Spatial Analysis of Public Health Resource Accessibility in Dane County

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1.Capstone Statement

This project examines spatial disparities in healthcare accessibility across Dane County, Wisconsin. It aims to evaluate local variations in access by generating an accessibility score based on buffer analysis around medical facilities and by measuring network-based travel distances from each census tract to the nearest clinic or hospital. The study also explores how these spatial measures relate to socioeconomic indicators such as household income and insurance coverage, with the broader goal of informing more equitable distribution of healthcare resources.

2.Introduction and Background

Review of capstone statement: This project examines spatial disparities in healthcare accessibility across Dane County, Wisconsin. It aims to evaluate local variations in access by generating an accessibility score based on buffer analysis around medical facilities and by measuring network-based travel distances from each census tract to the nearest clinic or hospital. The study also explores how these spatial measures relate to socioeconomic indicators such as household income and insurance coverage, with the broader goal of informing more equitable distribution of healthcare resources.

Equitable spatial access to healthcare is essential for population health: close proximity to providers improves survival in emergencies, whereas distance and poor coverage widen health-outcome gaps, especially for low-income or uninsured groups (Luo & Wang 2003, 866; Guagliardo 2004, 3). Such accessibility is shaped by the location of facilities, road networks, population density, and socioeconomic conditions (Wang & Luo 2005, 131–146). Numerous studies show a pronounced urban–rural divide—providers concentrate in cities while rural residents contend with longer travel times and fewer options—which can compound existing social inequalities.

Dane County, Wisconsin, home to more than 600 000 people, exemplifies this geography. Madison, the state capital, hosts a dense cluster of hospitals and clinics, yet large portions of the county are rural and sparsely served. Residents in these outer tracts may face substantial drives to obtain care, adding risk during acute events. This project therefore evaluates tract-level healthcare accessibility across Dane County and probes whether spatial disparities align with income and insurance patterns.

Methodologically, the study proceeds in two stages. First, a multiple-ring buffer analysis assigns each medical facility five distance bands (2, 4, 6, 8, 10 mi) weighted so that nearer rings contribute higher values; the summed score at every tract centroid forms an aggregate accessibility index. Second, ArcGIS Network Analyst calculates the actual driving distance from each centroid to its nearest provider, capturing road topology that straight-line buffers miss. These two spatial measures are then correlated with tract median household income and insurance-coverage rate to test whether economically disadvantaged areas experience inferior physical access.

By integrating buffer-based scoring, network distance, and socioeconomic variables, the study seeks to clarify whether healthcare inequality in Dane County is primarily geographic or socio-economic. The results are intended to inform planners and policymakers: tracts exhibiting low scores or long travel times could be targeted for new clinics, improved transport links, or mobile services to mitigate the rural–urban access gap.

3.Literature Review

Geographic Information Systems are increasingly being utilized to quantify health-care accessibility, which is broadly defined as the ease of access with which individuals get to medical care from a specific location (Guagliardo 2004, 1–2). Spatial accessibility has three legs: the presence of facilities, the demand in the form of populations, and the mobility impedance—distance, time, or cost—between them (Joseph & Phillips 1984, 78). Since use declines with distance, most measures employ distance-decay weights or travel cut-offs (Wang & Luo 2005, 133–134). In effect, closer providers weigh more in an accessibility measure, invoking Tobler's first law that "near things are more related than distant things" (Luo & Wang 2003,866).

The literature identifies two general sets of methods. Area-based measures group providers and populations over administrative regions—e.g. physician-to-population ratios or the two-step floating catchment area method (Wang & Luo 2005, 135–136). Such indices are revealing but susceptible to the selected spatial unit, a common illustration of the modifiable areal unit problem ; results differ if one employs census tracts instead of ZIP codes (McLafferty 2009, 1810–1811). Distance-based measures calculate actual separation between individuals and services instead. Methods employed include Euclidean distance, buffer analysis, and network travel distance or time (McGrail & Humphreys 2009, 854–855). Multiple-ring buffers—e.g., 1, 5, and 10 miles—translate distance decay into concentric service areas (Wang & Luo 2005, 136). Straight-line buffers ignore actual roads, though, and studies show that network distance or drive time better reflects actual access and has become de rigueur in health-GIS research (Probst 2007, 813–814).

An Australian synthesis confirmed that network-based measures outnumbered simple buffers (Douthit 2015, 612–613). Consequently, scholars have begun to use software such as ArcGIS Network Analyst to compute travel distance or time based on practical speeds (Guo 2023, pp. 4–5). Guo et al., for example, georeferenced closest-facility drive distances for millions of U.S. residents and revealed stark spatial inequalities (Guo 2023, 10–11). In particular, studies of accessibility move beyond distance measurement to dig up inequities and barriers. Researchers commonly examine correlations between spatial access and socioeconomic status, hypothesizing that social disadvantage and spatial disadvantage reinforce one another (Henry 2020, 3). Empirical research demonstrates that lower-income or more uninsured populations have greater difficulty accessing care (Nobles 2021, 130). Insurance itself is not a significant determinant: higher coverage raises service utilization (Kirby & Kaneda 2005, 20), while being uninsured will generally lead to delayed or foregone care (Youn 2023, 4). Such disparities point to how financial (income, insurance) and spatial barriers (distance) interact. Merging GIS-calculated accessibility measures with socio-economic data thus allows us to identify where disadvantaged populations are concentrating with gaps in services (Guagliardo 2004, 5). Extending this research, the current study uses ring-buffer scoring and network routing to measure access in Dane County and its relationship with insurance coverage and income.

