Revista Internacional de Ciencia y Tecnología de la Información Geográfica
International Review of Geographical Information Science and Technology

Mamnoon, I. (2024). A study of vulnerability, hazard, and risk in relation to food insecurity in the United States and Spain. *GeoFocus, Revista Internacional de Ciencia y Tecnología de la Información Geográfica* (Articles), 34, 5-27. http://dx.doi.org/10.21138/GF.827

A STUDY OF VULNERABILITY, HAZARD, AND RISK IN RELATION TO FOOD INSECURITY IN THE UNITED STATES AND SPAIN

Iman Mamnoon
Departamento de Geografía. Universidad Complutense de Madrid.
Edificio B, C/ Profesor Aranguren s/n, 28040, Madrid, España.
imamno01@ucm.es

ABSTRACT

This study applies a Geographic Information System (GIS) methodology to evaluate risk to develop a quantitative measure for the food insecurity suffered by the most vulnerable populations within a city. Risk is calculated by combining social vulnerability and hazard (inaccessibility of food supply) values, and this model of analysis is demonstrated in two case studies: the Southeast Quadrant of the District of Columbia in the United States and in the district of Puente de Vallecas in Madrid, Spain. In this procedure, GIS tools are applied to calculate the Social Vulnerability Index using data surrounding average income, level of education, unemployment rate and age, and proximity to supermarkets is used as the criteria for generating hazard values. Risk levels for census tracts in each case study are then calculated by combining rescaled vulnerability and hazard levels. The results of this analysis identify areas with a high level of food insecurity risk and are thus in urgent need of intervention measures within the two neighborhoods analyzed. In Puente de Vallecas the Census Section identified as a hot spot of high risk of food insecurity is 07913143, with a Social Vulnerability Index value of 1.646, in the range of 0.901 to 3.223 and Risk Value of 3, in the range of 3 to 10. In the Southeast Quadrant the high-risk areas selected for further study are Census Tracts 7601 and 7605 with Social Vulnerability Index Values 2.221 and 1.737, in the range of 1.040 to 3.525, and Risk Values 2 and 5, in the range of 0 to 10, respectively. A subsequent qualitative analysis of these specific areas informs the proposal of mitigation strategies specific to each case study. This proposal enables the monitoring of economic factors' impact on food insecurity, provides effective solutions to improve local food supplies (e.g., farmers' markets and urban gardens), identifies a widespread absence of mixed-use developments, and highlights the limitations of public transport offers in urban areas suffering from food insecurity.

Keywords: food insecurity; vulnerability; hazard; risk; GIS

ESTUDIO DE VULNERABILIDAD, PELIGROSIDAD, Y RIESGO ANTE INSEGURIDAD ALIMENTARIA EN LOS EE. UU. Y ESPAÑA

RESUMEN

Este estudio aplica una metodología de Sistemas de Información Geográfica (SIG) de evaluación de riesgo para desarrollar una escala cuantitativa de la inseguridad alimentaria que sufren las

Received: 03/08/2023 Accepted: 31/05/2024
Academic Editor: Dr. Ismael Vallejo www.geofocus.org

poblaciones más vulnerables dentro de la ciudad. Se calcula el riesgo mediante una combinación de valores de vulnerabilidad social y de peligrosidad (dificultad de acceso a la distribución de alimentos) y se experimenta este modelo de análisis en dos casos de estudio: el barrio sureste del Distrito de Columbia en los EE. UU. y en el Puente de Vallecas de Madrid en España. En este procedimiento se aplican las herramientas de SIG para calcular el Índice de Vulnerabilidad Social a partir de datos de ingresos medios, nivel de educación, tasa de paro y edad, y se utiliza el criterio de cercanía a los supermercados para generar valores de peligrosidad. Posteriormente, se procede a calcular los niveles de riesgo para cada sección censal en los dos casos de estudios mediante los niveles de vulnerabilidad y peligrosidad reclasificados, para facilitar este cálculo. Los resultados de este análisis identifican áreas con un alto nivel de riesgo de inseguridad alimentaria en los dos barrios analizados, que necesitan urgentemente medidas de intervención. En Puente de Vallecas, se identifica la sección censal 07913143 como punto caliente de alto riesgo de inseguridad alimentaria con un valor del Índice de Vulnerabilidad Social de 1.646495 en el rango de 0.901 a 3.223 y un valor de riesgo de 3 en el rango de 3 a 10. En el barrio sureste, se seleccionan las secciones censales 7601 y 7605 para estudios más profundos como zonas de alto riesgo. Esas secciones tienen valores del Índice de Vulnerabilidad Social de 2.221 y 1.737, en el rango de 1.040 a 3.525, y valores de riesgo de 2 y 5 en un rango de 0 a 10, respectivamente. Un análisis cualitativo de esas áreas específicas apoya una propuesta de estrategias de mitigación específicas para cada caso de estudio. Esta propuesta permite monitorizar el impacto de factores económicos en la inseguridad alimentaria, aporta soluciones eficaces que mejoran el suministro local de alimentos (como mercados de productos agrícolas y huertos urbanos), identifica una falta general de zonas que combinan áreas residenciales y comerciales, y detalla las limitaciones de la oferta de transporte público en áreas urbanas que sufren esta inseguridad alimentaria.

Palabras clave: inseguridad alimentaria; vulnerabilidad; peligrosidad; riesgo; SIG

1. Introduction

As the global population increases, more communities are likely to be plagued by food insecurity, making it a central challenge for the survival and wellbeing of society. In recent years, the Covid-19 pandemic has exacerbated the problem by amplifying existing inequalities in society by disproportionately affecting marginalized communities, thus increasing the urgency to study and solve food insecurity. Studies of food insecurity to date have used an array of analysis methods such as Geographic Information System (GIS) cartography, interactive maps, and interviews to examine the problem in diverse environments. Food insecurity tends to emerge in densely populated, low-income urban areas where access to affordable food retailers is limited by inadequate connection to public transport, lack of private vehicles, or simply an absence of supermarkets (The Annie E. Casey Foundation 2021). Large supermarkets are the preferred source of groceries as they tend to have lower prices and greater availability of nutritious foods–such as produce, dairy products, and meat–in comparison to convenience stores or gas stations for example (Kaufman *et al.* 1997). However, with the onset of urban sprawl, many chain supermarkets have moved their locations away from the inner city in favor of the suburbs where land is cheaper, and their customer base buys in bulk with a reliable stream of income and a personal vehicle (Eckert & Shetty 2011). These factors contribute heavily to the development of urban food insecurity, which has become endemic in cities worldwide.

The idea of food insecurity was first expressed using the term "food desert" to describe an area in which residents have limited access to affordable and nutritious food due to high prices, inadequate transportation, a general dearth of food retailers, or a combination of the three as consequences of retail migration away from urban areas (Beaumont *et al.* 1995). The definition of food deserts has since evolved, and modern sources apply numerical measurements and limits to delineate them. One such source is the United States Department of Agriculture (USDA), the engine behind most food research done in the United States, which defines food deserts as "tracts in which at least 500 people or 33 % of the population lives farther than 1 mile (urban) or 10 miles (rural) from the nearest supermarket" (USDA 2015). This description fails to consider the nuances of context—namely socioeconomic status of a population—and affordability, prompting researchers to enrich these basic definitions in a variety of ways. A comparative study of food desserts in Baltimore, Maryland and Madrid, Spain studied international differences in local food environments and framed the problem as the interaction between community and consumer food environments (Díez *et al*. 2016). Another study further extends the desert analogy to include "food swamps" and "food mirages". The former describes areas with adequate access to healthy food alongside an excess of less healthy food options, and the latter refers to places in which people live close to grocery stores but cannot afford them (Caporuscio 2020). In general, this study will employ the term "food insecurity" as it is more holistic and considers contextual factors more so than "food deserts".

The characteristics that define food insecurity depend heavily on the context in which it manifests. The original, "food desert"-centered concept referred to insufficient grocery store access in urban environments within capitalist nations with a high Gross Domestic Product (Beaumont *et al.* 1995). As this field expanded, scholars began to widen the scope of study beyond the sole focus on distance to food retailers. One report redefines suitable food retailer access to include "store quality, community acceptability, healthy and unhealthy food-marketing practices, product quality and affordability." (Karpyn *et al.* 2019). This range of attributes includes economic and contextual factors on a community scale, thereby providing a more complete understanding of food insecurity which, in turn, facilitates the development of potential solutions. More recent studies have also identified urban sprawl as a significant factor contributing to a community's food insecurity. A study published in Urban Studies designed a compactness index to describe the urban density of a region and found that density was significantly related to said region's food desert status at both a regional and neighborhood level (Hamidi 2019). The influence of compactness on food insecurity makes it an important characteristic to consider when studying why food insecurity emerges and how to address it. While these sources expand definitions of food insecurity, the geographic focus of these studies still lacks breadth as the bulk of this research is concentrated in Western nations, more specifically the United States and the United Kingdom (Long *et al.* 2020). A thorough and complete analysis of food insecurity requires expanding the scope of study to other countries as well, thus this analysis includes a case study in Spain.

Despite growing recognition of food insecurity as a global concern and effort to identify its causes and consequences, few scales have been developed to measure it. The Food and Agriculture Organization of the United Nations (FAO) has a sector that responds to global food security challenges; however, its strategies address global hunger and undernourishment as opposed to food insecurity or inaccessibility. Moreover, their offering of resources lacks a quantitative measure of food insecurity applicable in international contexts to perform comparisons or inform policy decisions. The singular scale elaborated by the FAO is a self-reporting survey consisting of eight qualitative questions (Fao.org 2023). This measure is extremely limited in its utility given that it is purely qualitative and does not consider any of the contextual factors previously mentioned. Academic studies done in this field also utilize mainly qualitative measuring techniques in which most data are gathered through consumer surveys and focus groups (Hendrickson *et al.* 2006). A review of sources studying food insecurity in low- and middle-income countries confirms that there is a dearth of measures across the entire field: "The lack of standardized food environment instruments and indicators identified in this review is broadly consistent with systematic review of literature from high income countries [as well]" (Turner *et al.* 2019). The importance of a standardized scale cannot be overlooked, and this study aims to initiate the development of such a measure by adapting an existing risk evaluation procedure to address food insecurity.

