Comparing Transportation Metrics to Measure Accessibility to Community Amenities

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Abstract: Landscape architects and urban planners play an important role in helping create inclusive, accessible communities. To do this, it is helpful to understand how the built environment and access to various amenities and places affect activities of daily community living. These activities can influence social engagement with others and satisfaction with one's social life. Thus, understanding how the built environment influences their choice of living can shed light on the ramifications to an individual's overall social satisfaction. As previous studies show, there are various methods for measuring accessibility. But to what extent are these metrics different or provide similar results? In the current study, we generate various geospatial models to measure distance, density, and accessibility. The metrics produced are then compared to identify how similar they are in measuring access to several different places. Results show that all metrics are statistically significant and similar, however, similarities range from poor correlation to very high correlation. The most consistent can then be used in future studies to identify how well they correlate to stated access, actual access, and the influence on social satisfaction.

Keywords: Accessibility, spatial analysis, destinations, place types

1 Introduction

A tenant of landscape architects and urban planners is to improve the quality of life in communities. An essential variable in this equation is improving the satisfaction of social life as a result of community integration (SEEMAN 1996, YEN & SYME 1999) and development patterns. To accomplish this, landscape architects, policymakers, and urban planners need to know how social and environmental factors impact community integration and, ultimately, satisfaction with social life. Prior work in the discipline has shown that if we create improved integration of people within their community, people experience a higher level of social satisfaction (CHRISTENSEN et al. 2010).

Several factors affect the level of satisfaction with social life among people, including factors influenced by the surrounding neighborhood. For example, social factors such as place attachment (CAO et al. 2020, HUR & MORROW-JONES 2008) and neighborhood cohesion (Liu, 2017), make higher rates of satisfaction (MITCHELL et al. 2013, OKTAY et al. 2021). Additionally, environmental factors including landscape and green space (BOTTICELLO et al. 2014, YOUSSOUFI et al. 2020), mixed land use (BEARD et al. 2009, CAO et al. 2020) destinations and urban amenities (ALLEN 2015, SATARIANO et al. 2010), and street connectivity (GÓMEZ et al. 2010) also play a role in facilitating social satisfaction. However, there is no standardized rule used to calculate how built environment factors and the proximity to urban amenities are associated with the level of social satisfaction. Further, there are limited studies that systematically compare accessibility measures (KAPATSILA et al. 2023). Not only can it be important to compare the results from a range of accessibility metrics, but equally important is the level of technical difficulty required to accomplish each. In this paper, we explore accessibility to common community places in which individuals take part in a range of dif-

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ferent activities (JONES 1981). These places include areas of outdoor recreation, grocery stores, retail stores, restaurants, and others. Throughout this paper, we refer to these places as “place types”. Since accurate metrics are necessary for effective policy development and implementation, we are keen to ask: to what extent do different accessibility metrics agree with each other”? Specifically, how different are geospatial techniques for measuring and quantifying access to place types by neighborhood?

There is a diverse knowledge and broad understanding of the linkages between the level of satisfaction among individuals and environmental factors including neighborhood and place types (SAMMER et al. 2012, WHITE & SUMMERS 2017). There is, however, uncertainty about how accessibility to each place type affects social engagement. Given the potential importance of these places to facilitate social satisfaction, it will be helpful to identify a robust spatial metric that could explain the impact of place types on the level of satisfaction with social life. We could further use the spatial models to assess and promote policies that integrate people into their surrounding environments and communities. Understanding the relationship between place types and the level of satisfaction can inform how landscape architects and planners design inclusive communities. However, before we can understand this relationship, it is also important to understand how we assess accessibility.

One of the more basic measures of accessibility is to determine the degree of access from one location to another. Certainly, there are differences in the kinds of reliance on different modes of transportation across demographics (PARK et al. 2022). There are several ways for measuring accessibility. However, this paper is not focused on attempting to identify the range of multi-modal transportation accessibility techniques. Instead, we focus on understanding the consistency of different measures of accessibility, mainly because some models may be biased (GIANNOTTI et al. 2022). In this paper, we identify the degree to which six common spatial accessibility models are related. We generate a systematic comparison of these models by measuring the spatial pattern and accessibility to several place types. By identifying similarities, we can determine trade-offs between model complexity and consistency of the metrics. The easiest and most consistent models can then be used in future studies where empirical data about demographics, disability status, and travel behaviors can be used to identify the relationship between access to place types and social satisfaction.

