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A Geospatial Analysis of Food Deserts in Southwest Florida

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Abstract

This study conducted a geospatial analysis of food deserts through low-income and low-access census tracts across Southwest Florida (SWFL), focusing on the intersection of food accessibility, socioeconomic factors, and public health. Using data sourced from the United States Department of Agriculture (USDA) and the U.S. Census Bureau the research identifies and maps areas within SWFL that qualify as food deserts or regions with limited access to affordable and nutritious food. The analysis incorporates Geographic Information Systems (GIS) to visualize spatial variability and examine correlations between food access, income levels, and population demographics. The findings reveal that food deserts in SWFL are predominantly concentrated in low-income, socioeconomically vulnerable populations, and rural communities. Hendry, Glades, and parts of Lee and Collier counties exhibit significant food accessibility challenges. The spatial patterns suggest that food insecurity is not randomly distributed but closely tied to historical patterns of socioeconomic differences and urban development. The study highlights the role of transportation and the distribution of supermarkets and grocery stores in exacerbating food disparities. This research demonstrates the critical need for data-driven policy interventions that target vulnerable communities through improved public transportation, incentives for grocery retailers in underserved areas, and urban planning initiatives that integrate food access into regional development strategies. Ultimately, the paper contributes to the broader issue of public health by illuminating the spatial dimensions of food deserts in the SWFL region.

Keywords

Food Deserts, Low-Income, Low-Access, Food Equity, Geospatial Analysis

1. Introduction

Inequitable access to healthy nutritious food is a consistent issue among vulnerable communities. Food inequity refers to the unequal access to affordable, nutritious food, which disproportionately affects socioeconomically vulnerable populations. Food equity is a significant component of broader socioeconomic disparities and has far-reaching impacts on health, well-being, and overall quality of life [1] [2]. Socioeconomically vulnerable populations include but are not limited to racial and ethnic minorities, disabled persons, and elderly populations. There are many ways to measure and understand food distribution globally, regionally, and locally. Hunger is a term used to describe an individual suffering a prolonged, involuntary lack of food that results in physical discomfort, weakness, or pain that may be a consequence of food insecurity [3]. Food Insecurity can then be defined as a household level economic and social condition of limited or uncertain access to adequate food [3]. Food insecurity is measured through yearly census surveys using indicators such as going 24 hours without a meal, weight loss, not having the financial ability to purchase enough food or a balanced meal.

Food deserts are a key factor contributing to inequitable access to healthy, affordable foods for socioeconomically vulnerable populations. Food Deserts are defined by the USDA as areas that often have high concentrations of households with low incomes, inadequate access to transportation, and a limited number of food retailers providing fresh produce and healthy groceries for affordable prices [3]. As urbanization rapidly increases along with the global population, the number of grocery stores and supermarkets in these areas continues to decrease [4]. There are many reasons for this including high crime rates in these areas, as well as low-income neighborhoods that reduce profitability [5]. Many inner city grocery stores are unsuccessful due to low profitability, crime rates, and cultural biases [6]. The negative stigma surrounding neighborhoods with high minority and low-income populations plays a big role in the availability of food access [4]. A lack of reliable transportation is also an important factor in the development of food deserts as grocery stores and supermarkets get further away from residential urban areas [7]. The consequence of what was previously described is the declining nutritional quality of available and affordable food categorized as "empty calorie" food [5] [8] [9].

The terminology has shifted from using the term "food deserts" to describe these areas to using low income and low access to food. Since 2013, the Economic Research Service (ERS) has used the term "low-income and low access" to designate areas with limited access to healthy food, as it more accurately reflects what is statistically measured in the Food Access Research Atlas (FARA) [3]. Many of these areas are identified through census tracts using census survey data. Low Income (LI) tracts are defined by the USDA as tracts with the following criteria: poverty rate is 20 percent or greater; or the tract's median family income is less than or equal to 80 percent of the State-wide median family income; or the tract is in a metropolitan area and has a median family income is less than or equal to 80 percent. Low Access (LA) tracts are identified using multiple scales. LA at 1 mile and 10 miles where a significant number or share of residents is more than 1 mile (urban) or 10 miles (rural) from the nearest food store, is the most used indicator of a LA tract. Low Income and Low Access (LILA) tracts are the areas we are focusing on in this study.