Researchers studying resilient cities define risk, in the face of natural disasters and climate change, as the product of hazard level, exposition, and vulnerability (Siegel 2016). Hazard level refers to an event or force with the potential to inflict damage upon a community or the environment and is measured in terms of the capacity to cause harm and the probability of this event occurring (Siegel 2016). Exposition refers to the sum of assets that could be damaged, which in this study is negligible. In the analysis of risk to follow, hazard is contributed by a population's distance from food retailers which is not an event that has a dynamic probability but rather a fixed one, and consequently this study will omit probability. The final factor, vulnerability, establishes a link between human society and risk assessment by evaluating the severity of the problem and presence of existing preventative or protective measures (Fekete & Montz 2018). In this study, vulnerability refers to social vulnerability, or "the set of socio-economic factors that determine people's ability to cope with stress or changes" (Fuchs *et al.* 2012). Many fields combine social vulnerability factors into indices as a way to quantify and study how social vulnerability interacts with other phenomena and affects the population. Examples of social vulnerability indices and their calculations are presented in Section 3.2 of this study. A holistic calculation of risk provides a reference for evaluating, analyzing, and planning cities by considering each of these nuances. The existing literature surrounding food insecurity summarizes it as an issue that only has one solution, increasing food supply by working with, or incentivizing, supermarkets in affected areas (Eckert & Shetty 2011). However, sources have also established that this strategy has been ineffective (Hamidi 2019). This study intends to reframe food insecurity as an urban development problem instead of limiting solutions to negotiations with supermarkets using a nuanced evaluation of risk.

The objective of this work is the calculation of the risk level described above which attributes a numerical value to the severity of food insecurity instead of the binary designation of a region as a food desert, or not, that existing measures assign. This evaluation serves as a quantitative measure of food insecurity that can be applied to a multitude of food environments, considering their individual characteristics, with results that can be analyzed and used to assess, compare, and generate solutions for food insecurity worldwide. As a demonstration of this procedure, this study plans to analyze and compare two communities experiencing food insecurity, one in the United States and the other in Spain.

2. Study areas

In selecting study areas, this analysis took into consideration several criteria: areas with marginalized populations with respect to the city center, with a lower average income than the nation, and neighboring wealthier districts with more hegemonic populations. Using these search criteria, the focus of this study narrows to examine the Southeast Quadrant of Washington, D.C. and the neighborhood of Puente de Vallecas in Madrid more closely. These zones share common characteristics, including a similar number of residents and their locations within their respective capital cities. These similarities between the two areas enable a meaningful qualitative and quantitative comparison, enhancing the validity of the study. A summary of the relevant demographic characteristics of each area of study follows.

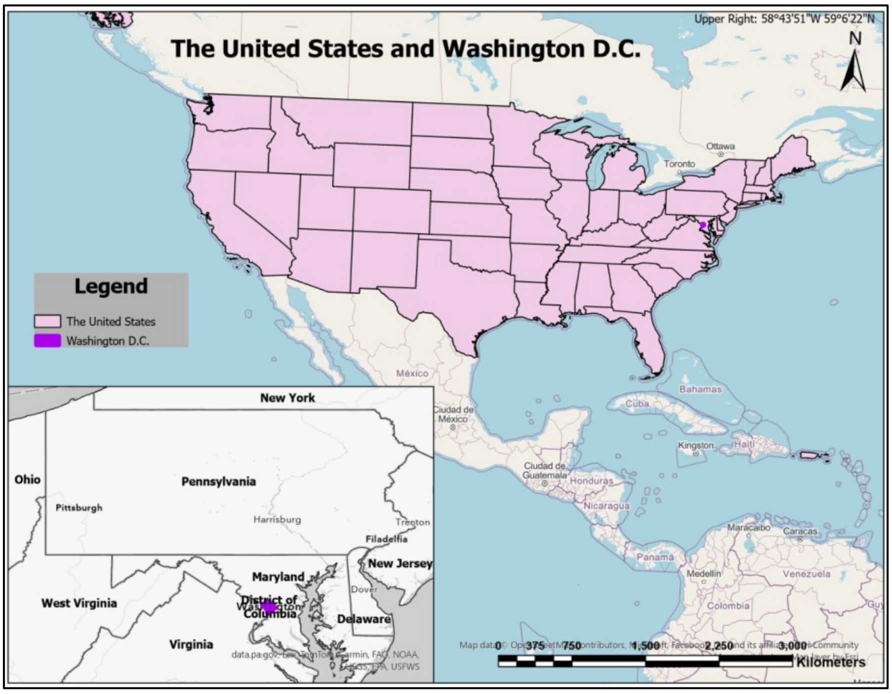

Figure 1. Map of the United States highlighting the location of Washington, D.C.
Source. Prepared by the author.

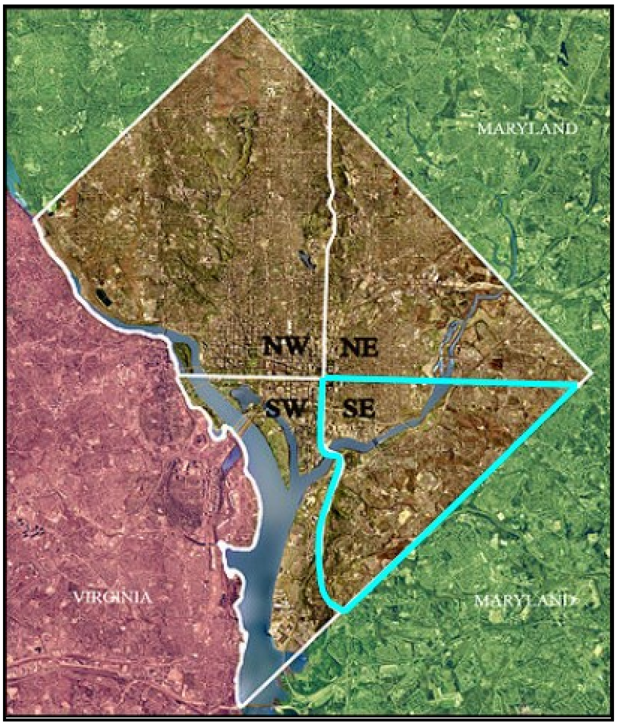

Figure 2. Satellite image of the quadrants of Washington, D.C.
Source. University of Illinois Library.

Figure 1 indicates the location of Washington, D.C. on the eastern coast of the United States and Figure 2 highlights the Southeast Quadrant within a map of D.C. The population of the Southeast Quadrant has a median age of 34 years, while that of the United States is 38.5 (U.S. Census Bureau quickfacts: District of Columbia 2023). The areas more central to Capitol Hill have a White majority population, but the percentage of the population that identified as Black on the US Census is over 50 % in the Southeast quadrant, which is higher than the national average and that of the surrounding areas (Policy Map 2023). On a socioeconomic level, the average per capita income in this sector is $29 000, which falls below the national average of $31 133 (U.S. Census Bureau quickfacts: District of Columbia 2023). Many of the census blocks in this region also share boundaries with blocks that have a six-figure per capita income (Policy Map 2023). The poverty rate in the entire District of Columbia was reported as 18 % in 2020, a figure which is 4 % higher than the national average for the same year (O'Hara & Toussaint 2020). Other important characteristics to consider in the context of vulnerability are unemployment rates and the population's general level of education. In Washington, D.C., 17.3 % of the population counts a bachelor's degree as their highest level of education completed, compared to a 37.9 % national average (Census Bureau Releases New Educational Attainment Data 2023). The unemployment rate for the city is reported as 8 %, a value that is over double the national unemployment rate of 3.5 % and contributes significantly to the vulnerability of the population (The Employment Situation 2023).

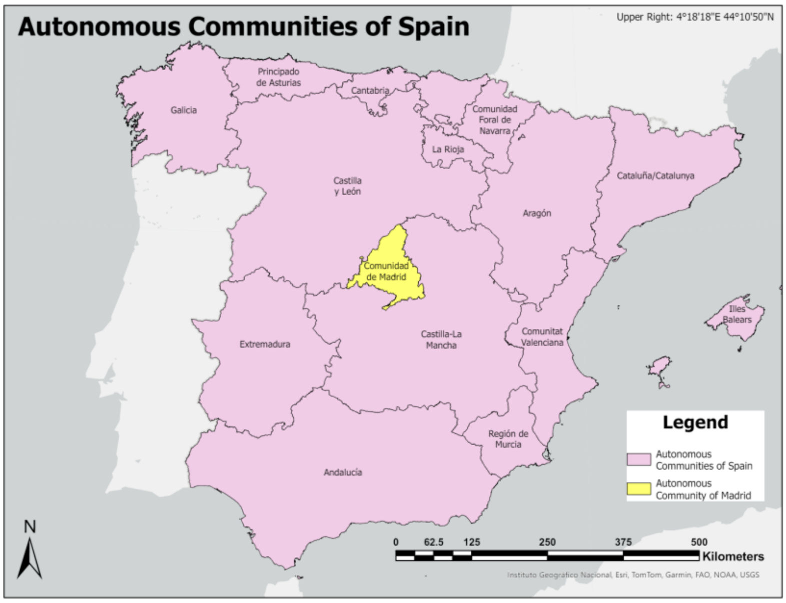

Figure 3. Map of Spain highlighting the location of the Autonomous Community of Madrid
Source. Prepared by the author.

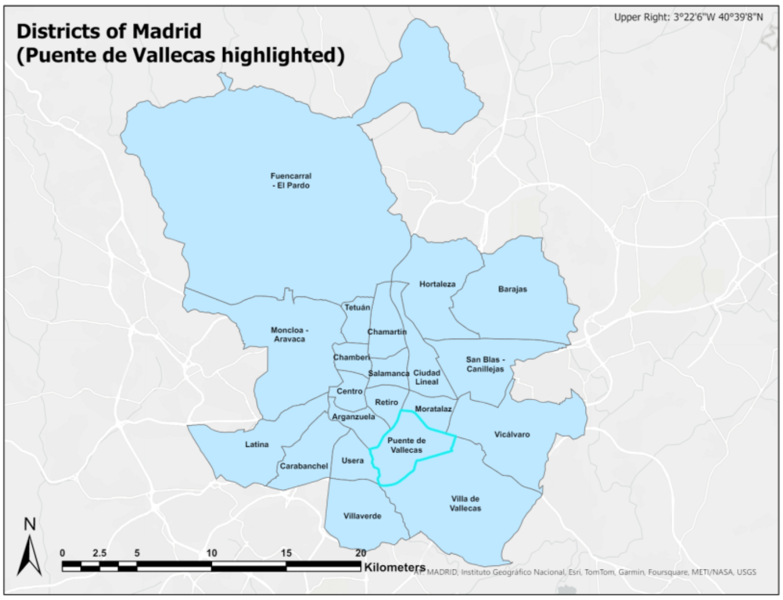

Figure 4. Map of the districts of Madrid
Source. Prepared by the author.

Figure 3 highlights the Autonomous Community of Madrid within Spain, and Figure 4 indicates Puente de Vallecas, the district within Madrid presented in this case study. In Puente de Vallecas, the average resident age is 43.23 years, which is nearly equivalent to the average for the city of Madrid, 44.18 years old, and almost a decade older than the average in the Southeast Quadrant (Portal de Datos Abiertos del Ayuntamiento de Madrid 2023). The district of Vallecas in general, including Puente de Vallecas, is a sector of Madrid known to have a large immigrant population; 20.3 % of the population of Puente de Vallecas is of a foreign nationality, while the percentage for the entire city of Madrid is 14.1 (Portal de Datos Abiertos del Ayuntamiento de Madrid 2023). Regarding socioeconomic factors, the net income per capita in Puente de Vallecas is €12 030, a figure only slightly over half the average for the city of Madrid which is €21 638. Just as in the United States case study, neighboring districts have a significantly higher per capita income. An example of this is the adjacent district of Retiro which has an average net income per person of €30 190 (Portal de Datos Abiertos del Ayuntamiento de Madrid

2023). In this case, Puente de Vallecas also suffers from a higher unemployment rate than the city of Madrid, 13.83 % and 9.87 % respectively (Echagüe 2022).