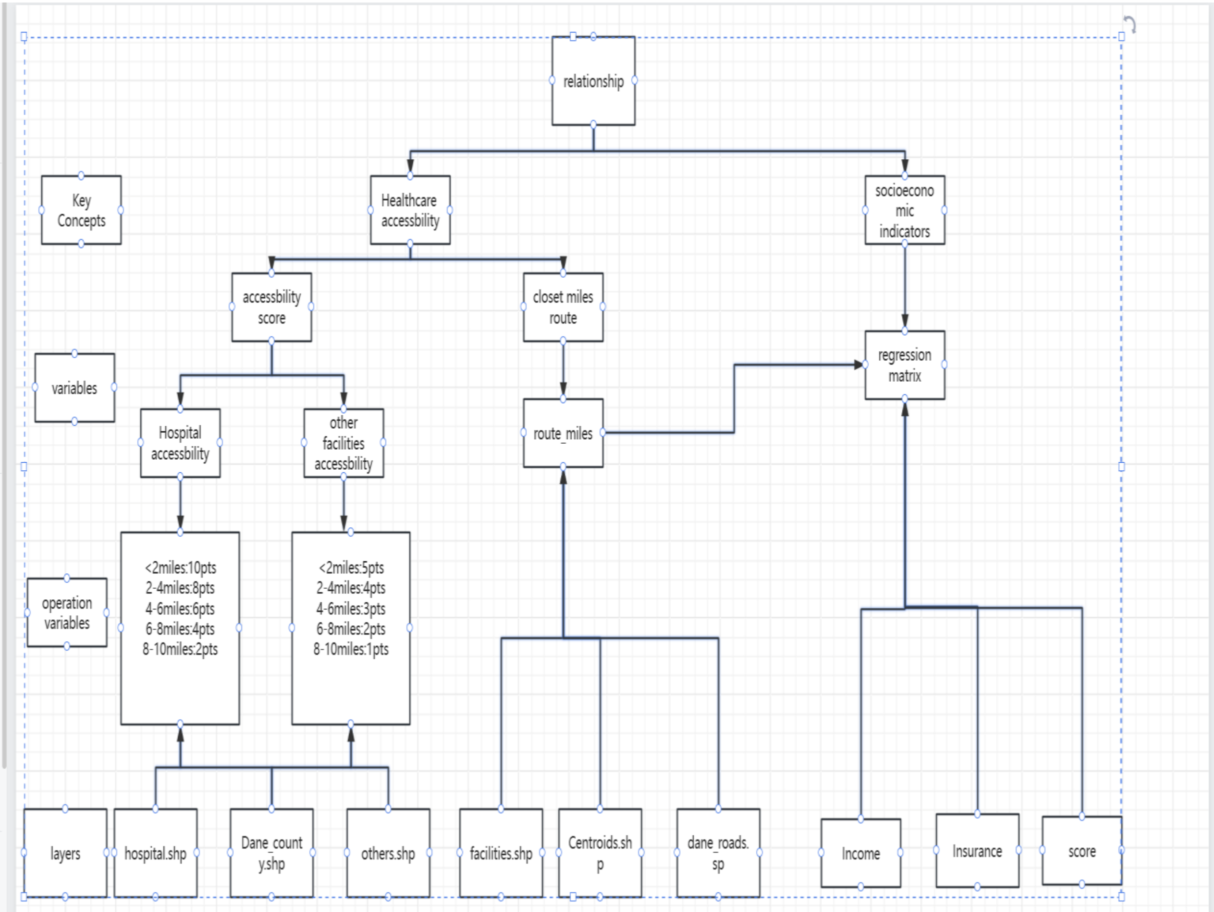


Figure 1 Conceptualization Diagram

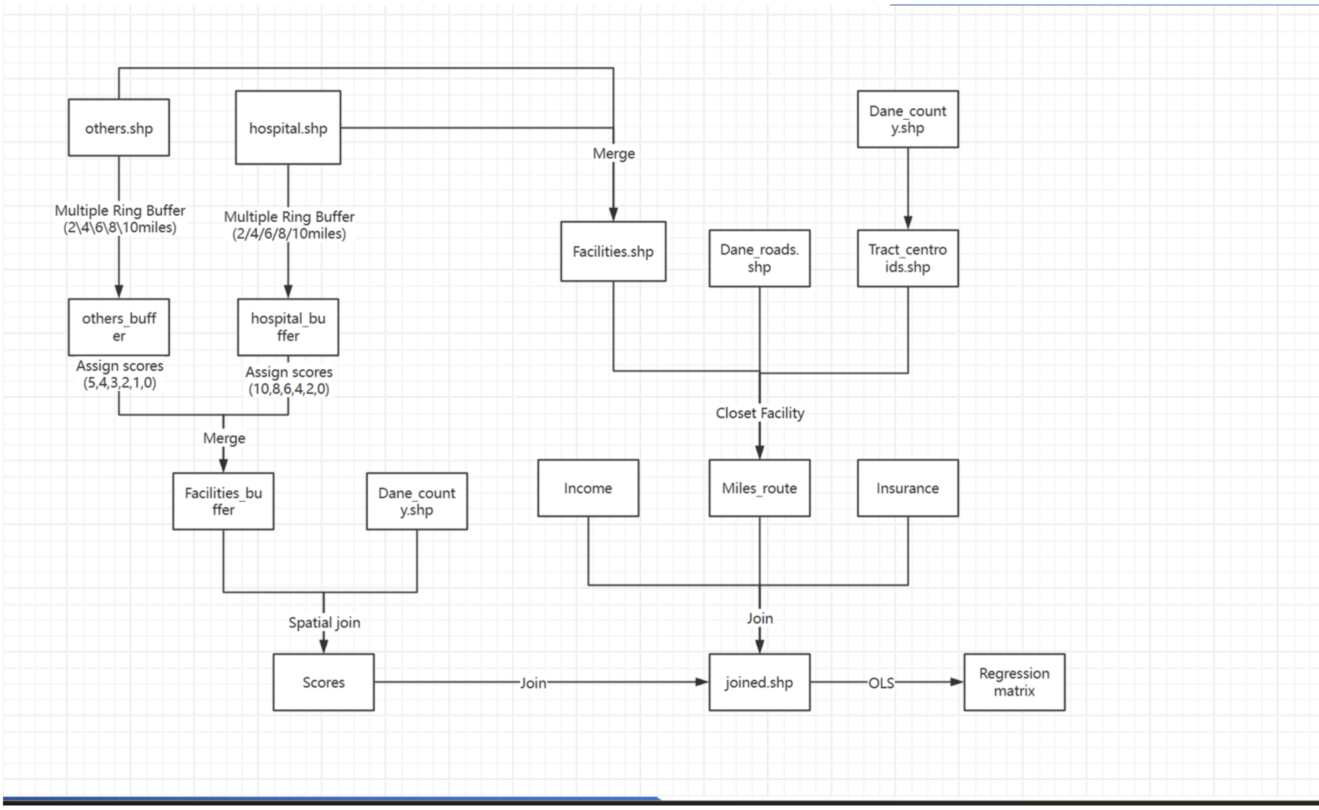
4.Methology

4.1 Study area and data

Our analysis focuses on Dane County, Wisconsin, and employs census tracts—purchased as a Dane_County.shp layer from data.census.gov—as our unit of analysis. The shapefile contains a polygon for each tract (n = 125) and an individual GEOID so that we may combine attribute tables. Two socioeconomic tables for tracts were also downloaded from the American Community Survey: one for household income and a second for insured and overall resident numbers. I calculated two new variables after joining these tables to the tract layer: insurance-coverage rate (insured ÷ total population) and its complement, uninsurance rate. Point data for medical facilities were downloaded in Overpass Turbo with the tags amenity=hospital|clinic and healthcare=urgent_care|health_care, giving a statewide inventory for Wisconsin.

Since residents in the areas around county boundaries may tend to receive services in other nearby counties if there are closer healthcare facilities there, I brought these variables into ArcGIS Pro, created a 10-mile buffer around the Dane County border, and clipped the statewide layer to the buffer. This created two pure point layers—Hospitals and Other Medical Facilities—containing all the facilities in Dane County and any within 10 miles of its border, which is equal to the widest distance band in my subsequent buffer-score analysis and prevents border bias. Road geometry and length were obtained from OpenStreetMap Geofabrik Wisconsin. and clipped to the same 10-mile envelope. While the download does not come with any speed information, the centerlines alone are adequate for driving distance calculation in a Network Dataset. Collectively, the tract polygons with income and insurance variables, the buffered facility points, and the road network comprise a coherent vector GIS stack that is utilized in both the straight-line buffer scoring and the network-based "closest facility" calculations that follow.

The General Implication Diagram is as follow, The diagram will depict every step in the GIS workflow utilized in this study



4.2Accessibility score calculation: Multiple-Ring Buffer Method

To convert the raw facility locations to a tract-level spatial access measure, we used an extended multiple-ring buffer method that accounts for both distance decay and the greater service capacity of hospitals compared to smaller clinics. The process was undertaken in four steps.

Stage 1 – Buffer creation. Five concentric, Euclidean rings at 2-, 4-, 6-, 8- and 10-mile radii were created for each of the geocoded facility points using the Multiple Ring Buffer tool in ArcGIS Pro.

