The influence of transport resiliency on community level food security

by

Shahadat Hossain

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Major Professor
Dr. Shakil Kashem

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Abstract

Transportation systems play a vital role in linking urban communities to food sources, yet the resilience of transportation systems and how it influences local level food security is not well understood. When severe weather disrupts transportation, vulnerable populations encounter difficulties accessing nutritious food, exacerbating existing inequities in food security. Despite the recognition of these interconnections, prior research often analyzed transportation resilience and food security independently, with limited exploration of their intersection. This study addresses this critical research gap by examining how transportation network resilience impacts food accessibility during extreme weather events. We hypothesize that areas with more resilient transportation infrastructure maintain better food access during disruptions, but that this relationship varies across socioeconomic characteristics.

We took the Kansas City Metropolitan Area as our case study and explored transport resilience and food security at the census block group level. Our methodology includes developing a Transportation Resiliency Index (TRI) incorporating measures of redundancy, mobility, and vulnerability. We paired this with mobile phone-based foot traffic data to food stores to create a Retail Food Activity Index (RFAI) that captures real-world mobility patterns rather than assuming local food accessibility based on distance to stores. We applied spatial regression models to evaluate how visitation to healthy food stores (as measured by RFAI) is influenced by transport resilience and distance to stores after controlling different socioeconomic variables. We developed this model for both normal weather conditions and a major snowstorm period.

Our analysis reveals significant patterns in food store visitation during both normal and snowstorm conditions. Transportation resilience emerged as one of the most significant

predictors across both scenarios, with its influence intensifying during disruptions caused by the snowstorm. Our model results also revealed stark socioeconomic disparities, with areas containing higher percentages of low-wage residents experiencing reduced food access, mirroring patterns of infrastructure inequality. These findings have significant implications for planning practice and policy. This study underscores the critical need to integrate transportation and food system planning to advance equity and resilience. This research provides a transferable methodology for identifying at-risk areas and a framework for developing targeted interventions to address food security at the local level.

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I owe my heartfelt thanks to my wife, Etu, for her endless love, understanding, and unwavering belief in me during the most challenging times. Her support has been my greatest source of strength. I am forever indebted to my parents, whose sacrifices, prayers, and encouragement have been the foundation of all my achievements. I also extend my warmest thanks to my friends and extended family for their constant support, encouragement, and motivation throughout this journey.

This accomplishment is not mine alone, it belongs to all of you.

Chapter 1 - Introduction

Food insecurity continues to pose a significant threat to global well-being, sustainability, and equitable development. Despite advances in food production and agricultural technology, more than 735 million people faced hunger in 2022, marking a concerning increase since 2019 due to the compounding effects of conflict, climate change, economic instability, and COVID-19 pandemic (FAO, 2023). Food insecurity is no longer confined to developing nations; it increasingly affects urban populations in high-income countries, where the challenge is less about food availability and more about access, stability, and affordability (Gray & Torshizi, 2021a; Hobbs, 2020a). In the United States alone, more than 34 million people, including 9 million children, lived in food-insecure households in 2021 (Coleman-Jensen et al., 2022). These figures underscore the critical need to investigate not just how much food is available but how resilient systems are in ensuring equitable and reliable food access, particularly under stress. One often overlooked but essential determinant of food security is the performance of transportation systems, which serve as the backbone of food distribution. Transportation networks connect farms to processing centers, markets, and consumers, enabling food to flow from farms to kitchen (Browne et al., 2016). However, these networks are increasingly vulnerable to extreme weather events, infrastructure failures, and policy disruptions. Floods, snowstorms, hurricanes, and heatwaves can temporarily or permanently sever access to food outlets, particularly in communities that already suffer from poor transit connectivity and limited resources (Loreti et al., 2022; Zeuli et al., 2018). As a result, transportation resiliency defined as the ability of a system to absorb, adapt to, and recover from disruptions has emerged as a critical lens through which to evaluate food system stability (Raub et al., 2021; Sullivan & Novak, 2024; Zimmerman et al., 2018).

Access to food is not just a matter of proximity but of connectivity and system performance. A household might live within theoretical reach of a grocery store, but real-world access is compromised if roads are damaged, public transit is unavailable, or mobility is restricted by income, disability, or extreme weather. In these contexts, transport resilience becomes a proxy for food accessibility, which is one of the core dimensions of food security (FAO, 2006). Disruptions in transportation disproportionately affect marginalized populations, including low-income households, communities of color, and the elderly, who are more likely to rely on public transportation or live in food deserts with limited access to fresh and nutritious food (Childs & Lewis, 2012; Delgado et al., 2023; Vahabi & Damba, 2013) . During crises like the COVID-19 pandemic, even well-resourced cities experienced breakdowns in food access due to strain on logistics and mobility systems (Kashem et al., 2021; Wei et al., 2024). Yet, despite the interdependence between transportation systems and food security, empirical research explicitly connecting transportation resiliency to community-level food security outcomes remains limited. Most existing studies have either focused on broader food supply chain disruptions at national or global scales (Moynihan et al., 2022; Peng et al., 2024) or examined transportation access in relation to static food desert mapping (Clark et al., 2024). While the conceptual relationship between transport infrastructure and food access is increasingly acknowledged in resilience planning (Raub et al., 2021; Romero-Lankao et al., 2018), few studies have quantified this relationship using indicators of transportation resilience and behavioral measures of food access at a neighborhood or census block group level. This empirical study seeks to address this gap by examining the extent to which the resilience of a city's transportation system influences local-level food security. Using the Kansas City Metropolitan Area (KCMA) as a case study which encompasses both urban and suburban food

deserts, this research examines whether areas with lower transportation resiliency exhibit reduced food access, especially during extreme weather events. The study constructs a Transportation Resiliency Index (TRI) incorporating Network Vulnerability Index (NVI), Network Redundancy Index (NRI), and Network Mobility Index (NMI) (R. A. H. El Rashidy & Grant-Muller, 2019). Food access is measured through the Retail Food Activity Index (R_FAI), which leverages foot traffic data to assess real-time visits to healthy versus unhealthy food outlets (Xu et al., 2023). By correlating these indicators across Census Block Groups of the study area, this study aims to empirically establish whether transportation resilience meaningfully influences food security at the community level.

The contribution of this research is threefold. First, it empirically investigates the relationship between transportation system resiliency and community-level food access, a connection that has been largely overlooked in existing literature. By utilizing a Transportation Resiliency Index (TRI) composed of the Network Vulnerability Index (NVI), Network Redundancy Index (NRI), and Network Mobility Index (NMI), the study offers a quantifiable assessment of transportation resilience at the census block group level. Second, the study employs a behavior-based measure of food access—the Retail Food Activity Index (R_FAI)—which captures real-time foot traffic to healthy and unhealthy food outlets, allowing for a dynamic understanding of food accessibility under both normal and extreme conditions. Third, the research provides practical insights for urban planners and policymakers by identifying spatial disparities in transportation resilience and food access, particularly during disruptive events such as snowstorms. These findings can help inform targeted interventions aimed at enhancing infrastructure resilience and improving equitable access to food in vulnerable communities.

Chapter 2 - Literature Review

2.1 Defining Food Security

Food security is defined by the Food and Agriculture Organization (FAO) as a condition in which "all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" remains a critical pillar of sustainable development and public health (FAO, 2006). Achieving food security requires stability across four core dimensions: availability, accessibility, utilization, and stability. Among these, accessibility, especially physical access to nutritious food has emerged as one of the most unevenly distributed elements, particularly in urban environments.

Despite global improvements in agricultural output and food production, access to healthy food remains deeply unequal, particularly in economically marginalized neighborhoods. This disparity is often less about a shortage of food and more about the systemic barriers such as economic, geographic, and infrastructural that prevent certain populations from obtaining it (Gray & Torshizi, 2021b; Hobbs, 2020b).

A growing body of research has drawn attention to "food deserts" referring to urban and rural areas where residents face limited access to affordable, nutritious food due to a lack of nearby supermarkets or grocery stores. These areas are disproportionately populated by low-income and minority households, who often rely on convenience stores or fast-food outlets that lack fresh produce and healthy options (Childs & Lewis, 2012; Dutko et al., 2012). In many cases, geographic proximity to a food retailer does not guarantee accessibility; factors such as transportation availability, sidewalk infrastructure, safety, and affordability also determine whether individuals can consistently and reliably reach nutritious food sources.

Traditional methods for identifying food insecurity at the neighborhood level have largely relied on static indicators like distance to the nearest grocery store or median household income. However, such approaches fail to account for behavioral and temporal patterns of food access, especially during disruptions like extreme weather events or transit service interruptions. To address this, researchers have developed more dynamic metrics like the Retail Food Activity Index (R_FAI), which measures the ratio of foot traffic to healthy food outlets compared to less healthy ones (Xu et al., 2023) . By tracking actual consumer visits, R_FAI provides a real-time and behaviorally grounded indicator of food access. It also captures fluctuations during periods of disruption such as snowstorms offering unique insights into how accessibility varies under stress.

Understanding and improving food accessibility, particularly in underserved communities, requires not only mapping where food outlets are located, but also analyzing how people interact with their food environment under changing conditions. As such, any comprehensive study of food insecurity must go beyond static measures and integrate behavioral, spatial, and infrastructural dimensions—especially those related to mobility and transportation systems.

2.1.1 Retail Food Activity Index

Traditional methods of assessing food access such as buffer-based measures of proximity to supermarkets can oversimplify complex behavioral dynamics. In response, newer approaches such as the Retail Food Activity Index (R_FAI) offer a more nuanced and behavior-based metric of food accessibility (Xu et al., 2023). Rather than relying solely on spatial distance, R_FAI measures actual consumer visits to healthy versus unhealthy food retailers, using mobile device foot traffic data to reveal real-time behavioral trends (Xu et al., 2023).

The strength of R_FAI lies in its ability to capture dynamic patterns of food access under both normal and extreme conditions. Incorporating R_FAI into empirical research provides a more grounded understanding of who accesses healthy food, when, and under what conditions. This is especially important in assessing the impact of transportation system performance on food access—allowing researchers to move beyond static notions of access and instead examine how real-world infrastructure supports or hinders food security in practice.

2.2 Defining Transportation Resiliency

The concept of resiliency in transportation systems has gained increasing traction in both research and planning practice, driven by the rising frequency of extreme weather events, aging infrastructure, and growing interdependencies across urban systems. In its most fundamental sense, transportation resiliency refers to a system's ability to withstand, adapt to, and recover from disruptions whether caused by natural disasters, system failures, or human-induced hazards as long as it continues to perform essential functions (Weilant et al., 2019; Zhou et al., 2019). As Zhou et al. (2019) argue, resilience distinguishes itself from related concepts such as reliability or robustness by emphasizing performance recovery over time, rather than just the resistance to failure. While robust systems may resist disruptions, resilient systems can absorb shocks, reorganize, and continue operating with minimal long-term loss in functionality. Gao and Wang (2020) reinforce this distinction, noting that traditional reliability metrics fail to capture the temporal dynamics and restorative behaviors essential to evaluating post-disruption performance.

Transportation resiliency, then, is not a single attribute but a multidimensional capacity, combining elements of system structure, network topology, governance adaptability, and user mobility. The RAND Corporation’s AREA framework (Absorptive, Restorative, Equitable

Access, Adaptive capacity) captures this spectrum well, emphasizing that resilient systems must not only endure and recover from stress but also adapt to evolving risks and continue to ensure equitable access to critical services, such as food, healthcare, and employment (Weilant et al., 2019).

The need for resilient transportation systems is particularly pronounced in urban settings, where high population densities and infrastructural interdependencies amplify the consequences of disruptions. As noted by Serre and Heinzlef (2018), urban infrastructure failures can trigger cascading effects, where a breakdown in transportation affects water, energy, and emergency response networks. Interconnectivity, while a strength in efficiency, becomes a vulnerability during crises, increasing the spatial scale and duration of disruptions. Similarly, Pitilakis et al. (2016) emphasize that due to the lack of redundancy and slow repair times, damage to transportation infrastructure during earthquakes or floods can severely impede emergency operations and economic recovery.

