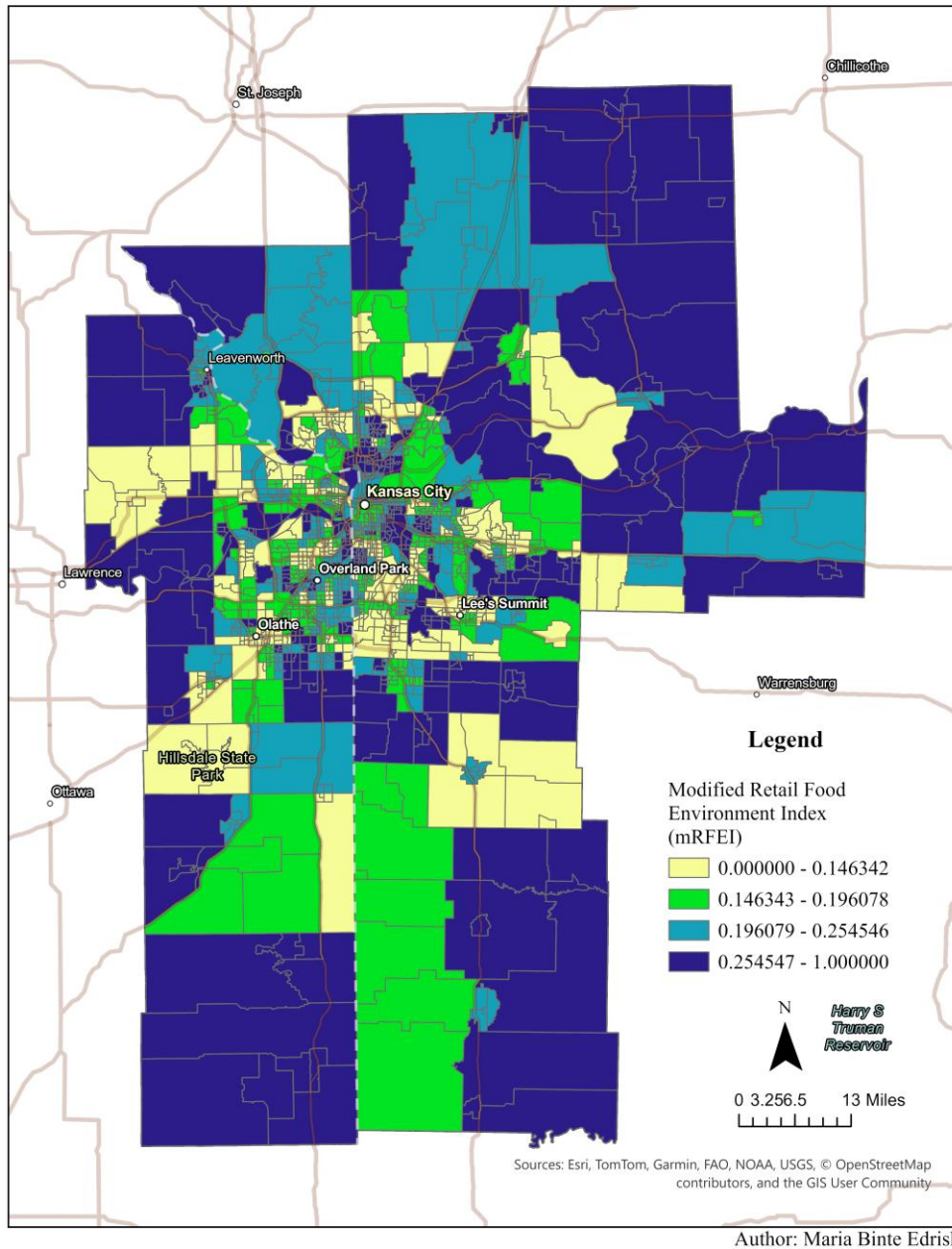


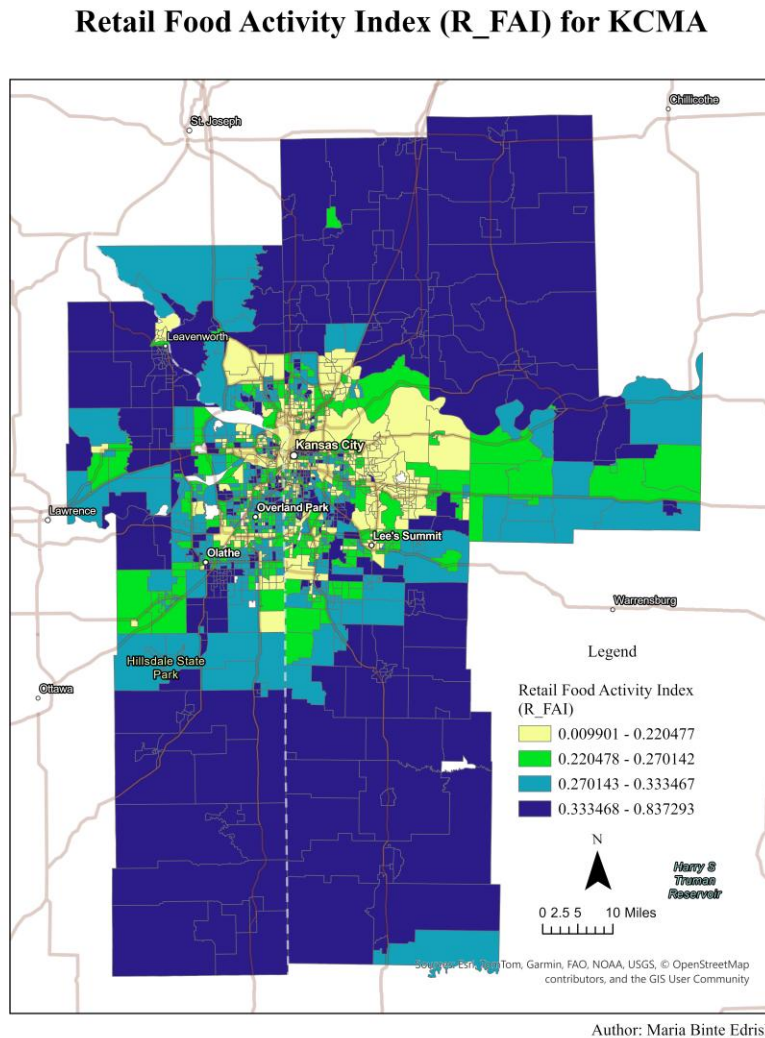
Figure 4.1 mRFEI shows that the high scores of retail food environment are concentrated in central areas of Kansas City, which extends to Overland Park, Olathe, and parts of Lee Summit, which have more healthy food stores. The peripheral regions, like the direction to Lawrence, St. Joseph, and south of Hillsdale State Park, on the other hand, have low mRFEI, and this is a sign that the retail food infrastructure is poor.

The R_FAI map represents the proportion of observed food-retailer visits made by residents of each CBG to healthy food outlets. Values ranged from approximately 0.01 to 0.84, indicating substantial variation in healthy food-retailer visitation across the study area. CBGs in the lowest category, with values from 0.009901 to 0.220477, recorded approximately 1 percent–22 percent of visits to healthy retailers. The second category, ranging from 0.220478 to 0.270142, represented approximately 22 percent–27 percent of visits, while the third category, from 0.270143 to 0.333467, represented approximately 27 percent–33 percent. CBGs in the highest category, ranging from 0.333468 to 0.837293, recorded more than approximately 33 percent and as much as 84 percent of observed visits to healthy food outlets. Higher R_FAI values therefore indicate a larger relative share of healthy-retailer visits, whereas lower values indicate that a greater proportion of visits were made to less healthy retailers. Because the index was assigned using visitors' inferred home CBGs, it captures food-retailer travel beyond the boundaries of residents' home neighborhoods.

In the map, light yellow areas have the lowest proportion of visits to healthy retailers, while dark blue areas have the highest proportion. However, a high R_FAI does not necessarily mean that a CBG contains many healthy food stores. Residents may travel outside their home CBG to visit healthy retailers, and those visits can still contribute to the R_FAI through the SafeGraph VISITOR_HOME_CBGS information. Similarly, a CBG may have healthy retailers

nearby but still receive a lower R_FAI if residents make a larger share of their observed visits to less healthy outlets.

Figure 4.2. R_FAI



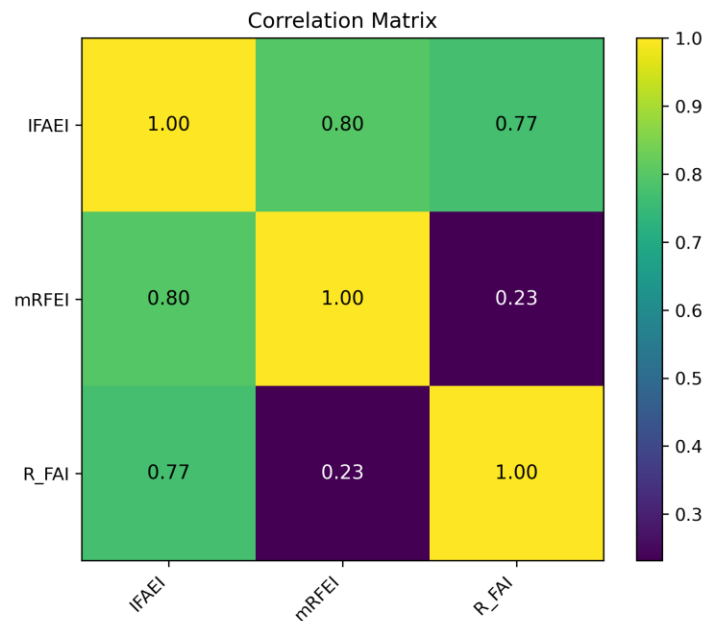
This tendency is a little less apparent for retail food activity, though more or less similar, as shown in Figure 4.2 (R_FAI). Higher retail activity is also highly concentrated in the central city, and particularly in the areas around central Kansas City and the suburban areas that surround Kansas City, since access to food resources is more mobility-based. However, a few of the fringes, like around Leavenworth, and the eastern side, which borders on Warrensburg, are

relatively low. This means that there could be geographic constraints there to access food, even though there are few retail stores.