These ranges were selected for two reasons. First, local traffic volumes suggest that a 2-mile trip in Dane County is generally under 10 minutes of driving during off-peak daytime hours, a window of time broadly deemed clinically "golden" for urgent care. Second, an upper limit of 10 miles keeps buffers wholly within or just outside county boundaries (≈ 38 mi at its widest point), encompassing sensible cross-border alternatives without watering down the analysis with far, highly improbable destinations.

Stage 2 – Distance-decay scoring. Each ring was given a stepwise decreasing weight with distance: Hospitals were scored 10, 8, 6, 4 and 2 points from inner- to outer-most band, while clinics/urgent-care facilities were scored 5, 4, 3, 2 and 1 points. The 2∶1 weighting reflects evidence that hospitals provide a wider range of emergency and inpatient services. A new field called Score was created in each buffer polygon and filled with these weights.

Stage 3 – Surface fusion. All of the hospital buffers were dissolved into one layer that maintained the Score attribute, and the same was done for clinic buffers. The two layers were added together, and polygons were allowed to overlap and—more importantly—stack their scores. Where, for instance, a tract is in the 2-mile ring of one hospital (10 pts) and the 4-mile ring of another clinic (4 pts), the composite surface now has a value of 14 pts at that point.

Stage 4 – Spatial aggregation to tracts. U.S. Census Bureau (2023) census-tract centroids were spatially joined to the composite surface using Intersect. The join accumulates all underlying scores and writes the sum to each centroid, which is transferred to the parent tract polygon by attribute join. This four-step procedure combines proximity, facility type and cumulative supply into one tract-level index that is transparent and reproducible computationally. All geoprocessing was conducted in NAD 1983 HARN Wisconsin South to preserve distance fidelity. A chart of the buffer logic and scoring hierarchy is shown below

Ring Width(miles)	Hospital score	Other-facilities score
0-2	10	5
2-4	8	4
4-6	6	3
6-8	4	2
8-10	2	1
>10	0	0

Figure4.2.1- scoring standard for hospital and other facilities

The result of this analysis in shown in Results, Analysis, and Discussion part of this essay.

4.3 Network Distance to Nearest Facility

In parallel with the buffer-based index, we derived a network driving distance for every census tract by means of the Closest Facility solver in the ArcGIS Network Analyst extension. A tract's centroid was defined as the origin, and every hospital or clinic within the 10-mile catchment was treated as a candidate destination. Using the cleaned OpenStreetMap centerlines, we built a road Network Dataset with one-way restrictions and "Miles" as the impedance. The solver then traced the shortest drivable route from each origin to its single nearest facility (Wang & Luo 2005, 134–135). Output attributes included the full path geometry and a field road_miles, which records the round-trip distance along roads.