Lastly, an estimated 10.9 % of the population of Puente de Vallecas had completed “estudios superiores, licenciatura, arquitectura superior, estudios superiores no universitarios, doctorado, estudios de posgrado” compared to 30.2 % of the city of Madrid (Portal de Datos Abiertos del Ayuntamiento de Madrid 2022). This educational gap between the district and the city as a whole is comparable to that between the Southeast Quadrant and Washington, D.C. These socioeconomic factors contribute to the vulnerability of the population, which in both cases tends to be greater than that of the surrounding areas.

3. Methodology

In order to achieve the outlined objectives, this study proposes several phases of analysis. The first is the acquisition and normalization of data for both study areas. Once complete, the calculation of a Social Vulnerability Index score for each census tract in both case studies can proceed. Next, a Hazard Value will be calculated and assigned to each census tract depending on distances from nearby supermarkets. These two factors, Social Vulnerability Index score and the Hazard Values, will then be normalized and combined, to assign a risk level for each census unit. Finally, a spatial clustering analysis will be performed on the risk levels to identify neighborhoods in each study area that are more susceptible to or have a more severe food insecurity problem. Once identified, an in-depth qualitative analysis of the neighborhoods and the proposal of case-specific mitigation strategies will be undertaken. The diagram below visually summarizes the proposed analysis to facilitate understanding, and the procedure depicted will be performed for each study area. An outline of this study’s methodology can be consulted in Figure 5.

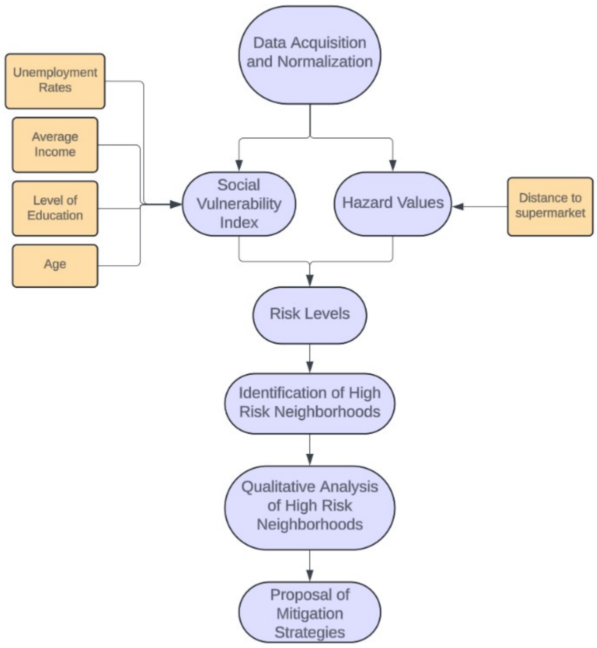

Figure 5. Flowchart of the methodology of this study
Source. Prepared by the author

3.1. Data Acquisition

The first step in this procedure was sourcing quantitative and cartographic data for each of the two case studies. The Social Vulnerability Index score required data for average income, unemployment rate, level of education, and age–specifically elderly population. While there are undeniably more factors that contribute to social vulnerability, such as healthcare access, average rent prices, private vehicle availability or family demographics, this study seeks to ensure that the analysis performed here is repeatable in other contexts and thus opts for a selection of factors proven to influence social vulnerability for which data is typically easily accessible. All the data, both quantitative and cartographic, for the District of Columbia were downloaded from the US Census Survey Explorer and pertains to the year 2021 as it was the most recent set of data available for download (Census Survey Explorer 2023). The cartographic data for Madrid—delineated by census section and district—utilized in this study is from the year 2019 as that was the most updated file provided by the Ayuntamiento de Madrid's open data portal and was downloaded in shapefile format with individual polygons outlining the census sections and districts (Portal de Datos Abiertos del Ayuntamiento de Madrid 2023). Also downloaded from this open data portal were unemployment rates, population by education level, and population by age data for the Autonomous Community of Madrid from the year 2022. The final source of social vulnerability data for the Madrid case study was the Instituto Nacional de Estadística (National Institute of Statistics) from which the most recent average income per person data were downloaded, corresponding to the year 2020. (Instituto Nacional de Estadística 2023).

The data analysis in this study was performed in ArcGIS Pro, which necessitated the preprocessing of some data sources into a viable format before being joined with layers containing the cartography of each area of study. In cases where the datum was measured as the number of people in that demographic group per unit of area, the variables also required normalization. One such variable was level of study in Puente de Vallecas which has multiple categories: none, illiterate, primary school, secondary school, "bachillerato" (optional final two years of secondary school that are obligatory for university entry), bachelor's degree, certificate, master's degree, and doctorate. This study utilized only the data for completion of bachillerato for simplicity and for standardization across education systems. Since the measurement given is the number of people per census section that have completed each level of study (not including those who went on to complete higher levels), it requires normalization and without the availability of population data per census section for Madrid, it was normalized by the area of each section–first converting it from meters to kilometers squared–using the following formula:

population_with_bachillerato_completed / (census_section_area / (1000*1000))

This calculation resulted in a value of people per square kilometer who have completed bachillerato for each census section. The same normalization process was carried out to calculate population over the age of 70 per square kilometer for each census section. Once this was finalized, all the variable data was carried over to a shapefile containing census section cartography of Puente de Vallecas.

As a whole, the data tables from the US Census Survey Explorer required less preprocessing and the columns of interest for this study are the estimate of total population 75 and older, estimate of total population between 24 and 65 years old that graduated high school, estimate of unemployment rate for population 16+, and estimate of median household income for occupied housing units. Of these values, the unemployment rate estimates, and median household income estimates did not require normalization. However, the maximum value for median household income is represented as "250,000+" and in order to be able to convert this to a numeric representation the '+' was removed and given that social vulnerability analysis is more concerned with the lower extreme of income, no further mitigating action was taken by this study. The age and education level data were normalized using the same formula previously detailed to arrive at values of population 75 and older and population that completed high school per square kilometer for each census tract. All of this data was transferred to a shapefile of the census tracts of the Southeast Quadrant of Washington, D.C. to facilitate cartography of the variables and further analysis.

Hazard Value calculation required an additional set of data consisting of coordinates for supermarkets in both areas of study. This data was downloaded from Open Street Maps using their Python package (osmnx) that allows the user to download, manipulate, read, and export geospatial data that is already categorized in the Open Street Maps database (Boeing 2017). Python was used to download the points labeled as 'shops' in Puente de Vallecas and Washington, D.C. and then search specifically for those identified as 'supermarkets' to obtain the relevant data points and their XY coordinates. The results indicate that Puente de Vallecas has a total of 67 supermarkets and the District of Columbia has 183, 10 of which are located in the Southeast Quadrant. The delimitation of the quadrants of D.C. is not recognized by the Open Street Maps database and thus the supermarkets downloaded cover the entirety of the city, whereas Puente de Vallecas is a recognized district of Madrid in the OSM database. This procedure completed the data acquisition phase of this study. Table 1 summarizes the sources and formats of the data used in this study.

Table 1. Summary of data sources and formats

Data	Source	Format
Unemployment rates in the Autonomous Community of Madrid (ACM) (for each neighborhood)	Ayuntamiento de Madrid (2022)	pdf
Average income per person in ACM (for each census section)	Instituto Nacional de Estadística (2020)	xlsx
Population by education level in ACM (for each census section)	Ayuntamiento de Madrid (2022)	shp
Population by age in ACM (for each census section)	Ayuntamiento de Madrid (2022)	shp
Cartography of census tracts in ACM	Ayuntamiento de Madrid (2022)	shp
Cartography of districts in the city of Madrid	Ayuntamiento de Madrid (2019)	shp
Unemployment rates in the District of Columbia (for each census tract)	US Census Explorer (2021)	xlsx
Average income per person in D.C. (for each census tract)	US Census Explorer (2021)	xlsx
Population by age in D.C. (for each census tract)	US Census Explorer (2021)	xlsx
Population by educational attainment in D.C. (for each census tract)	US Census Explorer (2021)	xlsx
Cartography of census blocks and tracts in D.C.	US Census Explorer (2021)	shp
Supermarkets in Puente de Vallecas with their coordinates	Open Street Maps (2023)	xlsx
Supermarkets in D.C. with their coordinates	Open Street Maps (2023)	xlsx

Source. Prepared by the author

3.2. Social Vulnerability Index (SoVI) Calculation

Social Vulnerability Index (SoVI) scores combine factors that contribute to vulnerability to generate a numerical representation of social vulnerability that can be analyzed and compared between different areas. In this study, the social vulnerability factors are age, unemployment rates, average income and education level for the population of interest. To begin this calculation, each of the vulnerability factors were rescaled in order to compute values with the same units that could then be summed to a final Social Vulnerability Index score. Previous studies that have calculated vulnerability indices rescale the data in two separate ways. The first is utilized by Wijaya and Hong in their assessment of social vulnerability for landslide disaster risk reduction (Wijaya & Hong, 2018). They applied the following formula for calculating the normalized value of vulnerability variable measurements:

$$Z_{ij} = (X_{ij} – M_j) / SD_j$$

where X_{ij} is the value of variable j at unit i, M_j is the average value of variable j, and SD_j is the standard deviation of variable j (Wijaya & Hong, 2018). An example of X_{ij} in this study would be the unemployment rate in a specific census section of one of the two study areas while M_j in the same case would be the average unemployment rate across all census sections of the study area in question. The authors then calculated the final social vulnerability index as follows:

$$SoVI = (\text{sum of } Z_{ij}) / N, \text{ from } j = 1 \text{ to } N$$

where N is the number of social vulnerability factors (Wijaya & Hong 2018). An alternate normalization method was used in a GIS-based case study of flood risk zoning in Nanjing, China (Chen *et al*. 2021). This study opted for a min-max rescaling approach to calculate the normalized values using the subsequent formula:

$$Z_{ij} = (X_{ij} – X_{jmin}) / (X_{jmax} – X_{jmin})$$

where X_{ij} is again the value of variable j at unit i, X_{jmin} is the minimum value of variable j, and X_{jmax} is the maximum value of variable j, and goes on to calculate the SoVI in the following manner (Chen *et al.* 2021):

$$SoVI = (\text{sum of } Z_{ij}), \text{ from } j = 1 \text{ to } N$$

Between these two rescaling techniques, this study elected the second method in order to prioritize simplicity and repeatability of the analysis, as it only requires the calculation of a minimum and maximum instead of an average and standard deviation. After making these calculations, the next decision point was determining how to sum the normalized social vulnerability variable values. The literature is also divided on this point between weighted and unweighted summation. The studies that opt for weighted sums typically weight the factors based on their eigenvalues, generated as part of a principal component analysis (Montz & Evans 2001). The principal component analyses in these studies were performed to determine which factors are most significant to the social vulnerability in the area of study or to consolidate a large array of variables into a more manageable set of factors. Given that this study only considers four social vulnerability factors, it was unnecessary to conduct a principal component analysis and without it, any assignment of relative weights in this case would be subjective and thus jeopardize the validity of the study and its results. Consequently, the present analysis utilized an unweighted sum to calculate the final social vulnerability index for each census tract.