4.2 Correlation Analysis of Food Access Indicators

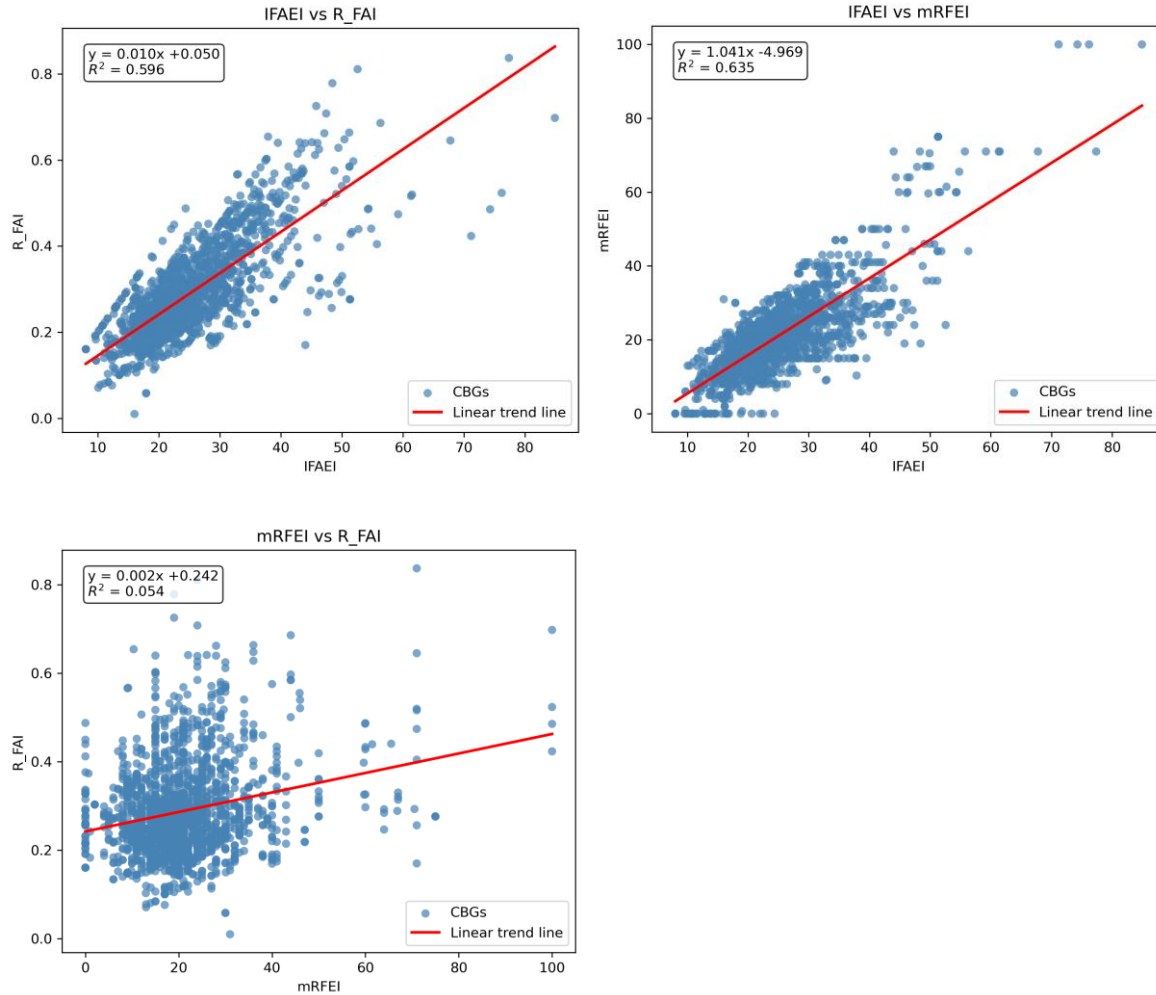
To examine the relationships among the constructed food access indicators, a correlation analysis was conducted between the IFAEI, mRFEI, and R_FAI.

Figure 4.3. Correlation Matrix of mRFEI, R_FAI and IFAEI for 2024



As illustrated in Figure 4.3 (Correlation Matrix), IFAEI demonstrates a strong positive correlation with both mRFEI ($r = 0.797$) and R_FAI ($r = 0.772$). These results indicate that the composite index effectively captures both the structural availability of food outlets and mobility-based access patterns.

Figure 4.4. Scatter Plot of R_FAI, IFAEI and mRFEI Scores at the Block Group Level in the KCMA

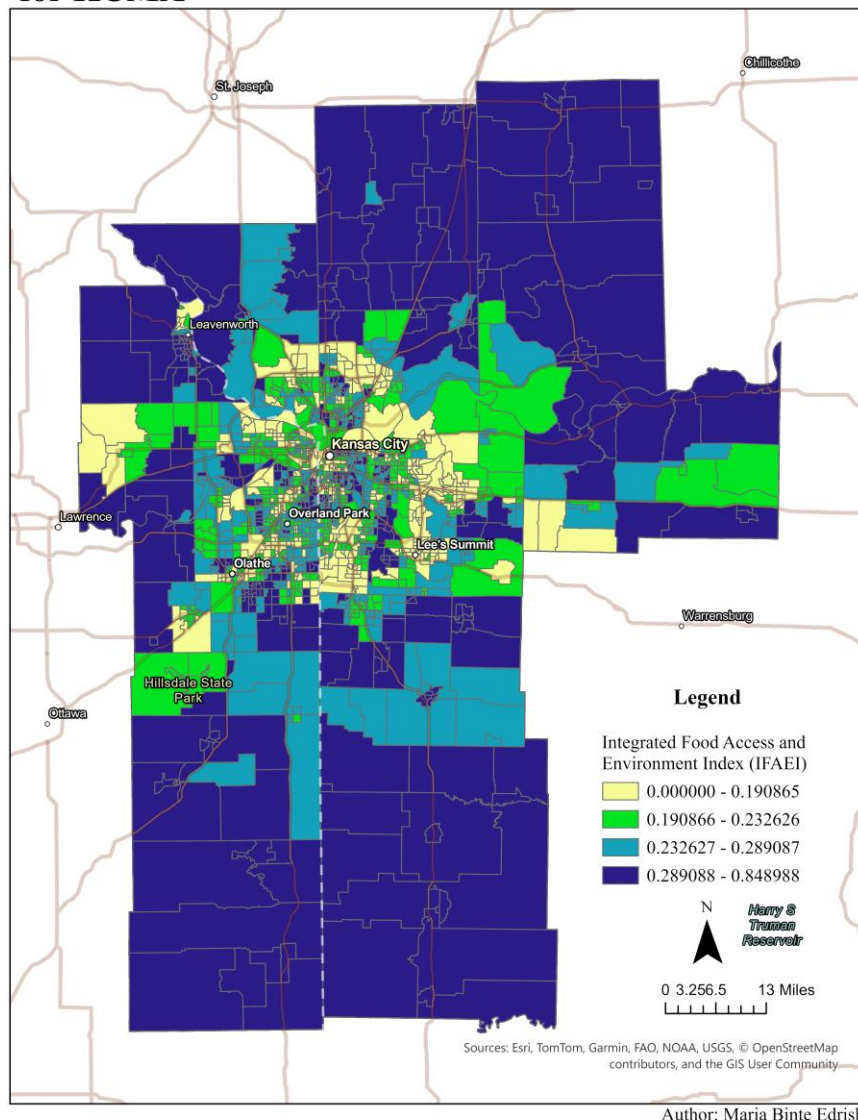


The scatterplots in Figure 4.4 further support these relationships, showing clear positive trends between IFAEI and each component index. The correlation analysis showed that IFAEI was strongly and positively correlated with both mRFEI ($r = 0.80$) and R_FAI ($r = 0.77$). In contrast, the relationship between mRFEI and R_FAI was weak ($r = 0.23$). These findings indicate that although both measures are strongly associated with the combined IFAEI, they capture relatively distinct dimensions of the food environment. The strong correlations between IFAEI and its component measures are expected because both mRFEI and R_FAI are incorporated into the construction of the index. These findings validate the conceptual framework of this study, where IFAEI integrates complementary dimensions of food

accessibility. By incorporating both availability and activity-based measures, the index provides a more comprehensive representation of food access conditions. This has important planning implications, indicating that effective interventions must consider not only the spatial distribution of food outlets but also the mobility and behavioral constraints influencing access.

Figure 4.5. IFAEI

Integrated Food Access and Environment Index (IFAEI) for KCMA



The integrated index shown in Figure 4.5 combines these dimensions and highlights a more complex pattern of food accessibility. While central urban areas generally demonstrate higher composite access, pockets of lower accessibility emerge even within the metropolitan core, suggesting localized disparities. Additionally, outer suburban and rural areas consistently display lower food accessibility, reinforcing the presence of structural and mobility-related barriers to food access. Notably, areas such as Leavenworth and parts of eastern Jackson County exhibit moderate retail presence but relatively lower activity levels, suggesting that the existence of food outlets does not necessarily translate into effective access. This reinforces the need to integrate both availability and behavioral dimensions in food access assessment. The results reveal a clear urban–peripheral gradient in food access, where accessibility declines with increasing distance from the metropolitan core.

These findings indicate that food access in the KCMA is not solely determined by retail availability but is also shaped by spatial interaction patterns and mobility constraints, underscoring the importance of a multidimensional assessment framework. The observed mismatch between mRFEI and R_FAI in several areas highlights the limitation of relying solely on static retail measures, as they may fail to capture actual accessibility experienced by residents.

4.3 Influence of Weighting on Vulnerability Representation

To assess the robustness and methodological sensitivity of the vulnerability framework, this study employed both equal-weight and AHP-weighted approaches. The equal-weight index was developed as a baseline representation in which all variables contribute uniformly to the overall vulnerability score. This approach is widely used in composite index construction due to its transparency and simplicity, particularly in the absence of clear justification for differential

weighting. However, such an assumption may not adequately reflect the uneven influence of socioeconomic, transportation, and health-related factors on food accessibility.

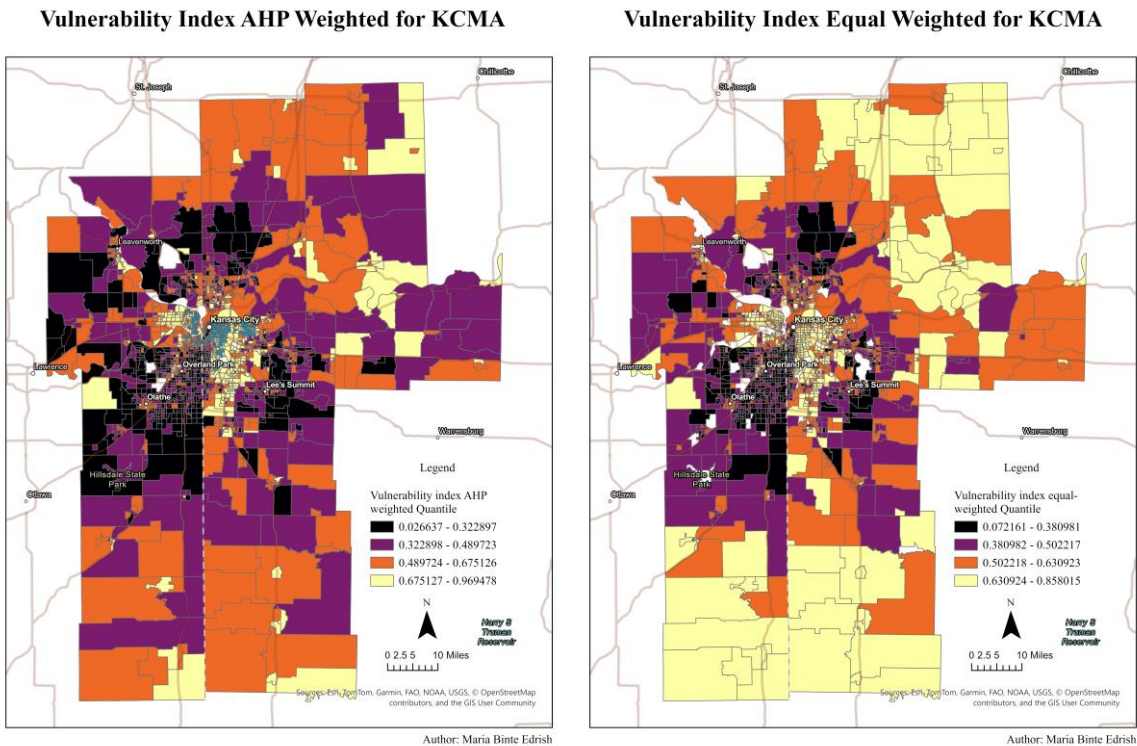
In contrast, the AHP-weighted index incorporates structured pairwise comparisons to assign relative importance to variables, allowing the model to better represent context-specific priorities (Saaty, 1980). The comparison between these two approaches was undertaken to evaluate whether weighting decisions influence the spatial representation of vulnerability and the identification of priority areas. Previous studies have emphasized that weighting schemes can significantly affect composite index outcomes and policy interpretations (Greene et al., 2011; Malczewski, 2006a).