The route table was joined back to the tract layer, creating a variable road_miles for subsequent analysis. Network distance captures road hierarchy, river crossings, and cul-de-sacs that a Euclidean buffer cannot (Guagliardo 2004, 3). For example, one tract lies only 5 straight-line miles from a hospital but, owing to Lake Mendota, its driving distance exceeds 11 miles; ignoring this would overstate practical access. Numerous health-GIS studies report similar discrepancies and therefore recommend network-based measures for accuracy (McGrail & Humphreys 2009, 855–856; Delamater 2013, 124).

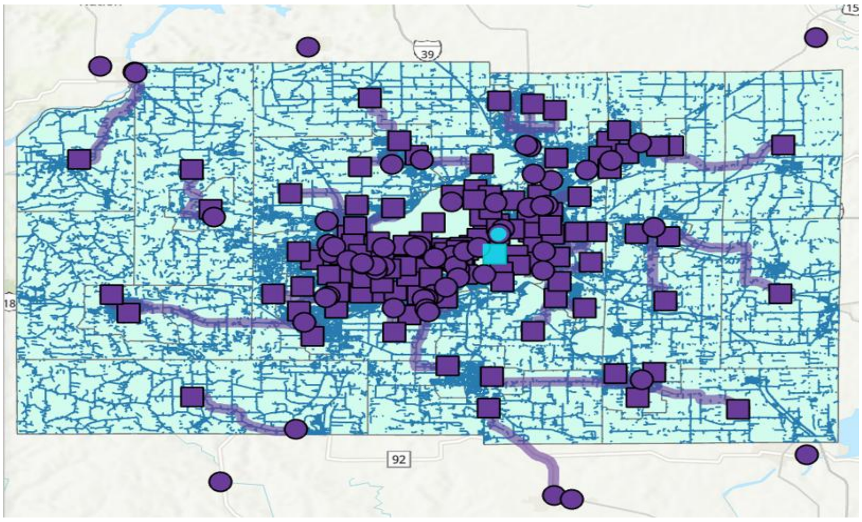


Figure4.3.1 Closet facilities analysis, the circle represents the facilities, the rectangle represents the centroids of each census Tract, the purple lines represents the route for each centroids to their closet facilities, if the route is long and obvious that means the route from the tract centroid to its closet facility is long

The result of this analysis in shown in Results, Analysis, and Discussion part of this essay.

4.4 Correlation Analysis

To explore the relationship between local socioeconomic conditions and accessibility to healthcare, Pearson correlation coefficients (r) were computed among four tract-level variables: accessibility score, network distance to the nearest facility, uninsurance rate, and median household income. Pearson's r quantifies the strength and direction of linear association on a scale from –1 (strong negative) to +1 (strong positive). Because the statistic is sensitive to missing data and extreme outliers, a thorough data-cleaning process came before calculation.

All four variables were taken directly from feature class Dane_County_SpatialJoin3_ExportFeatures in the Python environment of ArcGIS Pro. We imported the table into a NumPy array through arcpy prior to converting the outcome into a Pandas DataFrame for easier handling. Placeholder codes (e.g., –666 666 666) and negatives—both being invalid in this context—were both replaced with NaN, and NaN rows were deleted. The resulting DataFrame therefore captures tracts where all variables are valid and complete.

With data prepared, Pandas' corr(method='pearson') in-built function produced the 4 × 4 correlation matrix, rounded to three decimals and stored in Tract_Corr.csv for reference. This matrix serves Hypothesis check in the larger study design, it quantitatively tests whether tracts that are farther from care (larger network distance) or score lower on the buffer-based index also show lower insurance coverage and household income, as suggested by previous literature on spatial-social disadvantage.

5. Results, Analysis, and Discussion

5.1 Spatial Patterns of Accessibility

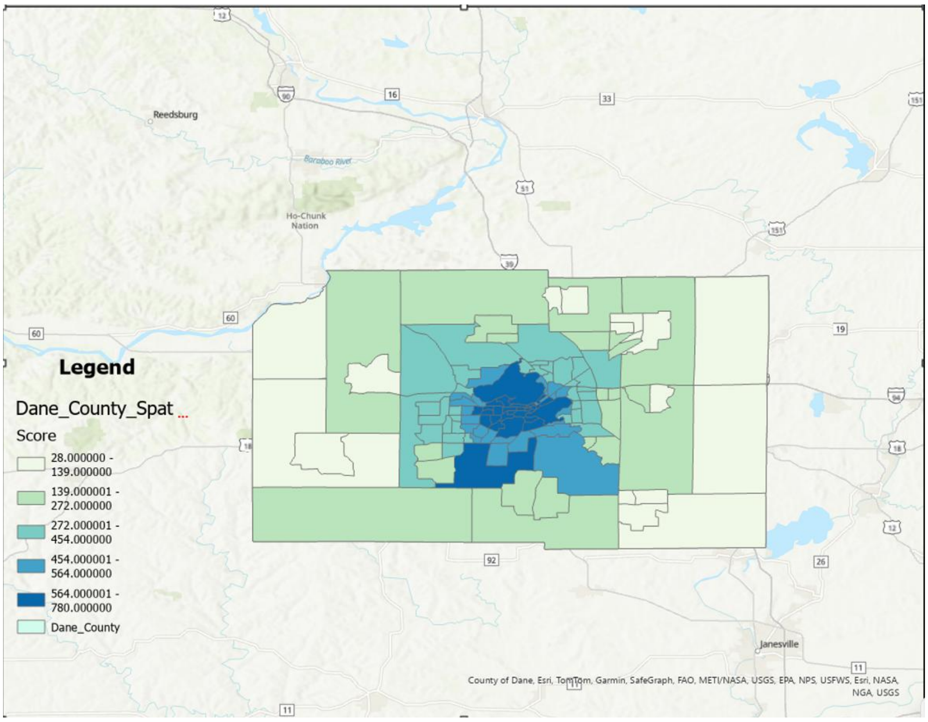


Figure 5.1.1 Dane County census tract accessibility scores.