2 Methods

Determining accessibility is a rather complex process. Transportation-related studies provide several means to produce an accessibility measure, with the most precise being produced using empirical data collected about individual travel patterns. However, these data can be particularly expensive to obtain and may be logistically prohibitive to obtain in some international contexts. In this study, we pursued comparing six different geospatial models that use aggregate data at the US Census block group level (heretofore: “block group”). To conduct our analyses, we used the Safegraph Point of Interest data points (POI) and aggregated these data into eight categories. Each category is then referred to as a place type. Six metrics were defined to represent the spatial pattern of place types. including, accessibility to different destinations (CAO et al. 2020), proximity to various destinations (TSEMBERIS et al. 2003), the density of place types (YANG 2008), and spatial models (GIANNOTTI et al. 2022, LUO & QI 2009). More specifically our metrics are: 1) Average proximity to place types, 2) frequency of place types (count of place types within the block group), 3) Density of place types (using kernel density), 4) The number of block groups (in USA, referred to as block groups) within the service area of place types, 5) the gravity model, and 6) two-step floating catchment area (2SFCA). Each of these metrics measures accessibility to place types, but it is important to note that the level of technical difficulty varies widely. Furthermore, variables used to calculate each metric can differ. For instance, 2SFCA and gravity model considers population, while frequency metrics and the kernel density focus on the number of place types in a unit (e. g. block group). As a study area, we analyzed data from across the Greater Salt Lake City, UT region in the USA. Some items, including accessibility and distribution of place types, were selected from neighborhood satisfaction scales developed by (GUTTING et al. 2021, OKTAY et al. 2021). This technique provides a simple proxy for determining the extent of access to place types KWEON et al. (2010) produced similar measures based on different place types by limiting the distance of an accessible amenity to a respondent's home. Conducting a correlation between the metrics results can provide insight into the similar results that we can get.

Two density measures were produced, *frequency of place types (count of urban place types within the block groups)* and *density of place types (using kernel density)*, Metric #1 and #2, respectively. Metric #1 counts the total number of the selected place types intersecting with a block group, using spatial selection. Metric #2 uses kernel density to calculate the density of features and place types in a block group (YANG 2008). Kernel density was performed by the planar option, which is appropriate for the analysis on the local scale.

For *average proximity to place types* (Metric #3), we generated a set of origin locations that would provide a meaningful context for trips from within each block group. Every intersection of the road network within each block group became an origin node. Intersections within the block groups balance the trade-off between identifying every building from which people travel to and from, but also provide more precision than the centroid of the block group. We calculated the median distance of travel using Safegraph datapoints and set as a travel distance to get to different destinations from the intersection nodes. Driving distance was used because there is limited information about alternative use of public transit. Then, the average proximity from all origin nodes to all place types within the travel distance was calculated. Figure 1 shows the average proximity, by block groups, from origins to each place type.

The number of block groups within the service area of place types (Metric #4) flips the density calculation by starting from the place instead of the block group. To produce this metric, a service area was generated for each place type using a network analysis. The route distance was calculated based on the median distance that individuals reported as the travel distance to get to different destinations (similar to Metric #1). Then the number of place types by service area within each block group was calculated by spatial joining the service area with any intersecting block groups.

Then, the more established 2SFCA metric (Metric #5) was used for measuring accessibility to each place type. 2SFCA defines a catchment area around each location and computes the supply-to-demand ratio for the catchment area. The boundary of the catchment area can be delineated with the radius, travel distance, and travel time (LUO & QI 2009).

The other commonly used transportation metric we employed was the *gravity* model (Metric 6). The gravity model has been used to model human mobility and accessibility. The model considers the distance between two nodes and the population within the place type's service area as demand and is inversely proportional to the power of the distance between them (BEIRÓ et al. 2018).

3 Results

Results of this systematic comparison are provided first as a correlation matrix (Table 1), then as a series of visual representations below. To demonstrate the statistical differences between each metric, we produced correlation tables for each of the eight different place types, by each of the different Metrics (or geospatial models). Here we show a summary table of the average correlation values across all eight place types. The purpose of this table is to highlight (in)consistencies between metrics and to identify potential sensitivities of these models across place types. Note, Metric #3 is inversely correlated with all other metrics. Thus, these were this inverted to positive values so the average correlation would maintain its accuracy of strength, regardless of signing. Consistently high correlation values with a relatively low standard deviation suggest that these Metrics are likely to produce similar results. This table highlights that Metrics #4, #5, and #6 maintain very high correlation and low variance across all place types. Metric #2 also seems to be highly correlated with Metrics #4, #5, and #6.

Table 1: Correlation Matrix Table depicting the average correlation (and standard deviation) of all eight place types for each metric. All data were statistically significant at $p < 0.001$.. Darker grey indicates higher correlation (good), and bolded standard deviation values indicate higher variance (poor). The four degrees of shadings indicate the correlations. White means low correlation, light grey means medium correlation and dark grey means a high correlation.

