Multiscale Analysis of Spatial Accessibility to Acute Hospitals in Carinthia, Austria

Changzhen Wang (cwang94@ua.edu)
The University of Alabama

Michael Leitner
Louisiana State University and A&M College: Louisiana State University

Gernot Paulus
Carinthia University of Applied Sciences: Fachhochschule Karnten

Research Article

Keywords: Accessibility, acute hospital, proximity, generalized two-step floating catchment area method (G2SFCA), Carinthia

Posted Date: May 25th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2972249/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License
Multiscale Analysis of Spatial Accessibility to Acute Hospitals in Carinthia, Austria

Abstract

Studies on spatial accessibility to health care are well established in the US for examining disparities and inequities but lacking in Austria although both experience high health care spending and have hospital care as the largest payer. This study aims to address this gap by systematically examining multiscale spatial accessibility to acute hospitals in Carinthia, one of nine provinces in Austria. Using the most recent data, the study refines the proximity method by considering bypass behavior and the generalized two-step floating catchment area (G2SFCA) method by incorporating distance decay to examine accessibility at the census block and 250-meter grid levels while accounting for the classic Modifiable Areal Unit Problem (MAUP) and edge effects. The results reveal that, on average, travel times to the nearest acute hospitals are 16 minutes for census blocks and 21 minutes for grids, covering 58.8% and 76.2% of the population, respectively. For the three nearest acute hospitals, they increase to 25 and 31 minutes, covering slightly lower populations of 52.6% and 73.4%, respectively. The bypass behavior is more influential as 20% more population living in mountainous or rural areas need to travel more than 30 minutes. The G2SFCA method with a more pronounced distance decay tends to result in a more decentralized polycentric structure of accessibility and identify more areas with the poorest access. While the urban advantage is most evident in Klagenfurt and Villach, but not all areas close to acute hospitals enjoy the best accessibility as captured by the G2SFCA method. The two methods capture different profiles of accessibility. In combination, they can identify less accessible areas, which is a key priority for health policy to improve access. In addition, the MAUP tends to overestimate accessibility at a coarse level and in areas with less or sparsely
distributed populations. The edge effects tend to occur at the border when using the proximity method, but it is more sensitive if considering bypass behavior or using the G2SFCA method with a weak decay effect. This study provides valuable insights into the spatial accessibility of acute hospitals in Carinthia and highlights the challenges faced by rural, mountainous, and other underserved areas in accessing acute care, with significant implications for health equity and resource allocation. It also underscores the importance of considering different geographic units and edge effects for health care planning and management.

**Keywords:** Accessibility; acute hospital; proximity; generalized two-step floating catchment area method (G2SFCA); Carinthia
1. Introduction

Ensuring equitable access to high-quality care has become an essential principle of health policy in many countries around the world. Inadequate access to health care is associated with decreased utilization (Lin et al. 2015) and adverse health outcomes (Onega 2008). This can widen health inequity and exacerbate already high costs for individuals and society. A policy that is being implemented in many countries to improve health care access is universal health coverage (UHC). The World Health Organization (WHO) (2022) defined it as “all people have access to the full range of quality health services they need, when and where they need them, without financial hardship.” Although significant efforts have been made on reducing disparities and improving access, given the uneven distribution of populations and health care, it is unknown whether the health care offered at a given location is geographically accessible and available to all populations. Also, countries aiming for UHC have substantial health care costs, similar to those without UHC. For example, in 2021, Austria spent 12.2% of its Gross Domestic Product (GDP) on health care (Statistics Austria 2022) which is close to the US with 18.3% of GDP (American Medical Association (AMA) 2020). One of the major reasons for such high costs is the persistent disparities in access to care and health outcomes (Wang 2012). Moreover, both Austria and the US have hospital care as the largest payer of health care spending, accounting for 33.8% (Federal Ministry of Labour 2019) and 31.1% (AMA 2020), respectively. Due to the rapid development of Geographic Information Systems (GIS), studies on access to health care have been well established and have become a policy priority in the US. However, few studies have examined the spatial accessibility to hospital care in Austria, which is the focus of this paper.
In relative terms, Austria has the largest number of hospital beds and most hospital stays among all states in the European Union (Federal Ministry of Labour 2019). The hospital landscape is diverse and is composed of acute and non-acute hospitals, profit and non-profit hospitals, or public and private hospitals. An acute hospital (equivalent to acute care hospital in the US) refers to a hospital that provides short-term inpatient care for illness, disease, injury, surgery, or other acute medical conditions, such as emergency medicine, acute care surgery, urgent care, trauma care, and short-term inpatient stabilization (Hirshon et al. 2013). It can be divided into a general and specialized hospital. Non-acute hospitals solely provide specialized care which includes long-term care and rehabilitation centers (Federal Ministry of Labour 2019). Among them, the number of acute hospitals and their beds dominate the entire health care system in Austria (e.g., 45% of total hospitals and 70% of total beds) (Federal Ministry of Labour 2019). Thus, it is important to understand how accessible they are to the public so that the services can be better delivered to cope with the increasing costs and health disparities.