In recent years, the population in Southwest Florida has been increasing exponentially. It has a diverse population with varying numbers of residents in both urban and rural areas. Food insecurity may look different in urban and rural areas in the five-county region of southwest Florida. Seasonal workers, low-income workers and retirees on fixed incomes make up most of the population in the southwest Florida region, making it more challenging to understand food insecurity in the area. Using geospatial technology and software, we would like to investigate the various factors contributing to the development and identification of food deserts/LILA tracts. This project aims to utilize geospatial techniques to explore the demographic and socioeconomic factors involved in the development of food deserts or LILA tracts in Southwest Florida. This includes Lee, Collier, Charlotte, Hendry, and Glades County. Using GIS Software and census data for the years 2015 and 2019 for each county we can identify census tracts that have been classified as food deserts, also called "Low Income and Low Access" tracts. We aim to understand the occurrences of food deserts by looking at many socioeconomic parameters including the number of people using Supplemental Nutrition Assistance Program (SNAP) benefits/Food Stamps, distances from grocery stores or supermarkets, distances from food pantries, access to transportation, and walkability scores for specific areas. The demographic data includes population, ethnicity, age, gender, poverty rate, household size, and income. Geospatial tools such as muti-variate spatial analyses, local bivariate spatial analyses, multivariate clustering, cluster and outlier analyses, exploratory regressions, etc. may offer valuable analysis of the many variables and parameters. This study will allow us to understand the effects of urbanization on food access and the development of food deserts. This will also help us identify relationships between specific demographic and/or socioeconomic factors and the origin of food deserts. This study will be essential for improving access to healthy nutritious foods.

2. Methods

Demographic and socioeconomic data, including population characteristics, ethnicity, poverty rate, low-income and low-access areas (LILA), and other relevant economic and social variables, were obtained for the five-county region of Lee, Collier, Hendry, Charlotte, and Glades from the United States Department of Agriculture (USDA) Food Access Research Atlas [3]. This dataset provides information on food access and associated factors at the census tract level across the United States, encompassing indicators such as low income, limited access to grocery stores and supermarkets, poverty rates, and ethnic composition, among others. These variables were used to explore potential relationships or patterns related to food access across the census tracts.

The Environmental Systems Research Institute (ESRI) ArcGIS Pro (v3.3) software was employed for visualizing the food access data and conducting spatial and statistical analyses [9]. There were no missing values within the dataset used in the paper. After acquiring the data from a reliable source, we reviewed the dataset and converted the necessary data to the proper format. It was combined into a geospatial layer and reviewed for discrepancies while joining the dataset using the Join Tool. The FIPS Codes, unique codes given to each Census area, were used to join the datasets. Food Access data for the years 2015 and 2019 were imported into ArcGIS Pro, and LILA census tracts were visualized. To enable efficient spatial and statistical analysis, the data was reprojected into a Universal Transverse Mercator (UTM) Zone 17N coordinate system.

Spatial clustering patterns of LILA census tracts were assessed using the Spatial Autocorrelation tool, which identifies whether the LILA tracts are clustered, dispersed, or randomly distributed. This tool applies Moran's I index, z-scores, and p-values to determine the statistical significance of the observed patterns [10]. The null hypothesis, which posits that spatial features are uncorrelated, was rejected if the results indicated statistical significance (e.g., $p\text{-value} < 0.05$). Statistically significant clustering was observed for LILA tracts (with 0 indicating non-LILA and 1 indicating LILA tracts).

To identify clusters of high-value areas, specifically those tracts exhibiting both low income and low access to food, the High/Low Clustering tool was employed. This tool utilizes the Getis-Ord General G statistical method to detect clusters of high or low values, thereby revealing statistically significant concentrations of LILA tracts [11].

In addition, outliers within these clusters were identified using the Cluster and Outlier Analysis tool, which applies Anselin Local Moran's I statistics to detect hot spots, cold spots, and spatial outliers [12]. A high positive z-score indicates a feature surrounded by similar values, while a low negative z-score represents a statistically significant spatial outlier.

To investigate the relationship between key demographic variables and food access, the Local Bivariate Relationship (LBR) and Spatially Constrained Multivariate Clustering (SCMC) tools were applied. LBR analyzes the relationship between two variables for statistical significance using local entropy, categorizing the relationships into six types: Not Significant, Positive Linear, Negative Linear, Concave, Convex, or Unidentified Complex. The independent (explanatory) variable selected for this analysis was food access (as determined by the presence of LILA tracts). SCMC was used to identify spatially contiguous clusters of census tracts based on multiple demographic variables. This method generates visual representations and boxplots, which illustrate the interquartile range (IQR) and highlight the variables most influential in defining each cluster. The clusters produced by SCMC represent spatial groupings of similar tracts, offering insight into the demographic patterns associated with food access.

To further assess food accessibility, additional layers representing the driving and walking distances (within 10 minutes) to grocery stores were overlaid on the map. These layers were publicly available [13]. For the Walk Time analysis, only walkable streets were included. This means highways and other roads that can't be walked on were excluded. However, areas near grocery stores with overpasses or underpasses are still considered walkable, as people can cross through them safely. For the Drive Time analysis, all types of roads were included, so it reflects how far someone could drive in 10 minutes under normal conditions. The results are shown in the Lines layer, which highlights which starting points are within 10 minutes of a grocery store, based on whether the person is walking or driving. This data defined Grocery stores according to the North American Industry Classification System (NAICS) code 445110, which corresponds to supermarkets and other grocery retailers, excluding convenience stores [14] [15]. These establishments sell canned and frozen foods, fresh fruits and vegetables, and fresh and prepared meats, fish, and poultry. The grocery store data (ESRI Policy Maps) is publicly available and was used to generate visual representations of accessibility within the study area.