Metric	2	3	4	5	6
1	0.287 (0.095)	0.301 (0.059)	0.248 (0.054)	0.162 (0.045)	0.202 (0.037)
2		0.439 **(0.434)**	0.880 (0.030)	0.816 (0.061)	0.849 (0.040)
3			0.548 (0.066)	0.449 (0.036)	0.505 (0.047)
4				0.869 (0.032)	0.922 (0.015)
5					0.939 (0.029)

To depict these data visually, several maps were generated (Figures 1-6, for Metric #1 – #6, respectively). Given the diversity of values for each of the different Metrics, we created Table 2, which identifies the grouping of values for each of the different legends. Using these visuals one can see differences in the relative distribution of high to low access to various place types. For instance, Metric #1 shows a clear visual difference from the other Metrics (which is also clear in Table 1). Also, the overall consistency of Metric #2 with Metrics #3 – #6 is also fairly apparent in these figures. Note, the groupings used in these figures were not the values used to conduct the correlations (correlations were not run by groups). Instead, correlations were conducted on the raw values produced from each metric for each of the block groups. The figures are providing only a visual reference with the groupings of data produced using Natural Jenks, these groupings were not used in the correlation analysis. The figures only symbolize the results of the metrics for access to outdoor recreation.

Table 2: Legend Values for Figures 1-6. There are five tones of green, each associated with a grouping of values for each Metric. Metric #1 shows the number of place types within a block group (absolute measure). Metric #2 shows the density of place types using kernel density (relative measure). Metric #3 is the average proximity (meters) from the road intersection, and origin points, to the five closest outdoor recreation places (absolute measure). Metric #4 shows the number of block groups within the service area of each place type (absolute measure). Metrics #5 and #6 show the results of the two-step floating catchment area and gravity model, respectively (and are relative measures).

Legend Color	Metric #1	Metric #2	Metric #3	Metric #4	Metric #5	Metric #6
Light	0-1	1-2	2817-4667	2-45	0.000-0.0008	0.005-0.517
	1-3	2-2.5	2006-2817	46-76	0.0008-0.001	0.517-1.112
	3-9	2.5-3.5	1478-2006	77-113	0.001-0.003	1.112-1.888
	9-19	3.5-5.5	1013-1478	114-159	0.003-0.005	1.888-3.054
Dark	19-47	5.5-10	357-1013	160-220	0.005-0.006	3.054-4.575

A summary description of these figures is provided here. Figures 1 and 2 illustrate the results of the count of place types within each block group (Metric #1) and the density of place types using kernel density (Metric #2). The darker color indicates that a block group has a greater number and density of urban place types. Alternatively, as the color gets lighter, there are fewer place types and a lower density of place types. Figure 3 illustrates the results of the average proximity to place types. The darker color shows a shorter distance to the outdoor recreation and as the color becomes lighter, it shows a longer distance to the destination. Figure 4 illustrates the results of the number of block groups within the service area of each place type (Metric #4). Darker colors indicate a higher number of block groups within the service area of a place type, while lighter colors indicate fewer block groups. The two-step-floating catchment area (Metric #5) method is used for comparing the number of place types that are accessible within a catchment area and the gravity model, commonly used in transportation analysis is provided in Metric #6. Larger values for these metrics show better accessibility (LIU et al. 2022). The darker color indicates a higher index, meaning that access to place types is better in that block group. In contrast, a lighter color indicates a lower index which means lower accessibility to the place types in the block group.

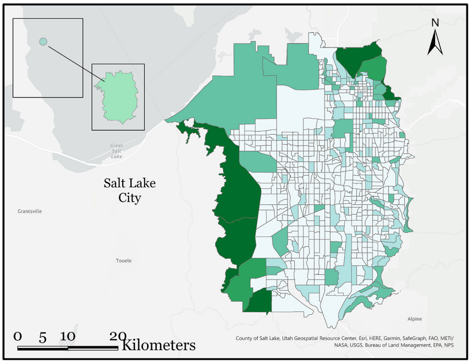

Fig. 1: Metric #1. Count of outdoor recreation places within each block group

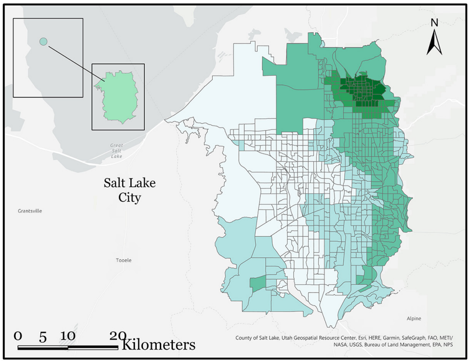

Fig. 2: Metric #2. Density of outdoor recreation places using kernel density

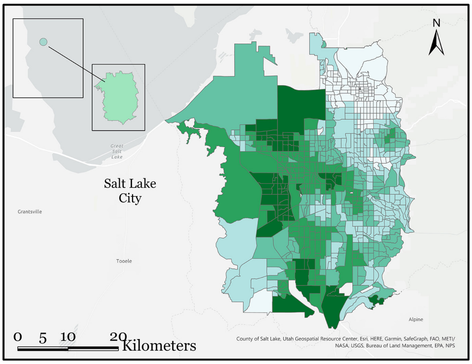

Fig. 3: Metric #3. Average proximity from road intersection, origin points, to the five closest outdoor recreation places

