Multi-Scale Community Resource Accessibility in LA County: A case study of neighborhood resource accessibility in Los Angeles County and the USC area

Chenyi Weng

SSCI575 - Spatial Data Science

Professor Yi Qi

December 02, 2025

1. Introduction

1.1 Background

Accessibility is an important topic in urban research because it describes how easily people can reach the services needed for daily life. According to Pearce et al. (2006), differences in access to food, transportation, and public services can influence health, well-being, and social equity. In walkable neighborhoods, even small variations in the location of essential services can greatly affect daily routines. The area around the University of Southern California (USC) is a student-centered environment where most movement happens on foot. This makes accessibility to markets, restaurants, and bus stops especially important for people living in this community.

Spatial accessibility is often measured using floating catchment area models. According to Luo and Wang (2003), the 2SFCA method gives a clear way to evaluate the balance between supply and demand. Later studies introduced distance-decay weights to better represent real travel behavior on foot. According to Luo and Qi (2009), the E2SFCA method reduces the weight of facilities located farther away, which produces more realistic accessibility patterns. Micro-scale accessibility studies also help reveal fine spatial differences. According to Jamtsho and Corner (2014), small study areas make it possible to identify inequalities that are not visible in large regional analyses.

Because the USC neighborhood contains many services within short walking distances, it is suitable for building-level analysis. According to Delamater (2013), accessibility can change significantly even within small walking ranges, which makes micro-scale analysis valuable for understanding local conditions. These ideas form the foundation of our research.

1.2 Study Objectives

The objective of our study is to measure accessibility to three categories of daily-life resources which are markets, restaurants, and bus stops. We focus on the USC Department of Public Safety (DPS) area and use the E2SFCA method to identify patterns of access within the neighborhood and explore how easily residents and students can reach these essential services.

1.3 Research Questions

Our study addresses the following research questions.

1. What are the spatial patterns of accessibility for markets, restaurants, and bus stops within the DPS area.
2. Do the three resource types follow similar patterns or show different forms of spatial clustering.

These questions guide our analysis and help us understand how the walkable environment functions for people who live and study near USC.

1.4 Significance

This study is significant because it provides detailed information about accessibility at a micro scale. Most large-scale studies cannot capture small variations that directly affect students and residents. By focusing on building-level accessibility, our research highlights local strengths and weaknesses in the availability of daily services. The findings can support planning decisions, improvements to pedestrian infrastructure, and discussions about resource distribution in the USC neighborhood. The results also demonstrate how E2SFCA can be used for small, dense communities where walking is the primary travel mode.

2. Study Area

2.1 Macro Area (LA County)

As shown in *Figure 1*, the macro study area is Los Angeles County. This region provides a broader context for understanding the urban environment surrounding USC. According to the Los Angeles County GIS Portal (2020), the county contains thousands of census tracts with different levels of population density, service access, and built environment characteristics. Including the macro area helps introduce the regional setting before narrowing down to the local neighborhood around USC.

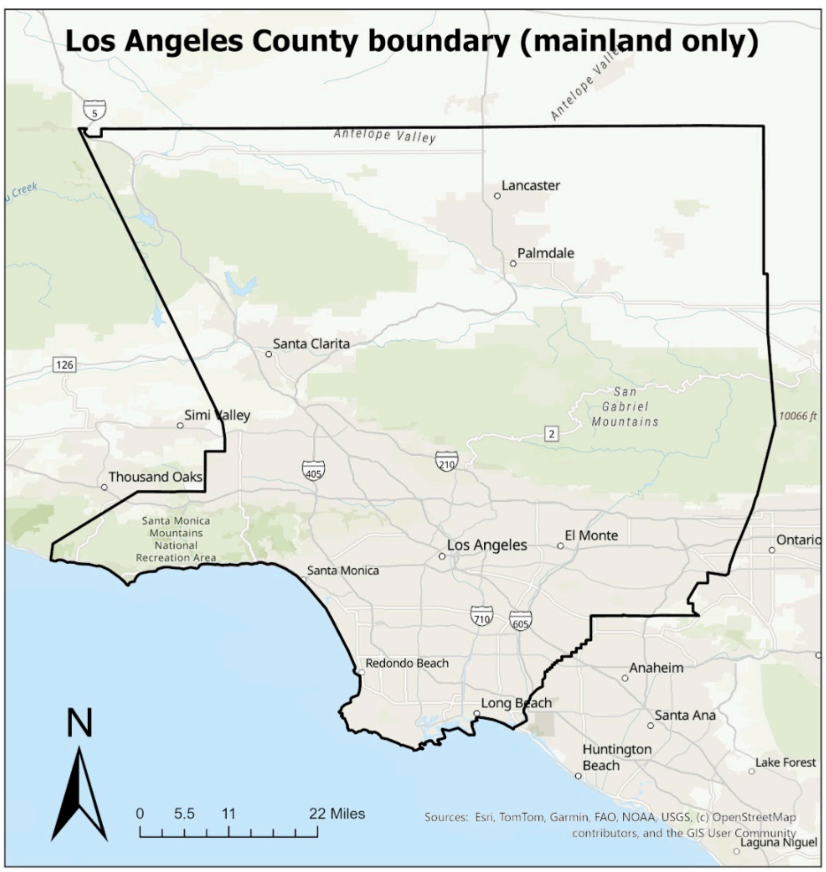

Figure 1. Los Angeles County boundary defining the macro study area.

2.2 Micro Area (USC DPS)

As shown in *Figure 2*, the micro study area is the USC DPS boundary, which covers student housing complexes, academic buildings, restaurants, markets, and multiple bus stops. The area is compact and highly walkable, making it suitable for micro-scale accessibility analysis. The DPS boundary defines the area where students and residents most frequently walk in their daily routines. This localized focus allows us to study accessibility at the building level.

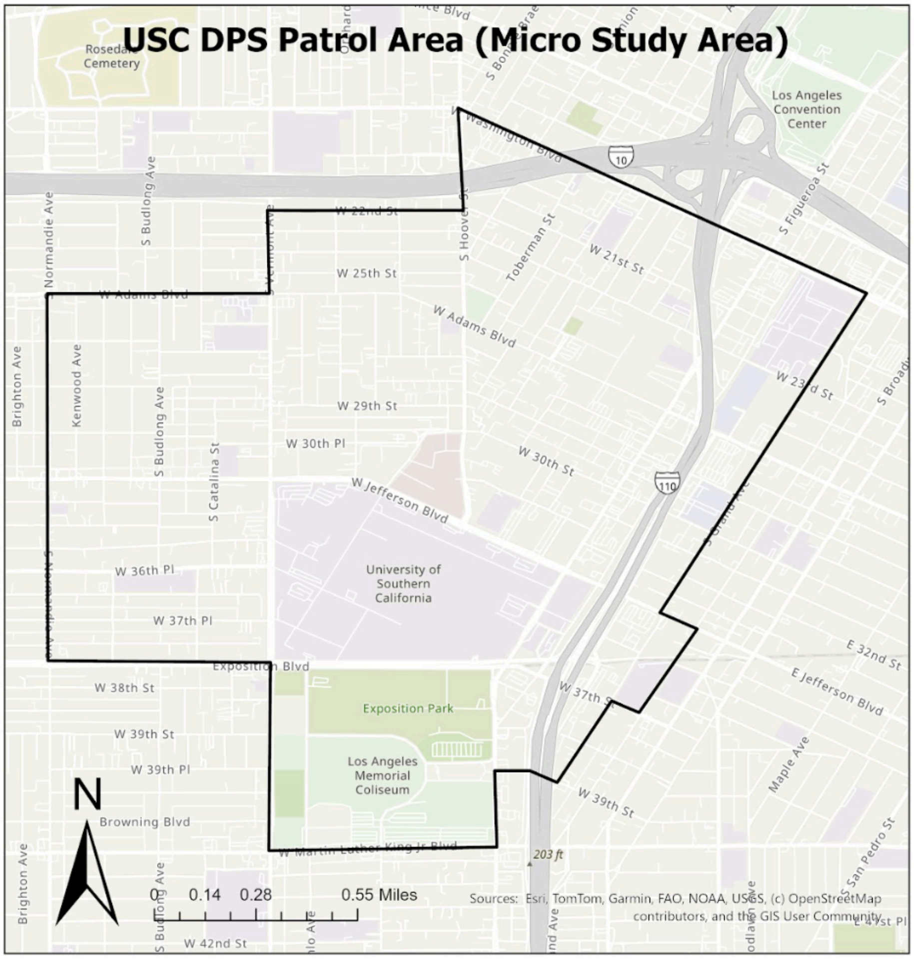

Figure 2. USC DPS patrol area defining the micro study area.

2.3 Why DPS is suitable for micro-scale accessibility

The DPS area is appropriate for this research for three main reasons.

1. It includes a variety of essential services located within short walking distances.
2. It contains a dense network of buildings and streets, which supports detailed accessibility modeling.
3. Walking is the dominant mode of travel in this neighborhood, which aligns well with the E2SFCA method that uses distance-decay functions to represent walking behavior.

According to Jamtsho and Corner (2014), compact and walkable areas are ideal for fine-scale accessibility research. Overall, these factors make the DPS area a suitable environment for building-level analysis.

3. Data

3.1 Data Sources (dataset table)

Dataset Name	Description	Source Link
LA_Census_Tract.shp	2020 Census tracts of Los Angeles County	https://egis-lacounty.hub.arcgis.com
LA_Population.csv	2023 ACS 5-year population estimates for LA County	https://api.census.gov
usc_dps_boundary.shp	USC Department of Public Safety patrol-area polygon (DPS area)	https://dps.usc.edu/patrol
usc_dps_markets.shp	Market and supermarket locations within USC DPS area, extracted from OSM using osmnx	OSM (via Python OSMnx)
usc_dps_restaurants.shp	Restaurant locations within USC DPS area, extracted from OSM using osmnx	OSM (via Python OSMnx)
usc_dps_buildings.shp	Building footprint polygons within USC DPS area, extracted from OSM	OSM (via Python OSMnx)
USC_DPS_BusStop.shp	Metro Bus Stops clipped to DPS boundary	https://developer.metro.net/gis-data/
LA_boundary_no_island.shp	Los Angeles County boundary with islands removed	LA County GIS hub

Table 1. Summary of Datasets and Sources

As shown as *Table 1*, our project combines demographic, urban infrastructure, and administrative boundary datasets to support the analysis of accessibility within the USC Department of Public Safety (DPS) area. The population data are derived from the 2023 American Community Survey (ACS) 5-year estimates, which provide tract-level population counts for all of Los Angeles County. Census tracts and the LA County boundary serve as fundamental reference layers for spatial alignment. Facility data, including markets, restaurants, and building footprints, originate from OpenStreetMap. These datasets capture local amenities and the physical structure of the built environment within the DPS area. Metro bus stop locations are sourced from the official Los Angeles Metro GIS portal, providing an accurate inventory of transit access points. The USC DPS patrol-area polygon defines the geographic extent of our study and serves as the clipping boundary for all facility layers. Together, these datasets allow us to model both supply and demand for urban services and compute accessibility across census-defined population units.

3.2 Data Format and Attributes

All datasets used in the project are stored in ESRI Shapefile or CSV format. Spatial datasets contain geometry fields representing points or polygons. The LA Census Tract layer includes unique GEOID codes and basic administrative attributes. The population CSV file contains tract-level population counts that were later joined to the spatial tract layer. The OSM-based facility layers include descriptive attributes such as amenity, shop, name, and address information, depending on the feature type. Building footprints are stored as Polygon geometries and include general OSM tags that characterize building usage when available. The bus stop dataset contains stop identifiers, names, and categorical information relevant to public transit. To support the accessibility analysis, we added standardized fields such as *SupplyID* and *Supply_Capacity* across all supply layers. Each layer was converted into a consistent projected coordinate system (UTM Zone 11N) to ensure accurate distance calculations.

3.3 Validation Data

We performed internal validation by visually inspecting all spatial layers within the study boundary. Census tracts, facility points, and building footprints were checked for proper alignment and completeness. Population counts were reviewed to ensure that the join between the ACS dataset and the Census Tract shapefile was accurate based on the GEOID field. For the OSM-based datasets, we verified that markets, restaurants, and building footprints appeared in plausible real-world locations by comparing them to basemap imagery. The bus stop dataset was cross-checked with the Metro-provided spatial layer to ensure that only stops within the DPS boundary were included in the final dataset. This combination of spatial verification and attribute checking ensured that the datasets were sufficiently reliable for accessibility modeling.

