Mapping Food Deserts in Washington, D.C.: A Multi-Criteria Evaluation Approach

Abstract

This report examines food accessibility disparities within Washington, D.C., using Multi-Criteria Evaluation (MCE) modeling. Two models were developed: (1) the Mayor's baseline model combining median age, income, and grocery store distance, and (2) an enhanced model that incorporates additional social and transportation accessibility indicators, including poverty rate and bus stop density. The results highlight distinct food deserts concentrated in eastern Washington D.C., particularly east of the Anacostia River. The enhanced model refines the identification of underserved areas with both social and infrastructural disadvantages in accessing healthy food.

Introduction

Food deserts are areas where residents have limited access to affordable and nutritious food. According to the Centers for Disease Control and Prevention (CDC), food deserts are "areas that lack access to affordable fruits, vegetables, whole grains, low-fat milk and other foods that make up a range of a healthy diet" (CDC, 2017). The U.S. Department of Agriculture (USDA) defines them as low-income census tracts where a substantial number of residents live far from a supermarket or large grocery store (USDA, 2021). These conditions often contribute to health inequities, including higher rates of diet-related chronic diseases. In Washington D.C., disparities in grocery access are high. East of the Anacostia River, over 160,000 residents are served by only five grocery stores, highlighting a pressing urban equity challenge.

This analysis aims to assist the D.C. Mayor's Office in identifying food deserts through spatial analysis and Multi-Criteria Evaluation (MCE). Two models were created: the Mayor's baseline model (using age, income, and distance to grocery stores) and an enhanced model that includes poverty rate and bus stop density to better reflect social and infrastructural accessibility. Both models use standardized and rescaled variables to assess the relative vulnerability of each census tract.

Data & Methods

Data were compiled from the U.S. Census Bureau (ACS 2019), American Community Survey 2019 and Open Data DC (ACS, 2019; Open Data DC, 2019; TIGER/Line Census Tracts, 2019; U.S. Census Bureau, 2019). Variables include Median Age (Table B01002), Median Household Income (Table B19013) and Poverty Rate (DP03_0128P). Spatial layers, including grocery store locations, bus stops, military bases, parks, and waterbodies, were sourced from Open Data DC. All datasets were reprojected to NAD 1983 (2011) StatePlane Maryland FIPS 1900 (Meters) for spatial consistency.

The Euclidean Distance tool was applied to grocery store point data to estimate accessibility. Waterbodies were used as barriers to reflect realistic travel constraints. Bus stops within 400 meters (which is equivalent to 5-minute walk) of each tract were counted using spatial analysis and then their density (counts/sq.km) was calculated. Z-scores were used to standardize income, age and poverty and Min-Max scaling was applied to normalize values between 0 and

1 for spatial accessibility measures such as grocery distance and bus stop density. Each variable is on a 0-1 scale, where 1 = worst condition (more food-desert-prone). The rescaling of poverty, age and income using bins achieves this manually. For distance and density variables, min-max scaling naturally does the same without needing cutoffs. Finally, an MCE score was computed for each tract (higher MCE values indicate more food-desert-prone). The formulas used for all these calculations are:

Z-Score Normalization

$$Z_i = \frac{X_i - \bar{X}}{s}$$

where Z_i= standardized (z-score) value for observation i, X_i= original value, $\bar{X}$= mean of all values and s= standard deviation

Min-Max Normalization

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}$$

where X_i'= rescaled value between 0 and 1, X_i= original value and $X_{\min}$, $X_{\max}$= minimum and maximum of the variable

Multi-Criteria Evaluation (MCE) Weighted Sum

$$\mathrm{MCE}_i = \sum_{k=1}^{n} w_k \cdot X_{ik}'$$

where MCE_i= composite index (food desert score) for tract i, w_k= weight of factor k (such that $\sum w_k = 1$) and X_{ik}'= normalized or scaled value of factor k for tract i

Weighting Scheme

The two maps (Map 1 and Map 2) were generated had different factor weightages for their MCE calculation. The weights used for Map 1 were determined based on the Mayor's priority criteria. Each factor of Map 2 was assigned a weight based on literature review and federal guidance. The following table justifies the variables and their scaling methods used:

Table: MCE Variable Calculation

Map 1 Variables

Variable Name	Scaling Method	MCE Weight	Weight Justification	Justification for Inclusion
Median Age	Z-score (reclassified)	0.15 (for Map 1) 0.10 (for Map 2)	Age has minimal influence on mobility	Elderly residents often face access barriers