To operationalize this complex concept, scholars have proposed composite indices that incorporate multiple dimensions of resiliency. Among the most cited is the model by El Rashidy and Grant-Muller (2019), which synthesizes three key components to assess the resilience of road transport networks:

Network Vulnerability Index (NVI): This index evaluates the susceptibility of the network to failures based on topology, critical nodes, hazard exposure, and structural weakness. A network with high centrality and limited alternative routes is typically more vulnerable to cascading failures (Ahmed & Dey, 2020; R. A. H. El Rashidy & Grant-Muller, 2019) .

Network Redundancy Index (NRI): Redundancy refers to the presence of multiple alternative paths or connections within the system. A high NRI suggests that the network can

reroute traffic or services in case of failure, thereby minimizing the disruption's impact. Redundancy is especially vital in high-density urban areas where a single link failure can paralyze mobility (Gao & Wang, 2021; Zhou et al., 2019) .

Network Mobility Index (NMI): This component captures the efficiency and fluidity of movement across the network, reflecting travel time, congestion levels, and ease of access under typical and disrupted conditions. A resilient network should not only be structurally sound but also facilitate efficient movement for diverse users under varying demand scenarios (Ahmed & Dey, 2020; R. A. H. El Rashidy & Grant-Muller, 2019).

Together, these indices can be aggregated to form a Transportation Resiliency Index (TRI), enabling planners and researchers to quantify and compare the resilience of different areas or systems. Importantly, such metrics support evidence-based decision-making by highlighting where infrastructure upgrades, redundancy enhancements, or emergency response investments are most needed.

2.3 Transportation Resiliency and food security

Urban transportation systems are critical enablers of food access, particularly for populations that rely on public transit or active mobility to reach food retailers. In many metropolitan areas, disruptions to transportation infrastructure whether from weather events, infrastructural decay, or operational inefficiencies can directly hinder an individual's ability to obtain nutritious and affordable food. These disruptions disproportionately affect low-income and socially vulnerable populations, who often reside in areas with limited food retail options and rely more heavily on public transportation (Childs & Lewis, 2012; Delgado et al., 2023).

Resilient transportation systems are increasingly viewed as fundamental for ensuring the continuity of food access during both normal operations and times of crisis. In contexts such as natural disasters, pandemics, or extreme weather, the ability of transit networks to absorb, adapt to, and recover from shocks determines whether individuals can maintain routine access to essential goods including food (Jenelius & Mattsson, 2021; Sullivan & Novak, 2024). Studies have documented how flooding, winter storms, and transit shutdowns have effectively cut off food access, especially in food desert communities and neighborhoods with limited grocery infrastructure (Loreti et al., 2022; Zeuli et al., 2018).

Research has also emphasized that transportation accessibility plays a more significant role in food security outcomes than previously assumed. A strong transportation system does more than enabling food delivery, it provides individuals with the physical and temporal flexibility to access food when and where it is needed. High travel times, limited transit coverage, and poor infrastructure can create structural barriers to food access even in areas not classified as food deserts. Sullivan and Novak (2024), for instance, used a spatial vulnerability model to show that communities with longer travel times to retail food outlets experienced reduced accessibility, particularly under emergency conditions.

While much of the literature has traditionally focused on proximity-based measures of access, recent studies have begun to incorporate behavior-based and systems-level perspectives. These include indicators such as travel frequency, mode dependence, and travel time variability during disruptions. For example, Bella et al. (2024) highlight how alternative delivery methods like volunteer-driven or crowdsourced food delivery emerged in response to mobility constraints during COVID-19, offering important insights into how mobility systems must be responsive and adaptable to ensure continued food access in vulnerable areas.

The equity dimension of transportation resiliency remains a central concern. Poor infrastructure quality, infrequent service, and long travel distances disproportionately affect certain demographic groups, including recent immigrants, the elderly, and those with disabilities (Neustroeva & Shishigina, 2022; Vahabi & Damba, 2013). These barriers are often not just spatial but socioeconomic, shaped by income level, cultural food preferences, and financial access to transportation. Resilience planning that fails to consider these factors risks excluding the very populations most at risk of food insecurity.

In sum, the literature demonstrates that food accessibility is deeply intertwined with transportation resiliency. While conceptual frameworks have outlined this relationship, empirical studies are still emerging, particularly on the community scale. Understanding how the transportation system performs both under normal and stressed conditions and shapes food access behaviors is essential for informing more resilient and equitable planning approaches.

2.4 Planning and Policy Responses to Transportation-Food Access Gaps

Despite increasing scholarly attention to the relationship between transportation resilience and food security, planning and policy frameworks have been slow to operationalize this intersection. Urban and regional transportation plans often prioritize congestion, infrastructure maintenance, and safety but rarely incorporate food access as a formal planning consideration (Raub et al., 2021; Sullivan & Novak, 2024). Similarly, food access initiatives tend to be driven by public health or social service agencies, with limited integration of transportation metrics or infrastructure concerns (Delgado et al., 2023). During the COVID-19 pandemic, many municipalities adopted emergency food access measures, such as volunteer-based delivery networks and pop-up food distribution sites, to address mobility-related barriers. These strategies

demonstrated the feasibility of transportation-food system coordination but were largely reactive and temporary (Bella et al., 2024). Long-term transportation plans still rarely account for how disruptions such as weather events or transit cuts affect equitable access to food, especially in transit-dependent communities.

Globally, efforts to integrate transportation planning with food access remain inconsistent. In high-income contexts, planning documents often mention resilience in broad terms but lack localized tools or indicators to evaluate how transportation system failures influence household-level food access (Delgado et al., 2023) . In low- and middle-income countries, studies highlight how inadequate rural road infrastructure can isolate entire populations during rainy seasons, with direct consequences for food insecurity (Achilana et al., 2020; Codjoe & Owusu, 2011).

There are some exceptions. For example, spatial vulnerability mapping has been used in a few jurisdictions to identify neighborhoods at high risk of access disruption during emergencies (Clark et al., 2024; Zeuli et al., 2018). Likewise, national infrastructure investment frameworks, such as Zambia's rural transport strategy, have begun incorporating food logistics goals (Wang et al., 2023). However, these are not yet widespread or embedded into mainstream resilience planning processes. As Zhao and Lee (2023) caution, technology-driven responses like online grocery platforms or autonomous delivery may widen food access gaps unless they are designed with equity in mind. For planning responses to be effective, they must be informed by localized evidence, integrate behavioral patterns, and reflect the specific challenges of low-income and mobility-constrained populations. This study responds to that need by linking empirical food access behavior with transportation system resilience indicators, offering planners a model for assessing vulnerability and equity at the neighborhood level.

2.5 Methodological Approaches in Existing Research

Over the past two decades, researchers have applied a wide range of spatial and statistical modeling techniques to study food access and transportation systems. These methods have been instrumental in identifying areas of concern like quantifying disparities and simulating potential disruptions, but they also reveal several methodological gaps that this study seeks to address.

GIS-based spatial analysis remains the dominant approach in food accessibility studies. Researchers commonly use GIS tools to map proximity to supermarkets, classify food deserts, or visualize service areas under various transportation conditions (Major et al., 2018; Zeuli et al., 2018). However, these proximity-based models often assume that all individuals travel uniformly and neglect real-time system behavior or user constraints.

To address spatial dependence, several studies incorporate spatial lag and spatial error models, which account for autocorrelation across geographic units. Sullivan and Novak (2024), for instance, used spatial lag modeling to assess how transit travel times influenced food access in vulnerable communities. Geographically weighted regression (GWR) has also been used to detect localized effects of infrastructure or demographic variables on access outcomes (Agnusdei et al., 2022).

In resilience research, network-based and simulation models have gained traction for evaluating transportation system robustness. Mattsson and Jenelius (2015) employed scenario-based simulations to evaluate how access to key services changed under different failure events. Similarly, Santos et al. (2024) modeled N-1 failures to identify critical transport nodes for food distribution. Yet, such models are often used in supply chain logistics rather than community-level food accessibility assessments.

More recently, behavior-based indicators like foot traffic data or travel logs have emerged as powerful tools to measure actual food access behavior. Xu et al. (2023) developed the Retail Food Activity Index (R_FAI), which tracks real-time visits to healthy and unhealthy food retailers. While R_FAI provides a more dynamic measure than traditional distance-based indicators, it has not yet been widely integrated with system-level resilience assessments.

A key limitation across much of the literature is the lack of integration between transportation resilience indicators (e.g., NVI, NRI, NMI) and food access models. Most studies either focus on static infrastructure conditions or analyze access under normal operating circumstances. There is little empirical research that examines how disruptions in transportation networks such as extreme weather or service outages affect food access patterns in real communities.

This study addresses these methodological gaps by integrating spatial regression models and spatial autocorrelation analysis with two complementary indicators, the Transportation Resiliency Index (TRI) and the Retail Food Activity Index (R_FAI). By applying these tools to both normal and disrupted conditions (e.g., during winter weather events), the research offers an empirical assessment of how transportation system performance quantified through components such as network vulnerability, redundancy, and mobility shapes behavioral food access patterns at the community level. In doing so, it provides a novel contribution to the literature by combining infrastructure-focused resilience metrics with real-time, behavior-based access data, offering a robust framework for evaluating spatial disparities in food access under varying mobility conditions.

Chapter 3 - Study Method

3.1 Study Area

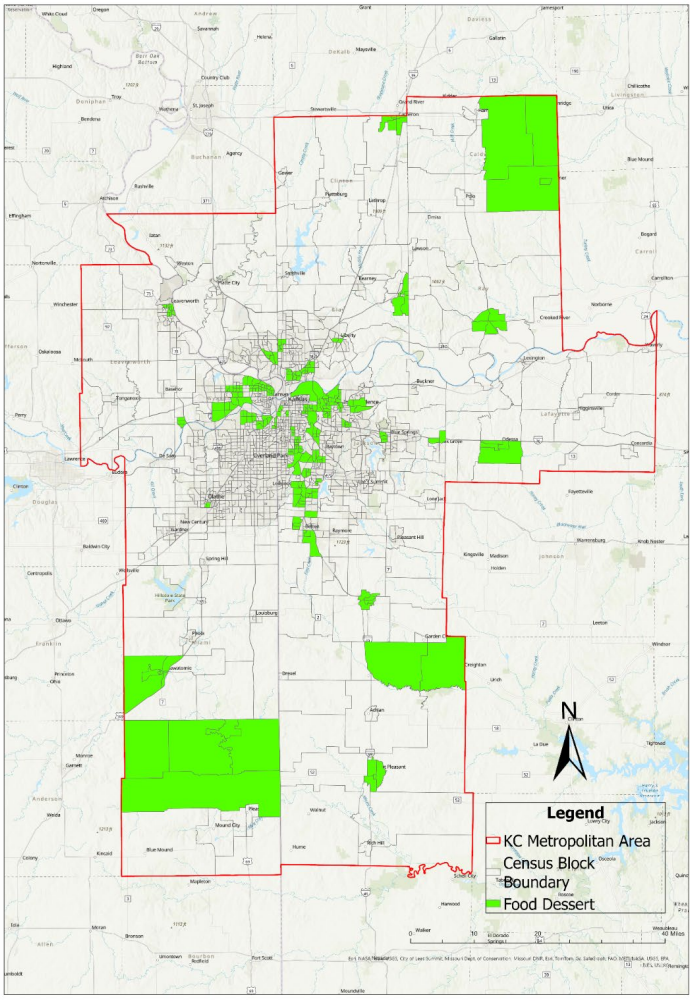
The study focuses on the Kansas City Metropolitan Area (KCMA), a bi-state region encompassing counties in both Missouri and Kansas. It is one of the 50 largest metropolitan areas in the United States, with a population exceeding 2 million residents. The region includes a mix of urban, suburban, and rural communities, making it well-suited for examining spatial variation in transportation access and food security outcomes across different contexts.