3.4 Limitations of the Datasets

While the datasets are appropriate for our analysis, several limitations exist. OpenStreetMap data rely on community contributions and may be incomplete or inconsistent, especially for smaller facilities that are less frequently mapped. Some restaurants or markets may be missing, misclassified, or lack attribute information. Census tract boundaries are relatively large and may not perfectly represent population distribution within the DPS area. As a result, assigning population counts to a smaller custom study area introduces some spatial uncertainty. Additionally, ACS population estimates include sampling error, which propagates into the demand calculations. Building footprint data represent physical structures but do not include information about building function, occupancy, or population counts. The Metro bus stop dataset represents stop locations but not service frequency or ridership, meaning our analysis captures spatial availability rather than service quality. Despite these limitations, the combined datasets provide a robust basis for modeling accessibility and identifying spatial patterns within the USC DPS area.

4. Data Wrangling

4.1 Data Preprocessing (Macro area: LA County)

We began the macro level preprocessing by preparing a clean and accurate boundary for Los Angeles County. We first downloaded the national county polygons from the U.S. Census TIGER database and selected the polygon that represents Los Angeles County. The original polygon included several offshore areas such as Catalina Island, which were not needed for our analysis. To solve this issue, we used a Python script to keep only the largest polygon and remove the extra offshore components. The resulting boundary file, named *LA_County_no_islands.shp*, is shown in *Figure 1*. After creating a clean county boundary, We downloaded the 2020 Census Tracts from the LA County GIS Hub. These census tracts were then clipped to the cleaned county boundary using the Clip tool in ArcGIS Pro. The output, named *CensusTracts_LA_Clip*, contained the correct geometry and spatial extent for all census tracts within Los Angeles County. This clipped layer is presented in *Figure 3*.

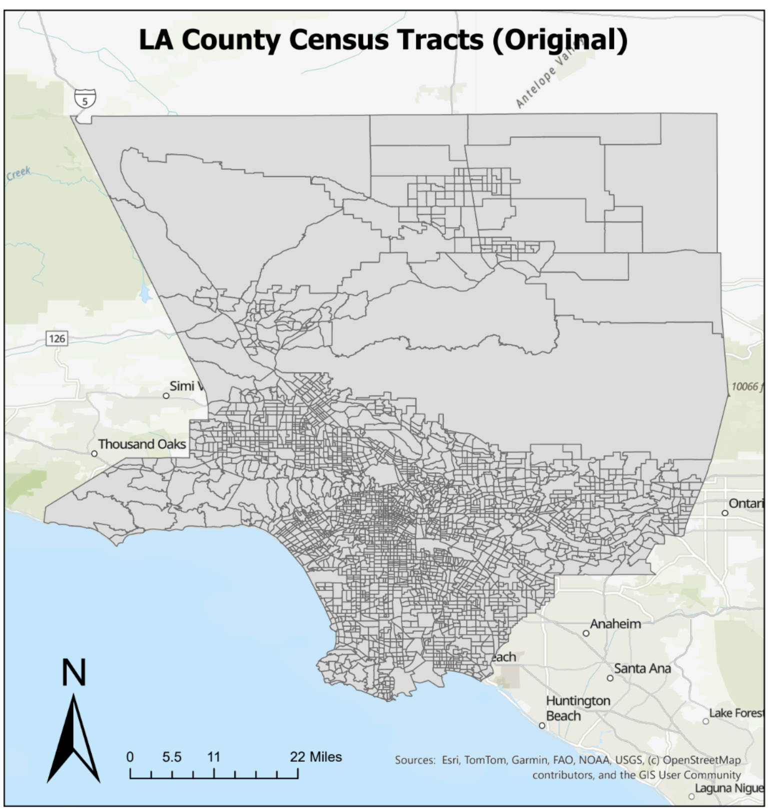

Figure 3. Clipped 2020 Census Tracts Within Los Angeles County

Next, we prepared the demographic information needed for the analysis. We downloaded the 2023 ACS five year population estimates (Table B01003) from the Census API. The population table contained a GEO_ID field that stored long identification strings. We created a new field called *GEOID_clean* and used Python to extract the last eleven characters of each GEO_ID so that it would match the standard census tract format.

To complete the join, we created a corresponding GEOID field inside the *CensusTracts_LA_Clip* layer. The field was generated by combining the state FIPS code for California, the county FIPS code for Los Angeles County, and the tract code stored in the CT20 attribute. Once both datasets shared the same identifier format, we performed an attribute join in ArcGIS Pro using GEOID from the census tracts and GEOID_clean from the population table. The join successfully added the B01003 population estimates to each census tract, as shown in *Figure 4*.

CensusTracts_LA_Clip

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete Copy

		GEO_ID	NAME	B01003_001E	B01003_001M	Unnamed: 4	GEOID_clean
1	110	1400000US06037101110	Census Tract 1011.10;...	4152	441	<Null>	06037101110
2	122	1400000US06037101122	Census Tract 1011.22;...	4198	852	<Null>	06037101122
3	220	1400000US06037101220	Census Tract 1012.20;...	3434	446	<Null>	06037101220
4	221	1400000US06037101221	Census Tract 1012.21;...	3931	618	<Null>	06037101221
5	222	1400000US06037101222	Census Tract 1012.22;...	2572	397	<Null>	06037101222
6	300	1400000US06037101300	Census Tract 1013; Los...	4210	470	<Null>	06037101300
7	400	1400000US06037101400	Census Tract 1014; Los...	3489	526	<Null>	06037101400

Figure 4. Joined Census Tracts With 2023 ACS Population Attributes

After completing the join, we calculated population density at the tract level. We added a new field named *PopDensity* (type: Double) and used a Python expression to divide total population (B01003_001E) by the tract area in square kilometers:

float(!B01003_001E!) / (!Shape_Area! / 1000000)

The calculated PopDensity field successfully appeared in the attribute table with realistic values that ranged from very low density in rural tracts to extremely high density in urban areas. We then visualized population density in ArcGIS Pro using Graduated Colors with the Natural Breaks (Jenks) classification and five classes. This method provides a meaningful way to highlight areas of high and low density across the county. The final population density map is presented in *Figure 5*.

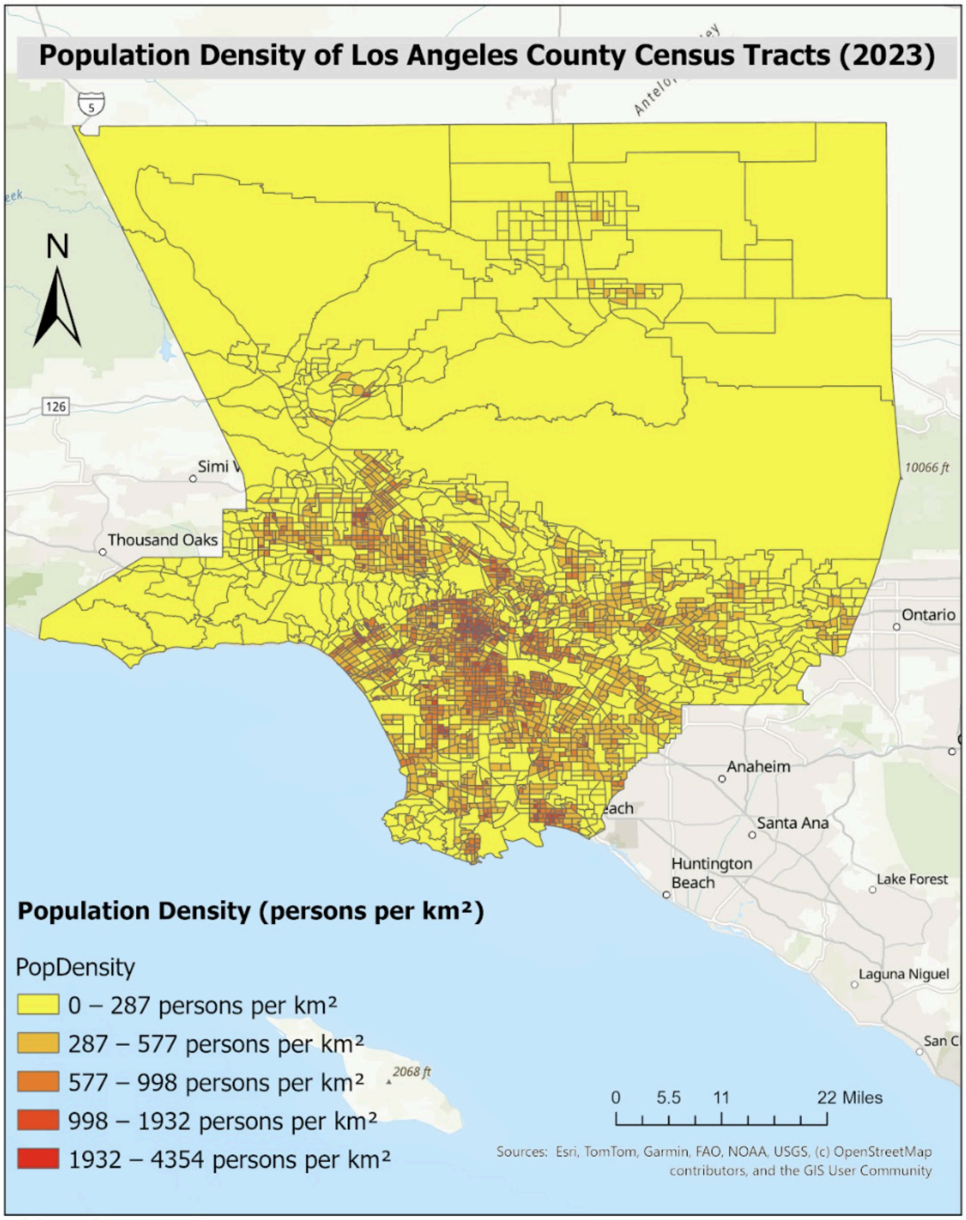

Figure 5. Population Density of Los Angeles County Census Tracts (2023)

We produced a county scale population density map to illustrate how residents are distributed across Los Angeles County. As shown in *Figure 5*, census tracts are symbolized using a Natural Breaks (Jenks) classification based on persons per square kilometer. Low-density census tracts, symbolized in light yellow, tend to appear in the less developed outer areas of Los Angeles County, particularly toward the north and other fringe zones. Higher density tracts, shown in darker orange and red, concentrate in central and southern urban areas such as Downtown Los Angeles and surrounding neighborhoods.

4.2 Data Preprocessing (Micro area: DPS)

For the micro-area analysis, we first prepared all geospatial datasets required to describe the built environment and urban activity patterns within the USC Department of Public Safety (DPS) patrol area. Our preprocessing began with obtaining the official DPS boundary in polygon format. The boundary was projected to the WGS 84 geographic coordinate system to ensure compatibility with additional datasets derived from OpenStreetMap (OSM) and the Los Angeles Metro GIS portal. We used this boundary as the spatial extent for all subsequent data extraction and clipping procedures.

To obtain micro-scale amenities within the DPS area, we collected point-based features directly from OSM using Python. We worked in Google Colab and installed the *osmnx* and *geopandas* libraries to automate data acquisition. After reading the DPS boundary shapefile and converting it into a polygon geometry, we queried OSM for specific feature types. For markets, we extracted all points tagged as “supermarket,” “convenience,” or “marketplace.” For restaurants, we queried the attribute *amenity = restaurant*. Because OSM often returns mixed geometry types, we filtered each dataset to retain only point geometries to avoid write errors when exporting to shapefiles. We applied a similar process to download buildings, except in this case we extracted polygons and multipolygons associated with the tag *building = True*, producing a detailed footprint layer of the built environment. In all cases, the cleaned geometries were exported to shapefiles and prepared for visualization in ArcGIS Pro.

Public transit features were obtained from the Los Angeles Metro developer GIS portal, where we downloaded the most recent countywide bus stop database. Each bus stop contains attributes listing the routes that serve it, and the dataset represents each stop as a unique point. Because our analysis focuses exclusively on the DPS patrol area, we clipped the countywide bus stop layer using the DPS boundary in ArcGIS Pro. This produced a refined subset of transit stops located entirely within or immediately adjacent to the patrol zone.