The results indicate that while both approaches produce broadly consistent spatial structures, the AHP-weighted index introduces notable shifts in the intensity and concentration of vulnerability. These differences suggest that certain dimensions exert a stronger influence on food access conditions than others, and that equal weighting may obscure such effects. By explicitly accounting for the relative importance of variables, the AHP-based approach enhances the analytical sensitivity of the model.

4.3.1 Vulnerability Index Analysis and Weighting Comparison

This section examines the spatial distribution and methodological implications of two alternative approaches to vulnerability index construction: an equal-weight vulnerability index and an AHP-weighted vulnerability index. The purpose of this comparison is to assess how weighting assumptions shape the representation of neighborhood vulnerability across the Kansas City Metropolitan Area and, by extension, influence the identification of priority areas for intervention.

Figure 4.6. Vulnerability index/ Need equal weighting and AHP weighted for KCMA



4.3.1.1 Equal-Weight Vulnerability Index

The equal-weight vulnerability index is presented in Figure 4.6, where all contributing variables are assumed to have identical influence on the overall vulnerability score. The resulting pattern reveals a comparatively balanced spatial distribution of vulnerability across the study area, with higher-vulnerability clusters concentrated primarily in the urban core and in selected peripheral locations. As a baseline approach, the equal-weight index is analytically useful because it offers a transparent and easily interpretable representation of vulnerability without imposing differential importance across variables. However, this same simplicity may also limit its sensitivity, as it assumes that all dimensions contribute uniformly to neighborhood disadvantage. In doing so, it may attenuate the influence of variables that are more strongly associated with food access vulnerability in practice.

4.3.1.2 AHP-Weighted Vulnerability Index

The AHP-weighted vulnerability index, shown in Figure 4.6, incorporates variable importance through pairwise comparisons (done by urban food system experts) and consistency-tested weighting. While the overall spatial structure remains broadly comparable to that of the equal-weight index, the AHP-weighted surface reveals more pronounced concentration and differentiation in high-vulnerability areas. Neighborhoods characterized by overlapping socioeconomic disadvantages and transportation-related constraints appear more distinctly emphasized. This pattern indicates that the AHP approach enhances the sensitivity of the index by allowing dimensions with greater contextual importance to exert stronger influence on the final vulnerability score.

4.3.2 Thematic Drivers of Vulnerability

To better understand the underlying structure of the vulnerability index, individual thematic components were examined, including socioeconomic (SocIndex), transportation (TrnIndex), health (HltIndex), and housing (HouIndex) dimensions. Each of these indices captures a distinct aspect of vulnerability and contributes differently to the overall spatial pattern observed in the composite index.

The spatial distribution of these thematic indices reveals notable variation across the Kansas City Metropolitan Area. Socioeconomic and transportation vulnerabilities tend to be more concentrated within the urban core, particularly in areas surrounding central Kansas City and extending toward adjacent neighborhoods. In contrast, housing and health-related vulnerabilities exhibit a more dispersed pattern, with pockets of elevated vulnerability appearing in both inner suburban and peripheral areas.

These differences indicate that vulnerability is not driven uniformly by all factors, but rather by the uneven influence of specific dimensions across space. This observation provides important justification for the use of a weighted approach in index construction, as equal weighting may obscure the dominant role of certain variables. By incorporating differential importance through the AHP method, the analysis is better able to capture the multidimensional and context-specific nature of vulnerability. Detailed maps of the thematic indices are provided in Appendix A.

4.3.3 Comparison and Justification of Weighting Approach

Taken together, the two indices demonstrate that weighting is not merely a technical adjustment, but a substantive methodological choice that affects how vulnerability is represented and interpreted. Although both approaches identify broadly similar areas of concern, the spatial allocation and relative intensity of vulnerability differ in meaningful ways. The equal-weight index provides a neutral reference framework, whereas the AHP-weighted index offers a more differentiated and context-responsive representation of neighborhood conditions as considered by local experts.

The stronger clustering observed in the AHP-weighted index suggests that vulnerability is not uniformly driven by all factors but is instead shaped by the uneven influence of specific dimensions. This distinction is important for planning analysis, as it affects which neighborhoods emerge as priority areas under the Need-Gap framework. In this regard, the AHP-weighted vulnerability index is also further explained and utilized on subsequent analysis and prioritization of intervention, as it offers a more analytically suitable and decision-relevant level of multidimensional food access vulnerability. Therefore, the inclusion of both methods is not redundant but essential for validating the framework and demonstrating the impact of weighting

assumptions. The AHP-weighted vulnerability index is ultimately adopted for subsequent analysis, as it provides a more decision-relevant representation of vulnerability.

Having further analyzed the tendencies of spatial variation, one will find that there are various interesting place-based variations in the equal-weight and the AHP-weighted index of vulnerability. In both maps, the Kansas City center is unsafe, especially towards the south, to Overland Park and Olathe, and a portion of it to the east and to the west of Lee's Summit. Nevertheless, the AHP-weighted index demonstrates the higher and more continuous concentration of high-vulnerability regions in these urban and inner-suburban areas, which proves the fact of a higher sensitivity to combined socioeconomic and accessibility limitations.

In contrast, the equal-weight index presents a more fragmented pattern, with high-vulnerability areas dispersed across both urban and peripheral regions. For example, areas near Leavenworth and western portions of the study area exhibit moderate vulnerability under equal weighting but appear more distinctly classified under the AHP-weighted approach. Likewise, in the same sense, there are areas in the southern and southeastern areas, such as around Hillsdale State Park and Warrensburg, where the categorization is drifting; that is, the influence of certain elements of vulnerability is even more dramatic when it comes to weighting.

These spatial differences highlight that the AHP-weighted index more clearly delineates clusters of vulnerability within the metropolitan core, while also refining the classification of peripheral areas. This suggests that weighting enhances the ability of the index to capture localized variations in vulnerability, thereby improving its relevance for targeted planning and intervention strategies

4.3.4 Need-Gap

Local Spatial Association Between IFAEI and Neighborhood Vulnerability

Of the 1,819 CBGs included in the analysis, 982 block groups, or approximately 54.0 percent, were not statistically significant at the 0.05 level. The remaining 837 block groups exhibited a statistically significant local spatial association. Among these observations, 164 block groups were classified as High-High, 244 as Low-Low, 237 as Low-High, and 192 as High-Low shown in Table 4.1.

Table 4.1. Cluster-wise spatial association of CBGs

Local spatial-association category	Number of block groups	Percentage of all block groups
Not significant	982	54.0 percent
High-High	164	9.0 percent
Low-Low	244	13.4 percent
Low-High	237	13.0 percent
High-Low	192	10.6 percent
Total	1,819	100.0 percent

The Low-High category was considered the most policy-relevant spatial pattern because the direction of the two indices differs. Higher IFAEI values indicate better food-access conditions, whereas higher Vulnerability Index values indicate greater neighborhood need. Consequently, a Low-High cluster identifies a focal block group with an IFAEI value below the metropolitan mean of 0.2493 that is spatially associated with neighboring block groups exhibiting above-average vulnerability. The Low-High block groups had IFAEI values ranging from approximately 0.0556 to 0.2480, confirming that all were below the study-area mean.

Figure 4.7 presents the results of the bivariate Local Moran's I analysis between the 2024 IFAEI and the Vulnerability Index. The map distinguishes statistically significant High-High,

High-Low, Low-High, and Low-Low spatial associations from block groups where no statistically significant local association was identified.

The map shows that Low-High clusters were concentrated primarily in the central and more urbanized portions of the metropolitan area. Jackson County, Missouri, contained 150 of the 237 Low-High block groups, while Wyandotte County, Kansas, contained 74. Together, these two counties accounted for approximately 94.5 percent of all Low-High clusters. The remaining Low-High observations were located in Clay County (seven), Ray County (three), Cass County (two), and Lafayette County (one). This concentration indicates that below-average food-access conditions associated with surrounding vulnerability were particularly prominent within the urban core rather than being distributed evenly throughout the metropolitan area.