Administratively, the KCMA includes 14 counties and 1533 Census Block Groups (CBGs). Key counties include Jackson, Clay, and Platte in Missouri, and Johnson and Wyandotte in Kansas. The metropolitan area is anchored by Kansas City, Missouri, and Kansas City, Kansas; two urban cores characterized by concentrated poverty, high proportions of minority populations, and known food access challenges. These urban centers are surrounded by lower-density suburban and rural zones, creating a diverse transportation and land use landscape that provides a robust context for spatial analysis.

The Kansas City Metropolitan Area was selected as the study site due to its relevance to food access challenges and its susceptibility to transportation disruptions. One of the primary reasons for its selection is the prevalence of food deserts across the region. According to the U.S. Department of Agriculture (USDA), multiple neighborhoods within Kansas City, particularly in central urban areas and older suburban communities are classified as food deserts. These areas are characterized by limited access to healthy food retailers such as supermarkets and grocery stores, combined with high poverty rates and low levels of vehicle ownership. These conditions exacerbate reliance on public or active transportation options, making the resilience and accessibility of transportation networks critical for food security.

In addition, Kansas City is regularly affected by seasonal winter storms, including snow and ice events that frequently disrupt local transportation systems. Such events disproportionately impact transit-dependent populations, particularly low-income and elderly residents who may already face structural barriers to food access. These disruptions create real-world conditions under which transportation resiliency can be assessed, offering an empirical basis for examining how system performance during weather-related stress events affects behavioral patterns in food accessibility. This combination of chronic food access disparities and acute mobility challenges makes Kansas City a suitable case for studying the intersection of transport resilience and food security.

Figure 1: Food Desert Map of Study Area (USDA, 2019)



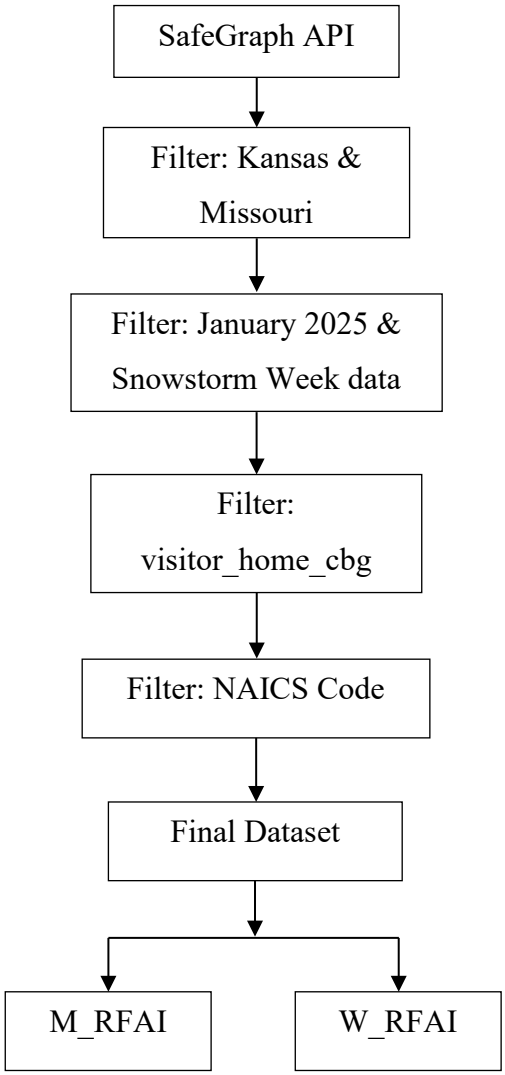
3.2 Data Collection

3.2.1 Retail Food Activity Index (R_FAI)

3.2.1.1 Processing Foot Traffic Data

This study utilized SafeGraph foot traffic data, accesses through Dewey and licenses from Advan to capture real-time food access behavior at the Census Block Group (CBG) level. The data pipeline followed a structured workflow, illustrated in Figure 2 to filter and process raw visit data into a behavior-based measure of food accessibility.

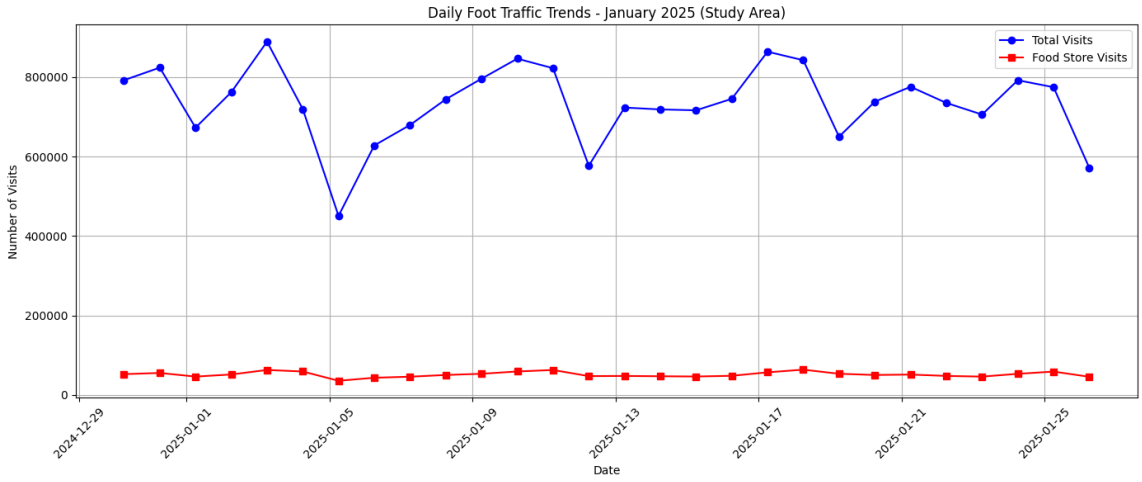
Figure 2: Mobility data processing workflow



The raw data was acquired using the SafeGraph API and first filtered to Kansas and Missouri, the states that include the Kansas City Metropolitan Area. From the regional subset, two timeframes were selected for analysis. The first captured routine mobility patterns across the full month of January 2025. The second focused on the snowstorm week from January 6 to January 13, a period marked by severe weather disruptions that affected the entire metropolitan area.

The snowstorm week was chosen because the Kansas City region experienced significant transportation disruption during that time. Following a record-breaking blizzard on January 5, a second winter storm on January 9 led to hazardous road conditions, widespread closures, and mobility constraints (Max McCoy, 2025). These disruptions created conditions under which real-world access to food was likely affected, especially for transit-dependent and vulnerable populations. As illustrated in Figure 3, overall foot traffic as well as foot traffic to food store took a drastically decline in the 2nd week due to snowstorm.

Figure 3: Foot Traffic Trend in January 2025 (Advan Foot Traffic data, January 2025)



Each visit record in the dataset was associated with a home CBG via the visitor_home_cbg variable. SafeGraph assigns this feature after examining nocturnal location patterns over a six-week period, specifically from 6:00 PM to 7:00 AM. The area where a device appears the most frequently throughout this time period is designated as its home base and assigned to a specific CBG. This technique allows visits to be ascribed to the CBGs where people live rather than the destinations themselves.

Figure 4: O-D map for a CBG ((Advan Foot Traffic data, January 2025)

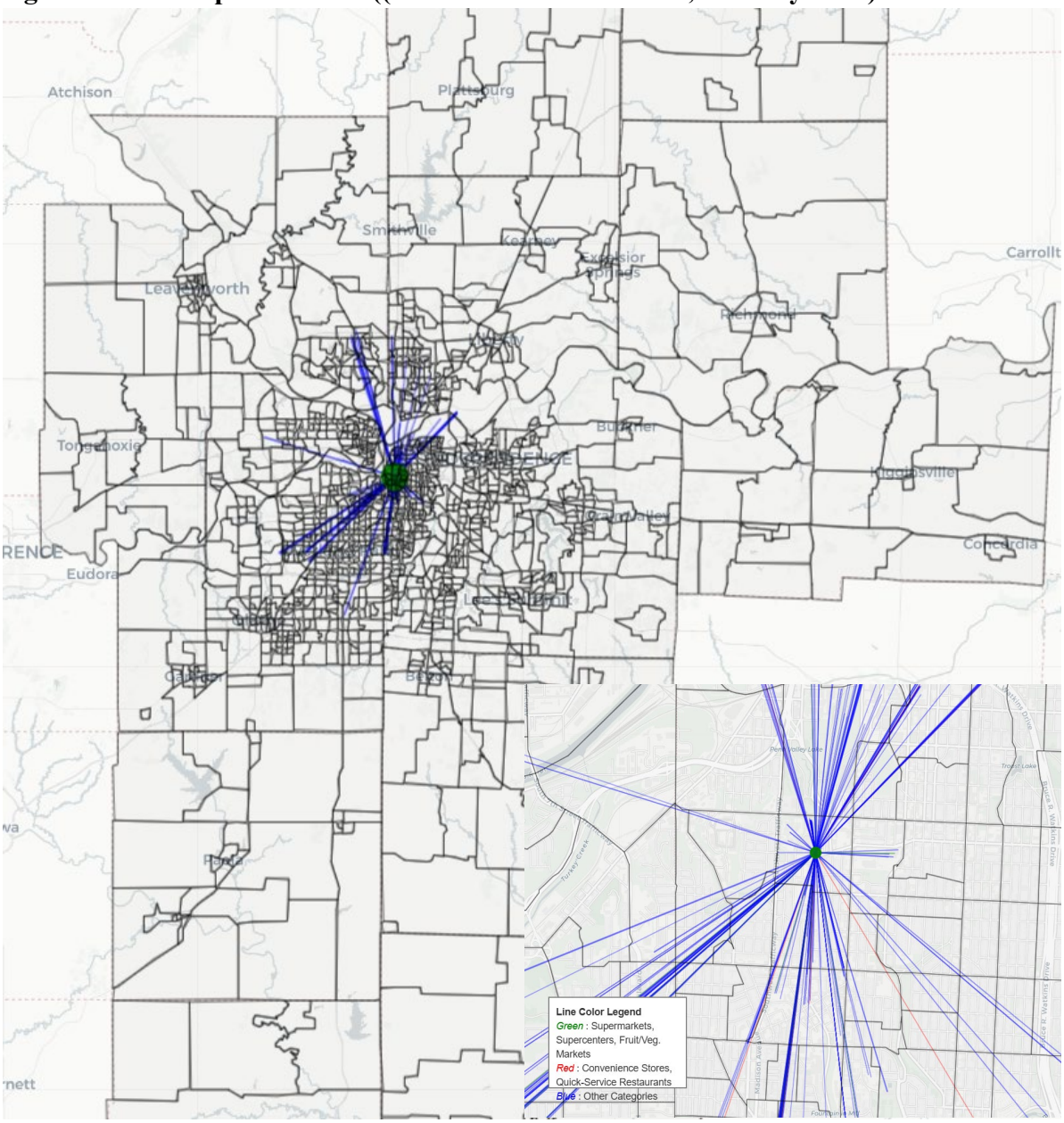


Figure 4 shows an Origin-Destination (O-D) map for a specific CBG in the Kansas City metro area. The lines depict travel patterns from the home CBG to various Points of Interest (POIs). Green lines show trips to healthy food retailers like supermarkets and fruit/vegetable markets, red lines reflect visits to unhealthy food outlets like convenience stores and quick-service restaurants, and blue lines represent visits to all other POIs. The inset shows a zoomed-in picture that emphasizes the dense clustering of destinations in the metropolitan core. Notably, the map shows that resident frequently travel long distances outside of their home CBG to get food or other services, highlighting the role of regional mobility in shaping food access.