Median Income	Z-score (reclassified)	0.30 (for Map 1) 0.15 (for Map 2)	Low income increases food insecurity risk	Economic access is a key USDA criterion
Distance to Grocery Store	Min-Max Scaling (squared distance)	0.55 (for Map 1) 0.25 (for Map 2)	Captures spatial inaccessibility directly	Core measure of physical access to food
		Additional Map 2 Variables		
Poverty Rate	Z-score (reclassified)	0.30	Strongest indicator of food affordability	Directly measures economic hardship
Bus Stop Density	Min-Max Scaling	0.20	Proxy for public transport access	Improves mobility to food sources

Source: (Smarsh, 2025; USDA ERS, 2012)

It is to be noted that higher MCE scores for Map 1 indicate tracts that are poorer, younger, and located farther from grocery stores (and are most likely the food desert areas), while high MCE values for Map 2 represent tracts with multiple disadvantages: older or poorer populations, farther from grocery stores, and with limited public transit options.

Results

Figure 1 shows the baseline MCE model map based on age, income, and grocery distance. The map highlights that the highest MCE values (0.38-0.95) appear concentrated in Anacostia and eastern Washington D.C., and isolated central tracts such as 64, 95.01, 88.03 and 108. These areas represent young, low-income communities located farthest from grocery stores and are most likely the food deserts. The use of quantile classification (where the darkest color represents the top 20% of tracts with highest MCE values) for this map made the comparison of the areas easier.

Figure 2 presents the enhanced MCE incorporating poverty rate and bus stop density. The use of Natural Breaks (Jenks) groups similar scores to isolate the true highest-need tracts (77.07, 77.08, 99.05, 74.01, 75.03, 75.04, 98.07, 98.10 and 109). The Jenks method slightly changed class boundaries but better revealed the most vulnerable areas, making it the preferred choice for policy targeting. At the same time, the inclusion of transit accessibility for this map improved the model by distinguishing areas where residents are spatially distant from grocery stores but benefit from nearby bus networks. This analysis reveals several tracts (notably in Southeast DC) remain both economically disadvantaged and poorly connected by bus routes. Inset maps of sites A, B, and C highlight potential areas for future grocery store investments based on highest MCE scores.

Conclusion

This study uses spatial Multi-Criteria Evaluation in identifying and visualizing food deserts in Washington, D.C. The Mayor's baseline model effectively highlighted existing disparities, but the enhanced model incorporating transportation access and poverty rates offers a more holistic view of vulnerability. Findings emphasize that areas east of the Anacostia River remain the most underserved. Policy interventions could prioritize expanding grocery infrastructure and improving public transit connections to these neighborhoods to promote equitable access to healthy food. Although the approaches taken for the evaluations already provide a strong foundation for equitable food planning, future work could improve this method by including actual travel times, store quality, and walking accessibility to better reflect real-world food access.

References

ACS. (2019). *Census Data API: /Data/2019/acs/acs1/profile/groups/DP03*. https://api.census.gov/data/2019/acs/acs1/profile/groups/DP03.html?

CDC. (2017). *Food Desert | Gateway to Health Communication | CDC*. http://medbox.iiab.me/modules/en-cdc/www.cdc.gov/healthcommunication/toolstemplates/entertainmented/tips/FoodDesert.html

Open Data DC. (2019). *Open Data DC*. https://opendata.dc.gov/

Smarsh, B. L. (2025). Public Transit Supports for Food Access: 2021 National Survey of Community-Based Policy and Environmental Supports for Healthy Eating and Active Living (CBS HEAL). *Preventing Chronic Disease*, *22*. https://doi.org/10.5888/pcd22.240458

TIGER/Line Census Tracts. (2019). *2019 TIGER/Line® Shapefiles*. https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2019&layergroup=Census+Tracts

U.S. Census Bureau. (2019). *Census Bureau—Advanced Search*. https://data.census.gov/advanced

USDA. (2021). *Food Access Research Atlas—Documentation | Economic Research Service*. https://www.ers.usda.gov/data-products/food-access-research-atlas/documentation

USDA ERS. (2012). *Access to Affordable and Nutritious Food-Measuring and Understanding Food Deserts and Their Consequences: Report to Congress | Economic Research Service*. https://www.ers.usda.gov/publications/pub-details?pubid=42729