In this study, the Social Vulnerability Index scores range from 0, representing areas with the highest vulnerability, to 4, representing low vulnerability. In order to adjust the scales of the individual variable values to this range of SoVI values, variables for which high values were indicative of high vulnerability needed to be inverted so that lower normalized values (Z_{ij}) of these variables correlated to higher vulnerability. This was the case for age and unemployment in Puente de Vallecas and the Southeast Quadrant as a higher elderly population and a high rate of unemployment both increase social vulnerability. For the United States case study, level of education also needed to be adjusted because the data excluded high school graduates that went on to pursue higher education which implies that a higher value for this datum is present in areas where more of the population did not advance beyond a high school diploma, which correlates to higher vulnerability. These variables were recalculated by subtracting their normalized values from 1 as follows:

$$\text{Rescaled } Z_{ij} = (1 - Z_{ij})$$

where Z_{ij} is the min-max normalized value of variable j at unit i. After completing this rescaling, an unweighted sum of the normalized values for each variable was performed to arrive at the final Social Vulnerability Index score for each census unit in each case study.

3.3. Hazard Value Calculation

Hazard is the other factor considered in this study's risk-centered evaluation of food insecurity and was based on each community's distance from supermarkets in the area. This analysis started by creating buffer zones around each supermarket with radii ranging from 0.5 kilometers to 2 kilometers using spatial analyst tools available in ArcGIS Pro. These radii were selected based on numerical definitions of food deserts generated by prior studies in the field and were each assigned a value between 1 and 4 (USDA Food Research Atlas & Healthy Communities Assessment Tool 2023).

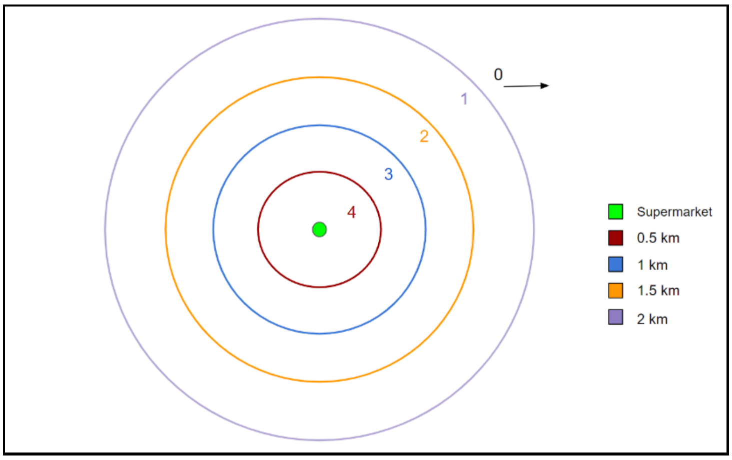

Figure 6. Buffer zones and their values based on distance from supermarket
Source. Prepared by the author

The values get lower as the buffer extends further away from the supermarket so that any distance beyond 2 km defaults to 0 as seen in Figure 6. A symmetrical difference was then performed to create rings that encapsulated only the area covered by the larger buffer without including the area already covered by the smaller radii buffer zones; for instance, a symmetrical difference between the 2 km buffer zone and the 1.5 km buffer generates a ring covering the area between 1.5 and 2 km away from the supermarket.

Once the rings for each distance were calculated, GIS tools were used to determine which census tracts intersected each ring, and the census tract's final Hazard Value was calculated as the sum of the values assigned to the rings it intersected. In Puente de Vallecas, the Hazard Values range from 3 (high hazard level) to 10 (low hazard level), while in the Southeast Quadrant, the range spans from 0 to 10 (high to low). The zero present in the latter range indicates that there are census tracts in the Southeast Quadrant that have no supermarket access within 2 km, a concerning finding that highlights an area that should be further studied.

3.4. Risk Level Calculation

The final data analysis step was to calculate a risk value for each census tract by combining the Social Vulnerability Index scores and Hazard Values according to the following equation that describes the relation between vulnerability, hazard, and risk: Risk = Σ Vulnerability x Σ Hazard (Siegel 2016).

	Hazard				
Vulnerability	Low (1)	Moderate (2)	High (3)	Very High (4)	Extremely High (5)
Null or Very Low (1)	1	2	3	4	5
Low (2)	2	4	6	8	10
Moderate (3)	3	6	9	12	15
High (4)	4	8	12	16	20
Very High (5)	5	10	15	20	25

Risk Level
Null or Very Low
Low
Moderate
High

Figure 7. Risk level determination from Vulnerability and Hazard Levels

Source. Prepared by the author

Before performing this calculation, the SoVI and the Hazard Values needed to be reclassified from 1 to 5 where 1 represents a low level of vulnerability or hazard and 5 represents high vulnerability or hazard. This was completed using Raster-based tools in ArcGIS Pro according to the range of each variable which can be referenced in Tables 2 and 3. Once the risk values were calculated, they were reclassified according to Figure 7 to determine the final risk level for each census tract.

Table 2. Reclassification intervals for Vulnerability Levels in both case studies

X = Social Vulnerability Index score	Vulnerability Level
$X \leq 0.8$	Very High (5)
$0.8 < X \leq 1.6$	High (4)
$1.6 < X \leq 2.4$	Moderate (3)
$2.4 < X \leq 3.2$	Low (2)
$3.2 < X \leq 4.0$	Very Low or Null (1)

Source. Own elaboration based on results from data analysis

Table 3. Reclassification intervals for Hazard Levels for each case study

Y = Hazard Value sum for Puente de Vallecas	Z = Hazard Value sum for Southeast Quadrant	Hazard Level
$3.0 < Y \leq 4.4$	$Z \leq 2.0$	Extremely High (5)
$4.4 < Y \leq 5.8$	$2.0 < Z \leq 4.0$	Very High (4)
$5.8 < Y \leq 7.2$	$4.0 < Z \leq 6.0$	High (3)
$7.2 < Y \leq 8.6$	$6.0 < Z \leq 8.0$	Moderate (2)
$8.6 < Y \leq 10.0$	$8.0< Z \leq 10.0$	Low (1)

Source. Own elaboration based on results from data analysis

4. Results

4.3. Social Vulnerability Index

Social Vulnerability Index scores are significant to this study because they can be used to identify the most socially vulnerable population in each studied area: Census Section 07913027 in Puente de Vallecas with a SoVI score of 0.9008 and Census Tract 9802 in the Southeast Quadrant with a SoVI score of 1.040441, both of which can be seen highlighted in their respective SoVI maps below (Figure 8). In the case of Puente de Vallecas, Census Section 07913027 is surrounded by other areas with similar Social Vulnerability Index scores, implying a somewhat similar level of vulnerability in the zone. On the other hand, the most vulnerable census tract in the Southeast Quadrant is surrounded by less vulnerable tracts, areas with higher SoVI scores. Tract 9802, the most socially vulnerable, has the lowest unemployment rate in the area of study as the rescaled unemployment variable value is 0 and has a considerably lower education level variable value, 0.351092 compared to the next most vulnerable tract which has a value of 0.562828. Further investigation would be valuable in order to better understand which factors impact food insecurity and to what extent, but does not fall within the scope of the study at hand.

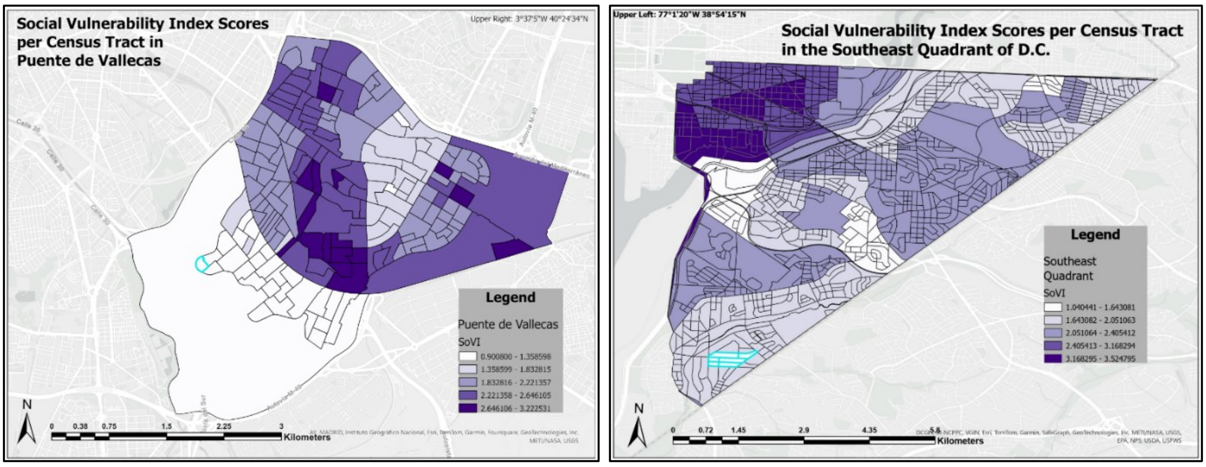

Figure 8. Maps of Social Vulnerability Index scores per census tract in Puente de Vallecas and the Southeast Quadrant

Source. Prepared by the author

As aforementioned, the Social Vulnerability Index score in each case study was calculated using four variables or factors: age of the population, unemployment, educational attainment, and median income. The distribution of each of these variable's normalized values across all census tracts is presented in Figures 9 and 10 below. The values presented were normalized and rescaled, if necessary, as described in section 3.2. Thus, one can interpret the maps considering that the lower the value, the more vulnerable that area is for each variable. For example, the area in Puente de Vallecas in which unemployment contributes most to the social vulnerability of the population is a large swatch in the southwest of the neighborhood. Further observation of the maps in Figure 9 reveals that age has a dissimilar distribution to the other variables in which its high normalized values are concentrated in the census tracts on the edges of this district. This pattern contrasts with the other factors whose higher values are concentrated more towards the center of the district although the clustering patterns within the center are not similar across these three factors. Figure 10 presents a similar set of maps for the Southeast Quadrant of Washington, D.C. In all four of these maps the tracts in the northwest corner of the area of study have high values, which indicates that the population in this area is the least socially vulnerable according to the variables studied. This result is unsurprising as this region forms part of downtown Washington, D.C. Beyond this similarity, no other common patterns of distribution between variables is immediately identifiable and none of the variables has an extremely distinct distributions to the rest. While these maps provide a glimpse into the patterns of distributions of the social vulnerability factors studied, further statistical analysis, which falls beyond the scope of this study, is needed to better understand the correlations between these variables.