3. Results

The Spatial Autocorrelation shows statistically significant (p-value < 0.05) clustering of LILA tracts, indicating these areas were spatially correlated to one another in 2015 and 2019.

In 2015, 19% of Lee County tracts (32 out of 165), 15% of Collier County tracts (11 out of 73), 21% of Charlotte County tracts (8 out of 38), 33% of Hendry County tracts (2 out of 6) and 100% of Glades County tracts (3 out of 3) are LILA.

In 2019, 16% of Lee County tracts (26 out of 165), 15% of Collier County tracts (11 out of 73), 13% of Charlotte County tracts (5 out of 38), 33% of Hendry County tracts (2 out of 6), and 100% of Glades County tracts (3 out of 3) are LILA.

3.1. Local Bivariate Analysis

In 2015, An analysis of LBR between poverty rate and LILA tracts shows no significant relationships in 27 out of 56 (48%) LILA tracts, a positive linear or concave relationship between 24 out of 56 LILA tracts (43%), a convex relationship is shown in 4 out of 56 (7%) of LILA tracts, an undefined relationship in 1 out of 56 (<1%) LILA tracts, and no negative linear relationships in any of the LILA tracts.

In 2019, An analysis of LBR between poverty rate and LILA tracts shows no significant relationships in 42 out of 47 (89%) LILA tracts, a positive linear or concave relationship between 4 out of 47 LILA tracts (9%), a convex relationship is shown in 1 out of 47 (2%) of LILA tracts, and no negative linear relationships or an undefined relationships are found in any of the LILA tracts.

In 2015, An analysis of LBR between Low Vehicle Access and LILA tracts shows no significant relationships in 33 out of 56 LILA tracts (59%), positive linear relationships in 13 out of 56 LILA tracts (23%) and an undefined relationship in 10 out of 56 LILA tracts (18%).

In 2019, An analysis of LBR between Low Vehicle Access and LILA tracts shows no significant relationships in 40 out of 47 LILA tracts (85%), positive linear relationships in 3 out of 47 LILA tracts (6%) and an undefined relationship in 4 out of 47 LILA tracts (9%).

3.2. Spatially Constrained Multivariate Analysis

In 2015, a spatially constrained multivariate analysis using the demographic variables; poverty rate, African American population, Hispanic population, and White population shows 4 clusters as seen in **Figure 1**. Cluster 1 shows an area with an average poverty rate, slightly above average African American, Hispanic, and White population. Within cluster 1, 22 out of 214 are LILA tracts (10%). Cluster 2 shows an area with a poverty rate and African American population well above average, a slightly above average Hispanic population, and slightly below average White population. Within cluster 2, 6 out of 9 are LILA tracts (67%). Cluster 3 shows areas with above average poverty rates, African American, and Hispanic populations, and a below average White population. Within cluster 3, 26 out of 51 tracts are LILA (51%). Cluster 4 shows an area with a slightly higher than average poverty rate, and well above average African American, Hispanic, and White populations. Within cluster 4, 3 out of 11 are LILA tracts (27%).

