Impacts of Catchments Derived from Fine-Grained Mobility Data on Spatial Accessibility

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Abstract

Spatial accessibility is a powerful tool for understanding how access to important services and resources varies across space. While spatial accessibility methods traditionally rely on origin-destination matrices between centroids of administrative zones, recent work has examined creating polygonal catchments – areas within a travel-time threshold – from point-based fine-grained mobility data. In this paper, we investigate the difference between the convex hull and alpha shape algorithms for determining catchment areas and how this affects the results of spatial accessibility analyses. Our analysis shows that the choice of how we define a catchment produces differences in the measured accessibility which correlate with social vulnerability. These findings highlight the importance of evaluating and communicating minor methodological choices in spatial accessibility analyses.

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1 Introduction

Spatial accessibility is an important field of research that examines access across space to vital resources and services like healthcare [11, 12, 14]. This makes spatial accessibility a powerful tool for identifying and analyzing disparities in access across space. Access is especially crucial for socially vulnerable populations – those who are socio-economically disadvantaged, disabled, with limited transportation, etc. – who may be less likely to overcome the barriers between them and the services they need. This means that spatial accessibility work must always be cognizant of how various methodological choices impact measures of accessibility and how these different patterns of access correlate with social vulnerability.

While spatial accessibility traditionally relies on origin-destination matrices between centroids of administrative zones, recent work in spatial accessibility has created polygonal catchments from fine-grained travel data [10, 11, 14]. These works have used fine-grained point data, such as travel-time on OpenStreetMap road networks [3] and Floating Car Data (FCD) [10], to more accurately determine catchments and service areas. To calculate these catchments from point data, researchers used convex hulls in Kang et. al. [11, 12] and alpha shapes in Jiao et. al. [10]. However, convex hulls have the potential to exaggerate the catchment area as they oversimplify the shape of accessible locations.

In this paper, we examine the implications of using the convex hull and alpha shape algorithms for defining catchments in spatial accessibility analysis with a case study in Cook County, Illinois, USA. In Section 2 we discuss our methods for determining spatial accessibility and catchments and Section 3 details our data. Section 4 gives our findings for our two research questions: (1) what are the differences in the accessibility measures when we compare the two approaches and (2) how do these differences correlate with social vulnerability? Section 5 concludes with a discussion of our findings and their implications.

2 Methods

2.1 Measuring Spatial Accessibility

Spatial accessibility analyzes the distribution of supply and/or demand across space. The Enhanced Two-Step Floating Catchment Area (E2SFCA) method is a common tool for calculating spatial accessibility [13]. The first step of E2SFCA determines the weighted ratio of supply and demand (R_j) for each supply location j using Equation 1:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \in D_r\}} P_k W_r} \tag{1}$$

where S_j is the degree of supply at location j, P_k is the degree of the demand or population at location k and W_r is the weight for travel-time zone r [13]. The travel-time between the supply location k and demand location j is given by d_{kj} and each step of the summation only considers supply/demand pairs k, j if the travel-time is within that step's travel-time threshold D_r ($d_{kj} \in D_r$). In the second step, each demand location sums the weighted supply-to-demand ratios of supply locations within the travel-time zones. The equation for Step 2 of the E2SFCA method is:

$$A_i = \sum_{j \in \{d_{ij} \in D_r\}} R_j W_r \tag{2}$$

where A_i is the access at demand location i and R_j, W_r are ratios and weights from step one. This yields a measure which can be interpreted as supply-to-demand ratios across space.

2.2 Calculating Catchments

An explosion in high-quality geospatial data and the development of cyberGIS for high-performance geospatial analysis [17] in recent years has led to a greater diversity in how travel-time catchments are defined. Mobility information is often given in the form of points

– nodes on road networks [12], mobile phone data [16], social media data [8], etc. – but there is some uncertainty in how we determine a service area from a set of points.

Our study examines two well-known approaches: convex hull [5] and alpha shapes [6]. The convex hull $\mathcal{CH}(S)$ of a set of points S is convex – meaning that the line between any two points in $\mathcal{CH}(S)$ is completely contained in $\mathcal{CH}(S)$ – and is the smallest convex set containing S [5]. Kang et. al. [12, 11] created driving-time polygons by calculating the ego-centric graph – the network around a node up to some distance threshold – on the road network around each supply location and used the convex hull to produce polygons. A similar approach was employed by Park & Goldberg using travel speed data in addition to the street network data [14]. The convex hull on a road network is given on the left of Figure 1.