After preprocessing all datasets, we visualized them together in ArcGIS Pro to verify spatial accuracy and to establish a clear spatial understanding of the DPS environment. The resulting map, *Figure 6* shows the distribution of buildings, markets, restaurants, and bus stops relative to the DPS boundary. Several spatial patterns emerge from the figure. Buildings are densely clustered around the university core, reflecting concentrated academic and residential functions. Restaurants and markets appear along major corridors such as Figueroa Street and Jefferson Boulevard, indicating highly active commercial zones. Bus stops are evenly distributed along primary streets, suggesting strong transit accessibility throughout the patrol area. These spatial relationships illustrate that the DPS micro-area is a compact, high-density urban environment with substantial pedestrian movement, diverse amenities, and a well-connected transit network.

Figure 6. Urban Facilities and Transit Features within the USC DPS Area

4.3 Demand Data Preparation and Calculation

In this part of the study, we prepared two types of demand data. The first type represents the residential population within the DPS area, and the second type represents buildings that may require access to public facilities. The overall goal was to create a consistent set of demand points that could support the accessibility analysis in later sections. To estimate the population within the DPS boundary, we started with the census tracts covering Los Angeles County. Each tract contained total population counts and was assigned an additional field called *orig_area*, which stores the original tract area in square meters. We then clipped the census tracts using the DPS boundary to extract only the portions of tracts that fall inside the study area. The output layer preserved the demographic attributes and provided a reduced geometry representing the portion inside the DPS boundary, as illustrated in *Figure 7*. For each clipped tract segment, we calculated its area and stored it as *clipped_area*. We then joined the original tract area back to the clipped layer using the shared GEOID field. This allowed us to compute the proportion of each tract that is located within the DPS boundary. The ratio of *clipped_area* to *orig_area* was used to estimate the local population, stored in the attribute *local_pop*. The calculation follows the formula:

$$local\_pop = pop\_total \times \frac{clipped\_area}{orig\_area}$$

This procedure provides a consistent estimate of population distributed across partially intersecting census tracts. *Figure 7* shows the clipped census tracts and their calculated fields, including *orig_area*, *clipped_area*, and *local_pop*.

DPS_CensusTracts

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete Copy

	GEOID_clean	Shape_Length	Shape_Area	LABEL	clipped_area	orig_area	local_pop	pop_total	area_ratio
1	6037221120	149.04994	1171.647963	2211.20	108.850093	317501.371092	1.009987	2946	0.000343
2	6037221500	27.742128	45.151531	2215.00	4.194731	380721.443688	0.03886	3527	0.000011
3	6037221601	5321.594036	30021.717887	2216.01	2789.120014	369896.582513	24.61144	3264	0.00754
4	6037221602	2110.81732	21462.983185	2216.02	1993.984361	522792.063053	8.478758	2223	0.003814
5	6037221710	7898.100312	2844564.842458	2217.10	264269.77842	327981.571163	2141.672377	2658	0.805746
6	6037221810	7479.188851	3273213.869152	2218.10	304092.735384	304336.037509	2431.054933	2433	0.999201

Figure 7. Clipped census tracts within the DPS area and calculated population fields (orig_area, clipped_area, local_pop)

In addition to population demand, we also created a spatial representation of buildings within the DPS area. The building footprints extracted from OpenStreetMap were originally polygons. Since later accessibility and matching steps in the workflow require point-based demand units, we converted all building polygons into centroid points. The conversion was done using the Feature To Point tool with the "Inside" option. This resulted in a building point layer where each point represents a single building footprint. *Figure 8* presents the distribution of these centroids across the DPS area.

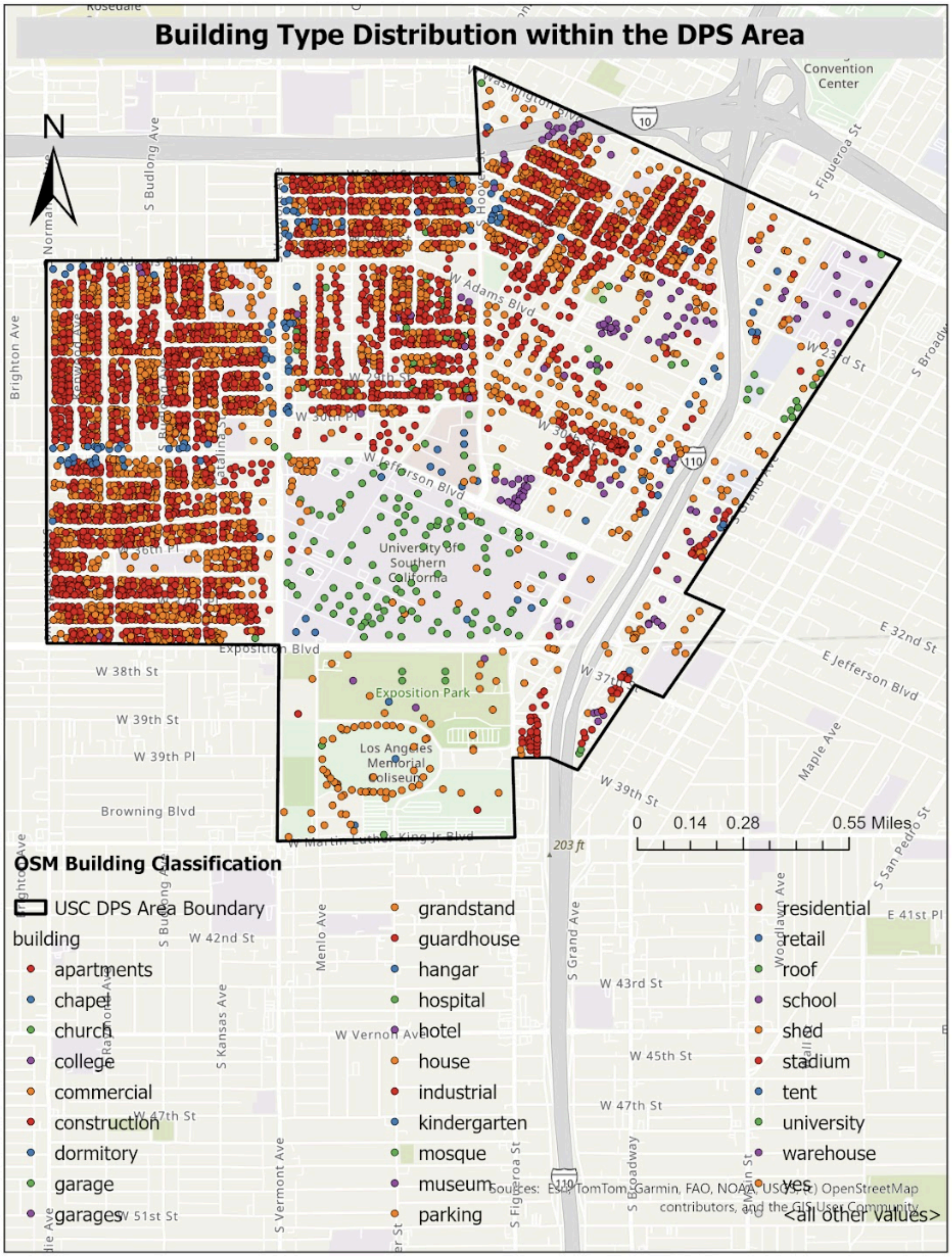

Figure 8. Building centroids generated from OSM building footprints

The OSM building dataset includes more than 30 detailed building types. Because the full set of categories is too granular for accessibility analysis, we grouped the buildings into five major classes. We created a new field, *building_group*, and used a Python expression in the Field Calculator to assign each building to one of the categories: Residential, Commercial, Institutional, Recreational, or Other. Categories such as apartments, houses, and dormitories were grouped as Residential, while types such as schools, universities, hospitals, museums, and other public service buildings were grouped as Institutional. After the classification, the resulting map displayed a clear spatial distribution of different building types across the DPS area. *Figure 9* illustrates the final building classification map, which summarizes the five groups and their locations.

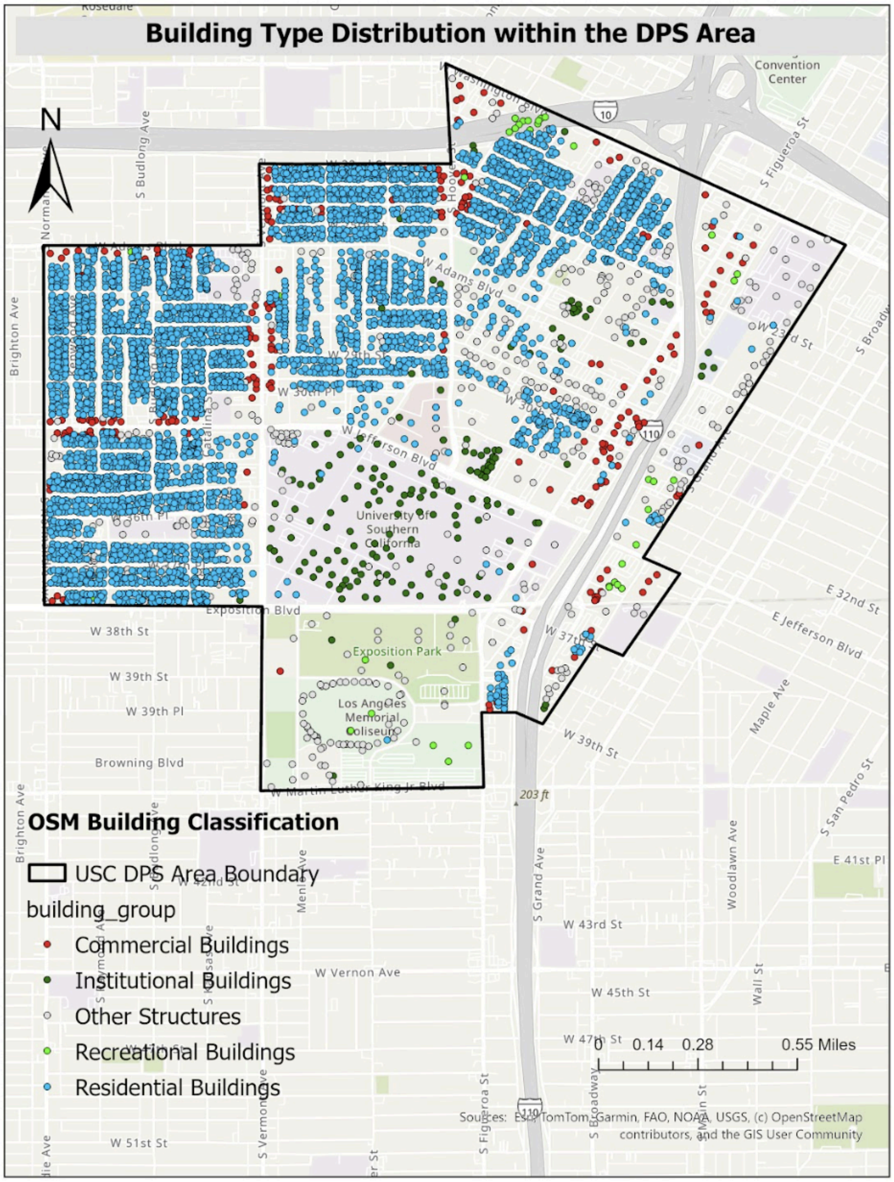

Figure 9. Building type classification map showing five generalized building groups

Through these steps, we prepared a complete demand dataset that includes both residential population estimates and building demand points. These layers form the basis for subsequent analyses of accessibility and spatial matching.

4.4 Supply Preparation (Markets, Restaurants, Bus Stops)

In this part of the project, we prepared the supply datasets that represent food and service access within the USC DPS Area. These supply layers include markets, restaurants, and bus stops, which were obtained from OpenStreetMap and imported as point features in ArcGIS Pro. To ensure spatial consistency across all datasets, we exported each feature class using a unified projected coordinate system. We selected NAD 1983 UTM Zone 11N because it provides appropriate units in meters and supports accurate distance-based analysis, which is necessary for the 2SFCA method used later in the workflow.

Each supply dataset was processed individually. We used the Export Features tool and saved the outputs as Markets_UTM, Restaurants_UTM, and BusStops_UTM. After exporting, we verified that all layers correctly aligned with the USC DPS boundary and were fully contained within the study area. This step ensured that no supply point remained in an unprojected coordinate system or outside the analysis zone.

Figure 10 shows the distribution of markets, restaurants, and bus stops within the DPS Area after projection. The map illustrates the relative clustering of supply locations, with restaurants and markets concentrated near major streets and around the USC campus, while bus stops are more evenly distributed across the area. The consistent coordinate system confirms that all three supply layers are ready for subsequent accessibility and catchment analyses.