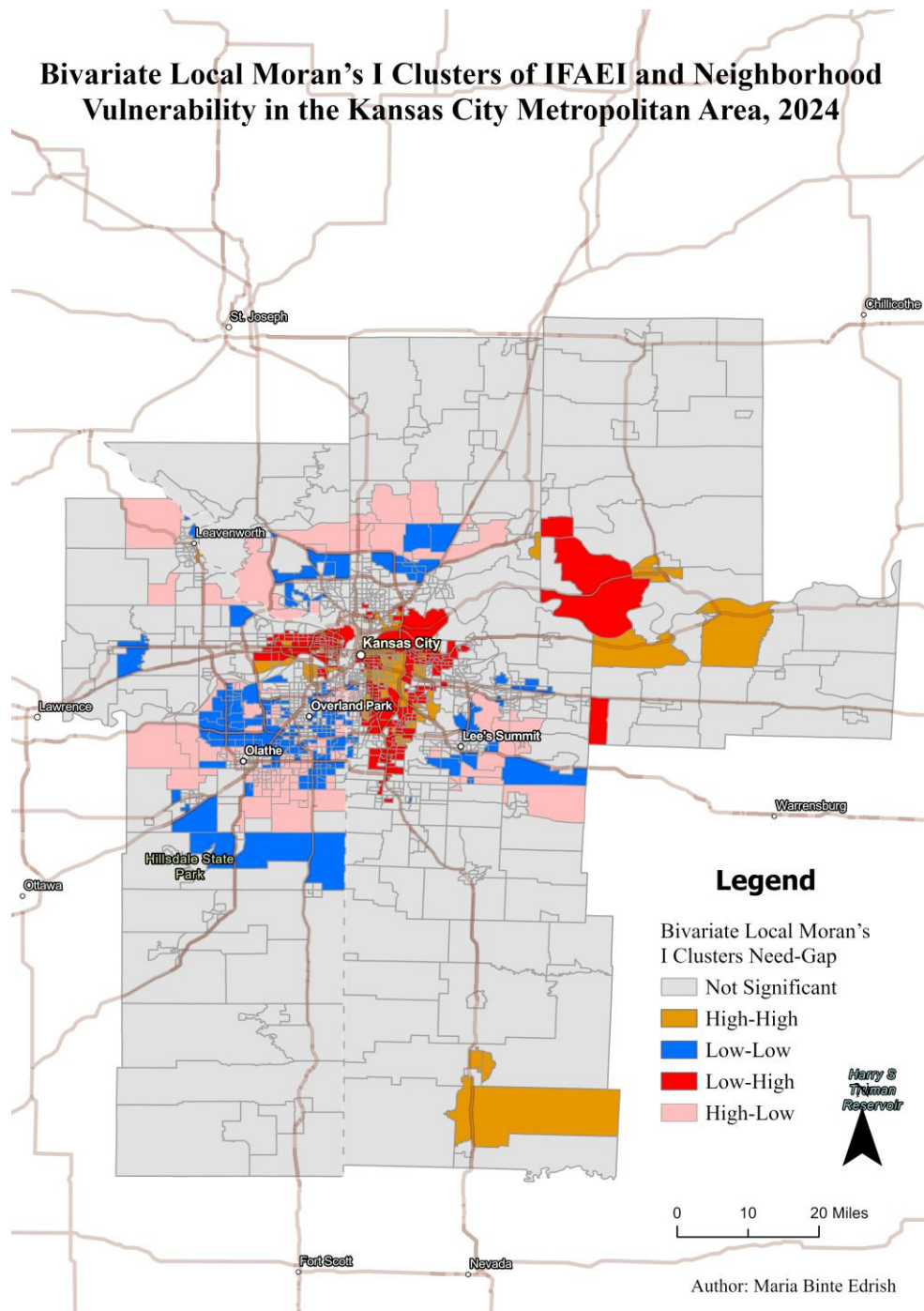
A supplementary comparison of the focal block groups' own vulnerability scores provided further support for the substantive interpretation of the Low-High pattern. Of the 237 Low-High block groups, 220, or approximately 92.8 percent, also had Vulnerability Index values above the metropolitan mean of 0.4950. Only 17 Low-High block groups had focal vulnerability scores at or below the study-area mean. Therefore, although the Local Moran's I definition is based on vulnerability in neighboring block groups, most of the identified Low-High block groups also exhibited above-average vulnerability within the focal geographic unit itself.

The High-High category, which included 164 block groups, should not be interpreted as the highest-priority condition. In the present analysis, High-High indicates above-average IFAEI in the focal block group and above-average vulnerability in neighboring block groups. These locations may contain vulnerable surrounding populations, but the focal block groups themselves have comparatively better food-access conditions. Similarly, the Low-Low category represents block groups with below-average IFAEI located near areas with below-

average vulnerability. Although these areas may experience limited food access, their surrounding socioeconomic context does not indicate the same level of vulnerability as the Low-High clusters.

Overall, the results demonstrate that food-access disadvantage and neighborhood vulnerability do not follow a uniform spatial pattern across the metropolitan area. More than half of the block groups exhibited no statistically significant local relationship, while significant Low-High associations were highly concentrated in Jackson and Wyandotte counties. The bivariate Local Moran's I analysis therefore provides a spatially explicit assessment of where poor food-access conditions coincide with broader concentrations of neighborhood vulnerability. These findings can support the subsequent AHP-MCDA analysis by identifying geographic areas that warrant closer examination, while the decision model can incorporate additional socioeconomic, demographic, and transportation criteria to determine final intervention priorities. The regions, like Overland Park, are more often classified by Low-priority categories, which indicate relatively more favorable socioeconomic, transportation, health and housing status, such as an increase in income and reduced general susceptibility. On the other hand, High Need-High Gap block groups are significantly concentrated in some of the neighborhoods within and around central Kansas City like Downtown Kansas City, the Crossroads, Forgotten Homes, 18 th and Vine, as well as Wendell Phillips, etc. The regions show the intersection of high social vulnerability and lack of access to food. It is also important to note that a lot of these neighborhoods are likewise grade D in terms of historical redlining, which further indicates that the current food access disparities are strongly linked to the historical trends of disinvestment and spatial injustice. Consequently, this means that these neighborhoods need closer attention to planning and specific intervention to combat the ongoing food access issues.

Figure 4.7. Bivariate Local Moran's I Cluster Map of the Integrated Food Access and Environment Index and Neighborhood Vulnerability in the KCMA, 2024



Source: Author's analysis using GeoDa and the 2024 IFAEI and Vulnerability Index datasets.

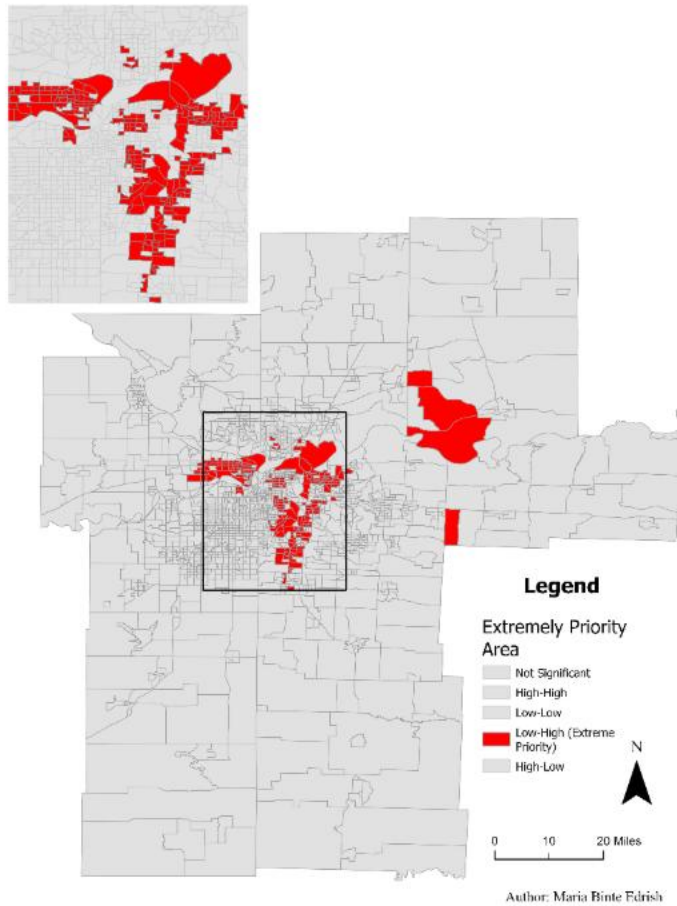
4.3.5 High Need-High Gap

This distinction is important when interpreting the map. Bivariate Local Moran's I do not automatically establish that a focal block group has both low IFAEI and high vulnerability. The Low-High classification technically means that a block group with low IFAEI is spatially associated with a high spatial lag of vulnerability. Nevertheless, the supplementary comparison demonstrates that most of the Low-High block groups also directly experienced above-average vulnerability. This consistency suggests that the identified clusters represent areas where food-access disadvantage is embedded within broader concentrations of socioeconomic and demographic need. The 237 Low-High block groups may therefore be described as spatially associated priority areas for additional investigation and intervention. A more conservative definition of extreme-priority areas could be applied to the subset of 220 block groups that met three conditions: below-average IFAEI, statistically significant Low-High spatial association, and an above-average focal Vulnerability Index. This distinction prevents all Low-High clusters from being interpreted as direct within-unit Need-Gap combinations while still recognizing the strong agreement between the local spatial results and the underlying vulnerability data.

Figure 4.8 presents the spatial distribution of High Need-High Gap areas, identified as statistically significant Low-High clusters in the bivariate Local Moran's I analysis.

Figure 4.8. High Need-High Gap (Extreme Priority Areas)

Extreme Priority Areas in the Kansas City Metropolitan Area



These census blocks are considered Extremely Priority Areas for future development. Overall, this chapter shows that food accessibility is not evenly distributed across the study area. By combining food environment measures with neighborhood vulnerability, the analysis identifies where access problems and social disadvantage overlap most strongly. These findings provide a clear basis for recognizing priority areas and supporting the next stage of the study.

Chapter 5 - Case studies

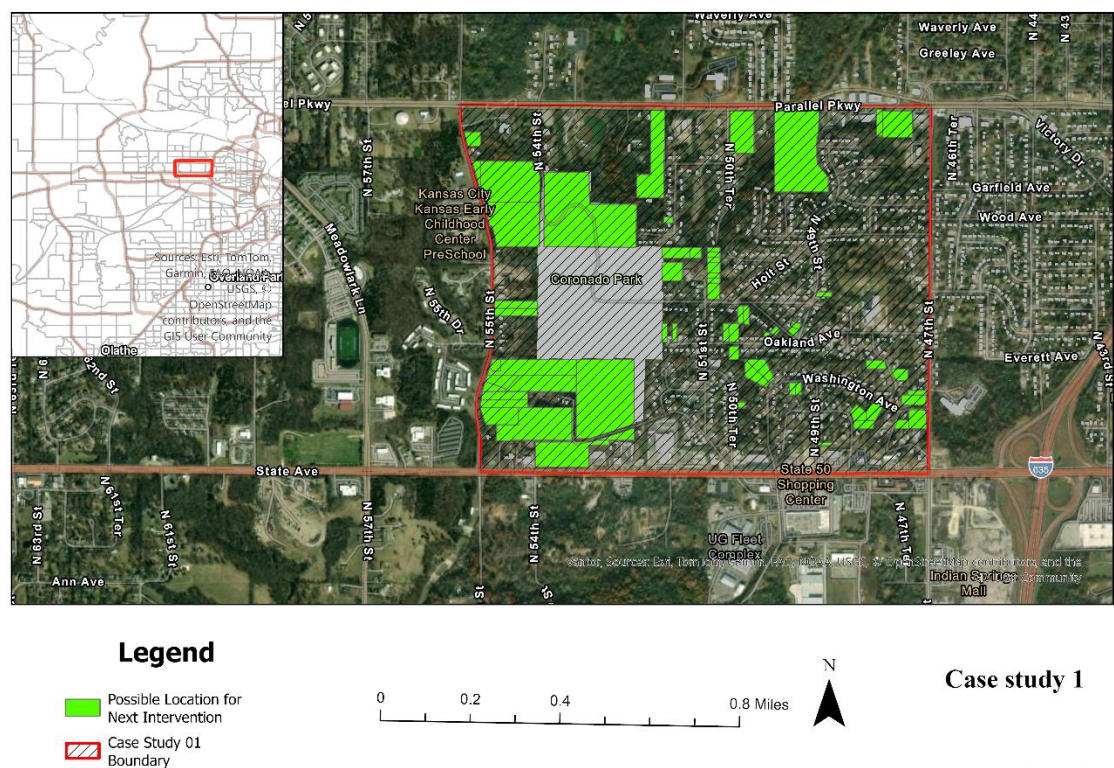
In chapter 5, five case studies based on the chosen areas of High Need - High Gap (Extreme Priority) are offered to discuss the viability of targeted urban food system interventions. The individual case studies assess the local site conditions, such as the availability of parcels, the environmental conditions, hazard exposure, building limitations, and feasibility of zoning, to identify the most suitable intervention options. Its results indicate that even in areas of priority there are appropriate solutions depending on local circumstances and space constraints. This chapter thus transcends general space identification by offering a more grounded site based knowledge of how food accessibility interventions could be tailored to neighborhood context in a realistic and practical manner.