Figure 5.1.1's map easily illustrates a spatial gradient in the health care's accessibility: census tracts within the urban core of Madison (dark blue) have the highest scores of accessibility, and outer rural tracts (light green) have lower scores. In particular, the downtown neighborhoods and University of Wisconsin–Madison campus area have the darkest hue (scores of 500–700), which indicates a high concentration of hospitals and clinics. By contrast, the outer tracts of the county (e.g. in the extreme north, west, and south) are light green and white, indicating low scores (of around 30–140). These patterns indicate increased proximity to the city center offers more desirable access, as would be anticipated.

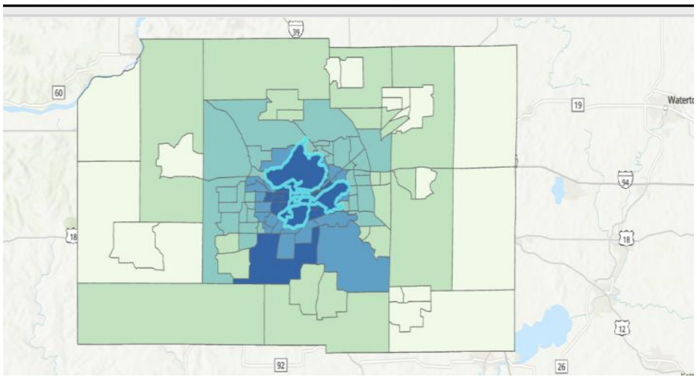


Figure 5.1.2. Top 10 tracts with highest accessibility scores.

As shown in Figure 5.1.2, the ten census tracts with the highest accessibility scores are clustered in central Madison and the near west side. These tracts correspond to major medical centers (for example, University Hospital, the VA Hospital, and downtown clinics) and high-density residential zones (including student housing). The highlighted tracts (outlined in bright blue) all lie close to one another near Lake Mendota and Lake Monona. Their scores far exceed the county average, which explains their selection. This reinforces that healthcare facilities are concentrated in the city center.

	OBJECTID	Score	road_miles	Shape	Join_Count	TARGET_FID	STATEFP	COUNTYFP	TRACTCE	NAMELSAD	GEOID	NAME
1	117	780	1.431729	Polygon	256	117	55	025	991702	Census Tract 9917.02	55025991702	9917.02
2	118	705	1.619214	Polygon	226	118	55	025	001402	Census Tract 14.02	55025001402	14.02
3	90	692	2.856901	Polygon	231	90	55	025	991703	Census Tract 9917.03	55025991703	9917.03
4	58	669	0.846197	Polygon	220	58	55	025	001000	Census Tract 10	55025001000	10
5	56	666	2.046016	Polygon	216	56	55	025	000700	Census Tract 7	55025000700	7
6	75	660	0.420035	Polygon	222	75	55	025	001200	Census Tract 12	55025001200	12
7	36	656	0.578456	Polygon	220	36	55	025	000902	Census Tract 9.02	55025000902	9.02
8	70	655	0.986355	Polygon	222	70	55	025	003200	Census Tract 32	55025003200	32
9	42	640	0.299723	Polygon	216	42	55	025	000901	Census Tract 9.01	55025000901	9.01
10	43	640	0.527233	Polygon	216	43	55	025	001101	Census Tract 11.01	55025001101	11.01

Chart 5.1.1 Top 10 tracts with highest accessibility scores.

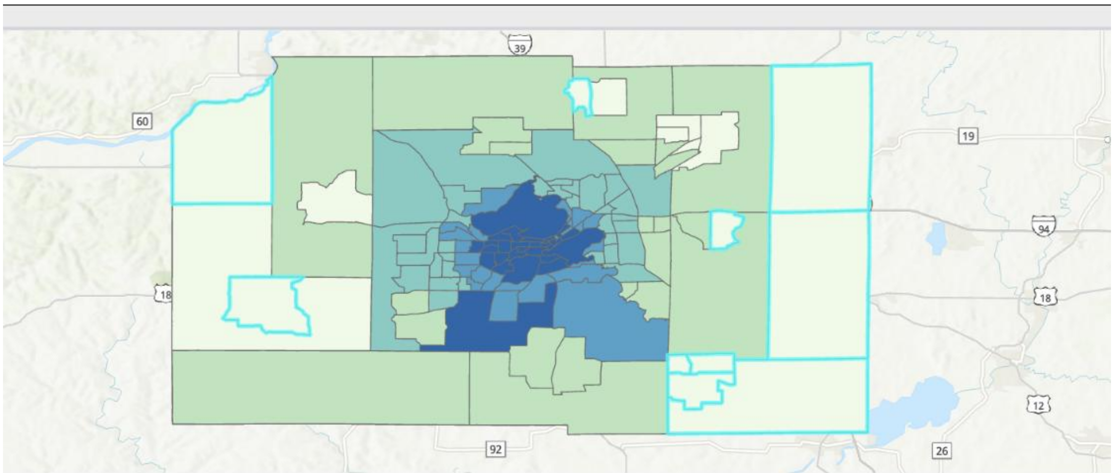


Figure5.1 3. Top 10 tracts with lowest accessibility scores.

Figure 5.1.3 highlights the ten tracts with the lowest scores (lined in turquoise). These are predominantly on the county edges: rural townships and exurban tracts to the north, east, and southeast. None of these tracts are located within the city of Madison; instead, they are sparsely populated tracts with limited health facilities. For example, a tract in eastern Dane County (near the Jefferson County line) is among the lowest scoring because its inhabitants must travel long distances to reach the closest hospital. Figure 5.1.2 alongside Figure 5.1.3 emphasizes the stark urban–rural dichotomy: core tracts have the benefit of high facility density, but peripheral tracts have poor access.