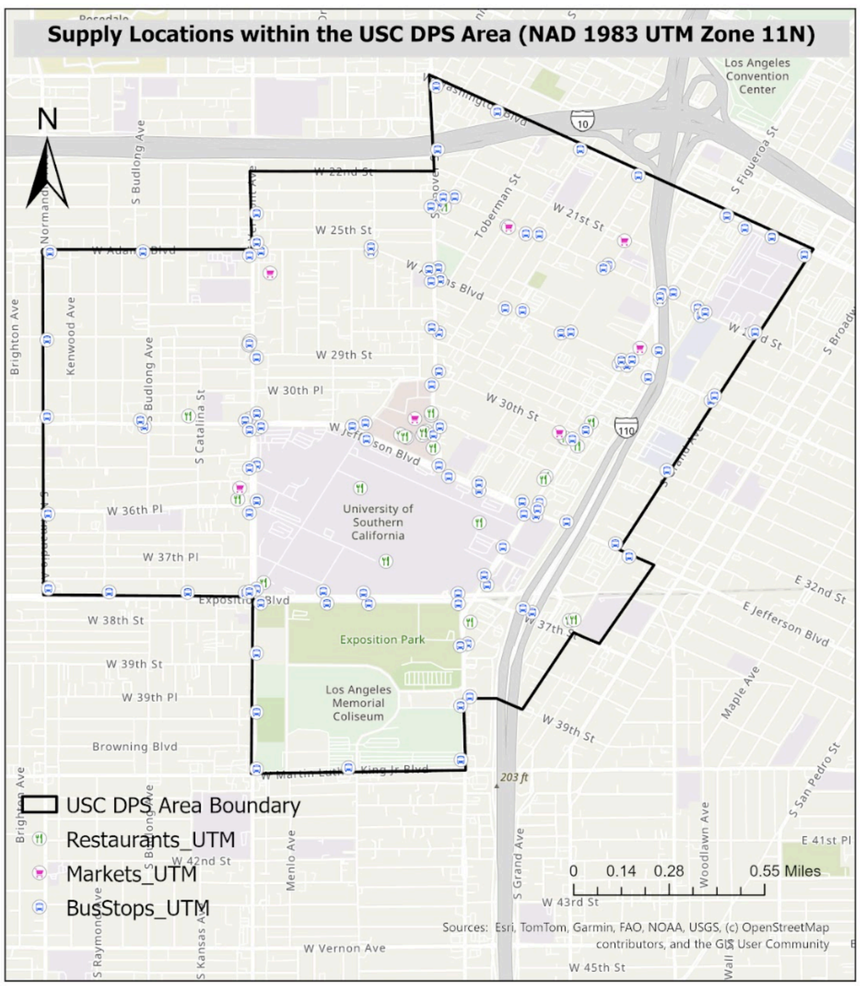

Figure 10. Supply Locations within the USC DPS Area (NAD 1983 UTM Zone 11N)

4.5 Distance Preparation for E2FCA

To prepare the distance inputs required for the E2FCA accessibility model, we created a set of near-distance tables that quantify the proximity between every building within the DPS area and the available supply locations. This step allows us to identify the closest market, restaurant, and bus stop for each building. Because all datasets were already projected into the NAD 1983 UTM Zone 11N coordinate system, the distances generated by ArcGIS Pro are expressed in meters, which is appropriate for later calculations in Step 1 and Step 2 of the E2FCA method.

We used the Generate Near Table tool to build three separate distance matrices: one for buildings to markets, one for buildings to restaurants, and one for buildings to bus stops. For each run, the buildings served as the input layer and the selected supply layer served as the near features. We set the search radius to 1000 meters and enabled the location output option so that the resulting tables would include both the coordinates of the demand points and the coordinates of their closest supply points. The tool also returned a unique ID for each nearest feature and the Euclidean distance between the building and that supply location.

Figures 11 through *13* summarize the results of this distance preparation step. *Figure 11* shows the near-distance table generated for markets. *Figure 12* displays the distance table for restaurants, and *Figure 13* presents the results for bus stops. Together, these three datasets establish the demand-to-supply relationships that are required for computing the Gaussian-based distance decay, the supply-to-demand ratios, and the final accessibility scores in the E2FCA workflow.

	OBJECTID *	IN_FID	NEAR_FID	NEAR_DIST	FROM_X	FROM_Y	NEAR_X	NEAR_Y
1	1	1	7	0.003511	-118.289506	34.020451	-118.292091	34.022826
2	2	2	7	0.006239	-118.287427	34.018681	-118.292091	34.022826
3	3	3	7	0.002917	-118.290854	34.020185	-118.292091	34.022826
4	4	4	5	0.006981	-118.281392	34.018651	-118.278784	34.025127
5	5	5	3	0.004802	-118.286453	34.021204	-118.284808	34.025716

Figure 11. Output of the Generate Near Table for Markets (Near_Markets)

	OBJECTID *	IN_FID	NEAR_FID	NEAR_DIST	FROM_X	FROM_Y	NEAR_X	NEAR_Y
1	1	1	5	0.002228	-118.289506	34.020451	-118.291089	34.018882
2	2	2	12	0.001805	-118.287427	34.018681	-118.285997	34.019784
3	3	3	5	0.001324	-118.290854	34.020185	-118.291089	34.018882
4	4	4	3	0.00179	-118.281392	34.018651	-118.282494	34.017241
5	5	5	12	0.001492	-118.286453	34.021204	-118.285997	34.019784

Figure 12. Output of the Generate Near Table for Restaurants (Near_Restaurants)

	OBJECTID *	IN_FID	NEAR_FID	NEAR_DIST	FROM_X	FROM_Y	NEAR_X	NEAR_Y
1	1	1	69	0.002118	-118.289506	34.020451	-118.288614	34.01853
2	2	2	66	0.000532	-118.287427	34.018681	-118.286944	34.018459
3	3	3	33	0.001651	-118.290854	34.020185	-118.291386	34.018622
4	4	4	17	0.000425	-118.281392	34.018651	-118.281793	34.01879
5	5	5	66	0.002789	-118.286453	34.021204	-118.286944	34.018459

Figure 13. Output of the Generate Near Table for Bus Stops (Near_BusStops)

5. Methodology

5.1 Study Area Distance Representation

To represent the baseline distance structure of the study area, we calculated the Euclidean distance from every building point to the nearest restaurant, market, and bus stop within the USC DPS boundary. All datasets were first projected into the NAD 1983 UTM Zone 11N coordinate system to ensure that distance calculations were expressed in meters, which provides a consistent and reliable basis for accessibility modeling. We then applied ArcGIS Pro's Near tool to generate distance attributes for each building point. These values were symbolized using graduated colors with Natural Breaks to highlight variations in proximity across the DPS area.

Figure 14 illustrates the distance from each building point to the nearest restaurant. The map shows clear spatial variations, with clusters of shorter distances concentrated along Vermont Avenue and Exposition Boulevard, while greater distances appear in the northern and southeastern residential blocks. *Figure 15* presents the distance to the nearest market. Compared to restaurants, markets are less evenly distributed, which results in a broader range of distances across the study area. *Figure 16* displays the distance to the nearest bus stop. Bus stops are more densely distributed compared to food sources, which results in generally shorter and more uniform distances, especially around Expo Park and the residential blocks near Jefferson Boulevard.

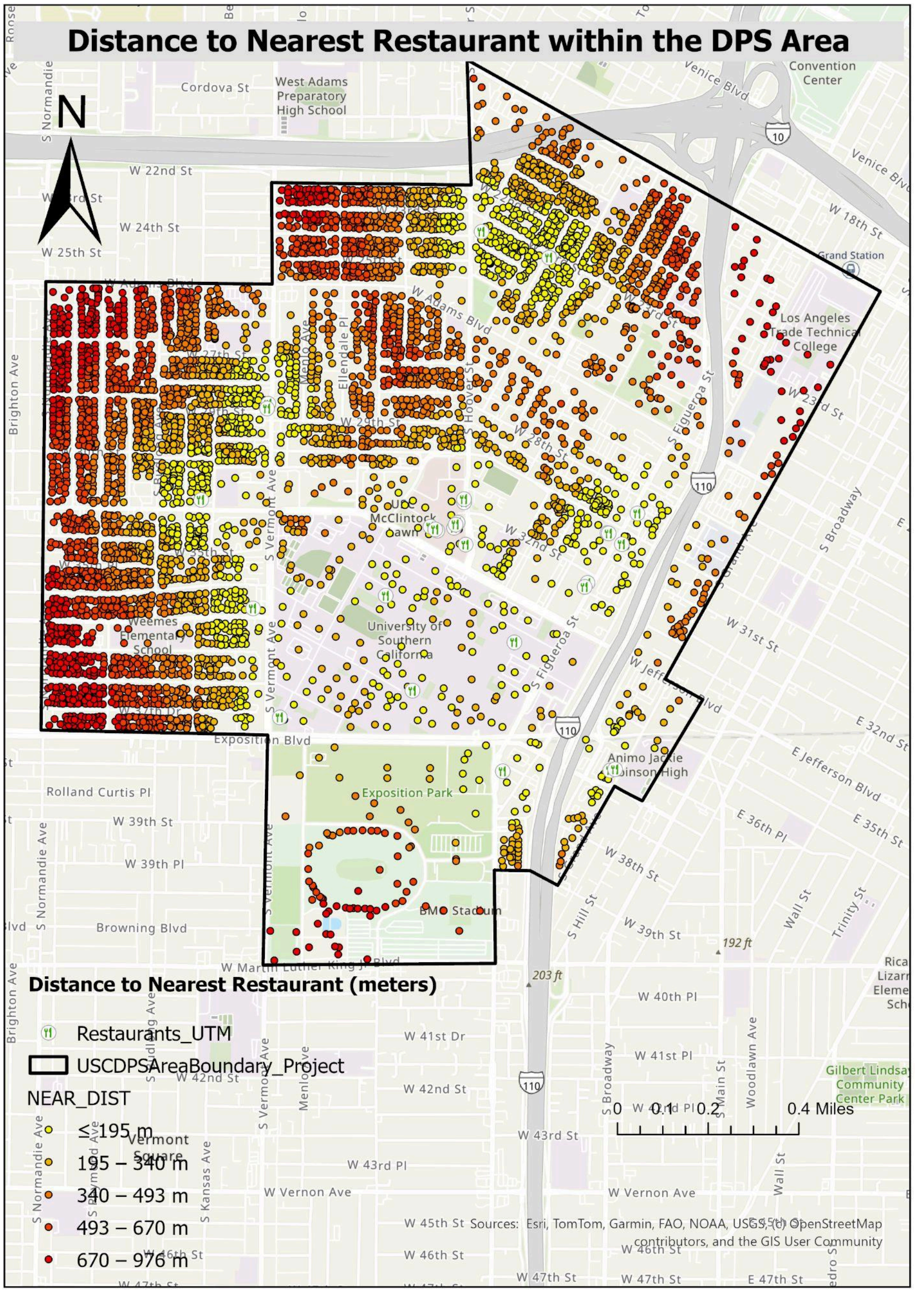

Figure 14. Distance to the Nearest Restaurant within the DPS Area.