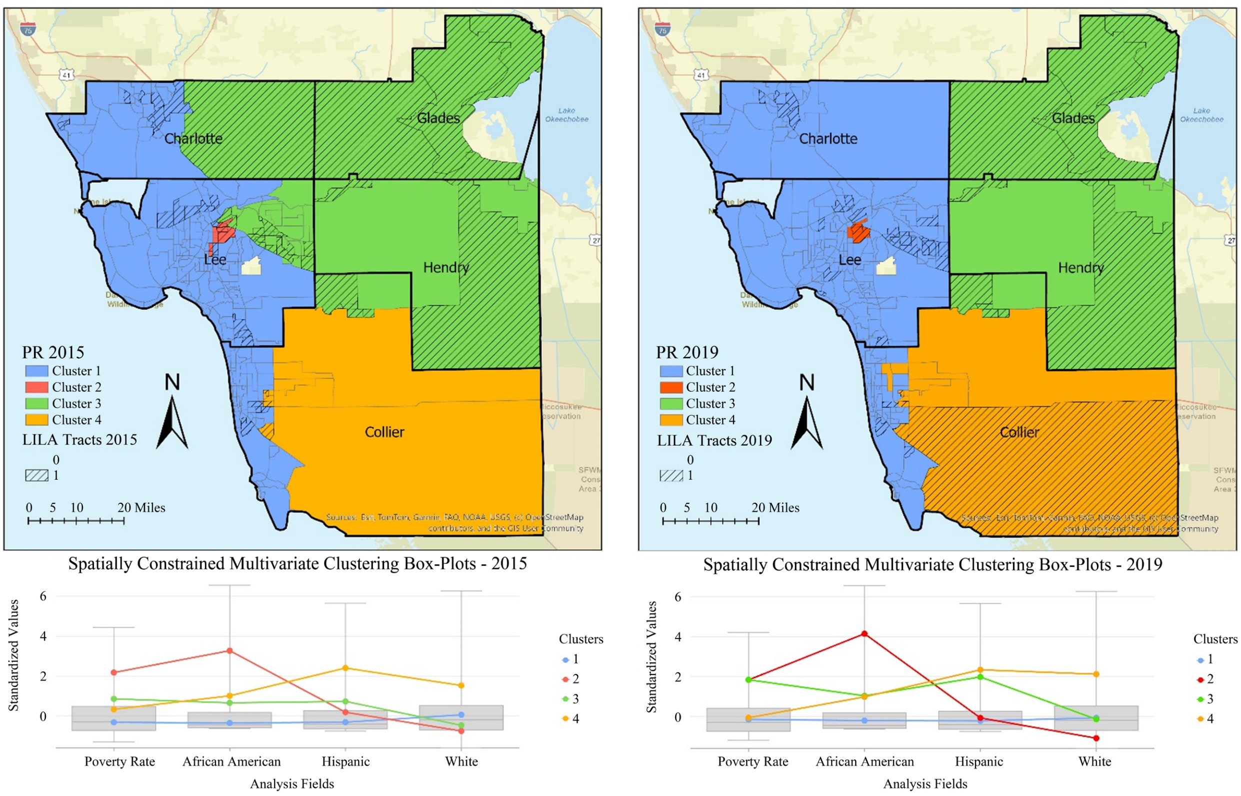

Figure 1. A spatially constrained multivariate analysis in 2015 and 2019 using the parameters poverty rate, African American, hispanic, and white populations. The figure shows many LILA tracts within clusters with high poverty rates and high socioeconomically vulnerable populations. It also shows LILA tracts in highly urban areas with low access to food, such as the Downtown Fort Myers Area.

The same spatially constrained multivariate analysis was conducted for 2019 as seen in Figure 1. Cluster 1 shows an area with an average poverty rate, slightly above average African American, Hispanic, and White population. Within cluster 1, 31 out of 253 are LILA tracts (12%). Cluster 2 shows an area with a poverty rate and African American population well above average, a slightly above average Hispanic population, and a below average White population. Within cluster 2, 3 out 6 are LILA tracts (50%). Cluster 3 shows areas with above average poverty rates, African American, and Hispanic populations, and an average White population. Within cluster 3, 9 out of 14 are LILA tracts (64%). Cluster 4 shows an area with an average poverty rate, and well above average African American, Hispanic, and White populations. Within cluster 4, 3 out of 12 are LILA tracts (25%).