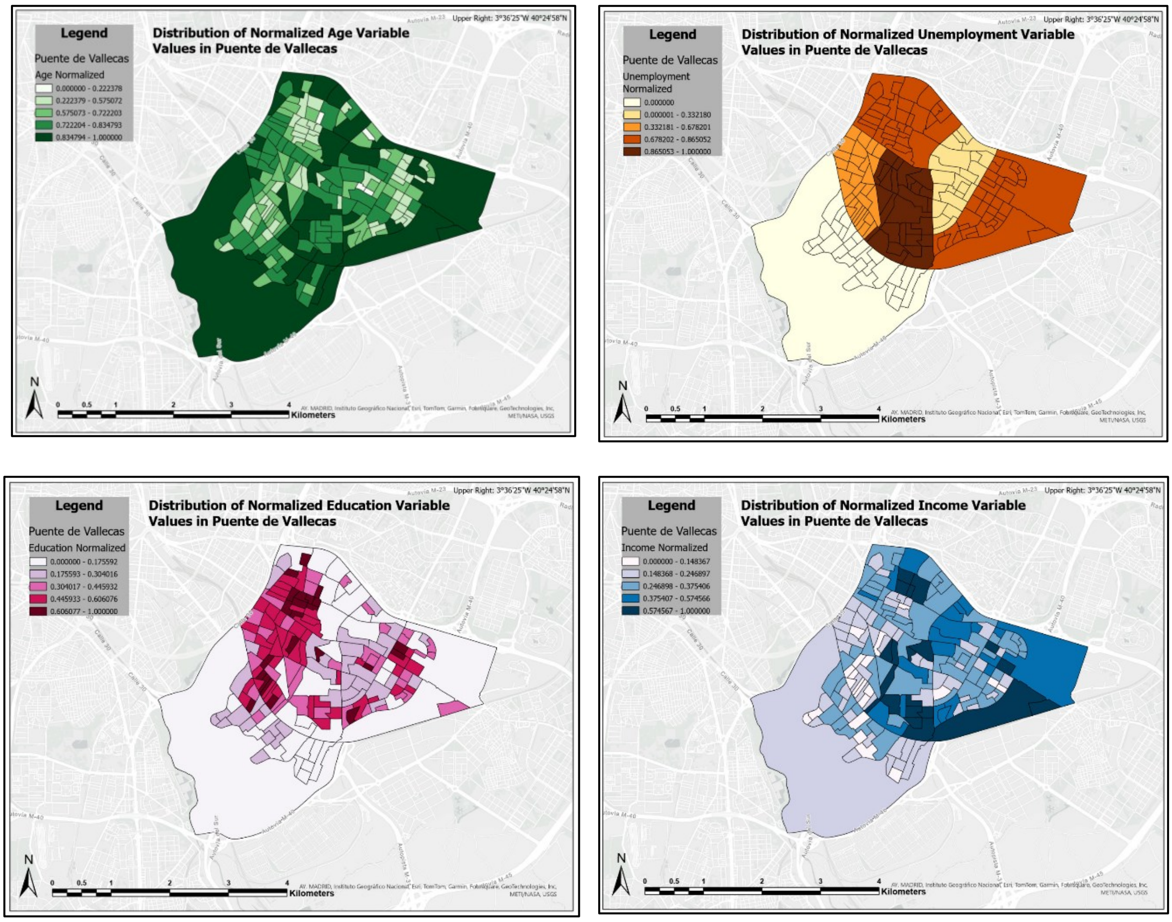

Figure 9. Maps of the Distribution of Social Vulnerability variable values in Puente de Vallecas
Source. Prepared by the author.

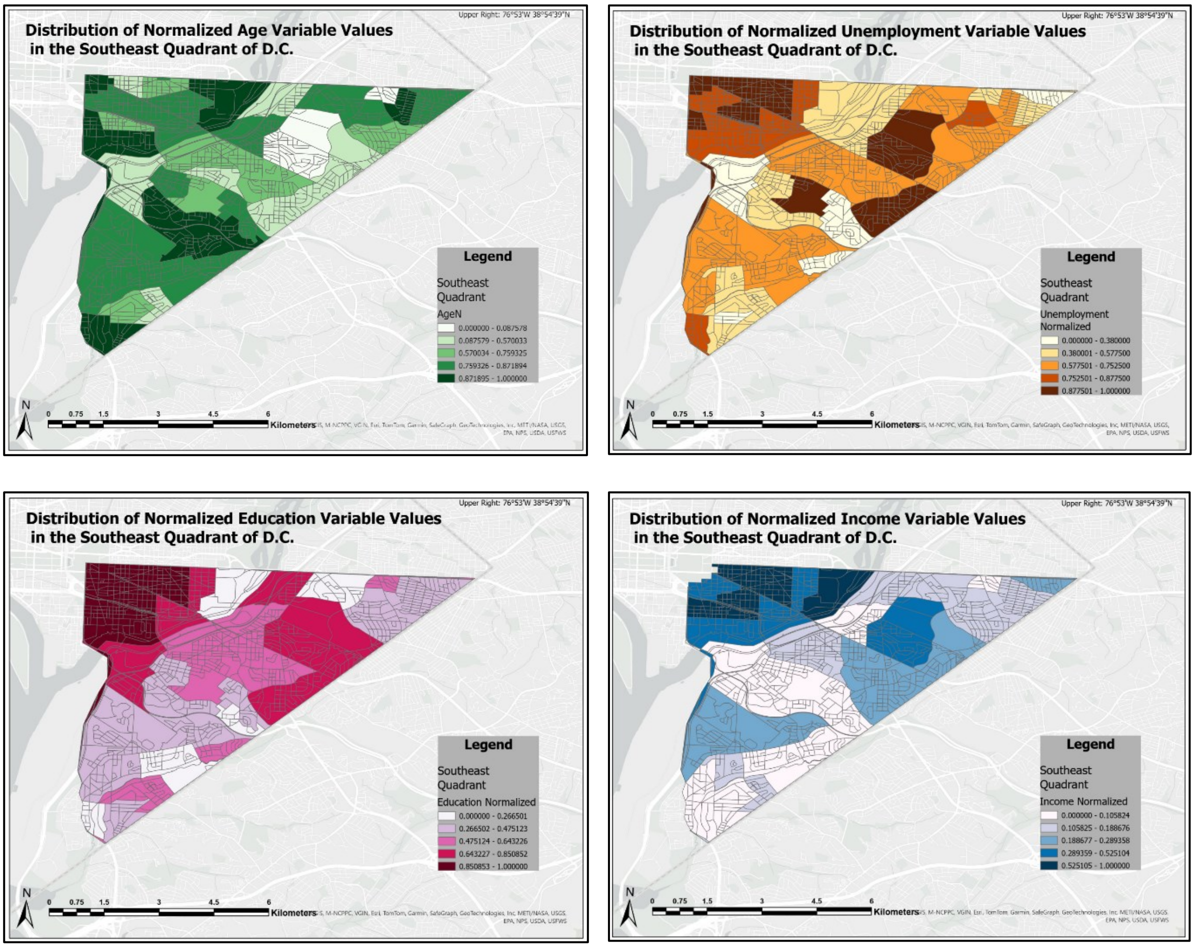

Figure 10. Maps of the Distribution of Social Vulnerability variable values in the Southeast Quadrant of Washington, D.C.
Source. Prepared by the author.

4.2. Hazard Values

As aforementioned, the Hazard Values for each census section were calculated based on distance from supermarkets and are displayed in the maps below (Figure 11). This portion of the analysis was critical as it introduced the element of inaccessibility to food that when combined with social vulnerability comes to represent food insecurity. Figure 11 displays the Hazard Values for each case study and shows that the census sections earlier identified as most vulnerable in each area of study have higher levels of hazard than their surrounding areas. Given that in these maps a higher Hazard Value indicates a lower level of hazard, Census Section 07913027 in Puente de Vallecas–the most socially vulnerable–stands out with much lower Hazard Value of 3, in comparison to its neighboring areas which have values greater than or equal to 5. A similar phenomenon can be observed in the case of Census Tract 9802 in the District of Columbia, but the difference is not as extreme: Tract 9802 has a Hazard Value of 4 or 5 while the section that surrounds it has a value of 6 or 7. This is interesting considering the presence of a supermarket within tract 9802 and is likely worthy of more detailed research in a future study.

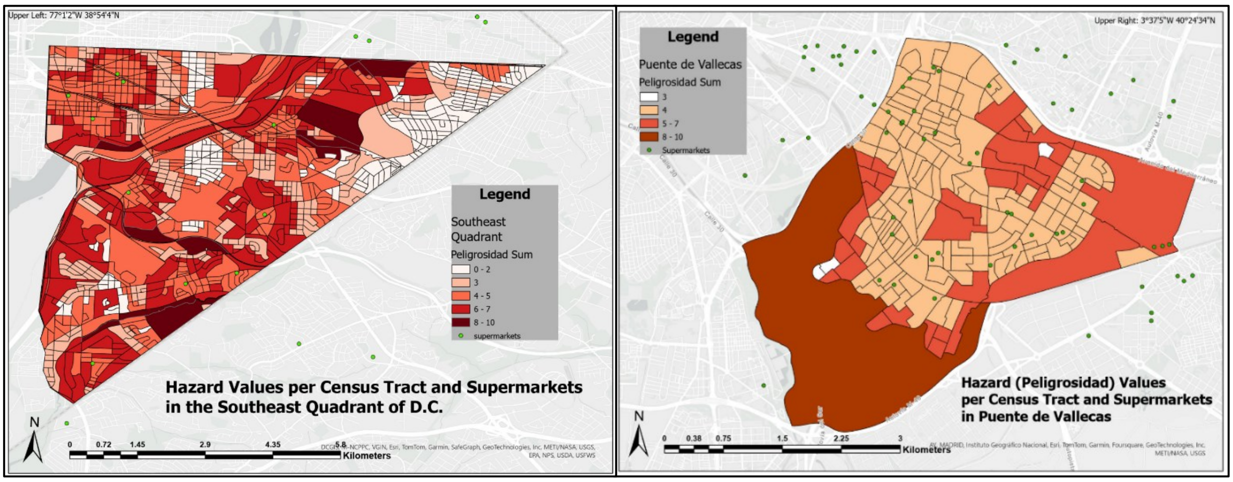

Figure 11. Maps of Hazard Values and supermarkets per census tract in Puente de Vallecas and the Southeast Quadrant

Source. Prepared by the author.