Alpha shapes instead use the Delaunay triangulation of the points [6]. Using the triangulation, the alpha shape algorithm filters out triangles based on their circumradius using an alpha parameter [1]. We follow the convention used by the Python `alphashape` package [2], by filtering out triangles in the Delaunay triangulation which have a circumradius greater than $1/\alpha$. The convex hull and alpha shape are related in that the convex hull can be thought of as an alpha shape with $\alpha = 0$; the Delaunay triangulation with all triangles [6]. Whereas the convex hull is like a rubber band around the points, the alpha shape is like shrink wrap being fitted to the points, with α telling us how long to apply the heat. Jiao et. al. (2020) [9] calculated hospital service areas (HSAs) using alpha shapes and isolated forest algorithm on taxi trajectory data and Jiao et. al. (2022) [10] calculated accessibility using these service areas. An alpha shape on a road network is given on the right of Figure 1.

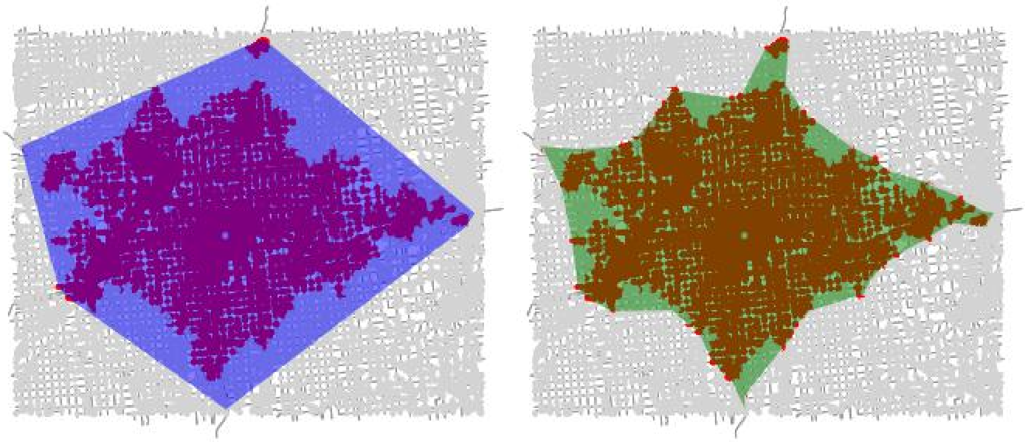


Figure 1 An example of the difference between convex hulls and alpha shapes on road network data. The street network nodes in red are within 30 minutes of the Carle Hospital in Urbana, IL while the grey nodes are not. The convex hull around the red nodes is on the left and the alpha shape (with $\alpha = 2^{-13}$ using Albers Equal Area Conic projection) is given on the right.

To determine catchments in our experiments, we calculated travel-time with the `osmnx` package [3]. First, we cleaned the road networks to remove all but the largest weakly and strongly connected components of the network, ensuring each hospital and census tract were reachable, and determined free-flow travel-times for each edge. Distance between nodes on the graph were calculated with the Python `networkx` package using Dijkstra's Algorithm. We collected the coordinates of each node within the travel-time threshold and created collections of points using the Python `geopandas` package. Using the collection of points, we were able to calculate polygonal catchments using the convex hull and alpha shape algorithms.

3 Study Area and Data

This study examined spatial accessibility for the general population to Intensive Care Unit (ICU) beds and its relationship with social vulnerability in Cook County, Illinois. This analysis required several different sets of data: (1) population and social vulnerability, (2) hospitals and ICU beds, and (3) road network data. Our population and social vulnerability data comes from the Centers for Disease Control (CDC) Social Vulnerability Index (SVI) which includes population estimates at the census tract level from the Amercian Community Survey 5-Year (2014-2018) [4]. The hospitals and ICU beds per hospital were obtained from the Homeland Infrastructure Foundation-Level Data Geoplatform[1]. Our road network dataset was obtained from OpenStreetMap using the Python `osmnx` package [3].

4 Results

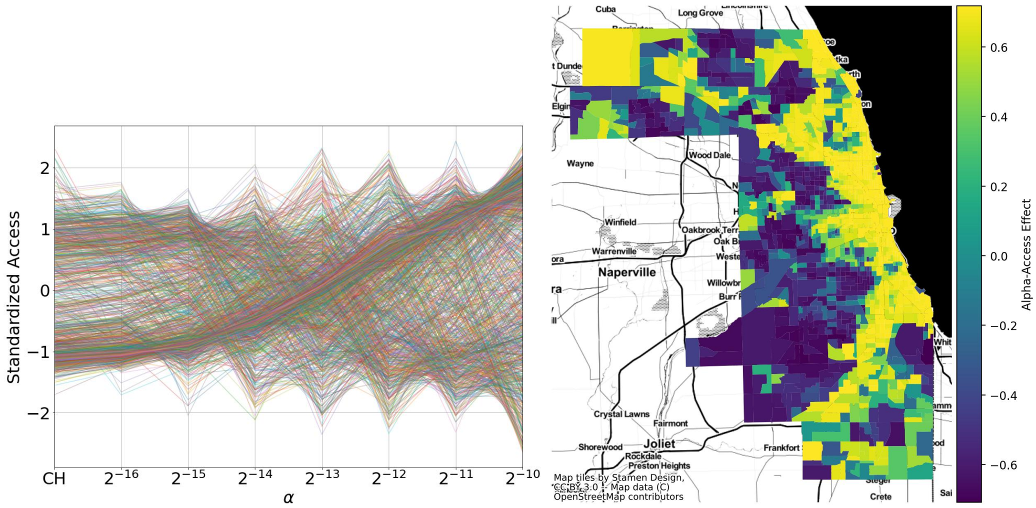
Our experiments answer two key research questions. First, what is the relationship between the alpha parameter and measured access across space? Second, does the relationship between alpha and access correlate with the CDC SVI? To accomplish this, we calculated alpha shapes using a range of alphas $(2^{-16}, 2^{-15}, \cdots, 2^{-6})$ and convex hulls around the 10, 20, and 30 minute travel zones for each hospital. Then, we calculated spatial accessibility using the E2SFCA method with the catchments produced.