For this study, mobility data was collected from all 1,533 CBGs in the Kansas City Metropolitan Area. The dataset was subsequently adjusted to include only trips made from these CBGs and directed to food-related retail outlets. This filtering technique ensured that the final dataset included food store visits generated by each CBG during both normal and snowstorm conditions. These visit counts provided the behavioral pattern underpinning for developing the Retail Food Activity Index (R_FAI) for the month and the week.

3.2.1.2 Index calculation

The Retail Food Activity Index (R_FAI) serves as a behavior-based metric for measuring food accessibility at the neighborhood level (Xu et al., 2023). Unlike traditional proximity-based approaches, which measure geographic distance to food outlets, the R_FAI captures actual consumer visits to food retailers using anonymized mobile device location data. In this study, visit data were sourced from SafeGraph, a commercial provider that aggregates foot traffic data from smartphones, allowing for a dynamic, real-world assessment of food access behavior across Census Block Groups (CBGs) in the Kansas City Metropolitan Area.

Retailers were classified into “healthy” and “less healthy” categories based on North American Industry Classification System (NAICS) codes, following the methodology outlined by Xu et al. (2023). Healthy food retailers included establishments such as supermarkets and grocery stores (NAICS 445110), warehouse clubs and supercenters (NAICS 452311), and fruit and vegetable markets (NAICS 445230). Less healthy food retailers comprised convenience stores (NAICS 445120) and limited-service restaurants or fast-food establishments (NAICS 722513). These categories reflect differences in the availability of nutritious food options and are commonly used in the food access literature (Glanz et al., 2007).

Unlike the USDA and CDC's initial modified Retail Food Environment Index (mRFEI), which distinguishes between "small" and "large" grocery stores based on employment size, Xu et al. (2023) categorized all grocery stores under NAICS 445110 as healthy food retailers, regardless of size. This change fits their larger behavioral approach, which values genuine consumer mobility patterns over static location-based analytics. Their Retail Food Activity Index (RFAI), created from large-scale GPS-based foot traffic data, records real-world visits to food stores, providing a dynamic and context-sensitive indicator of food access. This behavior-based classification is especially well-suited to the objectives of this thesis, which investigates how transportation system resilience affects food accessibility during extreme weather events. A mobility-focused indicator, such as the R_FAI, is better suited to capturing access differences in disrupted situations than traditional proximity-based indices. By focusing on observed visitation patterns, Xu et al.'s approach provides a more inclusive and realistic view of food access, which is especially important when assessing behavioral shifts during disruptions such as snowstorms, when residents may change their travel routes or preferred food outlets.

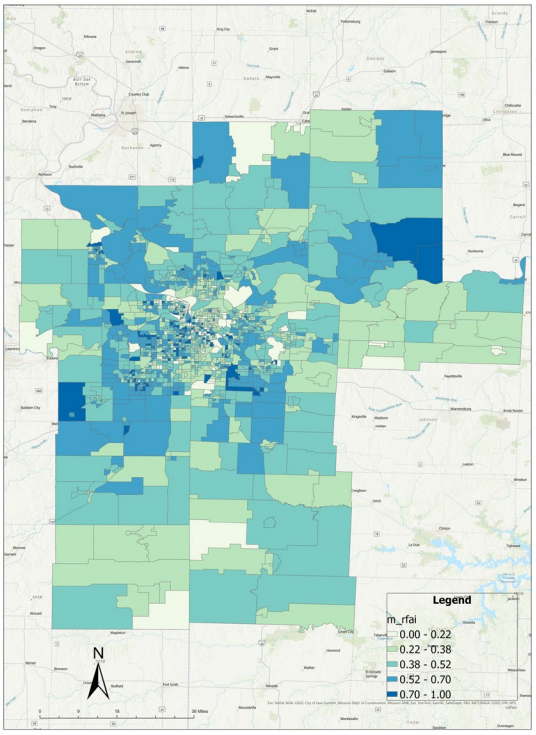
For each CBG, the R_FAI was calculated as the ratio of visits to healthy food retailers relative to the total number of visits to both healthy and less healthy food retailers. Formally, the index is expressed as:

$$R\_FAI = \frac{Visits\ to\ healthy\ food\ retailers}{Visits\ to\ healthy\ food\ retailers + Visits\ to\ unhealthy\ food\ retailers}$$

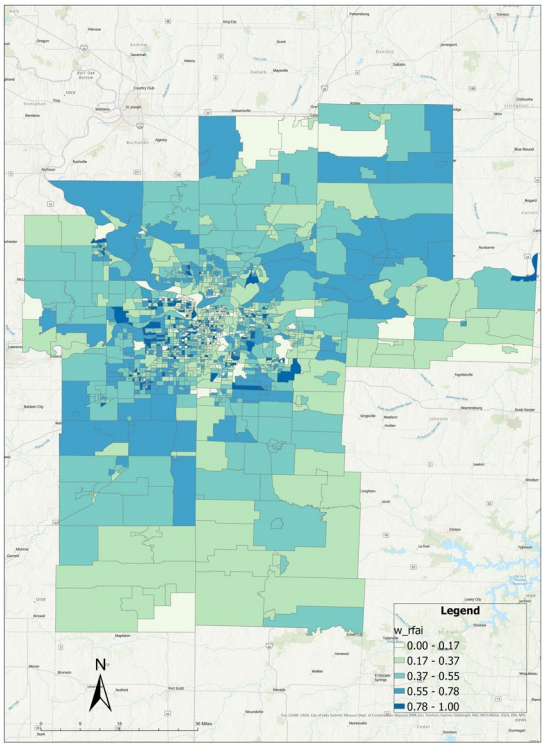
The R_FAI yields values ranging from 0 to 1, with higher values indicating a greater proportion of visits to healthy food outlets. Two temporal versions of the index were created for this study. A monthly R_FAI (M_rfaI) was calculated to represent regular food access behavior under normal conditions, while a weekly R_FAI (W_rfaI) was developed to observe short-term fluctuations in response to extreme weather events, such as snowstorms. Both versions were aggregated at the CBG level to facilitate spatial analysis of accessibility across neighborhoods.

The R_FAI enables a nuanced understanding of food access by incorporating not only the spatial distribution of food retailers but also real-time behavioral patterns. This approach accounts for mobility limitations, consumer choice, and the built environment in a way that static geographic indicators cannot. As demonstrated in prior research, including Xu et al. (2023), behavior-based indices like the R_FAI are effective in capturing disparities in access and better reflect actual food procurement activity in diverse urban environments.

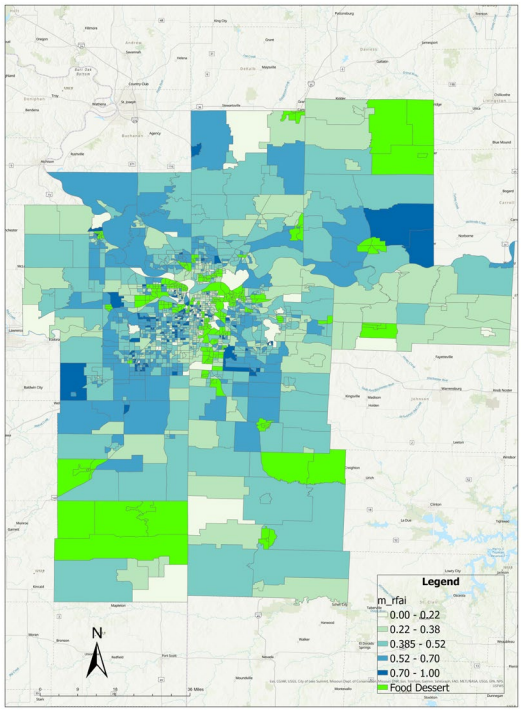
Figure 5: Distribution maps of R_FAI and Food Desert



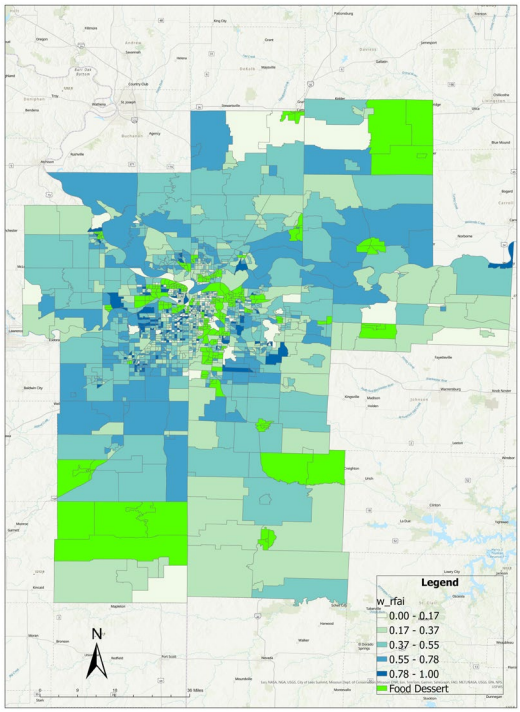
Distribution of m_rfai



Distribution of w_rfai



Overlap of m_rfai and food desert



Overlap of w_rfai and food desert

As illustrated in Figure 5, the weekly Retail Food Activity Index (w_rfai) demonstrates concentrated areas of high food-related mobility in Kansas City's urban core, whereas substantial swaths of the rural periphery particularly in the north, southeast, and southwest show very low values. These places appear to have minimal food activity, which could be attributed to lower population density, fewer food retail outlets, or restricted mobility patterns. In contrast, the monthly Retail Food Activity Index (m_rfai) has a slightly more spatially balanced distribution, with several rural and periphery locations exhibiting moderate values where weekly data suggested minimal activity. This implies that monthly aggregation may capture more steady or cumulative patterns of food-related movement that are less obvious in shorter-term weekly data. Notably, both indexes identify similar regions with ongoing food availability issues, notably in rural and outer suburban areas. However, the w_rfai exhibits more extreme low values in these locations, indicating a greater susceptibility to short-term disturbances or variations in food access behavior. In comparison, the m_rfai provides a smoother spatial pattern that most likely reflects long-term behavioral tendencies.

When comparing food desert areas to the Food Activity Index, both are somewhat aligned but not completely. While certain food desert-designated Census Block Groups (CBGs) do have low R_FAI values, notably in southern and northeastern rural areas, there are notable outliers. In many cases, food deserts develop in zones with moderate R_FAI levels rather than the lowest. This implies that, while food deserts are structurally disadvantaged in terms of availability to healthy food retailers and poverty level, real food-related mobility may differ depending on circumstances such as journey length, vehicle accessibility, or cross-border travel to stores in nearby areas.

3.2.2 Transportation Resiliency Index (TRI)

To assess the infrastructural capacity of neighborhoods to maintain mobility under both routine and disrupted conditions, this study constructed a Transportation Resiliency Index (TRI). The TRI is a composite metric designed to capture the resilience of local transportation networks across three key dimensions: vulnerability, redundancy, and mobility. The index provides a spatially explicit measure of how robust and adaptable the road network is within each Census Block Group (CBG) in the Kansas City Metropolitan Area.

The underlying road network data were derived from Bureau of Transportation Statistics (BTS) containing segments classified using the MAF/TIGER Feature Class Code (MTFCC) system, which reflects roadway hierarchy. These classifications allow differentiation between major arterials, collectors, and local streets, and are essential for estimating exposure to disruption and overall system performance. Each road segment was spatially joined to its corresponding CBG, enabling neighborhood-scale analysis. To improve network attributes, each MTFCC class was assigned roadway operational characteristics such as annual average daily traffic (AADT), speed limit, number of lanes, and lane width, as illustrated in Table 1. The figures shown are interpretive estimates derived from aligning MTFCC road classifications with conventional functional roadway classes as published in AASHTO (2018) and the Highway Capacity Manual (HCM, 2022). The MTFCC system of the United States Census Bureau classifies roads based on their physical and functional qualities, although it does not specify traffic or geometry metrics. As a result, the attribute values presented here represent normal ranges for comparable route types as described in transportation engineering literature, rather than official Census Bureau standards. When direct field data is not available, theoretical

estimation based on facility classification and engineering judgment is a well-established and widely recognized approach (Hylton & Miller, 2023).