Case Study 1

This case study is part of Coronado East neighborhood on Kansas side of city shown in Figure 5.1. Case Study 1 (GEOID: 202090439031) represents a highly significant target area for urban healthy food intervention because the average commute time is 22.63 minutes, reflecting a moderate time burden and the walkability index of 11.0 indicates low pedestrian accessibility, while also recording a low IFAEI score of 0.1812 (on a scale of 1), indicating a comparatively weak healthy food environment. In addition, the area shows a high composite vulnerability score (0.809), with particularly elevated social (0.843), health (0.902), and housing (0.805) vulnerability dimensions. Taken together, these values suggest that this is not simply an area with limited access to healthy food outlets, but also one in which residents are less able to compensate for those limitations because of broader structural disadvantages.

The analysis is based on single CBG which didn't consider any healthy stores outside of its boundary. Together, these theme-based indices highlight that food-access challenges in this case are driven primarily by social and health vulnerability rather than complete transportation isolation. A key distinguishing characteristic of this block group is the absence of any major health-food retail outlet, which exacerbates the severity of the food-access gap.

Figure 5.1. Case study 01 location



Potential Urban Healthy Food Intervention Options

Option 1: In-ground Garden

One feasible intervention for Case Study 1 is the establishment of a community garden or raised-bed gardening system on suitable vacant parcels within the block group. Given the high food-access gap and elevated vulnerability levels, community-based food production could

provide residents with direct access to fresh produce within their neighborhood. There is no strict or particular zoning code in Kansas City for in ground community garden and this option considered efficient (Unified Government of Wyandotte County and Kansas City, Kansas, n.d.). In ground garden can represent a relatively low-cost and quickly implementable intervention. Beyond improving food access, community gardens may also support community engagement, nutritional education, and neighborhood cohesion. In high-need areas such as Case Study 1, these benefits can contribute to both improvements in food access and broader social resilience.

Option 2: Farmers Market

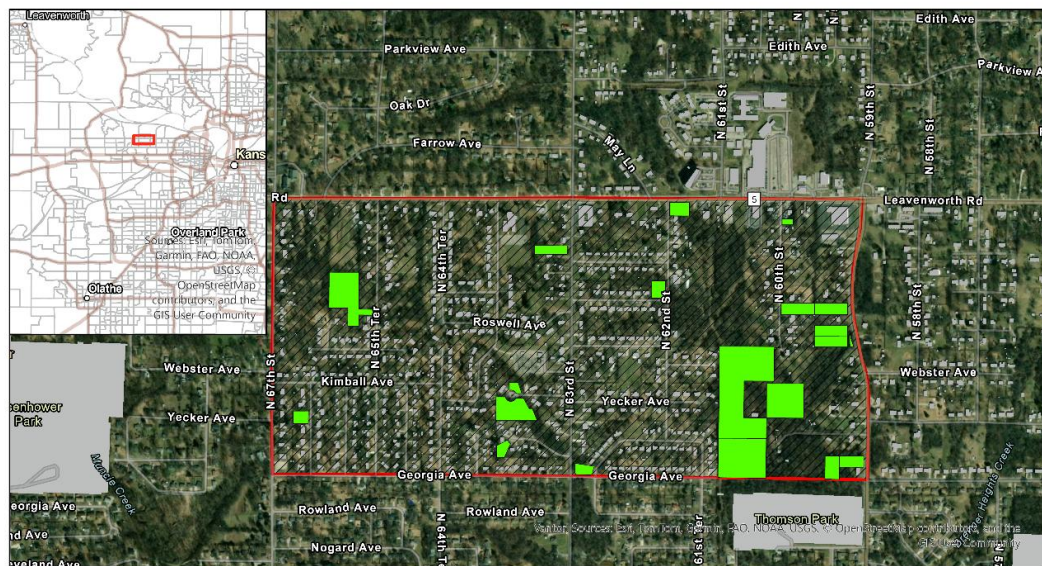
A second intervention option involves establishing a farmers' market or mobile fresh food market within accessible locations of the block group. This strategy can introduce fresh produce and healthy food options without requiring large-scale retail development. Farmers' markets can operate periodically on vacant parcels, parking lots, or civic spaces, allowing flexibility in site selection. The effectiveness of this intervention could be enhanced by its proximity to the 101 State Avenue bus route, which connects the neighborhood to downtown areas and regional destinations. Locating markets near transit stops or park-and-ride facilities could improve accessibility for both residents and vendors. Because farmers' markets require relatively limited infrastructure, they can serve as a practical short- to medium-term intervention that directly addresses food-access gaps while supporting regional food producers.

Case study 2

This case study is part of the Bethel neighborhood shown in Figure 5.2, the Kansas side of the city, right along with Leavenworth Road. Case Study 2 (GEOID: 202090443022) represents a critical intervention area characterized by a severely constrained healthy food environment combined with elevated multidimensional vulnerability. The block group records a

low IFAEI score of 0.1591 (on a scale of 1), placing it in the High Gap category while also falling into the High Need classification. This indicates a compounded condition in which food-access limitations intersect with broader structural disadvantages. The composite Vulnerability Index (0.811) reveals how these pressures are distributed across thematic dimensions. The Social Index (0.890) suggests significant socioeconomic stress, while the Health Index (0.850) reflects heightened exposure to health-related vulnerabilities. The Housing Index (0.652) indicates moderate housing-related challenges due to middle income housing with schools, and the Transportation Index (0.530) suggests that mobility constraints are present but not the dominant limiting factor. The average commute time is 21.25 minutes, reflecting a moderate time burden. The walkability index of 8.08 indicates low pedestrian accessibility. Despite adequate vehicle access, the combination of high poverty and low walkability suggests that residents may still face challenges in accessing nearby healthy food options. Unlike areas where limited access can be partially offset by nearby stores, this case reflects a structural absence of retail food infrastructure, making it a strong candidate for a retail-scale intervention.

Figure 5.2. Case study 02 location



Legend

- Case Study 02 Boundary
- Possible location for next intervention

0 0.13 0.25 0.5 Miles



Case study 2

Author: Maria Binte Edrish

Potential Urban Healthy Food Intervention Options

Option 1: Superstore (Primary Recommendation)

Given the absence of any major healthy food retail outlet within the block group, the development of a superstore or full-service grocery store is identified as the strongest primary intervention for Case Study 2. The block group itself contains approximately 1,555 residents, and nearby CBGs add a broader population base that could support a larger retail facility. This makes the case for a superstore stronger than in areas where demand would depend only on the immediate neighborhood. The block group lies along the Leavenworth Road corridor, which is served by Route 106 - Quindaro–Leavenworth, including the stop at Leavenworth Rd at N 67th St (Westbound). This corridor-based transit access improves the feasibility of a centralized food retail destination because it allows both local residents and nearby populations to reach the site without depending entirely on private vehicles. At the same time, the need for a superstore

remains strong because transit access alone does not substitute for the lack of proximate healthy food retail. Rather, the Route 106 corridor increases the practicality of a retail-scale intervention by improving potential customer access and reinforcing the site's role as a neighborhood and corridor-serving food node.

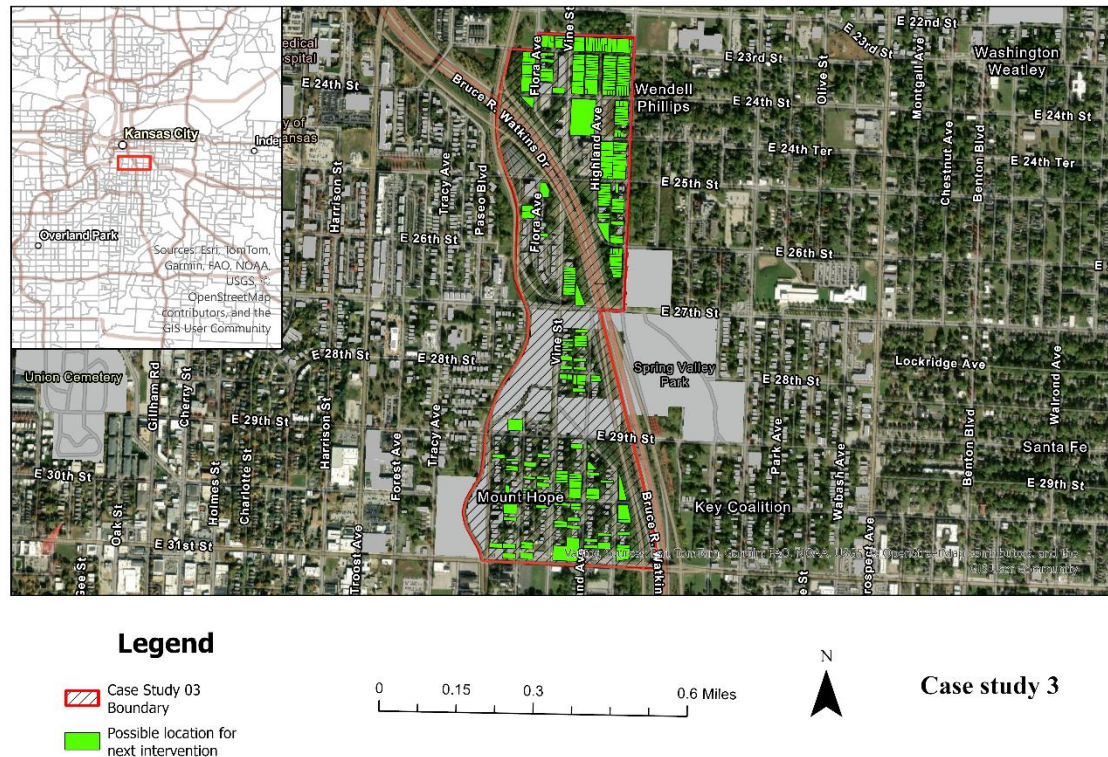
Option 2: Community Garden or Farmers Market (Secondary Strategy)

A second intervention pathway involves the establishment of a community garden or farmers market as a more localized and flexible food-access strategy. These interventions may be especially useful if retail-scale development is delayed, financially constrained, or phased over time. Community gardens can provide direct neighborhood-level food production, while farmers markets can introduce fresh produce through recurring, small-scale distribution. Both are well suited to vacant or underused parcels and can begin improving food access more quickly than permanent retail construction. The transportation setting also supports this option, though in a different way than for the superstore. Because the block group is located along Route 106 Leavenworth Road corridor, a farmers market placed near a bus stop or along a visible corridor location could benefit from better pedestrian and transit exposure. This could improve access for residents traveling within the corridor and make periodic market activity easier to reach for nearby households. However, the same transportation logic also reveals the limitations of this option. While corridor transit can help residents reach a market or garden site, these interventions do not provide the scale, product range, or consistency of a full-service grocery store. For that reason, community gardens and farmers markets are best understood here as supportive or interim interventions, rather than complete substitutes for the retail food gap identified in the analysis.