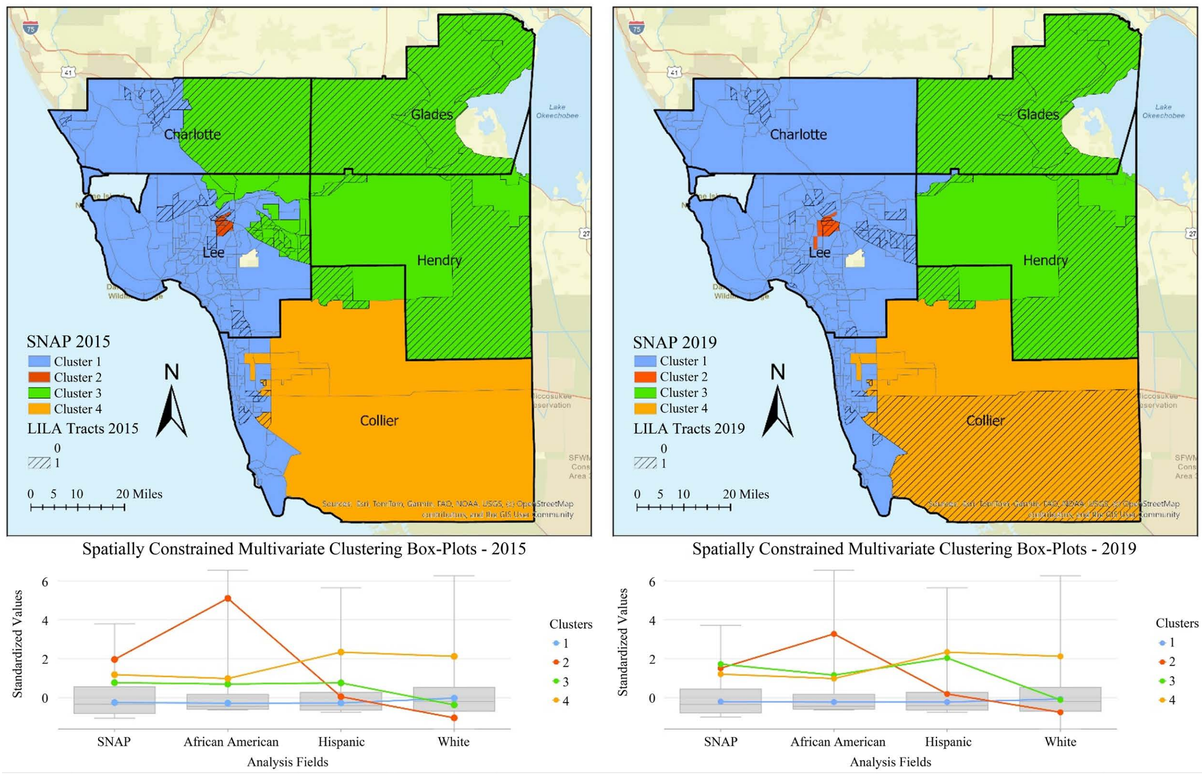

Figure 2. Spatially constrained multivariate analysis in 2015 and 2019 using the parameters SNAP benefits, African American, hispanic, and white populations. The figure shows many LILA tracts within clusters with high usage of SNAP benefits and high socioeconomically vulnerable populations. It also shows more SNAP benefits being used in areas with low access to food such as highly urban areas and more rural areas. The red cluster being the most striking as it is a highly urban area with a high usage of SNAP benefits and has the highest African American population showing 100% LILA tracts in 2015 and 50% LILA tracts in 2019.

In 2015, a spatially constrained multivariate analysis using the demographic variables; population receiving SNAP benefits, African American population, Hispanic population, and White population shows 4 clusters as seen in Figure 2. Cluster 1 shows an area receiving the average amount of SNAP benefits, slightly above average African American, Hispanic, and White population. Within cluster 1, 26 out of 225 are LILA tracts (12%). Cluster 2 shows an area with SNAP benefits and African American population well above average, a slightly above average

Hispanic population, and below average White population. Within cluster 2, 4 out of 4 are LILA tracts (100%). Cluster 3 shows areas with above average SNAP benefits, African American, and Hispanic populations, and a slightly below average White population. Within cluster 3, 23 out of 44 tracts are LILA (52%). Cluster 4 shows an area with higher-than-average SNAP benefits and African American population and well above average Hispanic and White populations. Within cluster 4, 3 out of 12 are LILA tracts (25%).

The same spatially constrained multivariate analysis was conducted for 2019 as seen in **Figure 2**. Cluster 1 shows an area with average SNAP benefits, slightly above average African American, Hispanic, and White population. Within cluster 1, 31 out of 251 are LILA tracts (12%). Cluster 2 shows an area with SNAP benefits and African American population well above average, a slightly above average Hispanic population, and a below average White population. Within cluster 2, 3 out 9 are LILA tracts (33%). Cluster 3 shows areas with above average SNAP benefits, African American, and Hispanic populations, and an average White population. Within cluster 3, 9 out of 13 are LILA tracts (69%). Cluster 4 shows an area with higher-than-average SNAP benefits and African American population and well above average Hispanic and White populations. Within cluster 4, 4 out of 12 are LILA tracts (33%).