Table 1: Road Network Data Attributes by MTFCC Code

MTFCC Code	Road Class	AADT (Typical)	Lane Width (ft)	Number of Lanes	Design Speed (mph)	Source
S1100	Primary Roads	15,000 - 50,000+	12	4 or more	70-80 (Rural), 70-75 (Urban)	(AASHTO, 2018; HCM, 2022)
S1200	Secondary Roads	3,000 - 15,000	11-12	2-4	45-55	(AASHTO, 2018; HCM, 2022)
S1400	Local Neighborhood Roads	500 - 3,000	10-11	2	20-30	(AASHTO, 2018; HCM, 2022)
S1500	Vehicular Trails	<500	9-10	1	10-20	(AASHTO, 2018; USFS, 2014)
S1630	Ramps	1,800 - 2,000 (pcph)	12-14	1-2	25-45	(AASHTO, 2018; HCM, 2022)
S1640	Service Drives/Frontage	1,000 - 5,000	11-12	2	30-45	(AASHTO, 2018; HCM, 2022)
S1740	Private Service Roads	<1,000	10-12	1	15-25	(ITE, 2016)

Each of the three components of TRI are discussed below.

3.2.2.1 Network Redundancy Index (NRI)

The Network Redundancy Index (NRI) captures the internal flexibility of a transportation network, reflecting its capacity to redistribute traffic flow during disruptions (Gonçalves & Ribeiro, 2020). In this study, the NRI was calculated following El-Rashidy & Grant-Muller

(2016) at the Census Block Group (CBG) level by combining two complementary indicators: Redundancy Index 1 (RI1), which measures the balance of traffic distribution across road segments using Shannon entropy, and Redundancy Index 2 (RI2), which estimates spare network capacity based on observed and theoretical traffic volumes.

The first component, RI1, applies the concept of Shannon entropy to evaluate how evenly traffic is spread across road segments within a CBG. For each segment i, the proportion of traffic flow is calculated as:

$$Pi = \frac{fi}{\sum_{j=1}^{n} fi} \qquad \text{(El-Rashidy \& Grant-Muller, 2016)}$$

where fi is the Annual Average Daily Traffic (AADT) of segment i, and n is the total number of segments within the CBG. Using these proportions, the entropy of the traffic distribution is computed as:

$$RI1 = -\sum_{i=1}^{n} Pi \,.\log\,(Pi) \qquad \text{(El-Rashidy \& Grant-Muller, 2016)}$$

Higher RI1 values indicate that traffic is more evenly distributed across available road segments, reflecting a greater degree of internal balance. This dispersion suggests that multiple routes are functionally in use, enhancing the network's ability to reroute traffic during disruptions and contributing to overall transportation resilience. In contrast, lower RI1 values imply that traffic is concentrated on a limited number of roads, increasing vulnerability to failure in those few critical links. Therefore, RI1 serves as a robust proxy for the availability of alternative routes and structural redundancy (El-Rashidy & Grant-Muller, 2016). As illustrated in Figure 6, alternative routed makes network redundant.

The second component, RI2, captures the network's spare capacity, which reflects the extent to which the system can accommodate additional traffic in the event of rerouting or sudden demand shifts. Capacity (Ci) for each road segment was approximated as the maximum observed AADT within its MTFCC class, while flow (fi) was calculated as the mean AADT for that same class. To account for missing observed flow values in real time, the mean AADT within the prescribed range for each road type was assumed to be the observed flow, with the highest value within the AADT range for each road type serving as the estimated capacity.

The spare capacity ratio is then calculated using the formula:

$$RI2 = \sum_{i=1}^{n} \left(\frac{Ci - fi}{Ci}\right) . Pi \qquad \text{(El-Rashidy \& Grant-Muller, 2016)}$$

Here, Ci is the estimated capacity for segment i, fi is the corresponding traffic flow, and Pi is the segment's proportional flow share. Higher RI2 values indicate a greater margin between capacity and usage, implying more room to absorb additional traffic loads without inducing congestion.

To compute the final Network Redundancy Index, RI1 and RI2 were aggregated using a weighted average, with 60% weight assigned to RI1 and 40% to RI2. This weighting reflects the primary importance of balanced traffic distribution while still accounting for available spare capacity (El-Rashidy & Grant-Muller, 2016). The composite NRI score is defined as:

$$NRI = 0.6 \times RI1 + \ 0.4 \times RI2 \qquad \text{(El-Rashidy \& Grant-Muller, 2016)}$$

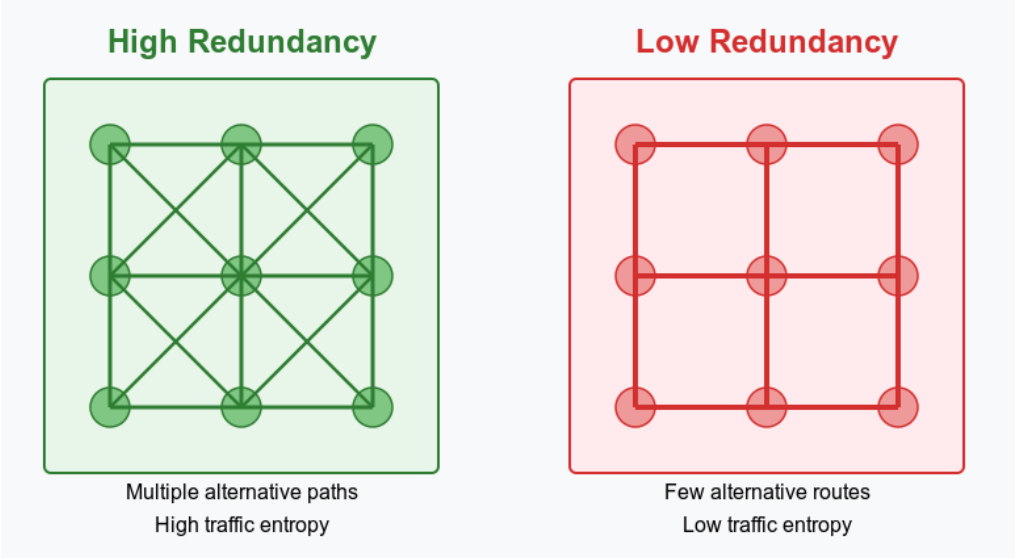
While El-Rashidy and Grant-Muller (2016) created the RI1 and RI2 indices to evaluate overall network redundancy, this study applies their methodology to the Census Block Group (CBG) scale. Specifically, RI1 and RI2 values were computed at the segment level before being

aggregated inside each CBG to capture localized redundancies. Because CBGs differ significantly in terms of road network extent, the final NRI values were adjusted by total road length to provide consistency across spatial units. The final normalized redundancy index was calculated as

$$NRI_{normalized} = \frac{NRI}{Total\ Road\ Length\ in\ CBG}$$

This index reflects both structural and functional redundancy in the road network. Higher NRI values indicate that a given neighborhood has more evenly distributed traffic flow and greater spare capacity, both of which are indicative of a transportation system that is better equipped to adapt during disruption and maintain access to critical services, including food outlets. The NRI serves as one of the three core components in the construction of the overall Transportation Resiliency Index (TRI).

Figure 6: Conceptual illustration of network redundancy



(Figure created by the author, 2025)

3.2.2.2 Network Mobility Index (NMI)

The Network Mobility Index (NMI) captures the ease with which individuals can move within the local transportation network. It integrates both the structural configuration of the road system and its operational performance, offering a comprehensive measure of accessibility at the neighborhood level (Jenelius & Mattsson, 2021). In this study, the NMI is constructed from two equally weighted components: the Physical Connectivity Assessment (PCA) and the Traffic Condition Assessment (TCA) following E. Rashidy et al. (2015) . Each index is independently normalized to a 0–1 scale before aggregation, with higher values indicating greater mobility.

The PCA quantifies how effectively the road network supports spatial connectivity and directness of movement. It is derived from two topological indicators: the Gamma Index and the Detour Index.

The Gamma Index (γ) measures the density of road connections in the network. It is calculated as:

$$\gamma = \frac{E}{[3(V-2)]} \qquad \text{(E. Rashidy et al., 2015)}$$

where E is the number of road segments, and V is the number of intersections (nodes) within the Census Block Group (CBG). A higher Gamma Index indicates a more interconnected street grid, offering greater flexibility for route choice and potentially shorter travel distances (E. Rashidy et al., 2015).

The Detour Index (DI) evaluates the efficiency of routes through the network. It is calculated as (E. Rashidy et al., 2015):

$$DI = \frac{GD}{TD} \qquad \text{(E. Rashidy et al., 2015)}$$

where GD is the Euclidean (straight-line) distance between the centroid of a given CBG and the centroid of its nearest neighboring CBG, and TD is the shortest travel distance between the two over the road network. As illustrated in Figure 7, a higher DI indicates more direct travel paths, which is preferable for mobility (E. Rashidy et al., 2015). Both the Gamma Index and Detour Index were normalized and averaged to yield the PCA:

$$PCA = \frac{\gamma + DI}{2} \qquad \text{(E. Rashidy et al., 2015)}$$

This formulation gives equal weight to the connectivity and directness of the network, recognizing that both are essential for facilitating efficient travel.

The TCA evaluates how well the network performs under typical traffic conditions, using two indicators (E. Rashidy et al., 2015): Free-Flow Travel Speed (FFTS) and the Volume-to-Capacity Ratio (V/C).

The FFTS was assigned to each road segment based on its MTFCC classification, with higher classes (e.g., primary roads) assumed to have higher travel speeds under normal conditions. This variable captures the design-level mobility potential of each road type.

The V/C ration was calculated then. The flow for each road segment was represented by the average AADT within its MTFCC class, while capacity was estimated as the maximum AADT observed in that class. The ratio is defined as:

$$VC = \frac{f}{C} \qquad \text{(E. Rashidy et al., 2015)}$$

where f is the average AADT and C is the class-specific peak AADT. This ratio provides a normalized measure of congestion, where lower values indicate more spare capacity and thus smoother traffic conditions.

To reflect the dynamic interaction between road design and congestion, the Traffic Condition Assessment (TCA) was calculated using the formula:

$$TCA = FFTS \times (1 - VC)$$ (E. Rashidy et al., 2015)

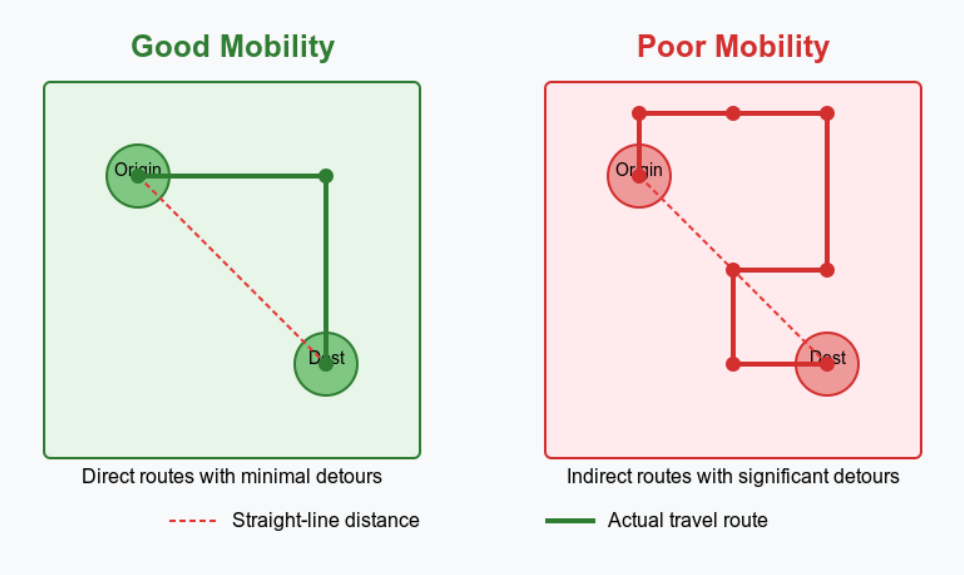
In this expression, FFTS (Free-Flow Travel Speed) represents the theoretical maximum speed achievable on a given road segment under ideal, uncongested conditions. (1 − VC) serves as a penalty factor that decreases the contribution of speed as congestion increases. A higher TCA indicates road segments that are both designed for efficient travel and currently uncongested. The TCA score for each Census Block Group (CBG) was determined by taking the mean of all intersecting road segment TCA values and assuming that each segment contributed equally to the overall CBG-level traffic condition.