Case Study 3

This case study is part of Mount Hope and Wendell Phillips neighborhood shown in Figure 5.3. The neighborhood is unique because there are lots of spaces occupied by a couple of churches and a famous park named Troost Lake Park. These characteristics made this CBG more viable for the open spaces, but it is not permissible to use for community gardening. This case study is also from the Missouri side of city. The index values for GEOID 290950162002 show that the area has a very poor healthy food environment (IFAEI = 0.1783 on a scale of 1), and a very high composite vulnerability (0.861). The social (0.977), housing (0.965), and health (0.862) burdens are the main things that make people vulnerable. Transportation vulnerability is much lower (0.041). The poverty rate of 64.10 percent indicating severe economic distress, the median family income of \$12,236, and the fact that 30.40 percent of families don't have a car are further signs that inhabitants have a lot of structural hurdles to getting food. Parcel feasibility findings indicate that raised-bed gardening is endorsed, however in-ground gardening, and supermarket development are not highlighted. Because of this, farmers market is the best main intervention. Raised-bed community gardening is a second alternative that may work with limited land-based options to make food production more efficient.

Figure 5.3. Case study 03 location



Unlike Case Study 2, this block group does not present strong conditions for large-scale retail development. Instead, the spatial structure suggests a more fragmented or land-constrained environment, where parcel sizes, land availability, or built form may limit the feasibility of a superstore-type intervention. The presence of smaller parcels, potential environmental constraints, or competing land uses shifts the planning focus toward distributed, community-based food strategies. At the same time, the area may still contain select vacant or underutilized parcels and existing building footprints that can support alternative food-access interventions. These conditions make it suitable for incremental and site-adaptive approaches, rather than a single large-scale investment.

Option 1: Farmers Market or Mobile Fresh Food Market (Primary Recommendation)

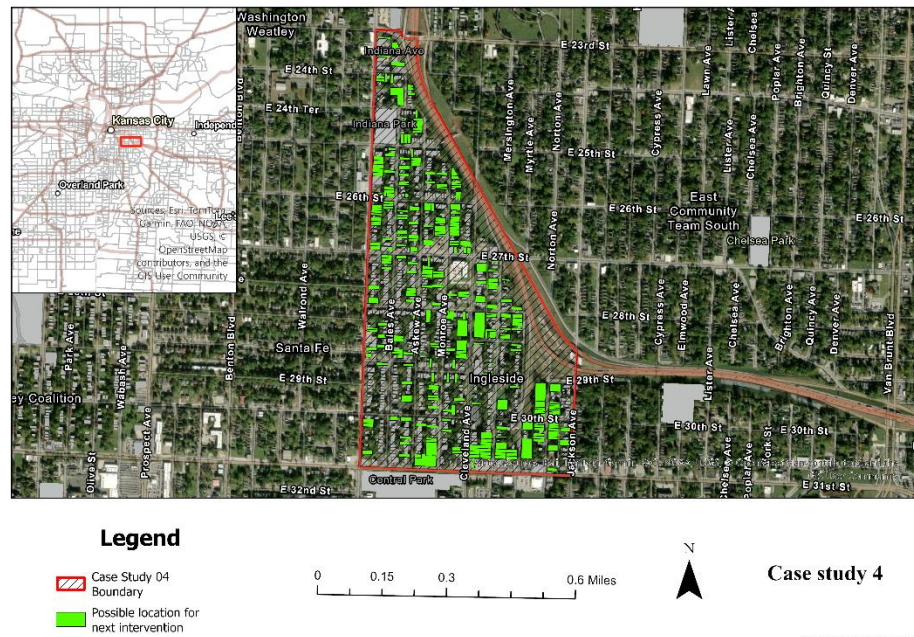
The most appropriate primary intervention for Case Study 3 is the establishment of a farmers' market or mobile fresh food market within accessible locations of the block group. This recommendation is justified by the presence of an existing large urban agriculture asset, Ophelia's Blue Vine Farm, which demonstrates that food production already occurs within the neighborhood, only for herbs and spices, yet the block group continues to exhibit a high food-access gap for absence of fresh foods. Despite having a farm with limited growing options, I need to reconsider the options of increasing capacity. This suggests that the major challenge is not simply the absence of local production, but the limited distribution, scale, and accessibility of fresh food within the broader community. A farmers' market would directly address this issue by functioning as a distribution-oriented intervention that increases the availability and variety of healthy food options. Option 2: Raised-Bed Community Garden (Secondary Strategy)

A secondary intervention option is the development of raised-bed community gardening systems on smaller suitable parcels within the block group. This strategy remains relevant because raised beds are adaptable to areas where soil quality is poor or where contamination concerns restrict in-ground cultivation. In the context of Case Study 3, raised-bed gardens would be most appropriate as a complementary intervention that expands community participation, educational opportunities, and small-scale supplemental food production. However, given the presence of Ophelia's Blue Vine Farm, additional raised-bed gardens should not be viewed as the primary solution to the neighborhood's food-access challenges. Rather, they would function best as supporting assets that reinforce local food resilience while the primary emphasis remains on improving food distribution and access at the neighborhood scale.

Case Study 4

Case Study 4 (GEOID: 290950165002) exemplifies a community where terrestrial food production is identified as the most viable and suitable intervention strategy based on the Need-Gap research outcome. This case study is from Ingleside neighborhood in the Missouri Side of the city which is right beside US 70 shown in Figure 5.4. There is nearby community service operated by Outreach Ministries and a couple of grocery stores outside the CBG. Still, this is considered as a priority for High Need-High Gap areas. The block group has a poor IFAEI score of 0.1927 (on a scale of 1), which puts it in the High Gap category. It is also in the High Need category. The total Vulnerability Index is 0.786, which shows that this region is quite burdened, even if it is not the most severe situation among the case studies chosen. The theme scores make the pattern of need further clearer: the Social Index is 0.910, the Transportation Index is 0.093, the Health Index is 0.711, and the Housing Index is 0.950. The poverty rate is relatively lower at 13.78 percent, but 16.73 percent of households lack access to a vehicle, indicating moderate transportation constraints. The average commute time is higher at 20.59 minutes, suggesting increased travel burden. They also show that the block group is a good place for a targeted intervention focused on community-based food production.

Figure 5.4. Case study 04 location



Potential Urban Healthy Food Intervention Options

Option 1: In-Ground Community Garden (Primary Recommendation)

The best primary intervention that should be implemented to Case Study 4 is the creation of an in-ground community garden, which is supported by the parcel-level feasibility outcomes that suggest the application of direct cultivation. This method enables it to utilize the available soil resources and can sustain more food production as compared to other more restricted systems. The use of in-ground gardens is especially effective in areas that are favorable in terms of quality of soil, slope as well as environmental factors since they allow cost effective construction without the necessity of high levels of infrastructure. The feasibility outcomes in this instance indicate that these conditions exist and in-ground gardening is a viable and scalable solution. Planning wise, this intervention is seen to directly contribute to the food-access gap by offering fresh food produced locally, as well as contribute to community engagement, food

education, and social cohesion. These advantages in a high-needed context go beyond food access to encompass more community resilience and well-being.

Option 2: Raised-Bed Community Garden (Secondary Strategy)

In Case Study 4, the availability of in-ground and raised-bed feasibility indicates that a hybrid solution can be suitable, where a bigger in-ground plot is taken, and smaller raised-bed units are scattered over the neighborhood. Although raised-bed systems can have a few more upfront set-up costs than in-ground gardens, the systems improve flexibility and allow more people to participate because food production can take place on a broader spectrum of locations.

Case Study 5

Case Study 5 (GEOID: 290950096002) is part of Marlborough East neighborhood from the Kansas City, Missouri side shown in Figure 5.5. It is near the Blue River and the US 71 highway that crosses between the CBG. It is a high-priority location for intervention because it has a poor healthy food environment and a high level of multidimensional vulnerability. The block group has a poor IFAEI score of 0.1648 (on a scale of 1), which puts it in the High Gap (Q1) category and makes it a High Need (Q4) group. The Vulnerability Index is 0.793, which means that there are a lot of disadvantages. The Social Index is 0.921, the Health Index is 0.874, the Housing Index is 0.768, and the Transportation Index is 0.409. The poverty rate is 30.53 percent, and 16.84 percent of households do not have access to a vehicle, indicating notable transportation limitations. The average commute time is relatively low at 15.61 minutes, suggesting that distance may not be the primary constraint. The walkability index of 9.33 indicates limited pedestrian accessibility. This breakdown by theme makes it clearer what causes vulnerability. These numbers show that the block group's susceptibility is mostly caused by social and health pressures, with some housing-related problems as well. Transportation

Figure 5.5. Case study 05 location



Potential Urban Healthy Food Intervention Options

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The best first step for Case Study 5 is to build a superstore or full-service food store. This advice is because there are no healthy food stores in the block group, nearby healthy verified store is Price Chopper which is 2.8 miles away from farthest point of that CBG, and that zoning rules in City of Kansa, MO, make it easier for bigger developments to happen. There are no specific regulations for commercial development and so setting up a superstore would provide a large choice of healthy food goods, including fresh produce. This alternative is much more likely to work since there are M1-5 and M3-5 zoning districts that allow for the sort of land use intensity and spatial arrangement needed for supermarkets to run (City of Kansas City, Missouri, 2025). A superstore is a better and longer-term solution to the food-access gap in this scenario than smaller-scale solutions.

Option 2: Farmers Market (Second Strategy)

As a backup plan, a farmers' market might be set up to make it easier for people to get food right away, especially during the planning and construction stages of a bigger retail project. This method may provide fresh fruits and vegetables to the neighborhood with little infrastructure needs. It can be used in flexible locations like empty lots, parking lots, or communal spaces. Farmers' markets may also be a way to develop local demand and get people involved in the community around healthy food availability. These treatments may work in the short term, but they may not be able to satisfy the demands of a high-need, high-gap population in the long run. So, they are better off in addition to a bigger retail-based solution than as a replacement for it.