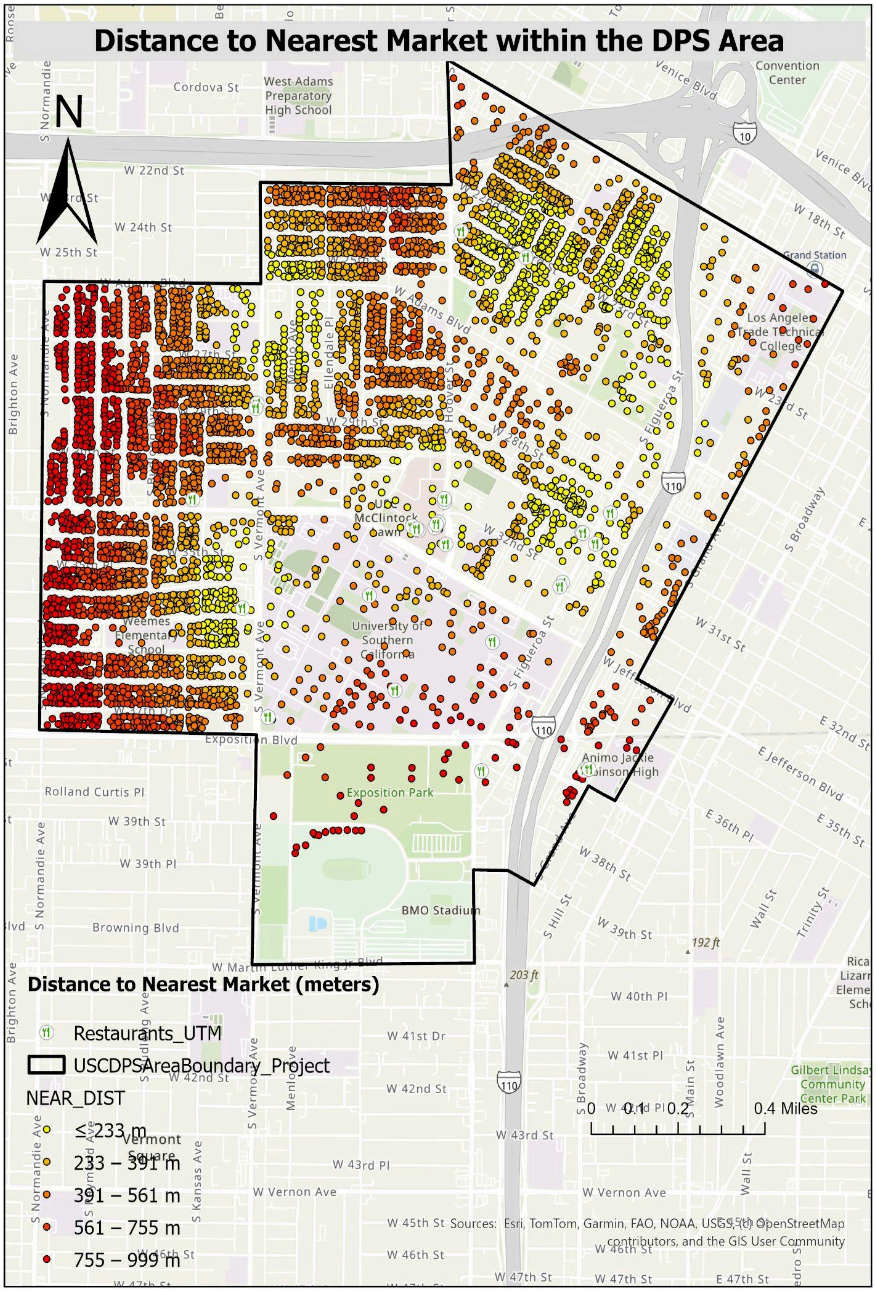

Figure 15. Distance to the Nearest Market within the DPS Area.

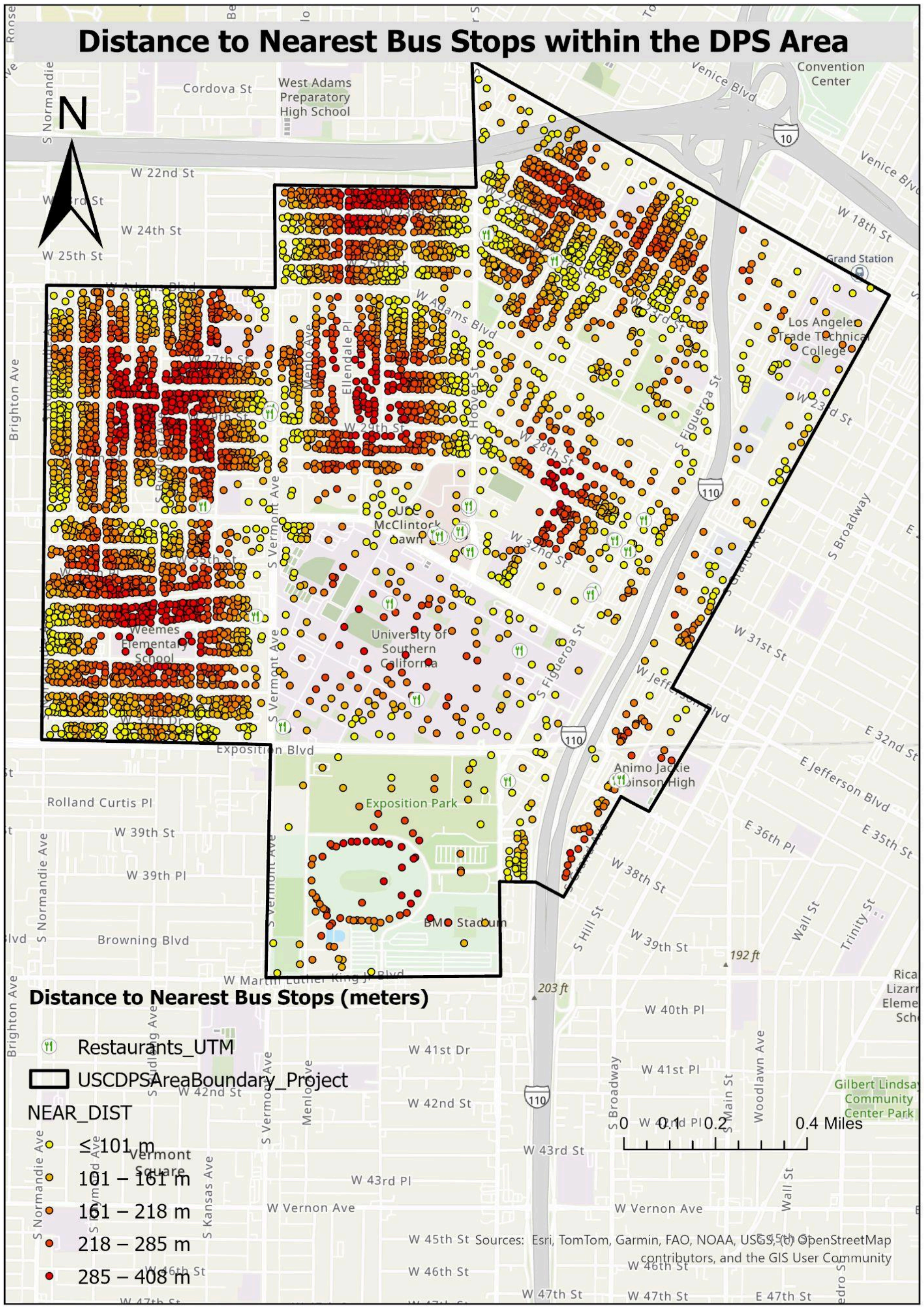

Figure 16. Distance to the Nearest Bus Stop within the DPS Area.

These distance maps form the core spatial framework for the later E2FCA analysis. They illustrate how the locations of key services differ throughout the DPS neighborhood and establish the basic distance patterns that shape supply–demand relationships and overall accessibility outcomes.

5.2 Supply–Demand Definition

To implement the E2SFCA model, we first prepared demand and supply layers in a consistent structure that allows the computation of demand-to-supply relationships. The demand layer represents buildings within the DPS area, while the supply layers include markets, restaurants, and bus stops. Each layer was processed to ensure that every point contains a unique identifier and a defined capacity value.

For the demand side, we used the *Buildings_Points_Project* layer and assigned each building a unique DemandID and a population value (POP). Since detailed household counts or residential population data are not available at the building level for the DPS area, we adopted a standard assumption used in many local-accessibility studies by assigning each building a POP value of 1. This allows the model to treat each building as an equal unit of demand. The resulting attribute structure is shown in *Figure 17*, where both DemandID and POP fields are successfully added to all building points.

Buildings_Points_Project

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete Copy

	_Y	NEAR_X	NEAR_Y	OBJECTID	IN_FID	NEAR_FID	NEAR_DIST	FROM_X	FROM_Y	NEAR_X	NEAR_Y	POP	DemandID
1	0451	-118.292091	34.022826	1	1	69	0.002118	-118.289506	34.020451	-118.288614	34.01853	1	1
2	8681	-118.292091	34.022826	2	2	66	0.000532	-118.287427	34.018681	-118.286944	34.018459	1	2
3	0185	-118.292091	34.022826	3	3	33	0.001651	-118.290854	34.020185	-118.291386	34.018622	1	3
4	8651	-118.278784	34.025127	4	4	17	0.000425	-118.281392	34.018651	-118.281793	34.01879	1	4
5	1204	-118.284808	34.025716	5	5	66	0.002789	-118.286453	34.021204	-118.286944	34.018459	1	5

Figure 17. Demand Layer Structure for Buildings within the DPS Area

For the supply side, we prepared three layers: *Markets_UTM*, *Restaurants_UTM*, and *BusStops_UTM*. Each supply point was assigned a unique SupplyID, which ensures that all supply points can be referenced consistently during the calculation of supply-to-demand ratios in Step 1 of the E2FCA method. We also added a Supply_Capacity field to each layer and assigned a value of 1 to all records. This assumption reflects equal service potential for all markets, restaurants, and bus stops within the DPS area. The updated supply tables, shown in Figures 17, 18, and 19, confirm that each point contains the required fields for the E2FCA model.

Buildings_Points_Project Restaurants_UTM Markets_UTM BusStops_UTM

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete

	OBJECTID *	Shape *	element	id	amenity	SupplyID	Supply_Capacity
1	1	Point	node	2643391587	restaurant	1	1
2	2	Point	node	4141781780	restaurant	2	1
3	3	Point	node	4547476734	restaurant	3	1
4	4	Point	node	5231970324	restaurant	4	1

Figure 18. Supply Structure for Restaurants within the DPS Area

	OBJECTID *	Shape *	element	id	addr_stree	name	shop	SupplyID	Supply_Capacity
1	1	Point	node	2578244375	Vermont Avenue	Ralphs	supermarket	1	1
2	2	Point	node	2643391588		Lee's Market	convenience	2	1
3	3	Point	node	5237417649	Hoover Street	Trader Joe's	supermarket	3	1
4	4	Point	node	5695236165	South Figueroa	7-Eleven	convenience	4	1
5	5	Point	node	6045067406	Figueroa Street	Cal Mart Beer & Wine...	supermarket	5	1
6	6	Point	node	7158037351	Estrella Avenue	Henry's Market	convenience	6	1
7	7	Point	node	11144812568	Vermont Avenue	Smart & Final	supermarket	7	1

Figure 19. Supply Structure for Markets within the DPS Area

	OBJECTID *	Shape *	STOPNUM	STOPNAME	LAT	LONG	SupplyID	Supply_Capacity
1	1	Point	56	Adams / Vermont	34.032672	-118.291204	1	1
2	2	Point	1490	Jefferson / Flower	34.021417	-118.278482	2	1
3	3	Point	1813	Flower / 23rd	34.030324	-118.273023	3	1
4	4	Point	1830	Exposition / University	34.018015	-118.286718	4	1
5	5	Point	1838	Exposition / Vermont	34.018475	-118.291864	5	1

Figure 20. Supply Structure for Bus Stops within the DPS Area

With *DemandID*, *POP*, *SupplyID*, and *Supply_Capacity* consistently defined across all four datasets, the study area is now fully prepared for calculating distance-decay–weighted accessibility in Sections 5.3 through 5.6. The structured preparation in this section ensures that demand and supply can be matched appropriately when computing service ratios and accessibility scores in the next steps of the methodology.

5.3 Gaussian Distance Decay Function

In our project, our team applied a Gaussian distance decay function to model how accessibility decreases as distance increases. This function assigns higher weights to supply locations that are closer to each demand point and gradually reduces the influence of facilities that are farther away. The Gaussian curve is smooth and continuous, which allows it to capture realistic spatial interactions within the DPS area. We used the standard Gaussian decay expression as below.

$$W(d) = \exp\left(-\frac{d^2}{\lambda^2}\right)$$

where d is the network-based or Euclidean distance between each supply point and each demand point, and λ is the decay parameter. A smaller λ causes the weight to drop rapidly with distance, which results in a localized accessibility pattern. A larger λ produces a slower decline and reflects a broader catchment area.

In our analysis, we selected a bandwidth that reflects walkable distances within the DPS community. The Gaussian weights produced here were used in both steps of the E2FCA method.

During Step 1, the decay function weights each demand point when computing the supply-to-demand ratio. During Step 2, the function weights each supply ratio when calculating the final accessibility score for all residential buildings.

This approach ensures that accessibility results reflect realistic travel behavior, where nearby resources contribute more strongly to local accessibility than distant ones.

5.4 E2FCA Step 1: Supply-to-Demand Ratio (Rj)

In the beginning step of the Enhanced 2FSCA method, we identified the set of demand locations that fall within a predefined search radius of every supply point. This step provides the foundation for calculating the supply-to-demand ratio Rj. To implement this process, we used Python and several scientific libraries including GeoPandas for spatial data handling, NumPy for numerical operations, SciPy's *cKDTree* for efficient nearest neighbor search, and Matplotlib for visualization. All supply datasets from markets, restaurants, and bus stops were merged into a single supply layer and matched with the building dataset that represents the demand side. All points were projected to the same UTM coordinate system to ensure correct distance computation in meters.