The final Network Mobility Index (NMI) is computed as the average of the PCA and TCA scores (E. Rashidy et al., 2015):

$$NMI = \frac{PCA + TCA}{2}$$

This equal-weighting approach recognizes that both network structure and traffic performance contribute equally to a neighborhood's mobility. Higher NMI values indicate that the local transportation network is both physically well-connected and operationally efficient (E. Rashidy et al., 2015).

Figure 7: Conceptual illustration of network mobility



(Figure created by the author, 2025)

3.2.2.3 Network Vulnerability Index (NVI)

The Network Vulnerability Index (NVI) is used to evaluate the fragility of the transportation network at the neighborhood level by examining the susceptibility of road segments to congestion and disruption. It identifies where the transportation system may fail to operate effectively under increased pressure or during external stressors such as winter storms. The NVI is calculated first at the road segment level using three distinct but complementary indicators and then aggregated to the Census Block Group (CBG) level to support spatial analysis and planning.

The first indicator, VA1, captures the instability risk of a road segment by assessing how likely it is to tip into congestion based on its flow-to-capacity ratio (El-Rashidy & Grant-Muller, 2014):

$$VA1 = \frac{f}{c} \times (1 - \frac{f}{c})$$ (El-Rashidy & Grant-Muller, 2014)

Here, f is the average daily traffic (AADT) and CCC is the estimated capacity, approximated using the maximum AADT observed within each MTFCC class. The function peaks when the road operates at 50% of its capacity—this is considered the most unstable operating condition, as small increases in traffic at this point can result in a rapid decline in service quality (El-Rashidy & Grant-Muller, 2014). When the road is nearly empty or fully saturated, VA1 values decrease. However, this does not mean the road is more resilient; rather, it reflects that VA1 is designed to measure dynamic fragility (El-Rashidy & Grant-Muller, 2014). The key insight here is that instability is highest when the road still has some buffer, but not enough to absorb added stress without consequence.

The second component, VA2, reflects the relative capacity of the road segment, capturing its structural robustness within the overall network (El-Rashidy & Grant-Muller, 2014):

$$VA2 = \frac{C}{C_{max}}$$ (El-Rashidy & Grant-Muller, 2014)

Here, C_{max} is the highest estimated capacity observed across all road segments in the study area. Segments with low relative capacity are more vulnerable because they have limited ability to accommodate rerouted traffic during disruptions, making them structurally weaker links in the network.

The third metric, VA3, measures the physical length of the road segment, where longer roads are assumed to have more influence on the connectivity and continuity of the transportation system. As illustrated in Figure 8, the logic is that longer segmentswithout any connections, if disrupted, are likely to affect larger portions of the network or require longer detour distances, thereby contributing more to systemic vulnerability (El-Rashidy & Grant-Muller, 2014).

$$VA3 = L$$ (El-Rashidy & Grant-Muller, 2014)

To construct the composite vulnerability score for each road segment, the three indicators (VA1, VA2, and VA3) are first normalized to a 0–1 scale and then averaged with equal weighting.

$$VI(a) = \frac{VA1 + VA2 + VA3}{3}$$

This approach ensures that the NVI accounts for multiple dimensions of vulnerability: the potential for instability, the underlying structural limitations, and the spatial extent of exposure. While VA1 may appear counterintuitive by assigning low scores to both underused and oversaturated roads, it provides a unique contribution by highlighting the "tipping point" conditions where roads are most fragile—those not yet failed but most likely to degrade rapidly under stress (El-Rashidy & Grant-Muller, 2014).

The final NVI value at the CBG level is calculated by aggregating the segment-level scores within each CBG using a length-weighted average. This ensures that longer segments exert more influence on the overall vulnerability score, consistent with their greater role in enabling or disrupting local mobility. Formally, this is expressed as (El-Rashidy & Grant-Muller, 2014):

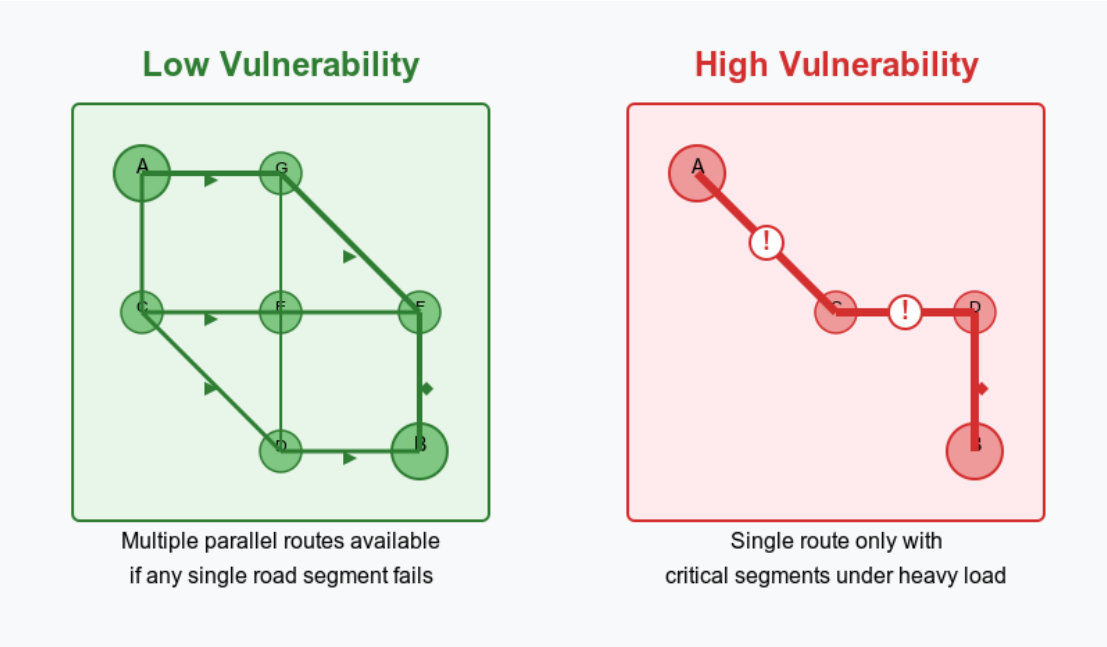
$$NVI_{CBG} = \frac{\sum(VI(a) \times L_a)}{\sum L_a}$$

where La is the length of each segment.

Higher NVI scores indicate neighborhoods that are more vulnerable to traffic disruptions—either because they contain unstable segments, roads with low capacity, or long stretches of infrastructure that are critical to network function. As part of the broader

Transportation Resiliency Index (TRI), the NVI offers a crucial dimension for identifying areas where improvements in capacity, redundancy, or route alternatives are most urgently needed.

Figure 8: Conceptual illustration of network vulnerability



(Figure created by the author, 2025)

3.2.2.4 Final Composite Index

The Transportation Resiliency Index (TRI) offers a composite assessment of how effectively a neighborhood's road network can absorb, adapt to, and recover from disruptions. It integrates three core dimensions of transportation system performance: vulnerability, redundancy, and mobility. These components are measured independently using the Network Vulnerability Index (NVI), Network Redundancy Index (NRI), and Network Mobility Index (NMI), each capturing a unique aspect of resiliency at the Census Block Group (CBG) level.

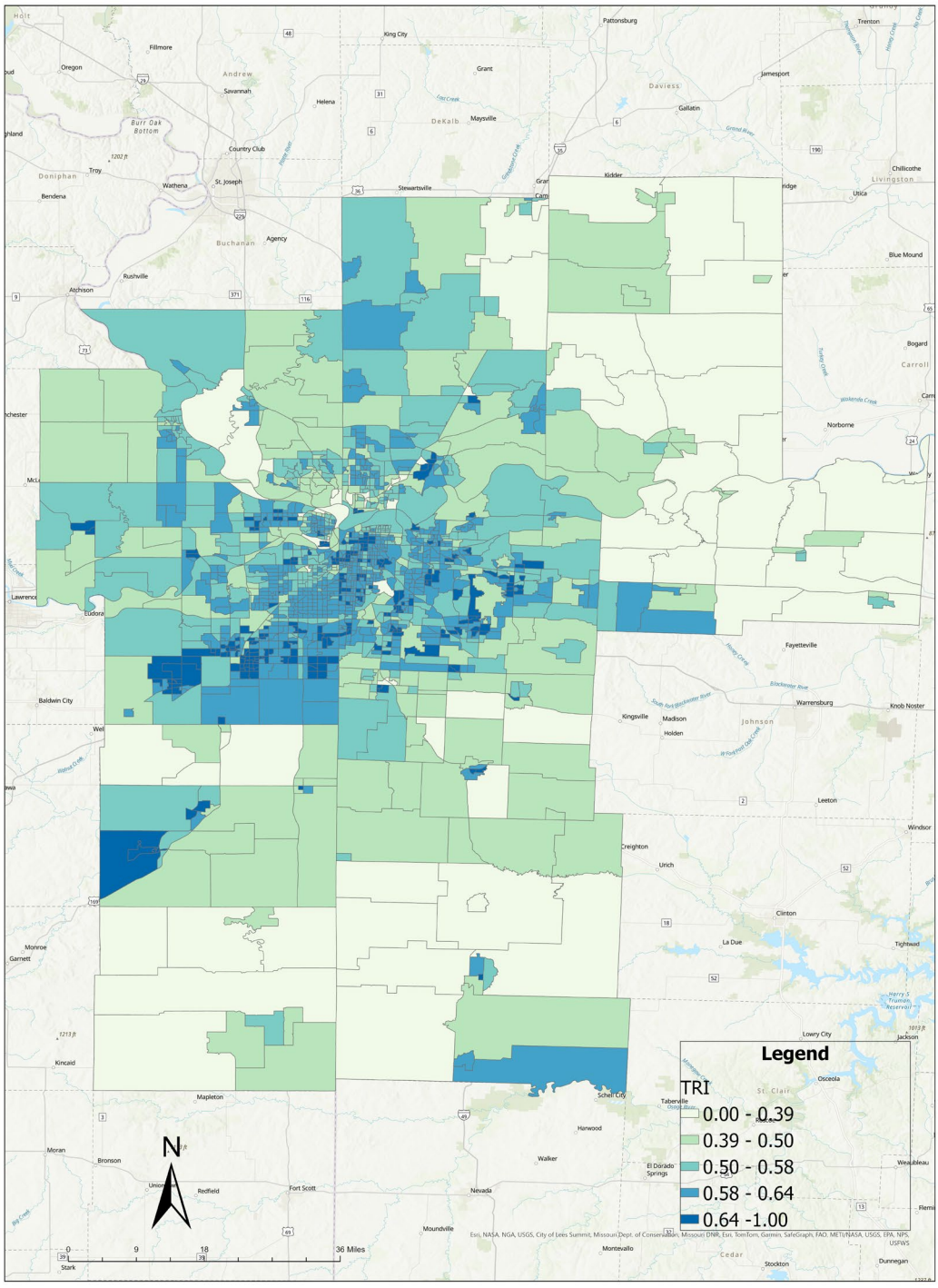
To compute the TRI, the three indices—NVI, NRI, and NMI—are first normalized to a common 0–1 scale to ensure comparability. In order to preserve uniform interpretation across all components, the Network Vulnerability Index (NVI) was inverted using (1−NVI), where larger

values signify better resiliency, because a higher NVI signals greater vulnerability and, thus, lower resiliency.

$$TRI = \frac{(1 - NVI) + NRI + NMI}{3}$$

As illustrated in Figure 9, the spatial distribution of resiliency across Census Block Groups (CBGs) in the Kansas City Metropolitan Area is depicted on the Transportation Resiliency Index (TRI) map. The findings show a distinct transportation resilience gradient between urban and rural areas. Because of the denser, more redundant, and better-connected road networks, the urban core and immediate suburban areas have higher TRI values (shown by darker teal tones), which represent enhanced resiliency. Conversely, lighter green hues indicate lower TRI values, which are primarily found in outer suburban and rural CBGs, indicating a lack of transportation resilience. Due to sparser road networks and fewer alternate routes, these localities probably suffer from decreased network redundancy, decreased mobility, and increased susceptibility to interruptions. Moderate resilience is shown by a few remote rural areas, which may be associated with important highway routes that offer improved connection. In general, the map shows notable spatial differences in transportation resilience, with urban communities more capable of absorbing and recovering from interruptions in the transportation system than their rural counterparts.