4.3. Risk Levels

Ordinarily, hazard and vulnerability values are used to calculate risk levels in the face of natural disasters or climate change, but this study used the formula to generate and evaluate food insecurity based on social vulnerability and distance from food retailers (Siegel 2016). Figure 12 presents cartographies of risk levels for each census tract in Puente de Vallecas and the Southeast Quadrant. In both cases, the census sections identified as most socially vulnerable and that have moderate to high hazard levels, also have high and moderate risk levels.

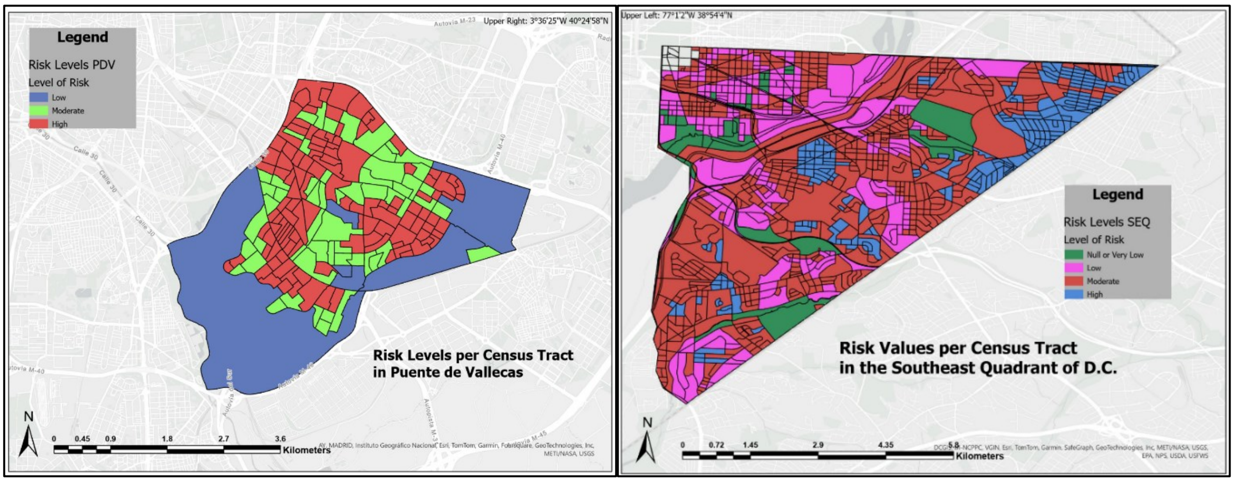

Figure 12. Maps of Risk Levels per census tract in Puente de Vallecas and the Southeast Quadrant

Source. Prepared by the author.

The risk level calculation provided insights into the severity of food insecurity for each census tract and developed a quantitative measure with more nuance than those previously existing. Additionally, it helped to identify which areas are most urgently in need of action. In order to converge on high-risk zones in Puente de Vallecas and in the Southeast Quadrant of D.C., a Hot Spot analysis, using the Getis Ord Gi* statistic, was performed to identify areas with high risk levels that are also surrounded by other high-risk-level zones. The highlighted areas will then be the subject of further qualitative study in order to propose food insecurity mitigation strategies that are most appropriate for each context. The results of the Hot Spot analyses can be seen in Figure 13 below:

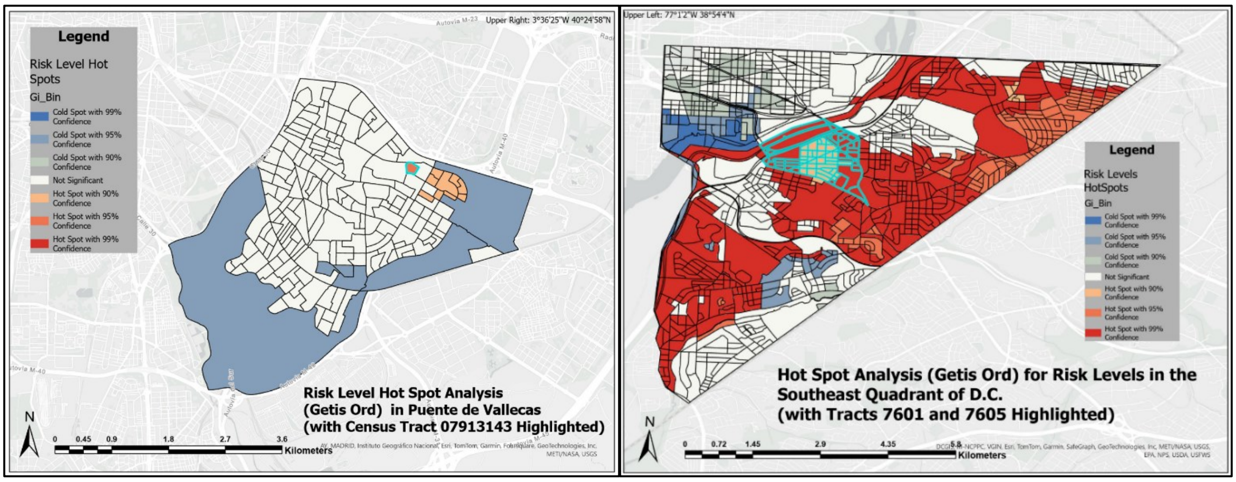

Figure 13. Maps of Hot and Cold Spots of Risk Levels in Puente de Vallecas and the Southeast Quadrant

Source. Prepared by the author.

Each map highlights the area that has been selected by this analysis for further study. In the case of Puente de Vallecas, Census Section 07913143 was chosen as it is the only Hot Spot. Interestingly, this area is not the same section previously highlighted as the most socially vulnerable with a high hazard level. The Hot Spot analysis in the Southeast Quadrant identified several Hot Spots, but Tracts 7601 and 7605 were selected for further study as they cover the majority of the central Hot Spot while also including parts of the surrounding areas with high risk levels.

5. Discussion

5.1. Puente de Vallecas Qualitative Analysis

Census Section 07913143 in Puente de Vallecas is part of the Portazgo neighborhood and has a Social Vulnerability Index score of 1.646495. The individual variable scores that contribute to this sum are 0.472599 for average income per person, 0.33218 for unemployment rate, 0.472921 for age, and 0.368795 for level of education. Of these four values, unemployment rate is the variable that contributes the most vulnerability, as it is the lowest value, and is somewhat actionable.

The only supermarkets within a half kilometer of tract 143 are a Día, an Ahorramás, and a Condis (three supermarket chains in Spain), the last of which is registered as permanently closed by Google Maps. A multiple lane highway separates the Día from Portazgo, and pedestrian access to it involves navigating to a pedestrian overpass and crossing a large, multiple-lane roundabout. These realities leave residents of Portazgo with only one supermarket conveniently accessible to pedestrians. Despite being a part of the city of Madrid, Portazgo has limited public transportation options. Only one metro line passes through Portazgo, Line 1, and there are no Renfe or Cercanías (suburban trains) that service this zone. In order to use the metro to cross the highway, and access the Día, one would have to detour 8 metro stops (Metro de Madrid Maps 2023). There are bus options, but data surrounding the full network of buses is not available in a format that facilitates analysis. Furthermore, news headlines from the past few years highlight the dangers of only having access to a singular metro line: "*La línea 1 de Metro cerrará 4 meses tras las elecciones del 28-M: afectará a 350.000 personas sólo en Vallecas*" ["Metro Line 1 will be closed for 4 months following the May 28th elections: 350,000 people will be affected in Vallecas alone"] and "*El Metro de Madrid, cayéndose a cachos: se derrumba el techo de la estación de Portazgo en Puente de Vallecas*" ["The Metro of Madrid is falling apart: the roof of Portazgo station in Puente de Vallecas has collapsed"] (De Diego 2023, Ramiro 2022). These interruptions in service, including four-month-long repair projects and the ceiling caving in as described above, leave the entire neighborhood of Portazgo without metro access and further exacerbate isolation from public transit.

5.2. Mitigation Strategies in Puente de Vallecas

Taking all the previous points into consideration, there are some possible mitigation strategies described by other studies and implemented in other communities that could be effective in the case of Census Section 01913143 in Puente de Vallecas. A study on supermarket redlining and a study performed by researchers from the University of Delaware both recommend the introduction of farmers' markets or community gardens to the area as food desert mitigation strategies (Karpyn *et al.* 2019, Zhang & Ghosh 2016). Madrid already has a network of urban gardens that allow members of the community to take home a share of the produce in exchange for weekly volunteer hours, however none are located in Puente de Vallecas (Programa Municipal de Huertos Urbanos comunitarios 2023). An urban garden counteracts food insecurity by providing access to fresh produce and increasing a community's involvement in their food supply. Ideally, the local government could fund the initiative to eliminate volunteer hours as a barrier to entry. Urban farms and community gardens form part of the food sovereignty movement that aims to connect communities to, and educate them about, their food supply (Long *et al.* 2020). The main advantage of this mitigation strategy is its ability to be implemented on a small scale without necessarily requiring government aid, which also allows it to be tested for effectiveness before investing additional resources. Community gardens also have the potential to generate, or deepen, a sense of community and could eventually come to provide jobs which would address the elevated unemployment rate that impacts social vulnerability in Portazgo (Karpyn *et al.* 2019).

Addressing public transportation infrastructure is a somewhat more challenging task as it requires more extensive funding and government involvement. That said, based on the analysis of the current metro access in Portazgo, this study recommends the addition of another metro line to service the same area, or a better connection to Line 9, so that the population of this area can access more supermarkets and is not left without metro access in circumstances where Line 1 is nonfunctional.

Another mitigation strategy that would involve long term planning and investment is implementing more mixed-use zoning and construction. This kind of intentional urban planning is recommended by other studies in this field in which the authors list among its advantages an increase in walkability and incentivizing food retailers to invest and expand into the area (Díez *et al.* 2016, Hamidi 2019). Clearly, these action items require long term planning and a significant allocation of resources, but when combined with the earlier farmers' market and community garden recommendations, they form a situation-specific, practical and varied food insecurity mitigation plan for this region of Puente de Vallecas.

5.3. Southeast Quadrant Qualitative Analysis

Census Tracts 7601 and 7605 form part of the Fairlawn and Randle Highlands neighborhoods in the Southeast Quadrant. Of the two, Tract 7605 is more socially vulnerable–according to this study's index–with a SoVI score of 1.736822 and variable values of 0.6509945 for level of education, 0.6275 for unemployment rate, 0.116996 for average income, and 0.482381 for age. Among these four contributing factors, average income is significantly lower than the rest; this drastic difference is also observed in Tract 7601, a sector with a social vulnerability index score of 2.220902 composed of 0.605677 from level of education, 0.73 from unemployment rate, 0.148158 from average income, and 0.737067 from age. These values are highly concerning and are evidence of Washington, D.C.'s longstanding income inequality plight. According to the D.C. Fiscal Policy Institute, "At 0.542 in 2016 —based on Census Bureau data—DC has the highest Gini coefficient when compared with the 50 states, and on par with Puerto Rico" (Naveed 2022). The Gini coefficient measures income distribution across households and a value of 1 represents complete inequity while 0 indicates a completely equal distribution. Not only was the Gini coefficient of D.C. the highest in the nation in 2016, but it has also since increased (Naveed 2022). This phenomenon is reflected in the incredibly low average income per-person in tracts 7601 and 7605 and merits further study of its causes and consequences.