To understand the relationship between alpha and access, we plotted for each census tracts standardized accessibility score based on each tested α value as shown in Figure 2a. For each census tract, we compiled the distribution of spatial accessibility measures for each value of alpha and standardized the data such that the mean was zero and standard deviation is one. It is hard to determine a clear relationship here: access in some census tracts increase while others decrease as alpha rises. However, it is clear from Figure 2a that our choice of convex hull versus alpha shape makes a significant impact on the measured spatial accessibility.

To quantify the relationship between alpha and access, we computed an "alpha-access effect" metric for each census tract, mapped in Figure 2b. The metric is the linear regression coefficient between log base two of the alpha values and standardized mean accessibility for each census tract. A positive alpha-access value indicates a positive relationship between the alpha value and the measured accessibility, whereas a negative value means the measured accessibility tends to decrease as the alpha value increases. The clustering in the map prompted us to check for spatial autocorrelation and we found a Moran's I of 0.465 and p-value of zero given by `pysal` using a Gaussian weight matrix. The map in Figure 2b shows positive values in downtown Chicago, against Lake Michigan, and generally declining values as we move west with some exceptions like O'Hare International Airport (north-western corner), the I-90 corridor (the yellow strip running from downtown Chicago to O'Hare), and the I-57 corridor (the yellow strip running south-west from the lake).

Lastly, we found a weak negative correlation (Kendall's τ: -5.45e-02, p-value: 3.06e-03) between the alpha-access effect and SVI. This is a statistically significant result at the 0.01 significance level and indicates that census tracts with high social vulnerability tend to also be the ones where measured spatial accessibility decreases as a function of alpha. Practically, this means convex hulls and low α alpha shapes tend to over-report access in socially vulnerable communities relative to higher α alpha shapes.

[1] https://hifld-geoplatform.opendata.arcgis.com/datasets/geoplatform::hospitals-1



(a) Standardized access as a function of α for census tracts in Cook County, IL

(b) Map of the "alpha-access effect" for census tracts in Cook County, IL

Figure 2 (Left) Plots of standardized accessibility by census tracts as a function of alpha for Cook County, IL. CH stands for Convex Hull and is an alpha shape with alpha equal to zero. (Right) A map of Cook County, IL giving the alpha-access effect of each census tract.

5 Concluding Discussion

In this paper, we explored how different catchment constructions (i.e., convex hull and alpha shape) affect spatial accessibility metrics that employ granular travel-time data. Our work shows that the differences are spatially autocorrelated and vary greatly depending on the alpha value used. In addition, we demonstrated that these differences in spatial accessibility – arising from the choice between convex hulls and alpha shapes – correlate with social vulnerability. This suggests that using convex hulls and low α alpha shapes for spatial accessibility may overestimate access for socially vulnerable populations which could have unintended policy implications.

While we cannot claim that either convex hulls or alpha shapes provide a ground truth for mobility, alpha shapes with appropriate values of alpha more accurately represent the data we have, as seen in Figure 1. Therefore, we can conclude that using convex hulls and inappropriately low α alpha shapes for constructing catchments tend to over-report access to ICU beds for those who are socially vulnerable in Cook County, IL. This may lead to policy-makers providing less support to socially vulnerable populations.

There is future work to do in this vein of research as more diverse spatial datasets and tools become available. It would be illuminating to apply this methodology to a variety of cities to see how much of our findings hold in cities generally. Additionally, our work used OpenStreetMap data, but there is a variety of mobility and transportation data which have potential for use in spatial accessibility studies including the Floating Car Data [10] and temporally dynamic mobility data [15]. Further work could also help to identify the circumstances in which convex hulls and alpha shapes more accurately describe real-world mobility which varies heavily based on individual-level characteristics [7].

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