Figure 9: Distribution of TRI



3.2.3 Socioeconomic and Demographic Data

To examine how transportation resiliency interacts with broader community characteristics, a set of socioeconomic and demographic variables was collected at the Census Block Group (CBG) level. These indicators were sourced from the U.S. Environmental Protection Agency's (EPA) Smart Location Database, which integrates data for 2020 from the American Community Survey (ACS) and other national sources. Each variable was selected based on its established association with food access and food security outcomes in prior research (Achilana et al., 2020) and used as a control variable to better isolate the effect of transportation resiliency on food accessibility.

The percentage of developed land within each CBG was included to capture the intensity of land use and level of urbanization. Highly developed areas may benefit from denser infrastructure and shorter distances to food outlets but can also face zoning-related limitations or congestion that hinders access (Ding & Gebel, 2012). Population density, measured as the number of residents per acre, was collected to account for the effects of residential clustering. While dense neighborhoods often support more retail and transit options, they may also experience increased demand pressures during disruptive events.

The percentage of vacant housing units was included as a proxy for neighborhood instability and disinvestment. Higher vacancy rates are frequently associated with reduced commercial services, including fewer grocery stores and weaker transportation connectivity (Dewar, 2015). Racial composition was captured through the percentage of residents identifying as white, to explore patterns of racial disparity in access to resilient infrastructure and essential services. Finally, the percentage of low-wage residents was included as a measure of economic vulnerability. Individuals earning lower wages often face greater challenges in maintaining food

access, especially when transportation systems are disrupted or require flexibility not supported by limited financial means (Jiao et al., 2012).

Taken together, these socioeconomic and demographic variables provide important context for understanding disparities in food access across communities. Their inclusion as control variables ensures a more accurate estimation of the independent effect of transportation resiliency on behavioral outcomes like food store visitation during normal and disruptive conditions.

3.3 Analytical Technique

3.3.1 Descriptive Analysis of Variables

In this study, we used both dependent and independent variables to examine the relationship between transportation resiliency and food access behavior across neighborhoods. As illustrated in Table 2, the dependent variables represent the Retail Food Activity Index, which we calculated under two conditions. One reflects average food access behavior over a typical month, while the other captures access patterns during snowstorm weeks. These indices are derived from SafeGraph foot traffic data and allow us to evaluate how frequently residents visit healthy food retailers compared to less healthy alternatives under both normal and disrupted conditions.

The independent variables include the Transportation Resiliency Index as our primary explanatory measure. In addition, we incorporated several control variables that represent neighborhood-level socioeconomic and built environment characteristics. These include the percentage of developed land, population density, the percentage of vacant housing units, the percentage of white residents, and the percentage of low-wage residents. These variables were

selected based on their well-established relevance in the literature concerning transportation equity, land use, and food security (Jiao et al., 2012; Ng & Acker, 2018).

Table 2: Descriptive analysis of variables

Variable	Description	Unit	Mean	Median	Std Dev	Source
Dependent variable						
log_m_rfai	Retail Food Activity Index (For Month)	Percentage	0.361	0.366	0.123	(Advan Research, 2025)
log_w_rfa	Retail Food Activity Index (Snow-storm week)	Percentage	0.358	0.364	0.164	(Advan Research, 2025)
Independent variable						
log_TRI	Transportation Resiliency Index	Index	0.463	0.476	0.07	(BTS, 2021)
Pct_develo	Percentage of developed land	Percentage	96.72	99.98	7.26	(EPA, 2021)
Pop_Den	Population Density	Number of people per Acre	4.647	4.12	3.97	(EPA, 2021)
Pct_vacant	Percentage of vacant household	Percentage	9.68	6.93	10.38	(EPA, 2021)
Pct_white	Percentage of white people	Percentage	68.41	78.75	28.00	(EPA, 2021)
Pct_lw	Percentage of low wage residents	Percentage	0.123	0.115	0.054	(EPA, 2021)

To improve the suitability of the data for regression analysis, we applied logarithmic transformations to the Retail Food Activity Index and the Transportation Resiliency Index. This

transformation helped reduce skewness, normalize distributions, and stabilize variance, which is important for meeting the assumptions of linear and spatial econometric models. It also enhances the interpretability of regression coefficients by allowing us to understand changes in the dependent variable in percentage terms relative to changes in the explanatory variables.

3.3.2 Regression Modeling and Spatial Dependence

To estimate the relationship between transportation resiliency and food access behavior across neighborhoods, we first employed a Multiple Linear Regression (MLR) model using Ordinary Least Squares (OLS). The dependent variable in the model was the log-transformed Retail Food Activity Index, while the key explanatory variable was the log-transformed Transportation Resiliency Index. Socioeconomic and built environment characteristics were included as control variables to account for potential confounding factors. The MLR model served as a baseline for understanding the direction and strength of associations in a non-spatial context.

However, given the spatial structure of the data where each observation represents a Census Block Group (CBG), we tested for spatial autocorrelation for our dependent variables. This was done using global Moran's I, which measures the degree to which similar values cluster in space. A significant Moran's I statistic in the residuals indicates that the assumption of independently distributed errors is violated, suggesting that spatial effects are present and that MLR results may be biased or inefficient (Anselin, 2001) Upon detecting spatial dependence, we applied two spatial econometric models: the Spatial Lag Model (SLM) and the Spatial Error Model (SEM). The Spatial Lag Model accounts for the possibility that the dependent variable in one location may be influenced by values in neighboring locations (Anselin, 2001), implying

spillover effects in food access behavior. Alternatively, the Spatial Error Model captures spatial autocorrelation in the error terms, representing unobserved spatial processes not directly measured by the included variables.

Based on diagnostic test results and model fit criteria, including a significant Moran's I test on OLS residuals, a highly significant Lagrange Multiplier (LM) test for spatial lag dependence, and a lower AIC value for the spatial lag model compared to OLS, we selected the Spatial Lag Model as the most appropriate specification for both the monthly and storm-week scenarios. The SLM incorporates a spatially lagged dependent variable to account for diffusion effects, under the assumption that food access behavior in one CBG may be shaped by the food access levels in neighboring areas. This formulation is particularly suitable in urban contexts, where travel behavior, shopping preferences, and local infrastructure often exhibit spatial interdependence. We used a queen contiguity spatial weights matrix to define neighborhood relationships, where CBGs are considered neighbors if they share a boundary or vertex. The weights were row-standardized to maintain comparability across units.

All regression models, including OLS and SLM, were implemented in R using the spdep package (Roger Bivand, 2023). This methodological approach enabled us to control for spatial dependence in the data, yielding more robust and accurate estimates of how transportation resiliency influences food access behavior at the neighborhood level.

Chapter 4 - Result & Discussion

This chapter presents the results of the spatial statistical analyses conducted to examine how transportation resiliency influences neighborhood-level food access behavior under both typical and disrupted conditions. The study assessed food access using the Retail Food Activity Index (RFAI) across two temporal scenarios: average monthly behavior and behavior during a snowstorm week. To ensure the robustness of the findings, the analysis incorporated spatial dependence diagnostics and spatial econometric modeling, reflecting the geographic structure of the data and the potential for neighborhood-level interactions in food access behavior. The analytical process followed a stepwise approach beginning with traditional regression analysis, followed by spatial diagnostics, and culminating in spatial econometric modeling.

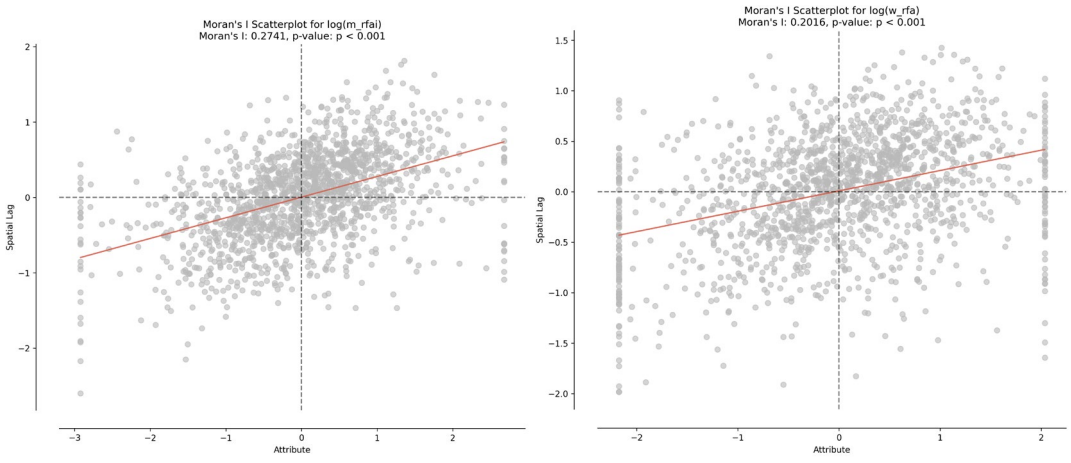
We first employed an Ordinary Least Squares (OLS) regression model to predict monthly food access behavior. The OLS model result, presented in Table 2, indicate that the Transportation Resiliency Index (TRI) is a significant and positive predictor of food access, alongside other built environment and demographic variables. Key predictors such as percentage of developed land, percentage of white residents, and lower levels of low-wage employment were all significantly associated with higher food access. The model yielded an adjusted R-squared of 0.1173 and an AIC of 3830.5, suggesting a modest fit. However, residual diagnostics from the OLS model revealed significant spatial autocorrelation, as shown by Moran's I ($I = 0.153$, $p < 0.001$). This indicated that the OLS model violated the independence assumption, potentially biasing its estimates.