	OBJECTID	Score	road_miles	Shape	Join_Count	TARGET_FID	STATEFP	COUNTYFP	TRACTCE	NAMELSAD	GEOID
115	40	91	4.678989	Polygon	42	40	55	025	013301	Census Tract 133.01	55025013301
116	51	83	5.327867	Polygon	40	51	55	025	013302	Census Tract 133.02	55025013302
117	53	83	1.587235	Polygon	45	53	55	025	012004	Census Tract 120.04	55025012004
118	105	79	6.555581	Polygon	21	105	55	025	012100	Census Tract 121	55025012100
119	106	64	8.809304	Polygon	22	106	55	025	013100	Census Tract 131	55025013100
120	116	60	9.855189	Polygon	27	116	55	025	011800	Census Tract 118	55025011800
121	87	52	11.990428	Polygon	25	87	55	025	011900	Census Tract 119	55025011900
122	99	43	1.783516	Polygon	12	99	55	025	012300	Census Tract 123	55025012300
123	96	36	1.415772	Polygon	10	96	55	025	012201	Census Tract 122.01	55025012201
124	97	36	2.075121	Polygon	11	97	55	025	012202	Census Tract 122.02	55025012202
125	103	28	10.552099	Polygon	19	103	55	025	012800	Census Tract 128	55025012800

Chart 5.1.2 Top 10 tracts with lowest accessibility scores

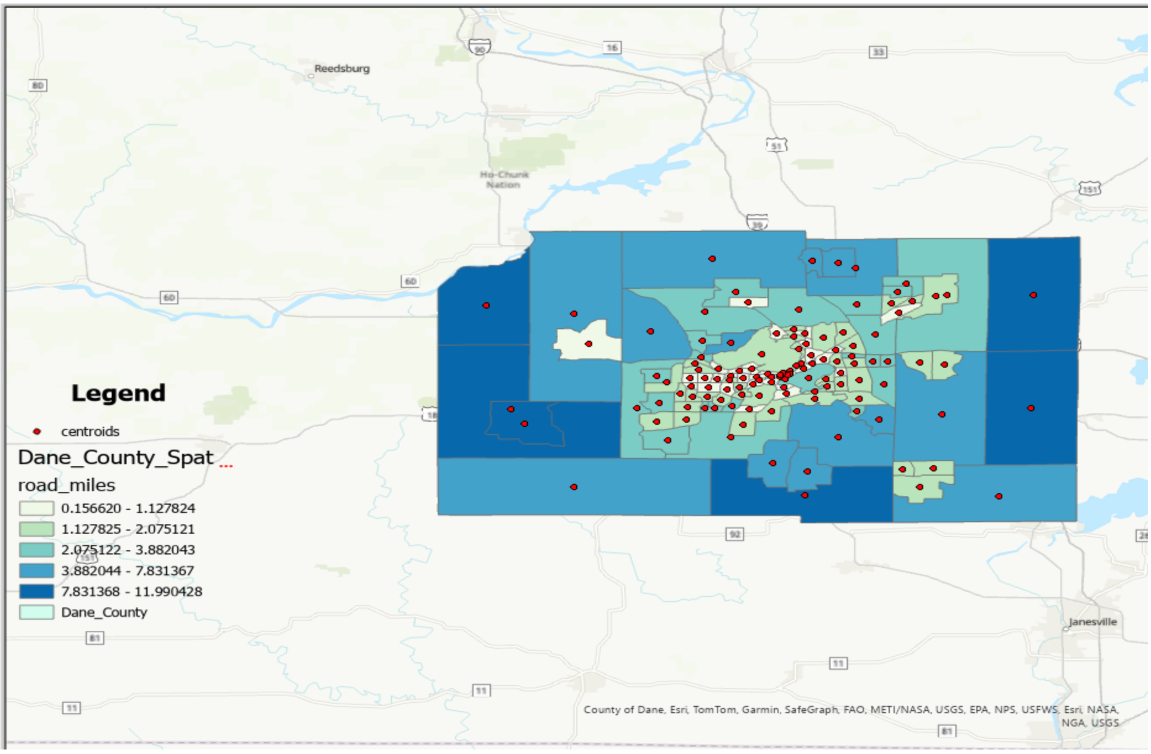


Figure 5.1.4 Road-network distance to nearest health facility (road_miles)

The map in Figure 5.1.4 displays the one-way driving distance from each tract to the nearest healthcare provider. Here lighter shades indicate short travel distances and darker blues indicate long distances. We see that inner-city tracts are pale green (short distances on the order of 0.2–1 mile), whereas distant rural tracts are dark blue (long distances up to 8–12 miles). Red dots mark the locations of the centroid of each census Tract. The distance map mirrors the accessibility map: urban tracts are close to many providers, and rural tracts are far from all providers.

	OBJECTID	Score	road_miles	Shape	Join_Count	TARGET_FID	STATEFP	COUNTYFP	TRACTCE	NAMELSAD	GEOID	NAME
1	1	487	0.15662	Polygon	186	1	55	025	001902	Census Tract 19.02	55025001902	19.02
2	45	590	0.269211	Polygon	208	45	55	025	001704	Census Tract 17.04	55025001704	17.04
3	44	601	0.29053	Polygon	209	44	55	025	001605	Census Tract 16.05	55025001605	16.05
4	42	640	0.299723	Polygon	216	42	55	025	000901	Census Tract 9.01	55025000901	9.01
5	35	552	0.348969	Polygon	197	35	55	025	000408	Census Tract 4.08	55025000408	4.08
6	82	624	0.385659	Polygon	213	82	55	025	001300	Census Tract 13	55025001300	13
7	75	660	0.420035	Polygon	222	75	55	025	001200	Census Tract 12	55025001200	12
8	38	620	0.509071	Polygon	211	38	55	025	001606	Census Tract 16.06	55025001606	16.06
9	43	640	0.527233	Polygon	216	43	55	025	001101	Census Tract 11.01	55025001101	11.01
10	32	590	0.560172	Polygon	208	32	55	025	001706	Census Tract 17.06	55025001706	17.06