A spatial index was built using *cKDTree*, which computes Euclidean distances between points. For each supply point j, the tree identified all demand points i located within an 800 meter search radius. This radius matches the scale of the USC DPS study area and is widely used in urban accessibility research involving walking distance. The neighborhood search follows the standard E2SFCA distance rule formulated as:

$$d(i, j) \leq d_0$$

where $d(i, j)$ is the Euclidean distance between demand i and supply j, and d_0 is the catchment threshold.

Two visualizations were produced to illustrate this step. *Figure 21* presents the spatial arrangement of all demand points and the combined supply points across the study area. *Figure 22* displays the complete set of supply catchments generated by the KDTree search. Each gray line represents a connection between a supply point and all demand locations within its catchment radius. This figure confirms that the algorithm correctly captured local clusters and distance-based relationships across the network. Together, these results validate that the supply-side catchments were constructed correctly and are ready for computing Rj in the next step.

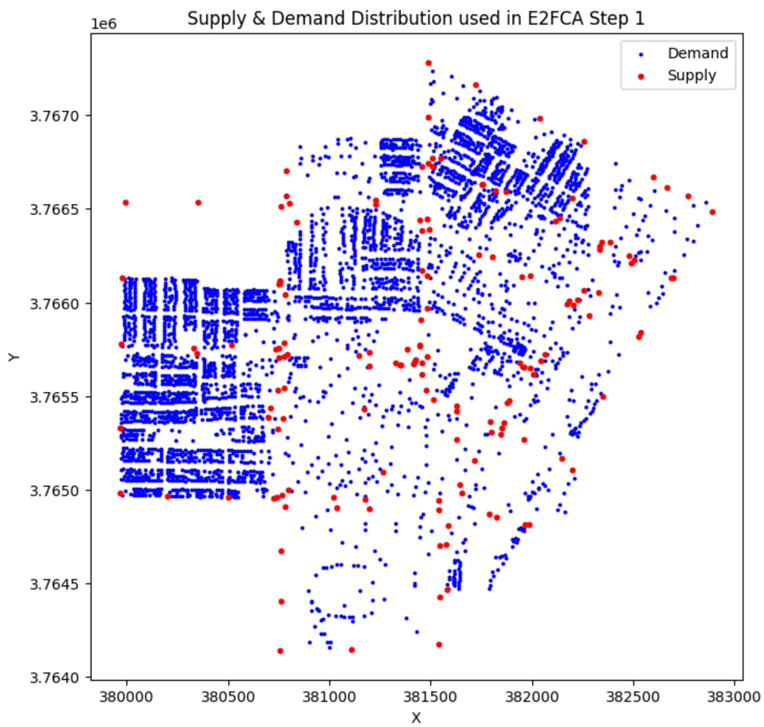

Figure 21. Supply and Demand Distribution used in E2FCA Step 1

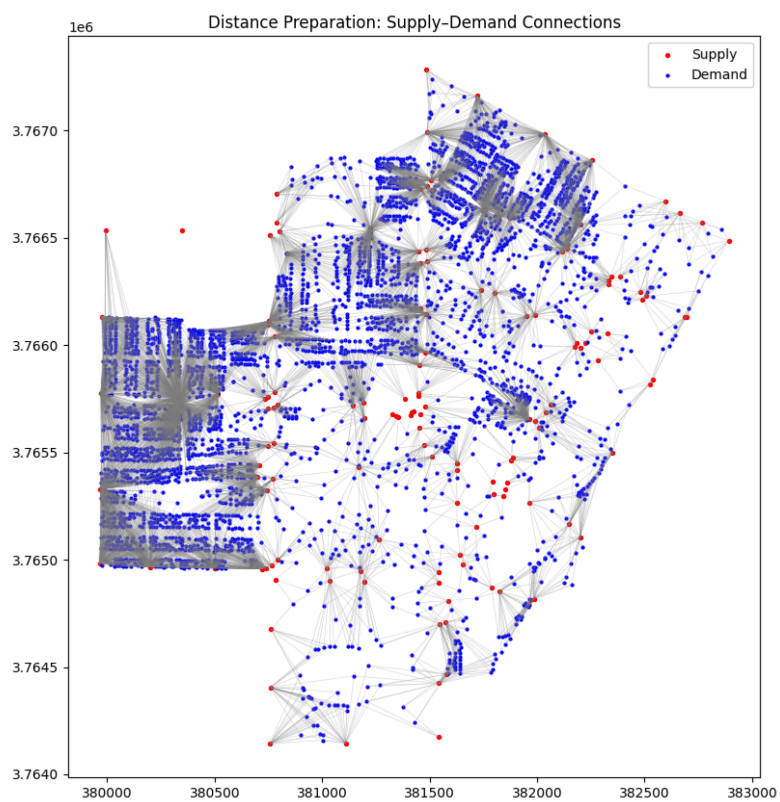

Figure 22. Distance Preparation: Supply–Demand Connections

5.5 E2FCA Step 2: Accessibility Score (Ai)

The next step of the E2SFCA method computes the accessibility score for each demand location. This score, denoted as *Ai*, represents the cumulative opportunity available to a given building after accounting for all accessible supply locations and the effect of distance decay. The analysis was implemented entirely in Python for consistency with the previous steps. Libraries used include GeoPandas for spatial data handling, NumPy and pandas for data processing, SciPy's *cKDTree* for efficient spatial queries, and Matplotlib for visualization.

In this step, each demand point searches for all supply locations within the distance threshold of 800 meters. The pre-computed supply to demand ratio Rj from Step 1 is then assigned to each demand point using a Gaussian decay function based on the distance between the demand and supply points. The decay function used is

$$w(d) = \exp\left(-\frac{d^2}{2\sigma^2}\right)$$

where *d* is the Euclidean distance and σ controls the rate of decay. For this study, σ was set to 300 meters to reflect typical walking distance conditions in urban Los Angeles. The accessibility score for each demand point is calculated as:

$$A_i = \sum_j R_j \cdot w(d_{ij})$$

which aggregates the weighted influence of all accessible supply sites.

Figure 23 illustrates the spatial distribution of accessibility across all buildings in the study area. Demand points are symbolized using a continuous color gradient where higher accessibility scores appear in yellow and lower values appear in dark blue. Supply locations are shown as red points to highlight their spatial influence on surrounding neighborhoods. The map reveals clear spatial clustering of accessibility, with central portions of the USC DPS area achieving higher scores due to denser supply coverage and favorable proximity patterns.

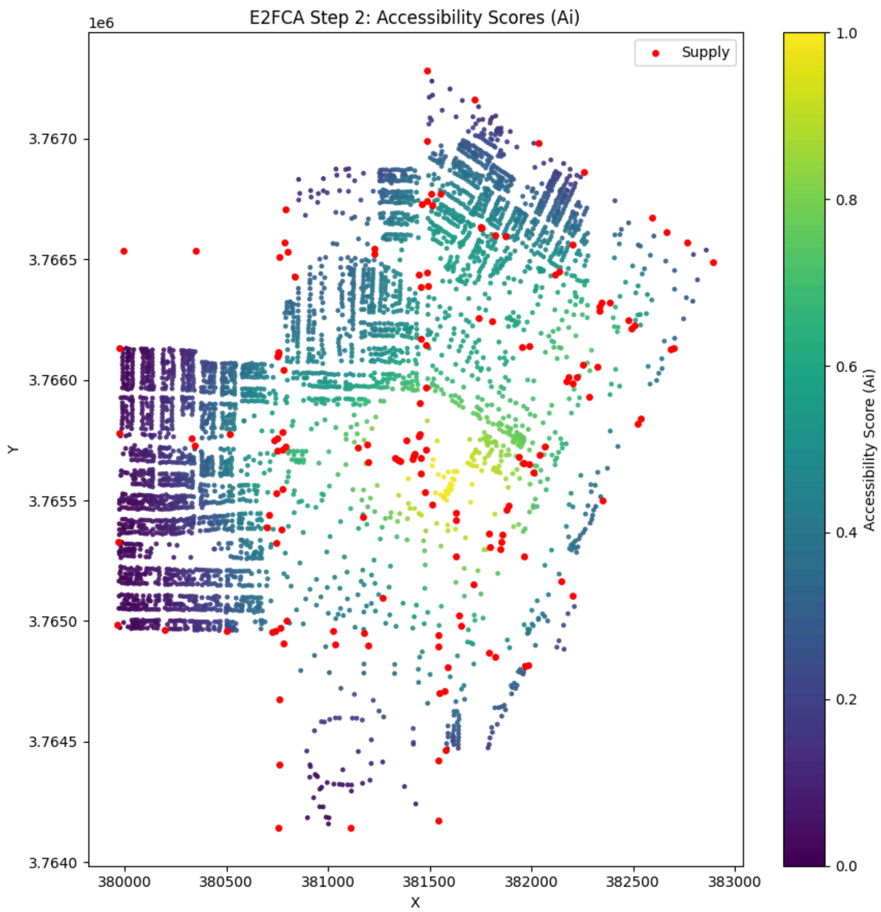

Figure 23. E2FCA Step 2 Accessibility Scores (Ai)

To support interpretation, summary statistics of the computed accessibility values were generated. The distribution shows a mean accessibility score of approximately 9.60 and ranges from 2.44 to 22.86 as shown as the below. These statistics provide a quantitative description of spatial inequality in accessibility and serve as the foundation for the comparisons presented in the Results section.

```
===== Accessibility (Ai) Statistics =====
         count    3707.000000
         mean        9.596756
         std         4.423208
         min         2.441762
         25%         5.814084
         50%         9.694189
         75%        12.476670
         max        22.864956
         Name: Ai, dtype: float64
```

5.6 Composite Accessibility Index (CAI)

To provide an integrated measure of overall accessibility within the USC DPS study area, we computed a Composite Accessibility Index (CAI) by combining the accessibility scores generated for markets, restaurants, and bus stops. The CAI captures the joint contribution of multiple daily-life resources and enables a more holistic interpretation of spatial inequality in access. The analysis was carried out in Python using *pandas*, *numpy*, *geopandas*, and *matplotlib*. The workflow followed the same logic used in earlier E2FCA steps, and the final index was derived after normalizing and aggregating the three accessibility components.

We first applied min-max normalization to each accessibility layer to ensure that markets, restaurants, and bus stops contributed comparably to the final composite score. The normalization process used the following formula.

$$A' = \frac{A - \min(A)}{\max(A) - \min(A)}$$

where A' represents the normalized accessibility value and A is the original E2FCA score. Following normalization, the Composite Accessibility Index was computed using a simple average of the three resource-based scores:

$$CAI = \frac{A'_{\text{market}} + A'_{\text{restaurant}} + A'_{\text{bus}}}{3}$$

This approach treats all resources equally and aligns with the goal of identifying general accessibility advantages rather than prioritizing a single resource type. However, *Figure 24* shows the statistical distribution of the resulting CAI values. The distribution is right-skewed, with most values concentrated between 0.05 and 0.30. The summary statistics also support this pattern. The mean CAI is approximately 0.23, and the third quartile reaches 0.31, indicating a relatively small proportion of locations with high overall accessibility. These characteristics are consistent with urban environments where access to multiple resources tends to cluster around central corridors.

Spatial patterns of the CAI are illustrated in *Figure 25*. Higher composite scores appear around the central east region of the study area, where market density, restaurant density, and bus stop availability overlap. Lower CAI values dominate the western and southern edges, which are farther from the major resource clusters. The combined representation highlights areas with strong multimodal access as well as neighborhoods that may benefit from future improvements in local services.

To help interpret how each resource contributed to the composite measure, *Figure 26* compares the spatial distribution of market, restaurant, bus stop accessibility, and the final CAI. The CAI map aligns closely with the spatial gradients found in the bus stop and restaurant layers, suggesting that these two resources exert stronger influence on the overall accessibility pattern in the DPS area. The market accessibility layer shows similar but slightly narrower clusters, and its inclusion in the composite index helps create a more stable and balanced measure across the entire study region.