Overall, this chapter demonstrates that the priority areas do not need an equally strong response. The analysis using the five case studies illustrates the influence of local land, environmental and regulatory conditions in intervention choice. These results reinforce the

practical usefulness of the research by connecting spatial need to place-based real-world solutions to planning.

Chapter 6 - Conclusion

Based on the findings of the combined Need-Gap analysis and the place-based case study evaluation, this chapter examines how the research can be generalized for food accessibility planning and urban food system decision-making. It also identifies the opportunities of continuing the study by making sure that it can further benefit future planning initiatives and policy interventions. Methodological limitations and contextual constraints that can limit generalizing the results are also discussed.

6.1 Implications for Research and Planning Practice

6.1.1. Methodological Advancements

This study attempts to develop a complete framework of spatial analyses for the measurement of food accessibility. Conventional research on access to food usually involves single measures, such as the distance to grocery stores or measuring overall food environment through the mRFEI. However, these metrics might not fully reflect the complexities of local food contexts. This research shows that a combination of food environment indicators mRFEI, R_FAI, and measures of vulnerability provides a better understanding of food access patterns at the local level. The research applies these components in the IFAEI, which is a more sophisticated way of measuring the availability of healthy foods, travel behavior, and the social factors influencing access.

The research explores the use of the GIS-based MCDA as an option for assessing food access and determining spatially appropriate intervention options. The suitability analysis for urban agriculture, farmers' markets, and other food system initiatives is one example of using spatial modeling to help make informed planning decisions. The methodological approach

provides a strong foundation for the current literature on the use of spatial decision-support tools for food system planning.

6.1.2. Strategic Planning and Policy Considerations

The result of this study provides significant guidelines for urban planning practice. The spatial analysis shows that areas with higher socioeconomic vulnerability are often found in areas of reduced access to healthful food environments, highlighting possible disparities in the distribution of food accessibility in those environments.

These findings suggest that planners and policy makers should focus on addressing food security in places where high vulnerability overlaps with limited food access. Delineation of these priority locations can enable planning agencies to more efficiently allocate resources and initiatives towards improving equitable food accessibility.

Moreover, the suitability analysis presented in this study shows that different food system reforms may be applicable in different local contexts. Urban agricultural programs may be more viable in a location with appropriate land, soil, and topographical conditions, yet have accessible community spaces.

The results therefore support the need for food accessibility factors to be included in comprehensive land use planning, community development plans, and public health programs. Integrating food system planning into comprehensive planning process may give local governments the opportunity to systematically address food access gaps.

6.1.3. Implications for Food System Planning

This study emphasizes the significance of accounting for both physical food settings and social vulnerability in the conceptualization of food system solutions. Strategies centered

exclusively on retail distribution may neglect the social and economic obstacles affecting food accessibility.

Findings of this study illustrate how planners might pinpoint regions where enhancements in food accessibility will yield the most significant societal advantage by integrating environmental and socioeconomic data. Such analytical methods can facilitate investments in community food projects, urban agricultural programs, local food markets, and other tactics designed to enhance local food systems. In some cases, a legacy neighborhood might influence the decision of new retail shops opening or new investments of other types of business.

The framework established in this study facilitates a more participatory and data-driven planning methodology, wherein geographical evidence aids stakeholders in evaluating prospective intervention sites and assessing community need.

6.1.4. Implications for Spatial Data Science and Decision-Making Support

This study illustrates the role of GIS-based spatial decision-supporting tools for dealing with complex urban planning problems. The amalgamation of different geographical datasets, including food retail locations and the effect of the environment and socioeconomic metrics, illustrates how spatial analysis may help to make rational choices.

Such analytical methods can help planners move from descriptive mapping to predictive and scenario-based planning instruments where spatial models can be used for studying the likely effects of different types of intervention techniques.

This research shows potential in the delivery of spatial indices and suitability modelling in data-driven planning frameworks that incorporate not only environmental studies and social equity factors, but also food system planning goals.

6.2 Future Research Directions

This study sets a foundation for a multitude of future research possibilities towards the improvement of food accessibility planning in mid-sized metropolitan areas. An imperative direction is the enlargement of the existing framework in a spatio-temporal approach that analyses not only existing problems associated with food accessibility, but also the future patterns expected. Forecasting neighborhood-level conditions for years such as 2027 or 2028 would make it possible to identify areas in which existing High-Need, High-Gap situations will be likely to continue, increase in severity, or change in the metropolitan environment. This extension would move the framework from a static assessment framework to a planning tool for proactive planning to help in anticipatory decision-making. Consequently, future work may help planners and policy makers to intervene sooner rather than later, when inequities are further embedded.

A relevant strategy is to have a utilization of forward-looking access forecasts in the goal that policy implications and regulatory awareness could be facilitated. If the research can identify neighborhoods that stand to continue to be underrepresented within current settings of development and policy, it could provide sound evidence for working with local governments, metropolitan agencies, and lawmakers on a long-term system of food planning. This would be especially helpful in the mid-sized metropolitan areas, where issues of food access often rate lower on the policy agenda than they do in larger urban areas. Subsequent research might explore how anticipated Need-Gap conditions might be translated into advance planning strategies, financing priorities, and policy responses without losing the integrity of the theoretical framework established in this study.

One promising way forward would be to put more emphasis on mobility and travel behavior in the analysis of food accessibility. This study acknowledges the role of food access in relation to the ability of households to access healthy food locations; however, future research may be able to improve on this aspect by taking into consideration more direct measures of accessibility and movement. This research could help to better understand the impact of the limitations of transportation, travel habits, and daily mobility patterns on actual access to food. This would lead to a more complete knowledge of the practical dynamics of accessibility of food and would also better respond to the actual experience of inhabitants with future planning suggestions.

Future research may be able to take the concept further by incorporating other characteristics of food accessibility poorly modeled with spatial and socioeconomic data alone. Subsequent research should examine how factors such as pricing, quality of food, cultural appropriateness, consumer desire, and store ability have an effect on the consequences of neighborhood food access. Integrating these characteristics would allow researchers to get closer to the authentic settings under which people make their choice regarding food and would help to distinguish between places that may appear spatially analogous to each other, but may function very differently in terms of their daily life.

A further possibility for a way forward is the integration of food accessibility planning in form-based planning and design methods. Form-based planning uses design regulations to promote pedestrian-oriented and walkable urban environments (Hansen, 2014). Integrating food accessibility is important because neighborhood planning must also consider the location and accessibility of food retailers (Eckert & Shetty, 2011). Moreover, form-based planning offers considerable potential to integrate food-access goals into the physical design of communities.

Future study of the integration of healthy food access issues, form-based codes, mixed-use area design, walkable retail environments, commercial market spaces, and community-oriented food supportive land use configurations is possible. This would help to facilitate the interface between food accessibility and the governmental and planning instruments that determine the development and transformation of neighborhoods over time.

Subsequent studies this research can also focus on place-based solutions. The current analysis shows how different high-priority neighborhoods may lead to different implementation scenarios depending on the local environment. Subsequent studies could consider a broader range of intervention strategies within communities, as well as the role of different combinations of land use, demographic characteristics, existing food facilities, and community constraints. This would improve the movement from conceptual identification to proactive planning and would add to the value of the framework when used in CBG-level decision-making.

In the end, future research would be improved by the increased collaboration with different stakeholders and community-based groups. This study has provided a theoretical framework to help identify the high-priority locations. It is imperative that further improvements include direct input from planners and public health officials, local groups, and community members to help validate the study findings and maximize intervention priorities. This, in turn, would contribute to the practical value of the model and ensure that planning solutions are supported both analytically and based on local knowledge and local institutional contexts.

6.3 Limitations of the Study

Several constraints must be recognized in the interpretation of the conclusions of this research. The research is mostly based on secondary sources of data collection, which implies that the analysis is affected by the quality, supply, classification, and temporal consistency of the

existing information. Demographic, socioeconomic, and food environment data may have reporting delays, measurement errors, or limitations in the definition that affect the accuracy of the results. The results should be regarded as a systematic and evidence-based representation of the state of food accessibility, not as a comprehensive evaluation of the living conditions in neighborhoods.

Another limitation of this study is related to the use of the integrated index and Need-Gap structure. This technique is effective to integrate in a cohesive analytical framework a variety of characteristics of disadvantage and access; nevertheless, it depends on methodological choices for variable selection, normalization, expert bias, and threshold determination. These are the decisions that are key to building the framework, but which may have an impact on the eventual identification of priority areas. Also, different indicator combinations may produce different results, particularly in communities defined by mixed or borderline circumstances.

An additional limitation of the study is the geographical unit of study. CBG, although useful in delineation of neighborhood-level disparities, are not a good representation of the actual geography of food-related diversions and consumption patterns. The analysis may also be affected by the Modifiable Areal Unit Problem (MAUP), whereby observed spatial patterns and identified priority areas may vary depending on the spatial scale and configuration of the geographic units used (Chen et al., 2022). Residents do not always obtain food within or adjacent to their neighborhood block group; they may, for example, visit surrounding cities because of convenience, transportation paths, employment sites, or regional purchasing habits, religious and cultural preferences, or food habits. The fact that R_FAI is calculated using safegraph data is one of the limitations since using the safegraph data to calculate R_FAI is not necessarily capturing the travel behavior of the people or their decision to travel further as there are some block that do

not even have the travel movement data due to the privacy concern. Safegraph is still using 2010 geographic boundary to record the travel behavior or number of trips happening from each CBGs. Residents of some areas of Leavenworth County may choose to shop in Lawrence rather than make the trip to the center of Kansas City, depending on proximity and accessibility. As a result, area-based research may not be a good representation of the actual spatial behavior of households, particularly in a multi-jurisdictional metropolitan area where cross-boundary food trips are common. There is a possibility to study regional travel behavior patterns to see the local food accessibility, and that might be a good source of local vs. global accessibility patterns.

Another limitation, graduate students represented 33.3 percent of the AHP participants, which could potentially introduce a greater academic or early-career perspective into the expert panel. However, a comparison of graduate-student and faculty/researcher weighting profiles found no statistically significant difference between the two groups. Nevertheless, the relatively small subgroup sizes limited the statistical power of this comparison, and the absence of statistical significance should not be interpreted as proof that the groups held identical perspectives. Future studies could include a larger and more professionally diverse expert panel.

A further weakness is that, although the study appreciates the importance of travel behavior and the state of mobility, it does not specifically measure all aspects of daily movement, route choice, trip chaining, or overall decision-making. Food accessibility is affected by geographical and economic necessity, but also by how a resident travels through transportation systems, time, and behavioral patterns. In the absence of direct behavioral data, the study cannot fully inform these dynamics, and thus, the results are a tremendous yet incomplete lens of understanding accessibility.

The bi-state nature of the Kansas City metropolitan region is also a constraint. This regional complexity adds to the value of this study; however, it also means that similar analytical process may not have the same planning outcome in different jurisdictions. Missouri and Kansas differ in their planning context, zoning laws, land use context, and implementation process. Thus, the same Need-Gap discovery can have different practical implications related to the local policy context. This limits the extent to which a single planning response can be generalized across the whole metropolitan region.