Chart 5.1.3 Top 10 tracts with the lowest distance from centroid to its closet medical facilities

116	105	79	6.555581	Polygon	21	105	55	025	012100	Census Tract 121	55025012100	121
117	19	178	6.675425	Polygon	84	19	55	025	013201	Census Tract 132.01	55025013201	132.01
118	115	146	7.223057	Polygon	78	115	55	025	012600	Census Tract 126	55025012600	126
119	73	151	7.831367	Polygon	86	73	55	025	012501	Census Tract 125.01	55025012501	125.01
120	121	180	8.664032	Polygon	92	121	55	025	012400	Census Tract 124	55025012400	124
121	106	64	8.809304	Polygon	22	106	55	025	013100	Census Tract 131	55025013100	131
122	116	60	9.855189	Polygon	27	116	55	025	011800	Census Tract 118	55025011800	118
123	103	28	10.552099	Polygon	19	103	55	025	012800	Census Tract 128	55025012800	128
124	114	127	11.854682	Polygon	65	114	55	025	012700	Census Tract 127	55025012700	127
125	87	52	11.990428	Polygon	25	87	55	025	011900	Census Tract 119	55025011900	119

Chart5.1.4 Top 10 tracts with the highest distance from centroid to its closet medical facilities

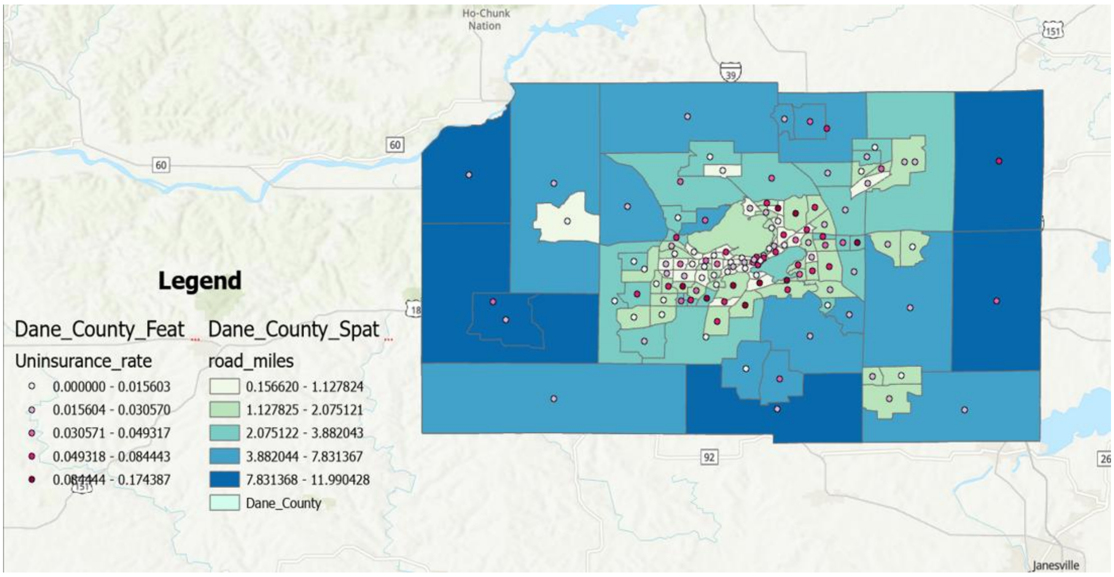


Figure 5.1.5. Uninsurance rate (dots) plotted against distance map. Figure 5.1.5 plots the uninsurance rate for every tract (color dots) over the road-distance map (shaded polygons). Red-to-white dots indicate differing degrees of uninsurance (legend). Observe that there is no discernible spatial patterning between distance and uninsurance. Some downtown tracts of low distance have mid-levels of uninsurance

(pink dots), due to the high densities of students. In contrast, the majority of rural regions (high distance) have minimal or no uninsurance rates (white dots), perhaps because these have older or entirely insured populations. The dashed overlay separates that high uninsurance is not associated systematically with poor access in Dane County.