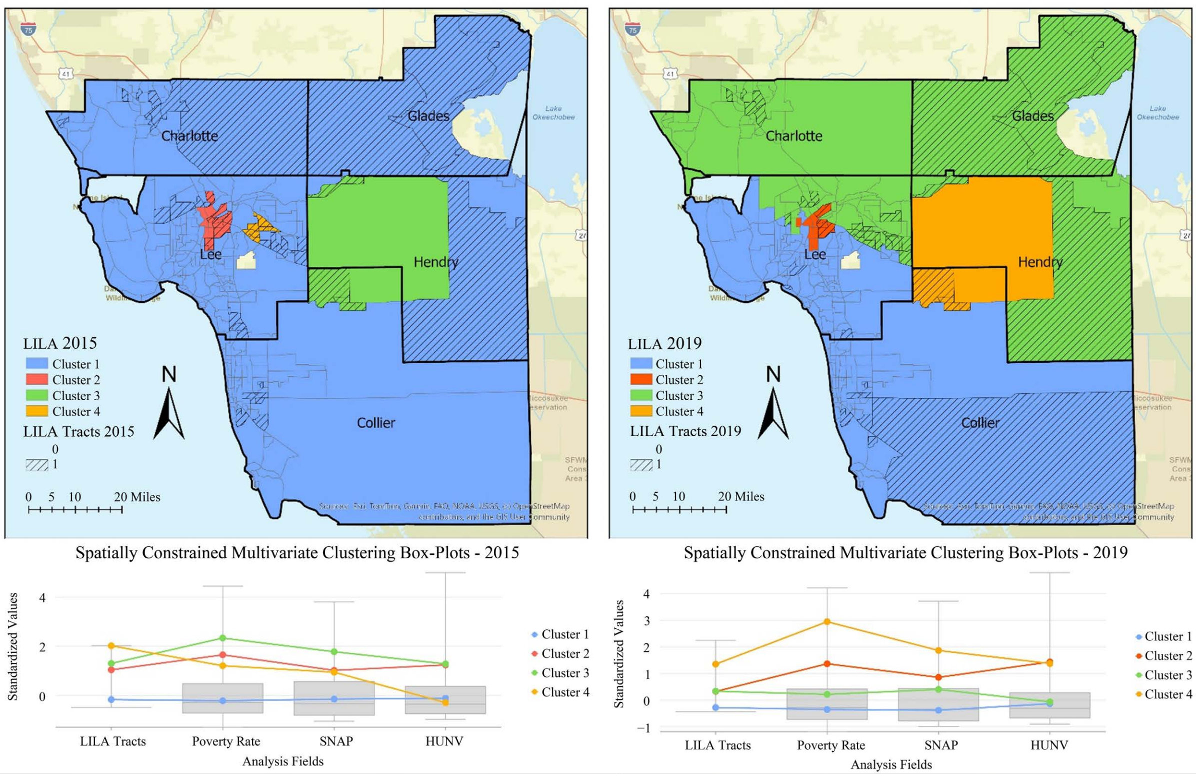

Figure 3. A spatially constrained multivariate clustering for SWFL in 2015 and 2019 using the parameters LILA tracts, PR, SNAP benefits, and populations without access to vehicles (HUNV). The figure gives an overall understanding that LILA tracts occur more frequently in urban areas, areas with high poverty rates, high usage of SNAP benefits, and low vehicle access. Many of these indicators occur at the same time in the same area. For example, cluster 2 (red) shows a high number of LILA tracts due to high PR, high usage of SNAP benefits, and a large population without access to vehicles in 2015 and 2019.

In 2015, a spatially constrained multivariate analysis using the demographic variables; LILA tracts, poverty rate, population receiving SNAP benefits, and population without access to vehicles (HUNV) shows 4 clusters (**Figure 3**). Cluster 1 shows an area with an average poverty rate, receiving slightly above the average amount of SNAP benefits, and a slightly higher than average population without access to vehicles. Within cluster 1, 33 out of 253 are LILA tracts (12%). Cluster 2 shows an area with poverty rate, SNAP benefits, and population without vehicle access well above average. Within cluster 2, 11 out of 18 are LILA tracts (61%). Cluster 3 also shows an area with poverty rate, SNAP benefits, and population without vehicle access well above average. Within cluster 3, 5 out of 7 tracts are LILA (71%). Cluster 4 shows an area with higher-than-average poverty rate and SNAP benefits but a lower-than-average population of people without access to vehicles. Within cluster 4, 7 out of 7 are LILA tracts (100%).

The same spatially constrained multivariate analysis was conducted for 2019. Cluster 1 shows an area with an average poverty rate, receiving the average amount of SNAP benefits, and a slightly higher than average population without access to vehicles. Within cluster 1, 10 out of 165 are LILA tracts (6%). Cluster 2 shows an area with poverty rate, SNAP benefits, and population without vehicle access as above average. Within cluster 2, 4 out of 6 are LILA tracts (67%). Cluster 3 shows an area with poverty rate, SNAP benefits, and population without vehicle access well above average. Within cluster 3, 29 out of 100 tracts are LILA (29%). Cluster 4 also shows an area with poverty rate, SNAP benefits, and population without vehicle access well above average. Within cluster 4, 4 out of 14 are LILA tracts (29%).

4. Discussion

The results of various spatial analysis show significant relationships between LILA tracts and demographic conditions. An LBR analysis of poverty rate and LILA tracts shows positive linear and concave relationships for poverty rates and socioeconomically vulnerable populations. Many of the relationships are seen in highly populated, urban areas such as Cape Coral, Downtown Fort Myers, and Lehigh Acres. Poverty rates are directly correlated with tracts identified as low-income areas, many of which are also low access tracts as well. Similar trends are also seen in Alabama in a similar study by Sisiopiku & Barbour (2014) and in Mississippi in a study by Goodman *et al.* (2020) [16]. A direct relationship between LILA tracts and socioeconomically vulnerable populations is exemplified. It is also supported by positive linear and concave relationships showing socioeconomically vulnerable populations receiving more SNAP benefits. These income-based findings are essential in understanding how low-income areas are affecting the number and distribution of LILA tracts within our five-county region. These demographic factors also play a role in the public perception of certain grocery stores, which affects their profitability and success rate [17]. Many grocery stores and supermarkets are not willing to open in LILA areas especially those located in the inner cities for multiple reasons. The first is low profitability caused by low-profit margins, higher overhead costs, the presence of low-income shoppers, low volume of sales per customer, and smaller purchases per trip [6] [18]. The second reason is high crime rates resulting in shoplifting, employee theft, and dishonesty commonly found in low-income urban areas as well as higher insurance rates and difficulty in getting loans for opening new stores [6] [19]. The third reason is cultural biases due to perceived anxiety based on conscious and subconscious biases about inner-city and socioeconomically vulnerable populations [20]. Therefore, supermarkets with fresh foods needed for healthy daily nutrition are becoming farther and farther away from the low-income neighborhoods.