Access to health care can be conceptualized into five dimensions: availability, accessibility, accommodation, affordability, and acceptability (Penchansky and Thomas 1981). Some studies classify it into potential accessibility and revealed accessibility based on whether patients truly utilize the care. In some circumstances, geographic data for revealed accessibility measurement are very limited, so a large body of literature focuses on potential accessibility to examine health disparities, inequities, or the effectiveness of the existing health care system, such as access to primary care (Del Conte et al. 2022; Demitiry et al. 2022; Guagliardo 2004; Hafner and Mahlich 2016; Luo and Wang 2003; Luo and Qi 2009; Wang, Vingiello, and Xierali 2020), cancer care (Onega et al. 2008; Xu et al. 2017), pharmacies (Ikram, Hu, and Wang 2015), hospitals or clinics (Alford-Teaster et al. 2021; Bauer et al. 2020; Weiss et al. 2020), daycare
centers (Fransen et al. 2015), and emergency medical services (Fritze, Graser, and Sinnl 2018; Li, Hu, and Gregg 2022). However, very few of literature is in Austria and it lacks to examine access to acute hospitals. For instance, Bauer et al. (2020) examined the access to intensive care unit (ICU) beds in 14 European countries and found that in Austria, the mean travel time to the closest hospital was 12.7 minutes. Hafner and Mahlich (2016) measured the access to physician care and found that the mean travel time of physician visits was 9.83 minutes in Vienna, Austria. Fritze, Graser, and Sinnl (2018) estimated the realistic travel times of patients to optimize emergency medical service stations in Lower Austria.

Centered on this topic, there has been much debate about which method is more accurate in estimating access to health care. Our review of the literature indicates that the commonly used measures include provider-to-population ratio, travel time or distance to capture proximity, and the generalized two-step floating catchment area (G2SFCA) method. While the first two measures are straightforward, they omit the crowdedness of facilities in high-demand seasons or choices of providers. For proximity, patients may not go to the closest facility for the care and some of them even bypass it. The G2SFCA method overcomes these issues, and it has become a popular measure in accessibility studies (Wang 2015: 110). This method accounts for a match ratio between health care supply and demand and their interactions captured by a decayed impedance. To adapt to more realistic scenarios including telehealth, spatial behaviors, and insurance for better accuracy, the G2SFCA method has been functionalized into different versions (Alford-Teaster et al. 2021; Del Conte et al. 2022; Fransen et al. 2015; Luo and Qi 2009; Shao and Luo 2022; Wang 2012). Despite that, the method’s complexity needs to be weighed against the increased computational cost and data availability. Because the proximity and availability of health care are two distinctive properties capturing certain aspects of accessibility,
this study will refine the proximity and G2SFCA methods to comprehensively measure the spatial accessibility to acute hospitals.