6. Exploratory Data Analysis

6.1 Building Distribution

We conducted an exploratory data analysis to characterize the spatial structure of the built environment and the placement of key resources in the USC DPS area before performing the accessibility computations. The goal of this stage was to establish the spatial context in which accessibility is produced and to describe the underlying patterns that influence later results. Building locations, markets, restaurants, and bus stops were extracted from OpenStreetMap and processed entirely in Python using GeoPandas, Shapely, and OSMnx. These libraries allowed us to retrieve point geometries, reproject them into the projected coordinate system used in the accessibility model, and visualize their spatial patterns. The preprocessing also included coordinate transformation using the GeoPandas function *.to_crs()*, which ensured that all input layers were aligned in the same projected space for distance-based calculations.

The spatial distribution of buildings provides the foundational representation of the built environment. The building points we retrieved from OpenStreetMap showed a regular block-like structure that matches the surrounding street grid. Dense clusters of buildings were observed along residential blocks, while open areas such as athletic fields and large parking lots had noticeably fewer structures. This pattern illustrates how population-related demand is likely concentrated along housing blocks, which becomes an important reference when interpreting accessibility outcomes.

We also examined the spatial distribution of markets and restaurants, which represent two of the primary service types in our accessibility model. Their locations were mapped in Python using Matplotlib, and the resulting distributions are displayed in *Figure 25* titled “Market Accessibility” and *Figure 25* titled “Restaurant Accessibility.” The restaurant distribution showed greater spatial density and wider coverage than markets, which aligns with expectations given the USC area’s concentration of student-oriented dining options. Markets appeared less frequent and more clustered in specific blocks, which suggests that food provisioning opportunities are unevenly distributed across the neighborhood.

Bus stop locations were visualized to represent transit availability and to support the later accessibility calculation. As shown in *Figure 25* titled “Bus Stop Accessibility,” the transit network revealed a linear pattern following major streets, with higher densities along Vermont Avenue and Jefferson Boulevard. This transportation layer provides essential mobility support in the accessibility model since transit nodes strongly influence how easily residents may reach food-related destinations.

For all three types of resources, we applied a distance decay–based accessibility calculation using a Gaussian decay function implemented in Python. The formulation used for each service type was:

$$A_i = \sum_j \exp\left(-\frac{d_{ij}^2}{2\sigma^2}\right),$$

where Ai denotes accessibility at building i, d_{ij} shows the Euclidean distance between building i and service location j, and σ controls the rate of decay. This formula was computed using NumPy vectorization to ensure efficient processing across thousands of building points. After generating individual accessibility surfaces for markets, restaurants, and bus stops, we standardized each score to the range [0,1] using min–max normalization and constructed a composite accessibility index by averaging the three standardized components.

The distributions of these accessibility scores were visualized in Python using Matplotlib. *Figures 25* display the spatial patterns for market, restaurant, and bus stop accessibility respectively, while *Figure 25* summarizes the combined accessibility surface. High composite accessibility values emerged near street intersections where resources were most concentrated. Lower values appeared near the southern and western edges of the study area where both food destinations and bus stops were sparse. To further illustrate the statistical distribution of the composite index, we generated a histogram shown in *Figure 24*. The histogram indicates that most buildings fall within the lower to mid range of accessibility scores, while a smaller portion achieves high accessibility due to proximity to multiple overlapping service types.

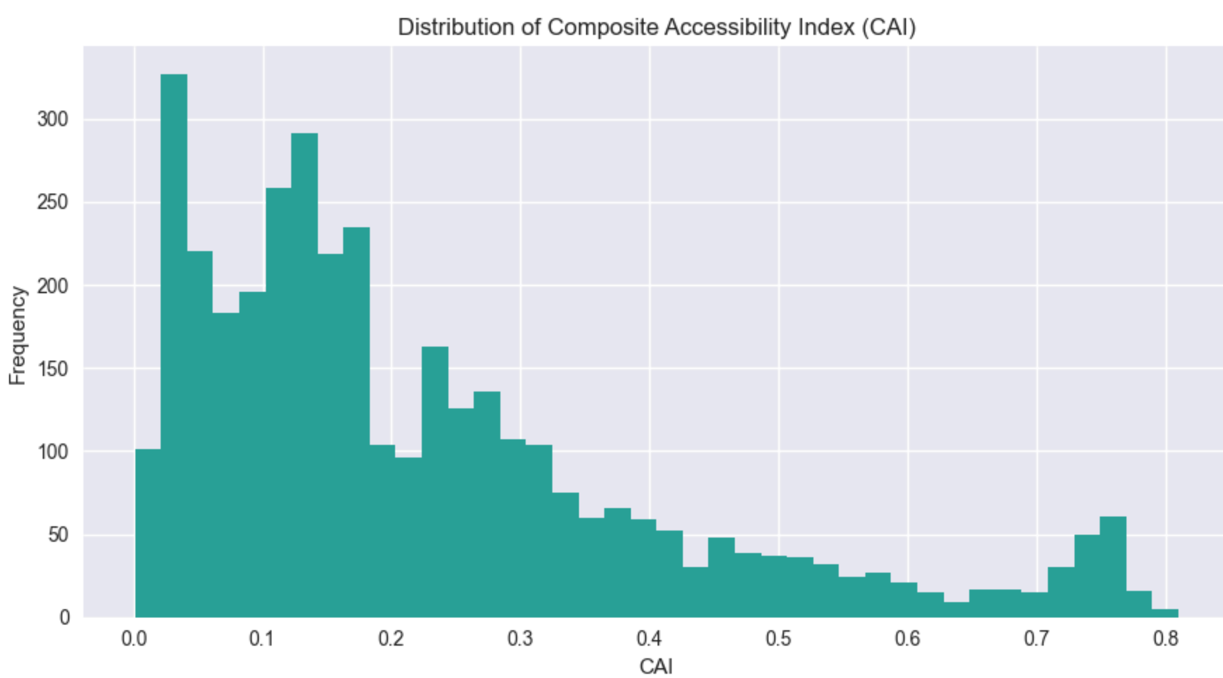

Figure 24. Distribution of Composite Accessibility Index (CAI)

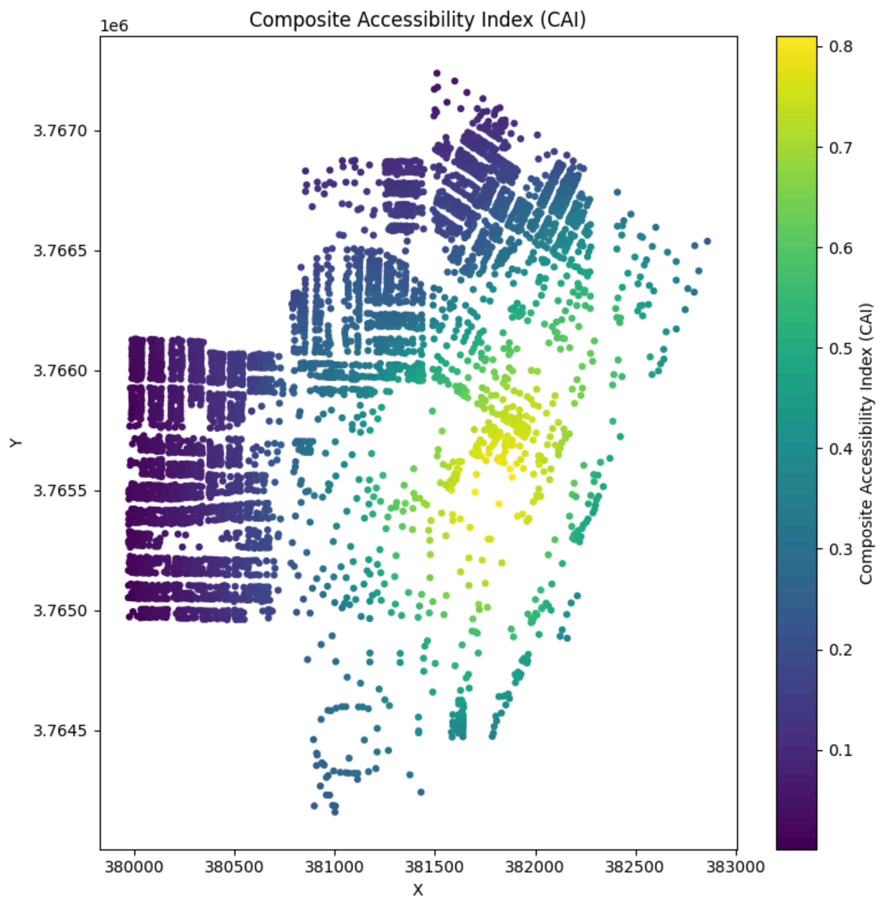

Figure 25. Composite Accessibility Index (CAI) Map

Together, these exploratory analyses allow us to establish a clear understanding of how built form and resource locations shape accessibility patterns. The spatial structures observed in *Figures 26* form the foundation for the interpretations presented in the subsequent sections of the report

7. Results

We evaluated accessibility patterns across the USC DPS study area by analyzing resource-specific accessibility scores derived from the E2SFCA method. The accessibility results were calculated in Python using GeoPandas, Pandas, NumPy, and Matplotlib, together within a Gaussian distance decay function of the form as following formula:

$$w(d) = e^{-(d^2/2\sigma^2)}$$

This function assigned higher weights to closer facilities, which allowed us to model realistic walking access within the neighborhood. The Python workflow integrated the demand and supply datasets processed earlier, computed weighted catchment areas for each market, restaurant, and bus stop, and then aggregated the weighted supply contributions to obtain point-level accessibility scores for all demand locations. After calculating the resource-specific accessibility indices, we merged the results into a Composite Accessibility Index (CAI) that summarizes overall access to essential daily resources.

The spatial patterns reveal important contrasts across resource types. The market accessibility distribution shows clusters of high values near Vermont Avenue and Jefferson Boulevard, where multiple small markets are located. These patterns are illustrated in *Figure 26: Market Accessibility Map*, which highlights several accessibility hotspots close to dense residential blocks. Restaurant accessibility, shown in *Figure 26: Restaurant Accessibility Map*, is more spatially concentrated. High accessibility zones appear mainly near the USC Village commercial area, while regions farther east show lower values because restaurants there are more dispersed. Bus stop accessibility exhibits a different pattern. As shown in *Figure 26: Bus Stop Accessibility Map*, accessibility is generally high across most parts of the study area because bus stops are evenly distributed along major streets such as Vermont Avenue, Exposition Boulevard, and Jefferson Boulevard.