The process to identify place-based solutions applied in this study can be further developed. The research outlines high-priority areas and explores how neighborhood context may be important in different planning scenarios, but the research does not fully analyze the long-term viability, cost, political acceptability, or implementation effectiveness of such options. The case study component, therefore, demonstrates planning potential, as opposed to the results of confirmed intervention. Further study is needed to assess the efficacy of solutions offered if they are implemented in actual planning and policy contexts.

Another concerning part of the place-based solution is to provide solutions on specific CBG. The case-study analysis was conducted at the individual CBG level and included only food stores located within the selected CBG boundary. Therefore, healthy food stores located just outside the boundary were not counted, even though residents may still visit them or have better options of healthy food access. For example, an Aldi store is located near the case-study 1 CBG boundary, but it was not included in the explanation because it falls outside the CBG boundary. The store was not intentionally left out; rather, the analysis consistently counted only stores located within each CBG. This might cause confusion to the user. In addition, a low IFAEI value does not depend only on the presence or absence of healthy food stores. The value is also

influenced by the number of less-healthy food stores within the CBG and residents' food-shopping travel behavior, as measured by R_FAI. Therefore, a low IFAEI score may result from fewer healthy food stores, a greater number of less-healthy stores, fewer visits to healthy food retailers, or a combination of these factors. As a result, a low IFAEI value should not be interpreted as showing that residents have no access to healthy food. The use of fixed CBG boundaries may underestimate residents' actual access to nearby healthy food stores and makes it difficult to explain a low IFAEI score using only one factor.

This study also encountered difficulty with tackling historically informed community circumstances. The patterns of development in the past might have an impact on the accessibility of food in the present, although these dynamics are not fully factored into the analytical framework applied in this study. Consequently, the framework can identify the areas of concentration of discrepancies, although it is unable to fully explain the historical processes that created them. This indicates that some of the neighborhood trends may require more in-depth qualitative or historical analysis, which was outside the scope of this study.

Ultimately, while the framework developed herein may be conceptually applicable elsewhere, the results developed are mainly relevant for the metropolitan area of Kansas City and similar mid-sized urban areas. Consequently, caution should be taken before transferring the results to different metropolitan contexts without considering local variations in urban morphology, governance, transportation infrastructure, neighborhood history, and food retail frameworks. The general value of the study lies in the analytical method used, though the practical application of the framework is context dependent.

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Appendix A - Survey Design

AHP Weighting Survey for Food Access Decision-Making in the Kansas City Metropolitan Area

Expert Survey for Food Access Decision-Making in the Kansas City Metropolitan Area You are invited to participate in a research study titled "GIS-Based Decision Support for Healthy Food Access Prioritization in the Kansas City Metropolitan Area." This research is being conducted for a seed project funded by Game-changing Research Initiation Program (GRIP), Kansas State University. Our research is to develop a GIS-based decision-support tool to identify priority areas for improving healthy food access in the Kansas City area. Your input will help determine the relative importance of different decision criteria used in the model. If you agree to participate, you will complete a short pairwise-comparison survey used for the Analytical Hierarchy Process (AHP). The survey will take approximately 5–10 minutes. Risks associated with participation are minimal and comparable to those encountered in routine online survey activities. No personal or sensitive information will be collected. Survey responses will be analyzed and reported only in aggregate form. The results of this study may inform future research and related studies on food accessibility and decision-support methods, and may be presented in academic publications or conferences in aggregated form. Participation is voluntary. You may decline to participate, skip any question, or withdraw from the study at any time without penalty. Questions about this survey can be directed to: Principal Investigator: Dr. Shakil Kashem, Associate Professor, LARCP, email:shakilkashem@ksu.edu 1086 Seaton Hall, Manhattan, KS 66506 Graduate Student: Maria Binte Edrish, Master of Regional & Community Planning, LARCP, Kansas State University. Email: medrish@ksu.edu IRB contacts Dr. Lisa Rubin Chair, Committee on Human Subjects Research (785) 532-3224 Dr. Brad Woods, Associate Vice President for Research Compliance (785) 532-3224 Kansas State University 203 Fairchild Hall, Manhattan, KS 66506

- ☐ YES, I have read and understood this consent form, and willingly agree to participate in this study. (1)
- ☐ NO, I do not want to participate in this study. (2)

This survey is part of a graduate research study at Kansas State University that aims to develop a GIS-based multi-criteria decision-support tool to identify underserved areas and prioritize food-

access interventions. Please compare the importance of the following major criteria that need to be considered for improving healthy food access: Socioeconomic Vulnerability: poverty, SNAP recipients, unemployment, income, education, age 65+, single-parent, race/ethnicity Transportation Constraints: no vehicle, mean commute time, stop density, walkability Health Vulnerability: disability, obesity, diabetes, high BP, chronic heart disease Housing Instability: rent burden, percent renters, vacancy, overcrowding Please respond based on your professional judgment to decide which group of factors should be prioritized in food access planning.

Q1. Between Socioeconomic Vulnerability and Transportation Constraints, which factor should be prioritized to improve food access?

- ☐ Socioeconomic vulnerability is significantly more important than Transportation Constraints (1)
- ☐ Socioeconomic vulnerability is moderately more important than Transportation Constraints (2)
- ☐ Socioeconomic vulnerability is slightly more important than Transportation Constraints (3)
- ☐ Both bear Equal importance (4)
- ☐ Transportation Constraints is slightly more important than Socioeconomic vulnerability (5)
- ☐ Transportation Constraints is moderately more important than Socioeconomic vulnerability (6)
- ☐ Transportation Constraints is significantly more important than Socioeconomic vulnerability (7)

Q2. Between Socioeconomic Vulnerability and Health Vulnerability, which factor should be prioritized to improve food access?

- ☐ Socioeconomic vulnerability is significantly more important than Health Vulnerability (1)
- ☐ Socioeconomic vulnerability is moderately more important than Health Vulnerability (2)
- ☐ Socioeconomic vulnerability is slightly more important than Health Vulnerability (3)
- ☐ Both bear Equal importance (4)

- o Health Vulnerability is slightly more important than Socioeconomic vulnerability (5)
- o Health Vulnerability is moderately more important than Socioeconomic vulnerability (6)
- o Health Vulnerability is significantly more important than Socioeconomic vulnerability (7)

Q3. Between Socioeconomic Vulnerability and Housing Instability, which factor should be prioritized to improve food access?

- o Socioeconomic vulnerability is significantly more important than Housing Instability (1)
- o Socioeconomic vulnerability is moderately more important than Housing Instability (2)
- o Socioeconomic vulnerability is slightly more important than Housing Instability (3)
- o Both bear Equal importance (4)
- o Housing Instability is slightly more important than Socioeconomic vulnerability (5)
- o Housing Instability is moderately more important than Socioeconomic vulnerability (6)
- o Housing Instability is significantly more important than Socioeconomic vulnerability (7)

Q4. Between Transportation Constraints and Housing Instability, which factor should be prioritized to improve food access?

- o Transportation Constraints is significantly more important than Housing Instability (1)
- o Transportation Constraints is moderately more important than Housing Instability (2)
- o Transportation Constraints is slightly more important than Housing Instability (3)
- o Both bear Equal importance (4)
- o Housing Instability is slightly more important than Transportation Constraints (5)
- o Housing Instability is moderately more important than Transportation Constraints (6)
- o Housing Instability is significantly more important than Transportation Constraints (7)

Q5. Between Transportation Constraints and Health Vulnerability, which factor should be prioritized to improve food access?

- o Transportation Constraints is significantly more important than Health Vulnerability (1)
- o Transportation Constraints is moderately more important than Health Vulnerability (2)
- o Transportation Constraints is slightly more important than Health Vulnerability (3)

- o Both bear Equal importance (4)
- o Health Vulnerability is slightly more important than Transportation Constraints (5)
- o Health Vulnerability is moderately more important than Transportation Constraints (6)
- o Health Vulnerability is significantly more important than Transportation Constraints (7)

Q6. Between Health Vulnerability and Housing Instability, which factor should be prioritized to improve food access?

- o Health Vulnerability is significantly more important than Housing Instability (1)
- o Health Vulnerability is moderately more important than Housing Instability (2)
- o Health Vulnerability is slightly more important than Housing Instability (3)
- o Both bear Equal importance (4)
- o Housing Instability is slightly more important than Health Vulnerability (5)
- o Housing Instability is moderately more important than Health Vulnerability (6)
- o Housing Instability is significantly more important than Health Vulnerability (7)

Q7 Working on food systems or community planning

- o <1 year (1)
- o 1-3 years (2)
- o 4-6 years (3)
- o 7-10 years (4)
- o 10+ years (5)
- o Other: (6) _____

Q8. Your role or affiliation

- o University faculty/Researcher (1)
- o Community/Regional Planner (2)
- o Nonprofit organization professional (3)
- o Public health professional (4)
- o Community advocate (5)
- o Graduate Student (6)
- o Other: (7) _____

Q9. Do you have any additional comments on factors influencing food access or the weighting process?

Q10. Emails (optional, only if you want to receive your response)

Appendix B - Descriptive Statistics

Appendix Table B.1. Descriptive Statistics of Vulnerability Variables

Variable	Group	Mean	Std	Min	Max
poverty_rate_pct	SOC_VARS	11.20	12.40	0.00	100.00
cash_or_snap_pct	SOC_VARS	8.47	11.79	0.00	100.00
unemployment_rate_pct	SOC_VARS	4.26	5.90	0.00	57.61
age65plus_pct	SOC_VARS	16.46	10.39	0.00	100.00
black_pct	SOC_VARS	13.21	19.81	0.00	100.00
hispanic_pct	SOC_VARS	11.50	15.20	0.00	100.00
hh_with_children_pct	SOC_VARS	30.33	15.69	0.00	100.00
no_vehicle_pct	TRN_VARS	5.96	9.41	0.00	100.00
mean_commute_time_min	TRN_VARS	24.71	6.08	2.50	55.22
stop_density_sqkm	TRN_VARS	2.81	6.61	0.00	98.82
walk_nat_index	TRN_VARS	9.95	3.86	1.67	19.50
DISABILITY_CrudePrev	HLT_VARS	32.68	7.84	17.60	59.30
OBESITY_CrudePrev	HLT_VARS	36.64	5.44	24.90	54.80
DIABETES_CrudePrev	HLT_VARS	11.59	3.41	4.10	26.70
BPHIGH_CrudePrev	HLT_VARS	34.75	5.33	17.80	54.70
CHD_CrudePrev	HLT_VARS	6.02	1.58	1.90	13.70
renters_pct	HOU_VARS	33.71	28.42	0.00	100.00
vacancy_rate_pct	HOU_VARS	7.09	8.66	0.00	57.96
overcrowding_pct	HOU_VARS	2.04	4.36	0.00	49.26

Appendix C - Theme-specific PCA Scores

Appendix Figure C.1. Theme-based vulnerability Index