Appendix: Map Design Summary

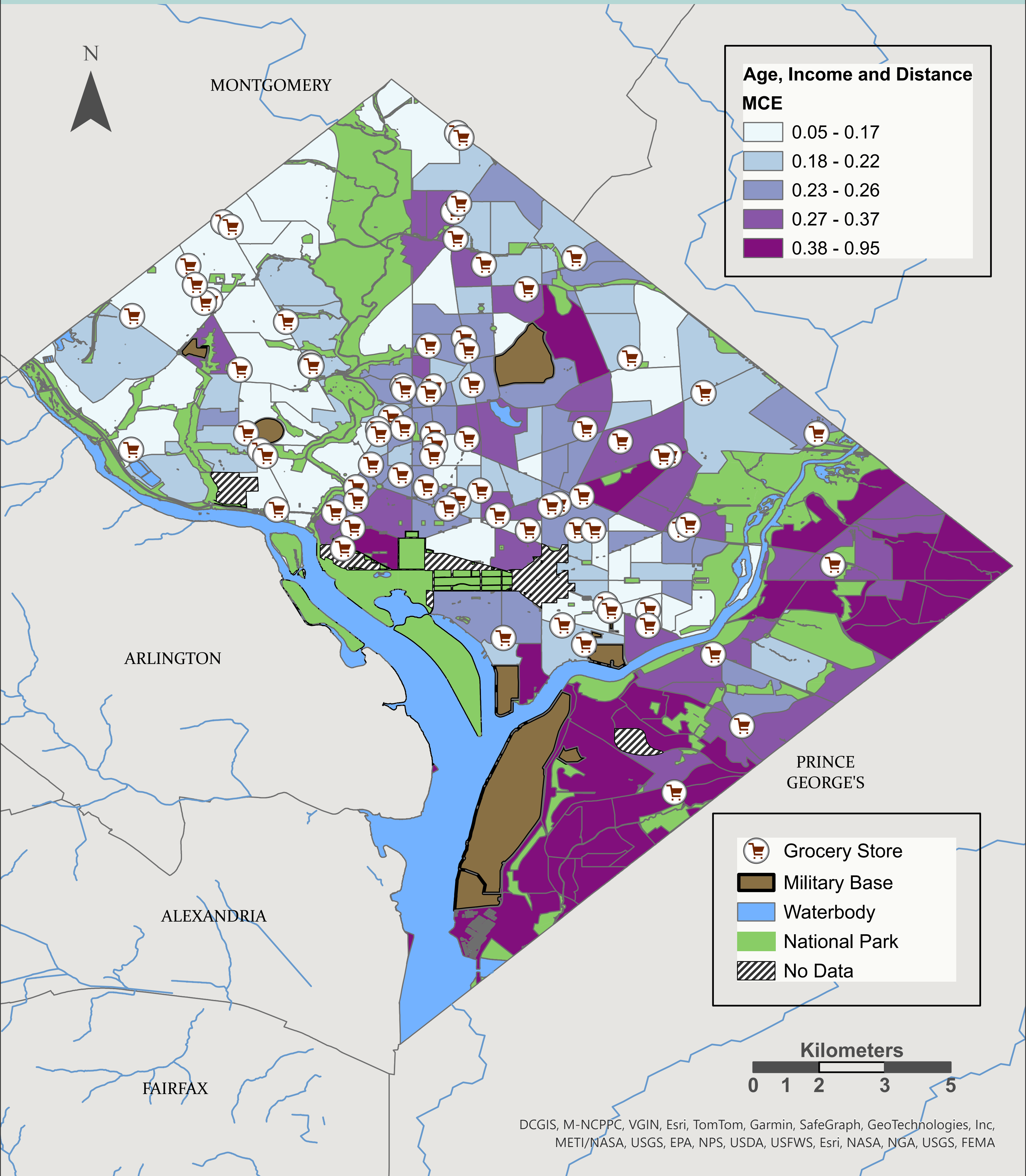
Map 1: This map shows food deserts across Washington, D.C., based on the Mayor's 2019 model. The MCE combines median age, income, and distance from grocery stores to identify areas most affected by poor food access. Darker purple shades represent higher vulnerability. Grocery store icons show service distribution and clearly highlight gaps in the eastern wards.

Map 2: This enhanced map adds poverty rate and bus stop proximity to the analysis, refining the identification of the food deserts. A dark purple to light-blue gradient shows severity and bus stop symbols display accessibility patterns, along with the previous elements like grocery store icon. Three inset maps (Sites A, B and C) zoom into areas with high poverty, few bus stops, and limited grocery access.

Both maps include a legend, north arrow, and scale bar and use the StatePlane Maryland FIPS 1900 (Meters) projection. Muted tones mark water bodies, parks, military areas and county boundaries provide context.