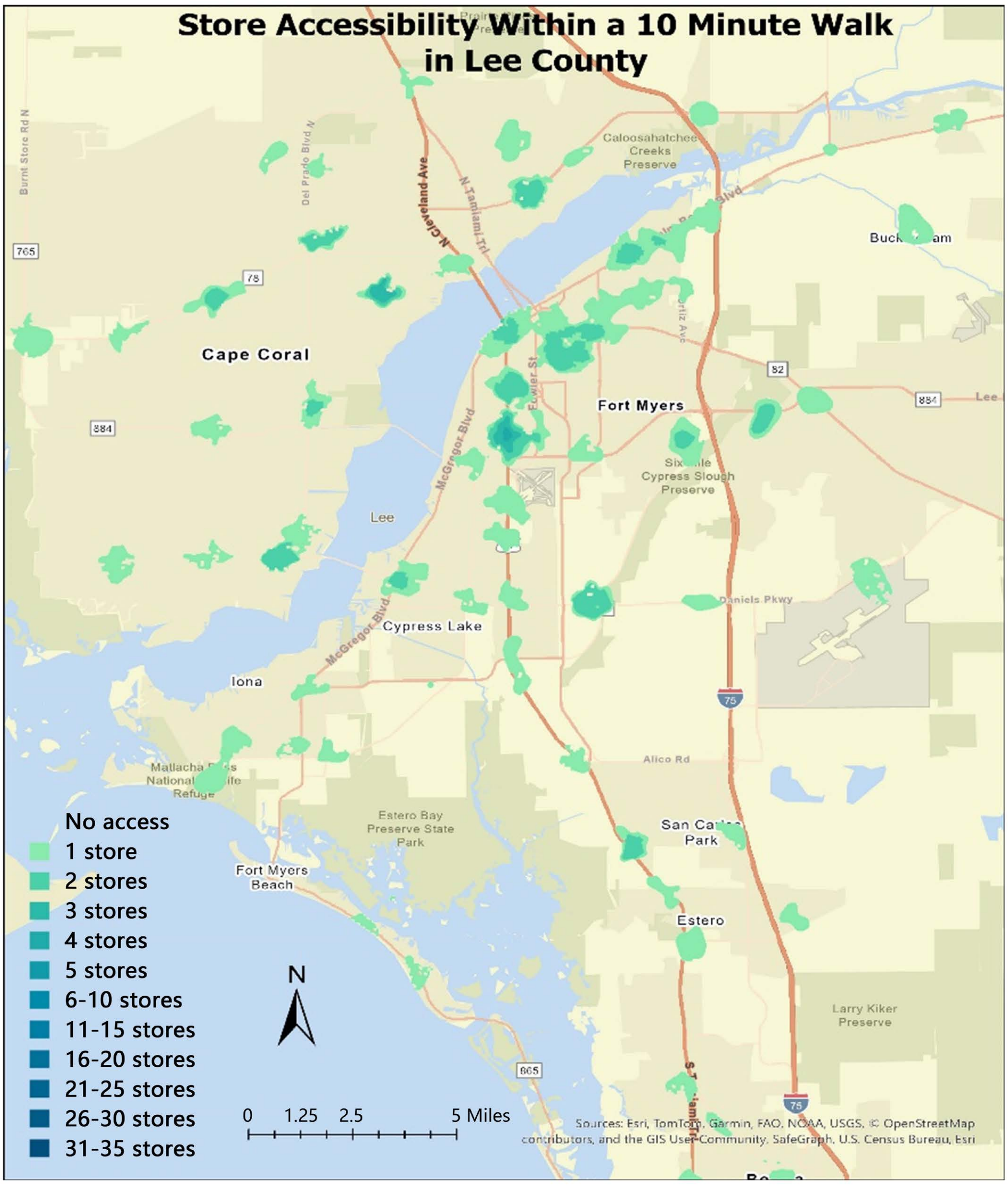

Figure 4. A map showing the 10-minute walkable grocery store access in Lee County 2024. In many areas there is only 1-3 stores available within a 10-minute walk.