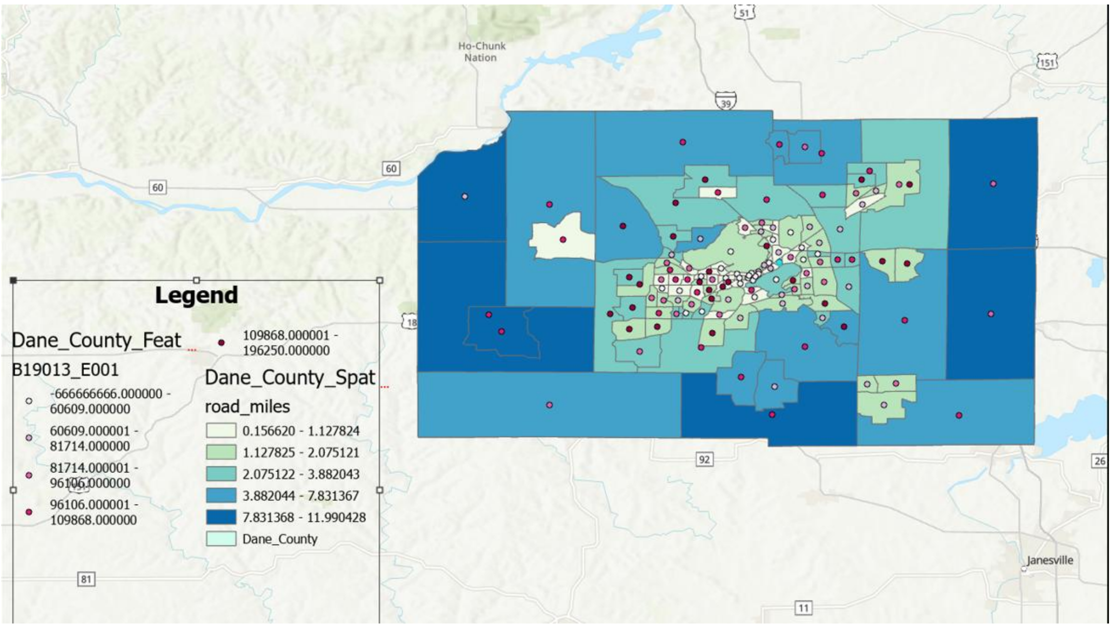


Figure 5.1.6. Median household income (dots) overlaid on distance map. Figure 5.1.6 shows median income by tract (red circles; darker = higher income) superimposed on the distance-to-care map. Once more, there is no simple spatial correlation. There are a number of remote tracts (dark blue) with higher incomes (large red dots at the county border), and some tracts in the middle have lower incomes (small dots near downtown). For example, certain suburban tracts in the far east and west (distance from medical facilities) appear on the highest income category, yet they have long travel distances. Likewise, most inner-city tracts with low income are closer to large facilities. Thus, as with uninsurance, income cannot be

readily attributed to accessibility here.

5.2 Correlation Analysis

To quantify the bivariate associations on a continuous scale, we calculated Pearson's product-moment correlation coefficient (r) among four variables: accessibility score, road-network distance to the nearest facility (Miles_route), uninsurance rate, and median household income per census tract. Pearson's r ranges from +1 (perfect positive linear association) to –1 (perfect negative), with 0 indicating no linear association. Following conventions widely used—$|r| \geq 0.50$ = strong, $0.30 \leq |r| < 0.50$ = moderate, $|r| < 0.30$ = weak (Cohen 1988,79)—we translate the correlation matrix (Figure 5.2.1) as follows:

	Score	Miles_route	Uninsurance_rate	median_Household_income
Score	1	-0.597	0.171	-0.246
miles_route	-0.597	1	-0.042	0.214
Uninsurance_rate	0.171	-0.042	1	-0.315
median_Household_income	-0.246	0.214	-0.315	1

Figure 5.2.1 correlation matrix

Score vs. Miles_route: r = –0.597 (strong negative). Tracts further from the nearest facility have much lower accessibility scores, as would be expected given that the score is distance-weighted.

Score vs. Uninsurance_rate: r = +0.171 (weak positive). Higher percentages of uninsured residents are not significantly related to higher or lower accessibility.

Score vs. Income: r = –0.246 (weak negative). Tracts with greater median incomes do so slightly, tend to have lower accessibility scores.

Miles_route vs. Income: r = +0.214 (weak positive). More affluent tracts, on average, drive a bit farther to the closest facility.

Miles_route vs. Uninsurance_rate: r = –0.042 (negligible). No linear association exists between uninsurance and miles driven.

On the whole, just the Score–Miles_route pair has a statistically significant linear correlation; none of the rest are in the weak category. The absence of significant correlations with uninsurance rate and income reflects that, for Dane County, these socioeconomic factors are not closely associated with spatial access to medical care.

5.3Interpretation and Discussion

The strong negative correlation between Miles_route and Score confirms a commonsensical result: access is ruled by distance. Tracts close to many facilities rank high, and far ones rank low. That is, our measures are internally consistent. The map and correlation together suggest that proximity to an urban place is the primary determinant of healthcare accessibility in Dane County. The weak correlations with socioeconomic attributes, on the other hand, demonstrate an intriguing spatial process. Why does income and insurance not follow access? Two reasons explain this. Firstly, the downtown area has a large population of university students and young adults. The students have low or no income and may be uninsured but live right next to UW Hospital and clinics, which allows them to have high access scores. Thus, low socioeconomic status neighborhoods can be very accessible due to central location. Second, some high-income neighborhoods are located at the edges of counties. For example, high-income bedroom suburbs or rural townships might not have local hospitals. These individuals have higher incomes and possibly good insurance but must travel further to care. This can result in the weak negative Score–Income correlation (r≈–0.25) and positive Miles–Income correlation (r≈+0.21), as in the data. Policy is another possibility: Wisconsin has fairly extensive healthcare coverage (e.g. Medicaid/BadgerCare expansions), so rural areas may have low uninsured rates despite being far away. Additionally, the small number of tracts (there are just 125 census tracts in Dane County) and heterogeneous local conditions permit outliers to confound an evident pattern. For instance, a wealthy suburb with a private clinic will still have a high "nearest hospital" distance despite the fact that the population is well-insured. Such subtleties likely weaken statistical relationships. In brief, then, the spatial maps and correlations all lead to the conclusion that in Dane County healthcare access is more a function of geography than of socioeconomic disparity. Central Madison—despite its lower-income student body—is very well served, whereas some higher-income but outlying districts are not. This trend implies that attempts at improving access in Dane County should be aimed at reducing distance to care (e.g., by boosting rural clinics or transportation).

6. Conclusion and Future Research

The key finding is that access to health care in Dane County is largely a function of spatial proximity. Our thematic maps (Figures 5.1.1-5.1.4) show tracts nearest the central city having the best access scores and shortest distances to facilities. Statistical modeling confirms a strong negative correlation between distance and access score (r

≈ –0.60), whereas correlations with income and insurance are weak (|r|<0.3). These results suggest that, contrary to some locations where worse access is experienced by poorer or uninsured populations, Dane County's main accessibility disparity is geographic. That is, being far from Madison (even if wealthy) is a greater barrier to care than being low-income or uninsured in the city. The policymakers and planners should therefore contemplate spatial responses – for example, telemedicine or rural health centers – to address the rural–urban access deficit in Dane County.

In future work, I plan to compile data from a larger set of regions to test whether socioeconomic factors such as income and health-insurance coverage are more clearly linked to healthcare accessibility at broader spatial scales. At the same time, I will extend the current study to investigate patterns of unequal access to medical services across a wider geographic area.

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