Table 3: OLS Model for m_rfai

Variable	Estimate	Std. Error	t-value	p-value
(Intercept)	-1.993	0.306	-6.512	<0.001***
log_TRI	0.699	0.138	5.080	<0.001***
Pct_develo	0.013	0.003	4.352	<0.001***
Pop_Den	-0.001	0.006	-0.234	0.815
Pct_vacant	-0.010	0.002	-4.103	<0.001***
Pct_white	0.007	0.001	7.424	<0.001***
Pct_lw	-1.574	0.413	-3.812	<0.001***
Significance: *** p<0.001, ** p<0.01, * p<0.05				
Adjusted R^2 = 0.1173; AIC = 3830.50; Residual SE = 0.8415; Moran's I = 0.153 (p < 0.001); LM Lag = 114.97 (p < 0.001)				

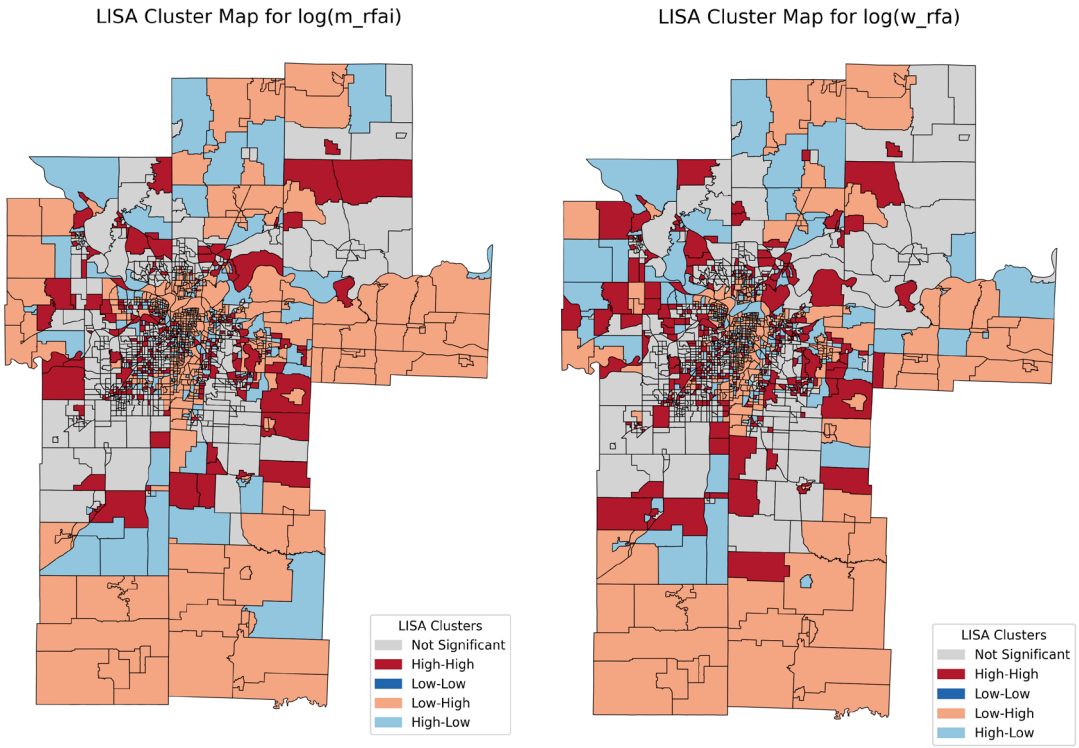
To further explore spatial structure in the dependent variables, we examined Global Moran's I of dependent variable Retail Food Activity Index (R_FAI). In both monthly and snowstorm cases, the results revealed meaningful levels of spatial autocorrelation (Figure 10).

Figure 10: Global Moran's I for m_rfai and w_rfai



This indicates that neighborhoods with similar food access behavior tend to be located near each other, rather than being randomly distributed across space. These spatial patterns are likely influenced by a combination of factors, including regional land use patterns, infrastructure layout, and the distribution of food retailers. The spatial clustering confirmed the need to apply spatial regression techniques, as standard linear regression would not adequately account for these geographic relationships.

Figure 11: LISA Cluster Map for R_FAI



While Global Moran's I verified statistically substantial overall geographical autocorrelation in Retail Food Activity Index (RFAI) values, Local Indicators of Spatial Association (LISA) were utilized to identify spatially dependent clusters. The LISA maps for monthly and snowy week RFAI (Figure 11) showed large High-High clusters in central

metropolitan regions, indicating high food activity surrounded by equally active communities. Low-High and High-Low clusters appeared on the outskirts, indicating local differences in food access. Low-Low clusters were minor or nonexistent. Clustering was particularly noticeable during the snowfall week, emphasizing the importance of harsh weather in exacerbating geographical disparities. These trends support the use of spatial regression models to account for localized effects.

To explore the appropriate form of spatial modeling, we conducted a series of Lagrange Multiplier (LM) tests based on the residuals from the OLS model. Both the LM test for spatial lag dependence (LM-Lag = 114.97, $p < 0.001$) and for spatial error dependence (LM-Error = 109.2, $p < 0.001$) were significant, indicating that spatial autocorrelation was present in the data. To determine the more suitable spatial model, we evaluated the robust versions of these tests. The Robust LM-Lag remained statistically significant (Robust LM-Lag = 6.089, $p = 0.0136$), while the Robust LM-Error was not significant (Robust LM-Error = 0.316, $p = 0.5743$). Based on these results, we selected the spatial lag model as the more appropriate specification.

The results from the spatial lag models, presented in Table 4, clearly show that socioeconomic conditions are strongly associated with food access in both normal and disrupted settings. Higher vacancy rates and greater shares of low-wage residents are consistently linked to lower levels of food access, reinforcing longstanding findings in the literature that communities with fewer resources face greater barriers to essential services. These relationships are in line with previous studies that have documented how structural disadvantage, housing instability, and economic precarity intersect to limit food access, particularly in urban areas.

Table 4: Comparison of Spatial Lag Model

Spatial Lag Model (For a Month)					Spatial Lag Model (During the Snow-Storm Week)			
Variable	Estimate	Std. Error	z-value	p-value	Estimate	Std. Error	z-value	p-value
(Intercept)	-1.518	0.297	-5.11	<0.001***	-2.21	0.51	-4.33	<0.001***
log_TRI	0.577	0.132	4.38	<0.001***	0.862	0.227	3.80	<0.001***
Pct_develo	0.012	0.003	4.34	<0.001***	0.019	0.005	3.87	<0.001***
Pop_Den	-0.003	0.006	-0.48	0.629	-0.026	0.010	-2.50	0.012*
Pct_vacant	-0.006	0.002	-2.75	0.006**	-0.015	0.004	-3.88	<0.001***
Pct_white	0.004	0.001	5.04	<0.001***	0.007	0.002	4.62	<0.001***
Pct_lw	-1.507	0.394	-3.83	<0.001***	-1.902	0.679	-2.80	0.005**
Significance: *** p<0.001, ** p<0.01, * p<0.05					Significance: *** p<0.001, ** p<0.01, * p<0.05			
Rho = 0.380 (p < 0.001)					Rho = 0.336 (p < 0.001)			

In contrast, areas with a higher percentage of white residents and greater shares of developed land consistently demonstrate stronger access to healthy food retailers. These findings align with existing research on racial and infrastructural disparities, where majority-white and well-developed neighborhoods are more likely to benefit from robust infrastructure, commercial investment, and service availability. Notably, while population density did not significantly affect food access under normal conditions, it became negatively associated with access during snowstorms, suggesting that denser urban areas may be more vulnerable to disruptions due to their greater reliance on systems susceptible to stress.

Crucially, the Transportation Resiliency Index (TRI) was significantly associated with food access in both models, affirming its central role in supporting daily and emergency

mobility. In the monthly model, TRI is already a strong predictor of higher food access levels. However, its influence becomes even more pronounced during the snowstorm week, when disruptions put additional stress on transportation infrastructure. This heightened impact emphasizes that resilient transportation systems not only enhance routine access to food but are critical in maintaining that access under adverse conditions.

By including socioeconomic and built environment characteristics as control variables, the models isolate and clarify the unique contribution of transportation resiliency. Even after accounting for factors like income, race, and neighborhood form, TRI remains a significant and positive predictor of food access. This demonstrates that transportation resiliency exerts an independent effect beyond the constraints of socioeconomic context. In other words, building more resilient infrastructure can have a tangible impact on food security, even in communities that face other systemic challenges.

Together, these results point to the importance of integrating resiliency planning with equity-focused urban strategies. Investments in resilient transportation systems, particularly in underserved areas, can enhance food access and buffer communities from the compounding effects of disruption and deprivation. The evidence from this study supports the view that transportation systems are not simply conduits for movement—they are critical enablers of equitable food access and long-term community resilience.

Chapter 5 - Conclusion

5.1 Implication

This study sets out to examine the extent to which transportation resiliency influences neighborhood-level food access, particularly in the context of climate-related disruptions such as winter storms. While food insecurity is a widely recognized global issue, its spatial and infrastructural dimensions—especially the role of resilient transportation systems in enabling consistent access to healthy food—have received relatively limited attention in the academic literature. By focusing on the Kansas City Metropolitan Area, a region marked by both infrastructural and socioeconomic disparity, this research contributes to a more nuanced understanding of how transportation systems shape food accessibility in urban environments.

To conduct this analysis, we developed a Transportation Resiliency Index (TRI) composed of three components: vulnerability, redundancy, and mobility. We also calculated a Retail Food Activity Index (RFAI) using mobile phone-based mobility data from SafeGraph to represent food access behavior under normal and snowstorm conditions. These indices, along with a set of socioeconomic and built environment variables, were analyzed using spatial regression models that accounted for the geographic interdependencies among neighborhoods.

The results show that transportation resiliency has a statistically significant and positive association with food access in both scenarios. Importantly, the effect of TRI is stronger during the snowstorm week, indicating that resilient infrastructure plays an even more critical role when systems are under stress. Socioeconomic factors, such as vacancy rates, racial composition, and income levels, were also found to be influential, consistent with prior literature that links structural disadvantage to limited food access. However, even after controlling for these

variables, TRI remained a significant predictor, underscoring its independent contribution to food system resilience.

These findings carry important policy implications. Urban planners, transportation agencies, and food system advocates must recognize that improving infrastructure resiliency is not solely a matter of mobility, it is also a pathway to promoting food equity. Interventions that enhance redundancy, improve travel efficiency, and reduce system vulnerability can help ensure that all communities, especially those that are historically underserved, maintain access to healthy food even in the face of disruptions.

By integrating spatial data, food access behavior, and resilience indicators, this study advances the empirical understanding of how transportation systems influence food access at the local level. It also reinforces the need for place-based planning approaches that prioritize equity, adaptability, and continuity. As climate-related events become more frequent and severe, the value of resilient infrastructure, especially in supporting essential services like food will only become more apparent. Building and maintaining resilient transportation systems must therefore be central to any strategy aimed at strengthening food security in urban areas.

5.2 Limitation

It is necessary to recognize that this study has a number of significant limitations. First, categorizing food companies into "healthy" and "less healthy" groups based only on NAICS codes could not be a good representation of how customers actually behave. For instance, while being categorized as healthy food shops, big-box retailers like Walmart frequently sell a lot of highly processed, less nutrient-dense goods, which may distort actual dietary habits (Ferdinands et al., 2023). The accuracy with which the Retail Food Activity Index (RFAI) represents the dynamics of food access in the actual world may be impacted by this classification restriction.

Second, rather than using local field measurements, the Transportation Resiliency Index (TRI) was built using estimated values for factors like AADT, which were based on national MTFCC requirements. Despite being widely used in transportation research, proxy-based approaches might introduce errors, particularly in rural or dynamic contexts where network features differ from national averages (Hylton & Miller, 2023). Third, the use of mobile phone location data (SafeGraph/Advan) introduces sampling biases because the dataset may underrepresent vulnerable populations and only represents a subset of the population, usually younger, wealthier people with smartphones (Meppelink et al., 2020). As a result, not all demographic groups' mobility behaviors may be well represented by the foot traffic patterns seen. Fourth, the study's food retailer database did not include alternative or informal food sources like farmers' markets, food cooperatives, and mobile food vendors, which can be important for local food access but are frequently underrepresented in conventional business listings (Liese et al., 2007). Lastly, this analysis did not specifically simulate public transportation infrastructure, which is a crucial component affecting food access and transportation resilience. People without private automobiles may have additional difficulties that are not entirely represented in a road network-only analysis, particularly in low-income areas (Widener et al., 2011).

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