Two characteristics stand out distinctly when examining these two neighborhoods: the lack of metro access and the separation of residential and commercial zones. The nearest Metrorail station for both neighborhoods is Potomac Ave, connecting them to the Blue, Silver and Orange lines at a distance of approximately 1.9 km. The next nearest station is Anacostia on the Green line 2.1 kilometers away (WMATA Trip planner 2023). However, in order to access the Potomac Ave station as a pedestrian, one must either take the bus, which incurs additional fare, or walk 30 minutes and cross both the highway and the Anacostia River. Consequently, the residents of Fairlawn and Randle Highlands effectively only have pedestrian access to the Green line, which still involves a half hour walk that would be cumbersome to make when carrying groceries. This route potentially eliminates the possibility of using Metrorail to access supermarkets for a portion of the population, especially those with preexisting mobility-impairing conditions. The only supermarket that falls entirely within a half kilometer radius of tracts 7601 and 7605 is a Safeway. The infrastructure surrounding this Safeway is heavily car dependent as it is in a commercial zone, disconnected from residential areas, and only accessible from a 4-6 lane throughway with limited sidewalks and no marked bike lanes or nearby metro stop.

5.4. Mitigation Strategies in the Southeast Quadrant

As described above, the fundamental issues contributing to food insecurity in Census Tracts 7601 and 7605 are low average income and a lack of supermarkets in an area accessible without private vehicle access. Similar to Census Section 07913143, this area would benefit from a diversification of land use in favor of mixed-use zoning instead of the existing, stark separation of residential and commercial zones that tends to create dependance on cars.

An examination of Fairlawn and Randle Highlands via Google Street View reveals that both neighborhoods are car dependent and primarily residential. Several streets pictured only have a sidewalk on one side and the area lacks bike lanes. These problems are likely hindering mixed use development which, if implemented, would encourage the introduction of more non-car mobility options–walking, biking, public transit–and could also motivate more grocery stores to invest in new locations in the area (Díez *et al.* 2016, Hamidi 2019). Practically, the diversification of land use is a solution requiring the investment of significant funds over the span of multiple years and thus would not alleviate the urgency of food insecurity problems in this area. As a more immediate solution, this study recommends a carpool program or a shuttle from these neighborhoods to the Safeway, or another nearby grocery store. Policy Map has published data about the average number of vehicles per household and indicates that tract 7605 has an average of 0.7 vehicles per household and tract 7601 has 1.1 on average (Policy Map 2023). These data suggest that there are enough vehicles in the area to successfully organize and implement a community carpool system. Ideally, any necessary resources for this initiative would be provided by the local government, but the involvement of non-profit organizations is another possible source of funding.

To alleviate the effects of income inequality, this study has identified food insecurity mitigation strategies that are able to leverage existing low-income assistance programs. Specifically in the Southeast Quadrant, SNAP (Supplemental Nutrition Assistance Program) benefits could be used in conjunction with a wider network of farmers' markets to make fresh produce available and affordable for the population of the Fairlawn and Randle Highlands neighborhoods. One advantage of this strategy is that the District of Columbia has an existing network of farmers' markets that could be extended to serve these neighborhoods as well instead, as opposed to having to develop one from the ground up, and another is that these markets already accept SNAP benefits as a valid form of payment (Policy Map 2023). The successful introduction of farmers' markets to this area would likely require local government involvement and funding, but not to an exorbitant level and the potential benefits are convincing. Overall, this study recommends three mitigation strategies for food insecurity in Census Tracts 7601 and 7605 over three different timespans: in the short-term, carpooling or shuttles to otherwise inaccessible supermarkets; in the medium-term, introducing farmers' markets that accept SNAP benefits to the area, and in the long-term, prioritizing mixed use development.

5.5. Limitations

While valuable, this study does have some limitations that should be considered. One such limitation is the exclusion of public transportation data. Considering a population's mobility is essential to an effective and holistic analysis of food insecurity, and this cannot be fully realized without analyzing public transportation networks and private vehicle usage. This study includes neither metro, bus, bike share networks nor private vehicle ownership and usage, which would further enrich the study of hazard level generated by distance to supermarkets, due to a lack of data available for both case studies. Another aspect of mobility that is not generally included in studies of food insecurity, including the present one, is trip chaining. Trip chaining is defined as the concatenation of journeys to various destinations with varied destinations into one trip (Currie & Delbosc 2011). This changing commuter behavior affects how mobility is studied, especially in cities, as the home is not necessarily the origin or destination of all travel anymore. In this field, trip chaining has the potential to heavily influence or alter which supermarkets are accessed by populations of high-risk areas. In addition to considering distance from supermarkets, a comprehensive study of food insecurity would be incomplete without an investigation of what other food options are available to residents, how they compare to supermarkets in distance and affordability, and how their presence might be impacting community health. In vulnerable urban areas, these non-grocery food retailers are often fast-food locations, a phenomenon so prevalent that researchers have designated a term to describe it: food swamps (Caporuscio 2020). As explained in the methodology, the social vulnerability factors utilized in this study were chosen for ease of data acquisition and analysis in order to facilitate the repetition of the risk analysis in other contexts. However, there are more social vulnerability factors that should also be considered including healthcare access, average rent prices, and family demographics. The inclusion of more variables might necessitate a principal components analysis to converge on the more significant factors amongst the variables. A final limitation of this study is that it does not analyze supermarket prices nor inventory. Previous studies in the field have developed indices to score supermarket affordability and the availability of healthy foods by generating baskets of staple items and their prices and stock in various grocery chains (Díez *et al.* 2016). In this same vein, analyzing the impact of global or more isolated recessions, and resulting inflation, unemployment and wage reduction, would also be a worthwhile addition to the body of work related to food insecurity.

The two factors affecting food insecurity that were most absent in this study were mobility and affordability. Future studies could mitigate this by enriching Hazard Value calculation with affordability data. One possible solution is to rank or score the supermarkets based on their prices of staple items and scale the value given to distance from this supermarket accordingly when calculating each census tract's Hazard Value. The other overlooked aspect of food insecurity here is mobility, which includes a consideration of private vehicle usage and public transit. Private vehicle access and use data could be included as a social vulnerability variable so that populations in which most or all residents use their own private vehicle are designated as less vulnerable than those in which the majority of residents are dependent on public transportation. By far the most complex factor to include would be mobility using public transportation, as most public transit networks are city specific and varied in type of vehicle. The proposed solution involves including public transit mobility in Hazard Value calculation by generating another set of buffers with radii reflecting a feasible commuting distance using public transit and summing the values assigned to each census tract according to which buffers it intersects with those calculated in the current study to arrive at a more comprehensive set of Hazard Values. These revisions of the methodology work to overcome limitations of the current analysis and improve the accuracy and validity of its results. A flowchart of the revised methodology can be consulted in Figure 14 below.

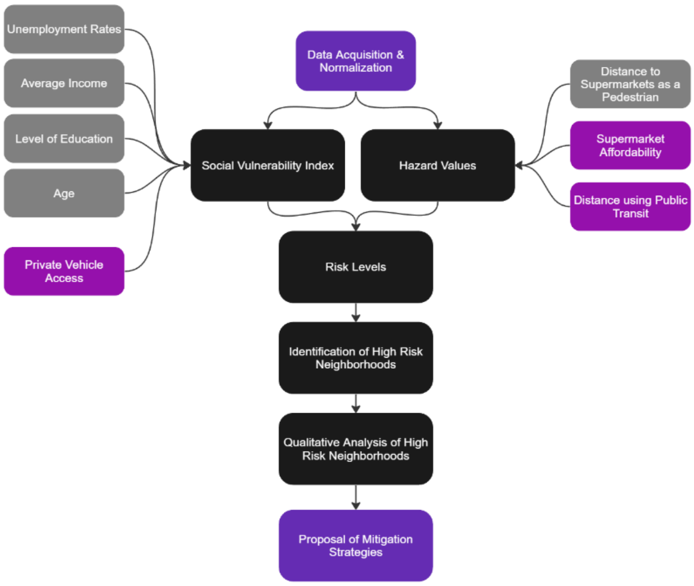

Figure 14. Flowchart of the revised methodology
Source. Prepared by the author

6. Conclusions

Although limitations exist in the scope and data considered in this study, the results remain meaningful. A comparison between the results in both case studies reveals certain economic problems, namely elevated unemployment rates and low average income, to be endemic on a more general level. This discovery serves to emphasize that food supply and insecurity are highly influenced by economic policy and conversely, economic policy could be a vital tool for combating food insecurity regardless of geography and is currently underutilized. An example of this could be raising the minimum wage in areas suffering from an extremely low average income per person.

Another similarity visible in both case studies is a lack of access to diverse public transit options. Of the high-risk neighborhoods studied, none is served by multiple metro lines within a convenient walking distance. Not only is the metro offering limited in variety, it is also somewhat limited in extension into more vulnerable areas. Clearly, both cases would benefit from substantial improvements to the extension and diversity of public transit options, and this issue likely extends to other urban contexts grappling with food insecurity. The implementation of transportation solutions falls under the jurisdiction of urban planning, offering a means to address food insecurity in this and other ways. Urban planning for mixed use development is another way that urban planning can be used to alleviate food insecurity severity. As seen in both qualitative case studies, high-risk neighborhoods often lack walkability and have a stark separation between residential and commercial zones, which isolates residents from supermarkets and discourages chains from investing in the region. An ideal solution to this would prioritize and facilitate mixed use development when considering urban planning strategies for these areas. The analysis realized in this study helps to highlight the importance of holistic planning strategies and their potential impact on food insecurity.

A final generalized solution inspired by this study is incorporating a local food supply in areas with a high risk of food insecurity. After researching both identified study areas, a pattern emerged in the mitigation strategies that best fit each context: the incorporation of a local food supply beyond chain supermarkets or other brick-and-mortar food retailers. Both community gardens and farmers' markets are mitigation strategies that also connect communities to their food supply and are recommended in the cases seen here because they are not excessively resource intensive. Their relatively low start-up costs allow them to have a more immediate impact than other strategies suggested and make them extremely adaptable to communities across the globe.

Overall, this study exemplifies a quantitative measure for food insecurity, on as small a scale as census tracts, which can be used to pinpoint areas in need of urgent intervention. Additionally, it also contributes two case studies that demonstrate the methodology from data acquisition to mitigation strategies and provide insight into the challenge of food insecurity, and its potential solutions, on a global scale.