FIGURE 1: FOOD DESERTS WITHIN WASHINGTON D.C. (2019) - MAYOR'S METHOD

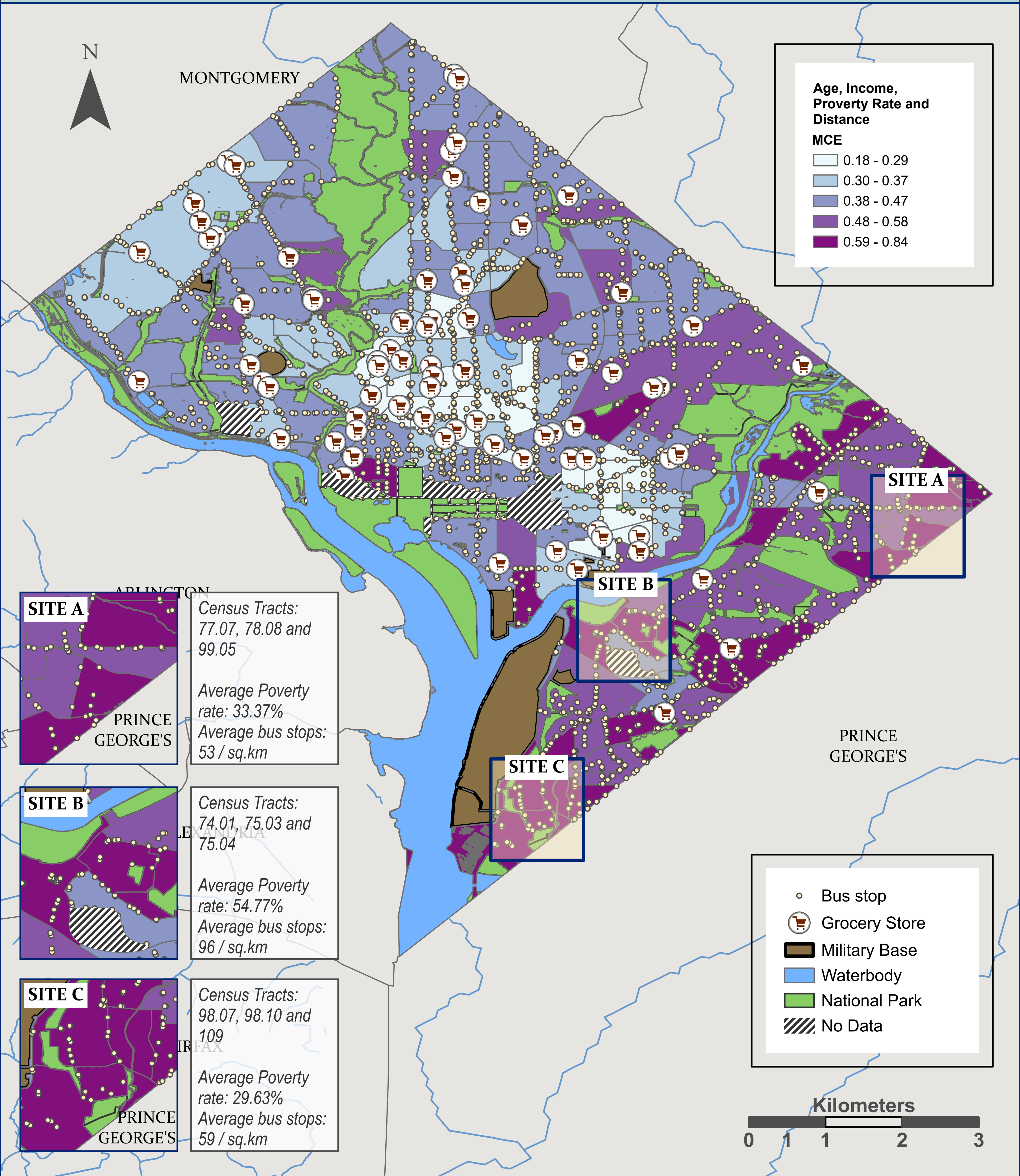
BASED ON AGE, INCOME AND GROCERY STORE DISTANCE



Fyrooz Khan | 10/25/25 || NAD 1983 (2011) StatePlane Maryland FIPS 1900 (Meters) || Source: Open Source Data DC, DC Tigerline, US Census, Maryland and Virginia Open Data

FIGURE 2: FOOD DESERTS WITHIN WASHINGTON D.C. (2019) - ENHANCED MODEL

BASED ON AGE, INCOME, POVERTY RATE, AND DISTANCE FROM BUS STOP AND GROCERY STORE



Fyrooz Khan | 10/26/25 || NAD 1983 (2011) StatePlane Maryland FIPS 1900 (Meters) || Source: Open Source Data DC, DC Tigerline, US Census, Maryland and Virginia Open Data