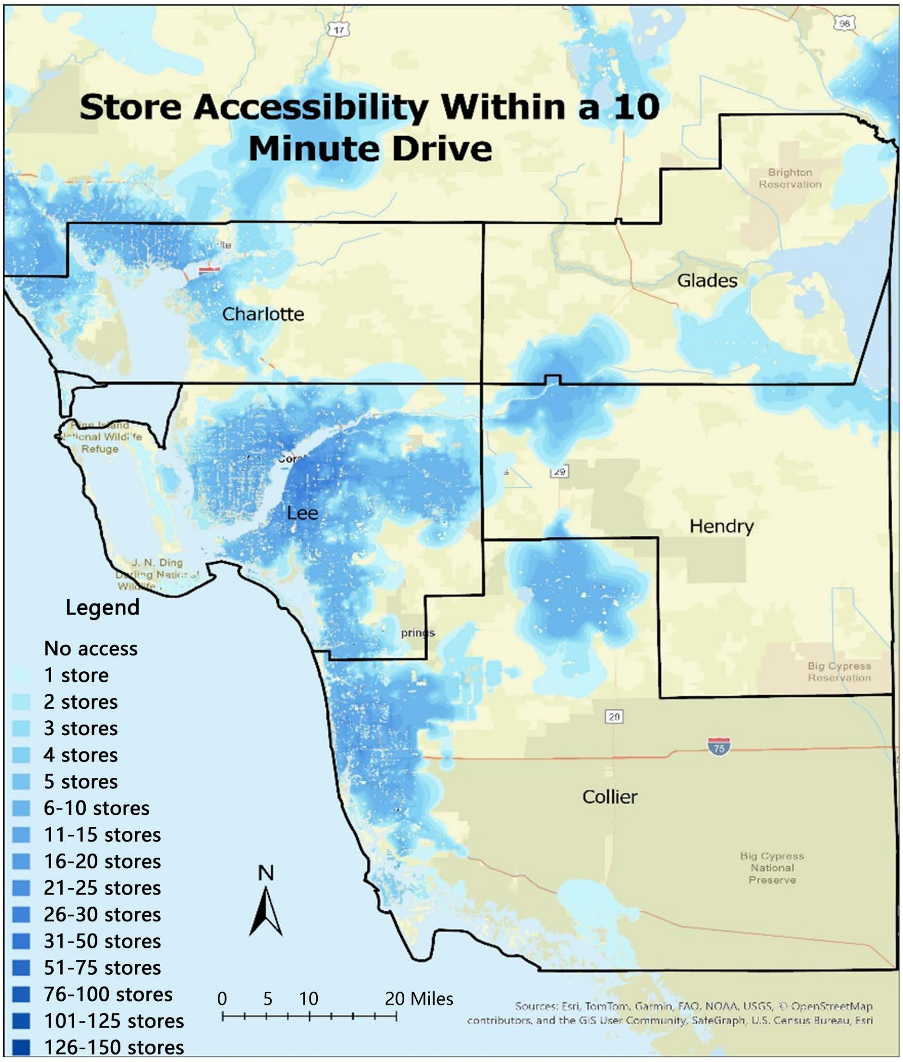

Figure 5. A map showing access to grocery stores within a 10-minute drive in the 5-county region 2024.

On the other hand, low access areas are shown through access to vehicles and the walking/driving distances to grocery stores. Many low access areas are correlated to rural areas without any access to public transportation. However, low access areas are still common among urban areas where low-income households do not have the ability to afford vehicles. In **Figure 4**, we can see the majority of central Lee County, including the 2 most populated areas (Cape Coral and Fort Myers) have no walkable access to grocery stores. There are many instances where there are a few stores within a 10-minute walkable range and one where there are more than 3 grocery stores within a 10-minute walkable range. Challenges are still present for disabled populations who are unable to walk to find access to food. Additionally, people are limited to the amount of groceries they are able to manually carry home. In **Figure 5**, we can see higher drivable access in the more populated counties such as Lee County and parts of Charlotte and Collier Counties. Majority of Glades, Hendry and Collier Counties shows little to no grocery stores within a 10-mintues drivable access range. It is likely because these counties are rural, not highly populated, and contain large wildlife preserves such as Big Cypress which can be seen in **Figure 5**. The complexity of food access is demonstrated when considering urbanization and the spatial distribution of grocery stores in urban vs rural areas.

Public Transportation and carpooling present alternatives to walking and driving however, these both present problems of their own. Public transportation often includes multiple bus and train rides to get to the desired destination causing a single grocery trip to take multiple hours to a full day. Carpooling can also become difficult when relying on someone else and their availability to provide the transportation necessary to get your next meal.

Urban agriculture such as community gardens, rooftop gardens, Controlled Environment Agriculture (CEA), and Hydroponics may offer a creative but effective solution to provide food deserts and LILA tracts with fresh, locally grown crops. Not only does this increase food security but also sustainability and economic growth within vulnerable communities. GREENBOX technology was designed for localized crop production in urban warehouse settings and provides a sustainable alternative to traditional crop production where limited space is available [21].

This study focuses primarily on demographic factors affecting food security, but future studies can consider other factors such as the impact of severe weather events such as hurricanes and how that affects food access. Additionally, other methods of transportation such as public transportation and carpooling, and biking can be considered and explored more in depth.

5. Conclusion

The main aim of this study was to use GIS spatial analysis to identify factors contributing to the development and occurrence of LILA tracts in SWFL. We found that urbanization in addition to multiple demographic factors has influenced access to fresh, nutritious food. Census tracts with socioeconomically stressed backgrounds are the most vulnerable because they are often living below the poverty line, linked to low-income neighborhoods with little to no access to grocery stores. The results from this work could inform policy and decision makers, communities, local governments, non-profit organizations, food banks and grocery store retailers on how to provide these communities with access to fresh, healthy, and nutritious foods.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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