References

About DCQ project. DC Quadrants Project. (n.d.). [accessed 01-05-2023]. https://www.dcqproject.com/home

Exploring America's food deserts. The Annie E. Casey Foundation. [accessed 14-02-2021]. https://www.aecf.org/blog/exploring-americas-food-deserts

Beaumont, J., Lang, T., Leather, S., & Mucklow, C. (1995). *Report from the policy sub-group to the Nutrition Task Force Low Income Project Team of the Department of Health*. Radlett, Hertfordshire: Institute of Grocery Distribution.

Boeing, G. (2017). OSMNX: New methods for acquiring, constructing, analyzing, and Visualizing Complex Street Networks. *Computers, Environment and Urban Systems*, 65, 126–139. **https://doi.org/10.1016/j.compenvurbsys.2017.05.004**

Caporuscio, J. (2020). *Food deserts: Definition, effects, and solutions*. Medical News Today. [accessed 15-032023]. https://www.medicalnewstoday.com/articles/what-are-food-deserts

Census Survey Explorer. United States Census Bureau. (n.d.). https://www.census.gov/data/data-tools/survey-explorer/

Census Bureau Releases New Educational Attainment Data. (n.d.). U.S. Census Bureau. [accessed 01-05-2023]. https://www.census.gov.

Chen, Y., Ye, Z., Liu, H., Chen, R., Liu, Z., & Liu, H. (2021). A GIS-based approach for flood risk zoning by combining social vulnerability and flood susceptibility: A case study of Nanjing, China. *International Journal of Environmental Research and Public Health*, 18(21), 11597. **https://doi.org/10.3390/ijerph182111597**

Currie, G., & Delbosc, A. (2011). Exploring the trip chaining behaviour of public transport users in Melbourne. *Transport Policy*, 18(1), 204-210. **https://doi.org/10.1016/j.tranpol.2010.08.003**

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards*. *Social Science Quarterly*, 84(2), 242–261. **https://doi.org/10.1111/1540-6237.8402002**

De Diego, S. (2023, May 10). *La línea 1 de Metro cerrará 4 meses tras las elecciones del 28-M: afectará a 350.000 personas sólo en Vallecas*. El Español. [accessed 16-06-2023]. https://www.elespanol.com/madrid/sociedad/20230510/linea-metro-cerrara-elecciones-28m-afectara-vallecas-sol/762673740_0.html

Díez, J., Bilal, U., Cebrecos, A., Buczynski, A., Lawrence, R. S., Glass, T. & Franco, M. (2016). Understanding differences in the local food environment across countries: A case study in Madrid (Spain) and Baltimore (USA). *Preventive Medicine*, 89, 237-244. **https://doi.org/10.1016/j.ypmed.2016.06.013**

Eckert, J., & Shetty, S. (2011). Food systems, planning and quantifying access: Using GIS to plan for food retail. *Applied Geography*, 31(4), 1216-1223. **https://doi.org/10.1016/j.apgeog.2011.01.011**

Echagüe, J. V. (2022). *Estos son los distritos con más (y menos) paro en la ciudad de madrid*. La Razón. [accessed 02-05-2023]. https://www.larazon.es/madrid/.

FAO response to Global Food Security challenges. InFocus. (n.d.). https://www.fao.org/in-focus/en/

Fuchs, S., Birkmann, J., & Glade, T. (2012). Vulnerability assessment in natural hazard and risk analysis: Current approaches and future challenges. *Natural Hazards*, 64(3), 1969–1975. **https://doi.org/10.1007/s11069-012-0352-9**

Fuchs, S., Thaler, T., Fekete, A., & Montz, B. (2018*). Vulnerability: An Introduction. In Vulnerability and resilience to natural hazards* (pp. 257–270). essay, Cambridge University Press.

Hamidi, S. (2019). Urban sprawl and the emergence of food deserts in the USA. Urban Studies, 57(8), 1660–1675. **https://doi.org/10.1177/0042098019841540**

Healthy Communities Assessment Tool. (n.d.). https://archives.huduser.gov/healthycommunities/indicator/184.html#:~:text=The%20Food%20Desert%20indicator%20is,supercenter%2C%20or%20large%20grocery%20store

Hendrickson, D., Smith, C., & Eikenberry, N. (2006). Fruit and vegetable access in four low-income food deserts communities in Minnesota. *Agriculture and Human Values*, 23(3), 371–383. **https://doi.org/10.1007/s10460-006-9002-8**

Home. PolicyMap. (2023). [accessed 01-05-2023]. https://www.policymap.com/

Instituto Nacional de Estadística. España. INE. (n.d.). https://www.ine.es/

Karpyn, A. E., Riser, D., Tracy, T., Wang, R., & Shen, Y. (2019). *The changing landscape of food deserts*. UNSCN Nutrition, 44, 46–53. **https://www.healthaffairs.org/doi/10.1377/hlthaff.2009.0740**

Kaufman, P. R., MacDonald, J. M., Lutz, S. M., & Smallwood, D. M. (1997). Do the poor pay more for food? Item selection and price differences affect low-income household food costs. *Agricultural Economics Report*, 759 (No. 1473-2016-120710). **http://dx.doi.org/10.22004/ag.econ.34065**

Long, M. A., Gonçalves, L., Stretesky, P. B., & Defeyter, M. A. (2020). Food Insecurity in Advanced Capitalist Nations: A Review. *Sustainability*, 12(9), 3654. MDPI AG. **http://dx.doi.org/10.3390/su12093654**

Madrid datos. (n.d.). [accessed 02-05-2023]. https://www.madrid.es/UnidadesDescentralizadas/UDCEstadistica/Nuevaweb/Publicaciones/Paro%20Registrado/Nuevos%20boletines/2023/6_Boletin.pdf.

Metro de Madrid Maps. Metro de Madrid. (n.d.). https://www.metromadrid.es/en/travel-in-the-metro/metro-de-madrid-maps

Montz, B.E., Evans, T.A. (2001). *Gis and Social Vulnerability Analysis*. In: Gruntfest, E., Handmer, J. (eds) Coping With Flash Floods. NATO Science Series, vol 77. Springer, Dordrecht. **https://doi.org/10.1007/978-94-010-0918-8_5**

Naveed, M. (2022, May 4). Income inequality in DC highest in the country. DC Fiscal Policy Institute. https://www.dcfpi.org/all/income-inequality-dc-highest-country/#:~:text=At%200.542%20in%202016%20%E2%80%94based,on%20par%20with%20Puerto%20Rico.

OpenStreetMap. (n.d.). https://www.openstreetmap.org/#map=6/40.007/-2.488

Organismo Autónomo Centro Nacional de Información Geográfica. (n.d.). Centro de Descargas del Cnig (IGN). Centro de Descargas del CNIG. https://centrodedescargas.cnig.es/CentroDescargas/

Portal de Datos Abiertos del Ayuntamiento de Madrid. En portada. (n.d.). https://datos.madrid.es/portal/site/egob

Portal de Datos Abiertos del Ayuntamiento de Madrid. Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico. (n.d.). https://datos.madrid.es/portal/site/egob/menuitem.c05c1f754a33a9fbe4b2e4b284f1a5a0/?vgnextoid=71359583a773a510VgnVCM2000001f4a900aRCRD&vgnextchannel=374512b9ace9f310VgnVCM100000171f5a0aRCRD&vgnextfmt=default

Programa Municipal de Huertos Urbanos comunitarios. Ayuntamiento de Madrid. (n.d.). https://diario.madrid.es/huertos/programa-municipal-de-huertos-urbanos-comunitarios/

Puente de Vallecas - Ayuntamiento de Madrid. (n.d.). https://www.madrid.es/portales/munimadrid/es/Inicio/El-Ayuntamiento/Puente-de-Vallecas/Puente-de-Vallecas/?vgnextfmt=default&vgnextoid=57b25969e83b8010VgnVCM100000dc0ca8c0RCRD&vgnextchannel=3970ca5d5fb96010VgnVCM100000dc0ca8c0RCRD

Rambsy, K., & Ossom-Williamson, P. (n.d.). Understanding D.C.'s geography. Lost in the City: An Exploration of Edward P. Jones's Short Fiction. https://iopn.library.illinois.edu/scalar/lost-in-the-city-a-exploration-of-edward-p-joness-short-fiction-/chapter-2---section-2.40#:~:text=North%2C%20South%2C%20and%20East%20Capitol,is%20the%20U.S.%20Capitol%20Building.

Ramiro, S. (2022). El Metro de Madrid, cayéndose a cachos: se derrumba el techo de la estación de Portazgo en Puente de Vallecas. El Plural. [accessed 16-06-2023]. From https://www.elplural.com/politica/espana/metro-madrid-cayendose-cachos-se-derrumba-techo-estacion-portazgo-puente-vallecas_286860102

Sharma, V. R., & Chandrakanta. (2019). Making Cities Resilient. Springer.

Siegel, F. R. (2016). Risk Assessment/Vulnerability. In Mitigation of dangers from natural and anthropogenic hazards prediction, prevention, and Preparedness (pp. 9–11). essay, Springer International Publishing. **https://doi.org/10.1007/978-3-319-38875-5_3**

The National Council on Aging. (n.d.). https://ncoa.org/article/what-can-you-buy-with-snap

The Employment Situation. (2023) (n.d.). Bureau of Labor Statistics. [accessed 01-05-2023]. https://www.bls.gov

Trip planner. Washington Metropolitan Area Transit Authority. (n.d.). [accessed 01-05-2023]. https://www.wmata.com/

Turner, C., Kalamatianou, S., Drewnowski, A., Kulkarni, B., Kinra, S., & Kadiyala, S. (2020). Food Environment Research in low- and middle-income countries: A systematic scoping review. *Advances in Nutrition*, 11(2), 387–397. **https://doi.org/10.1093/advances/nmz031**

U.S. Census Bureau quickfacts: District of columbia. U.S. Census Bureau. (n.d.). [accessed 01-05-2023]. https://www.census.gov/quickfacts/DC

U.S. Department of Agriculture. (2015). Food Access Research Atlas. USDA ERS - Go to the Atlas. [accessed 15-03-2023]. https://www.ers.usda.gov/data-products/food-access-research-atlas/go-to-the-atlas/

U.S. Department of Agriculture. (2011). Food Environment Atlas. USDA ERS - Go to the Atlas. [accessed 15-03-2023]. https://www.ers.usda.gov/data-products/food-environment-atlas/go-to-the-atlas/

Voices of the Hungry. Food and Agriculture Organization of the United Nations. (n.d.). https://www.fao.org/in-action/voices-of-the-hungry/fies/en/

Wijaya, A. P., & Hong, J. H. (2018). Quantitative assessment of social vulnerability for landslide disaster risk reduction using GIS approach (Case study: Cilacap Regency, Province of Central Java, Indonesia). *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, 42(4). **https://doi.org/10.5194/isprs-archives-XLII-4-703-2018**

Zhang, M., & Ghosh, D. (2016). Spatial Supermarket Redlining and Neighborhood Vulnerability: A Case Study of Hartford, Connecticut. *Transactions in GIS*, 20(1), 79-100. **https://doi.org/10.1111/tgis.12142**