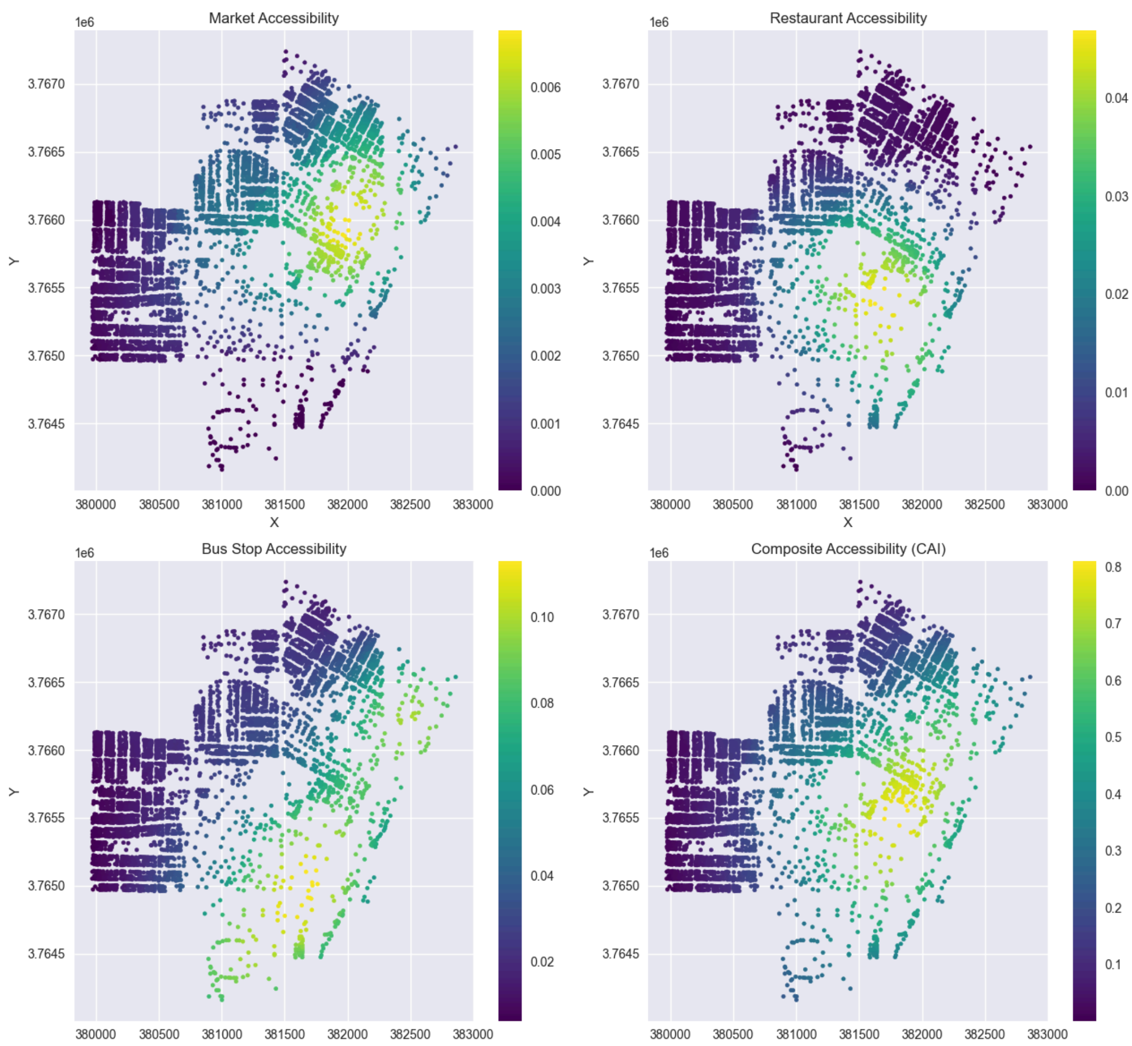

Figure 26. Accessibility Comparison Across Resource Types

We then examined overall accessibility by integrating the three resource-specific indices. The resulting composite index reflects the combined ease of reaching markets, restaurants, and bus stops. *Figure 25* shows that the highest CAI values occur near the western boundary of the DPS zone, where market density, restaurant availability, and bus stop coverage overlap. This result indicates that the area near USC Village and Vermont Avenue consistently offers broader access to daily resources. To further understand the statistical distribution of CAI scores, we plotted a histogram using Python's Matplotlib library. *Figure 24* shows that most locations fall within a moderate accessibility range, with fewer extremes at the low and high ends. We also generated a kernel density curve to visualize the continuous CAI distribution. As seen in *Figure 27*, the distribution has a single dominant peak, which suggests that resource accessibility across the study area is relatively cohesive although some pockets of lower access remain.

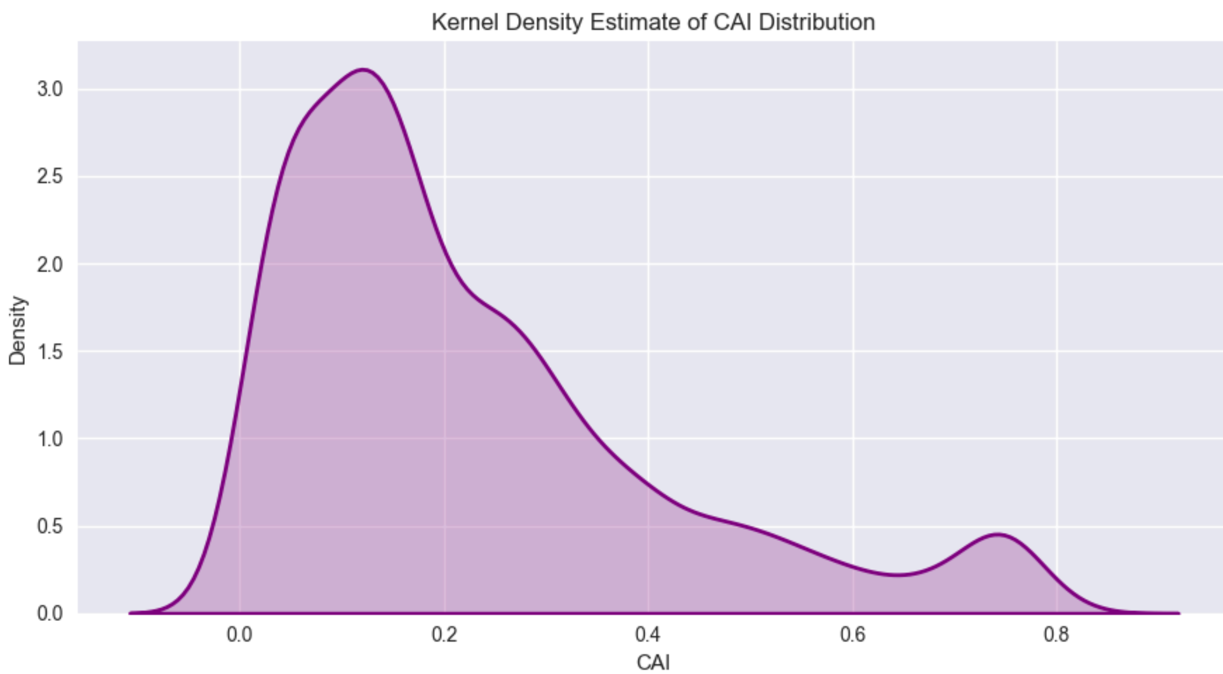

Figure 27. Kernel Density Estimate of CAI

Finally, we compared the resource types side by side to understand how accessibility levels differ across markets, restaurants, and bus stops. *Figure 26* presents a four-panel visualization of the three resource-specific indices together with the composite index. This figure demonstrates that although bus stop accessibility is consistently high, market and restaurant accessibility vary more significantly across the area. The composite index reflects this imbalance, producing an overall accessibility pattern that is strongest where all three resource types align. Collectively, these results provide a clear understanding of accessibility disparities within the DPS area and establish the foundation for the interpretation and discussion that follow in Section 8.

8. Discussion

8.1 Key Findings

In our study, we found that accessibility patterns within the USC DPS area vary substantially across different types of daily resources. Markets, restaurants, and bus stops demonstrate different spatial structures, and these differences directly influence the Composite Accessibility Index. Market accessibility tends to form localized hotspots near the western portion of the DPS area, while restaurant accessibility clusters strongly around the USC Village commercial zone. Bus stop accessibility is more uniform because transit stops are placed along major streets, which produces consistently higher accessibility values across much of the area. When we combined these resource specific measures into the Composite Accessibility Index, the results showed that the highest overall accessibility appears in locations where multiple resource types intersect. This confirms that resource co-location plays an important role in shaping spatial advantage within walkable neighborhoods.

8.2 Interpretation of Spatial Patterns

The spatial patterns we observed provide insights into how the built environment shapes daily mobility opportunities for residents and students. Areas with high CAI values generally occur close to Vermont Avenue and Jefferson Boulevard where restaurants, markets, and bus stops are concentrated. These areas benefit from short walking distances and dense supply distributions. In contrast, the southern and eastern parts of the DPS area show lower CAI values because they contain fewer markets and restaurants and sometimes lack nearby bus stops. This outcome is consistent with the Gaussian distance decay formulation we implemented in Python because greater distances sharply reduce accessibility contributions. The maps produced in our results section, including the Market Accessibility Map, Restaurant Accessibility Map, Bus Stop Accessibility Map, and the Composite Accessibility Index Map, illustrate how supply density and walkable distances work together to shape uneven accessibility across the neighborhood. The histogram and kernel density visualizations provide additional evidence that high accessibility conditions are confined to a smaller fraction of buildings, which reflects common patterns in compact urban environments.

8.3 Relationship to Existing Studies

The spatial trends revealed in our analysis align with earlier findings in the accessibility literature. Luo and Wang's 2SFCA model emphasizes the relationship between supply distribution and population demand, and our results confirm that these principles hold even at the micro scale. The improved distance weighted E2SFCA method described by Luo and Qi performs well in the DPS area because the Gaussian decay function helps represent real walking behavior. Our observed clustering of high accessibility near commercial corridors matches the observations of Jamtsho and Corner, who note that dense urban blocks amplify accessibility contrasts at small spatial scales. The general right skewed distribution of accessibility values also mirrors the conditions described by Delamater in studies of service concentration. Overall, our findings support the broader research that shows accessibility is not only a function of supply counts but also of spatial proximity and underlying neighborhood structure.

8.4 Limitations

Although our workflow produced meaningful and consistent results, several limitations exist in both the datasets and the methods. OpenStreetMap building footprints may not perfectly represent actual structures, and their level of detail varies across the study area. The Google Places and OSM points for markets and restaurants may omit recently opened or closed businesses, and their assigned capacity values are simplified. We applied equal supply capacities because building specific service volume data are unavailable. The distance calculations rely on Euclidean distance rather than network based distance because of methodological consistency with our Python implementation. This simplification may underestimate walking distance in areas with irregular road networks or restricted pedestrian paths. The Composite Accessibility Index also treats all resources equally, which may not reflect actual demand preferences among residents. Despite these limitations, the accessibility patterns we identified remain consistent with known local conditions, and the overall methodology follows the expectations outlined in the course instructions.

8.5 Future Work

Future studies could expand the analysis by incorporating additional resource types such as pharmacies, recreation areas, or student service facilities. A network based accessibility model could produce more accurate walking distances, especially near complex intersections or gated areas. The Composite Accessibility Index could also be refined by assigning different weights to resources based on survey data or behavioral models. Another direction would be to examine temporal variation in accessibility, especially for restaurants and bus stops that operate on varying schedules. Finally, the workflow could be extended beyond the DPS boundary to compare accessibility conditions between the USC campus and nearby residential neighborhoods. These extensions would help situate the DPS area within a broader urban context and provide more nuanced insights into resource availability and pedestrian mobility.

9. Conclusion

In conclusion, our study demonstrates that micro scale accessibility within the USC DPS area is shaped by the combined effects of resource distribution, walking distance, and the spatial configuration of the built environment. By applying the E2SFCA method with a Gaussian distance decay function, we were able to quantify the accessibility of markets, restaurants, and bus stops at the building level. The results reveal clear spatial inequalities across the neighborhood. Locations near major commercial corridors achieve high accessibility, while buildings along the southern and eastern edges experience limited access to essential services. The Composite Accessibility Index provides a holistic summary of these conditions by integrating all resource categories into a single measure. This index helps highlight the areas where service availability and pedestrian mobility are strongest. The findings not only answer our research questions but also demonstrate the value of combining Python based spatial computation with distance weighted accessibility models. The workflow is reproducible, scalable, and well suited for analyzing daily life resources in compact urban environments. Our results contribute to the understanding of accessibility around USC and provide a foundation for future improvements in service distribution and urban design.

10. Contribution

This project was completed through a collaborative effort among Xianhao Pan, Chenyi Weng, and Xiaocheng Zhang. All team members contributed to identifying data sources and collecting the spatial datasets used in this study, including the USC DPS boundary, building footprints, Google Places resources, and OpenStreetMap features. Chenyi Weng and Xiaocheng Zhang were primarily responsible for designing and producing the visualizations used throughout the analysis. Their work included developing the accessibility maps for markets, restaurants, and bus stops, as well as the Composite Accessibility Index and the distribution figures generated through Python. They also implemented key components of the spatial workflow, such as projection management, distance computation, and the construction of the E2SFCA calculations. Xianhao Pan focused on the written components of the study, ensuring that the literature review, methodological descriptions, and analytical discussions were clearly articulated and aligned with the course guidelines. He also contributed to data preparation and verification to ensure accuracy across all resource layers. Together, we designed the analytical framework, interpreted the results, and shaped the overall structure of the final project. Our combined efforts allowed us to complete a fully integrated accessibility assessment that meets the analytical and communication goals of the course.

References

Delamater, P. L. (2013). Spatial accessibility in suboptimally configured health care systems. *Health & Place, 24*, 30–43.

Google Developers. (2023). *Places API*. https://developers.google.com/maps/documentation/places

Haklay, M., & Weber, P. (2008). OpenStreetMap: User-generated street maps. *IEEE Pervasive Computing, 7*(4), 12–18.

Jamtsho, S., & Corner, R. J. (2014). Improving the 2SFCA method. *Applied Geography, 50*, 24–34.

Luo, W., & Qi, Y. (2009). An enhanced two-step floating catchment area method. *Health & Place, 15*(4), 1100–1107.

Luo, W., & Wang, F. (2003). Measures of spatial accessibility. *Environment and Planning B*, 30(6), 865–884.

Pearce, J., Witten, K., Hiscock, R., & Blakely, T. (2006). Neighbourhood access and resources. *International Journal of Epidemiology, 35*, 588–595.

U.S. Census Bureau. (2022). *ACS 5-year estimates*. https://api.census.gov