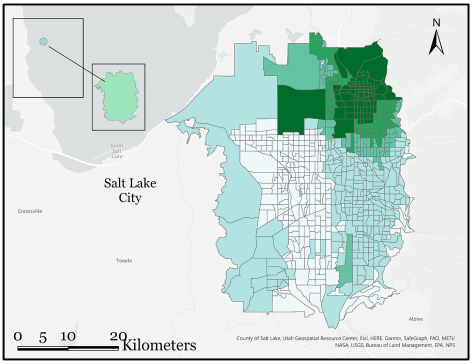

Fig. 4: Metric #4 Number of block groups within the service area of each outdoor recreation place

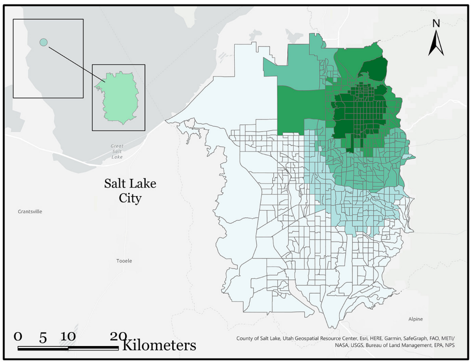

Fig. 5: Metric #5. 2 step floating catchment area for measuring accessibility to outdoor recreation places

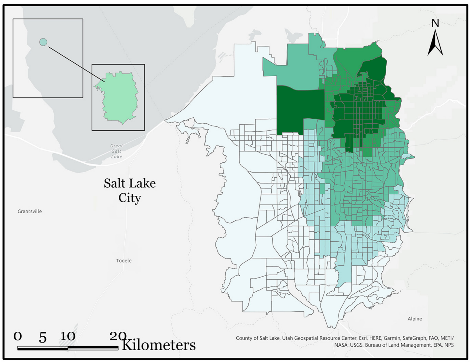

Fig. 6: Metric #6. Gravity model measuring the accessibility to outdoor recreation places

4 Discussion and Conclusion

Landscape architects are regularly involved in community design and transportation planning. Finding models that provide reliable metrics and are easy to perform can help facilitate rapid iterations of design and planning recommendations. In this study, we compared six metrics that measure accessibility to different place types and showed differences between them. Results indicate a high correlation between metrics #5 of the 2-SFCA method, #6 of the gravity model, #4 of the number of block groups within each place type service area, and #2 of the kernel density. Furthermore, we provide a stark warning about the dangers of using a single geospatial metric – especially if the metric needs further empirical evaluation to compare its reliability and effectiveness. The *2FSCA* (Metric #5) and *gravity* (Metric #6) models have been well published in the literature (KAPATSILA et al. 2023, LIU et al. 2022, LUO & QI 2009) but can be more complex to run than other metrics (Metric #2), though these are highly correlated. This comparison highlights the potential trade-off between model complexity and the outcomes. It will be important for future studies to ascertain the value of the more complex models. For instance, correlations between models might be high, but do they maintain the same level of consistency when other variables are included (e. g. demographics or disability status)? If reliability is maintained, then simpler methods should be used first, with the more complex methods becoming necessary only if there is a good empirically-sound reason.

Our analysis has shown that some models of accessibility differ quite substantially. At the same time, some of these models share a high statistical similarity. One of the challenges these models provide is that they can serve to validate actual travel times and provide data to inform planning policy. However, there are limited studies that attempt to connect these models to social satisfaction. Our results are aligned with other studies that compared simple cumulative opportunity measures and the measures produced by the gravity model to understand if there is a significant correlation or not between them. The results showed that cumulative opportunity measures can substitute complex measures like the gravity model (KAPATSILA et al. 2023). It can be argued that social satisfaction is an important indicator of the quality of life, perhaps more so than just assessing how long it takes someone to get from point A to B. Thus, to validate these models, a future study should study the statistical relationship between each model and how they relate to social satisfaction. Further, we also anticipate gathering empirical data on the time to travel and modes of travel for people living with disabilities. This information can then be used to compare differences between the general public and those with disabilities – not only for functional access to place types but more importantly for how the spatial relationship to these place types influences social satisfaction. The study can contribute to a wide range of fields, including landscape architecture, urban design, urban planning, and transportation planning. Yet, landscape architects do play an important role in helping design access to a range of different place types, particularly greenspace and open space. With this work, we have established the importance of testing different models to determine community access to place types, including outdoor recreation. This work provides a means to connect accessibility and the design of urban spaces, to create more suitable and equitable access to different place types for all citizens.

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