Both methods need an accurate estimate of spatial impedance from patients to their service providers. The measure ranges from a simple estimate such as Euclidean or geodesic distance to a complex estimate such as network distance or time on static road networks or online network data providers that consider real-time traffic conditions. While the network-based estimate is more accurate as most human movements generally occur along physical roads, there are concerns about the settings of data timeliness, computation, service request limits, speed limits, and dynamic traffic conditions. Moreover, this may require high-performance computers to store large travel estimates from patients to their providers. Fortunately, GIS enables us to address these issues, for example, using some online network data providers such as Google Maps, ArcGIS Online, and OpenStreetMap (OSM). These data have been used in some recent studies (Delmelle et al. 2019; Shao and Luo 2022; Wang and Wang 2022b), and their travel time estimations are shown to be largely consistent (Delmelle et al. 2019). Because of the merits of OSM (e.g., free, no limits of requests, high-quality, and up-to-date road network data (Shao and Luo 2022)), this study will use it to estimate the spatial impedance of people to acute hospitals.

Another issue is the selection of reliable geographic units on which valid measurement and analysis of accessibility can be conducted to inform health policy and planning. Indeed, how data are aggregated to different spatial units may have different results even with the same analysis. This is commonly known as the “modifiable areal unit problem” (MAUP) (Fotheringham and Wong 1991). As a classic geographic issue, MAUP has scale effects and zoning effects. As explained by Kwan (2009), the scale effect refers to the variations in results generated from the same analysis unit at different spatial resolutions, such as census tract versus
census block. In contrast, the zoning effect refers to the sensitivity of results obtained from the regrouping of zones at a given scale, such as hospital service areas (Wang and Wang 2022a). Though largely intractable, MAUP can be mitigated through some potential solutions. For example, Mu and Wang (2008) developed a scale-space clustering method that accounts for attribute homogeneity and spatial contiguity to delineate homogenous zones for analysis. Some other studies tend to select multiple spatial units and compare their results to minimize this problem (Wang, Wang, and Onega 2021b, 2021a; Xu et al. 2017). This study will examine the spatial accessibility to acute hospitals at the census block and grid levels to identify the possible influence.

In addition, health care accessibility may be subject to the classic edge effect (Van Meter et al. 2010; Chen 2017). Edge effect refers to less reliable or less stable results near the border of a study area if patients prefer to cross the border for care (Wang 2020). While some studies argue that the impact of edge effects may not be significant and should be examined on a case-by-case basis (Gao et al. 2017), others claim that overlooking the edge effect can result in underestimation of accessibility (Sadler, Gilliland, and Arku 2011; Van Meter et al. 2010). To avoid its potential impact, previous studies often create a buffer zone around the study area to measure accessibility (Dai 2010; Gao et al. 2017; Luo and Wang 2003; Shao and Luo 2022). In other words, they assume the presence of edge effects rather than directly examining their existence. This study will fill this gap by comparing the spatial accessibility to acute hospitals with or without a buffer zone to examine their impacts.

In short, this study will provide a comprehensive and multiscale measurement of the spatial accessibility to acute hospitals in Carinthia, Austria by improving two popular methods: proximity method and G2SFCA method. Both will be applied to the most recent data.
Additionally, they will account for the classic MAUP and edge effects. This study differs from previous health care accessibility studies in the following aspects:

(1) It will use the proximity method to estimate not only the travel time to the closest acute hospital, but also travel times to the second and third nearest acute hospitals, and their averages to account for real-world bypass behavior.

(2) While the proximity method captures the travel burden of patients, the G2SFCA method considers the availability of and competition for acute hospital care with a decayed impedance. Both will be examined at the census block and grid levels to identify where and how they are (in)consistent to assess the impact of the MAUP.

(3) Unlike previous studies using static road networks or samples data from Google Maps (Hu et al. 2020), this study will apply OSM, a high-quality, up-to-date, and free road network data provider, to estimate the spatial impedance from patients to providers.

(4) Since the edge effect is unknown, this study will compute the accessibility in Carinthia with and without its surrounding buffer zone using the above two methods to examine possible impacts.

To our best knowledge, there has been no study examining the spatial accessibility to acute hospitals in Austria. The study will contribute to our understanding of how accessible acute hospitals are, using the Austrian province of Carinthia as an example, and whether and how the selection of two different geographic units and edge effects will influence accessibility. Further, it will provide policymakers and decision makers with some insights into acute hospital care delivery, management, and planning to improve access and achieve health equity in one Austrian province.
2. Study Area and Data Preparations

2.1. Study Area

The study area is Carinthia, the southernmost province in Austria. As shown in Figure 1, it is bordered by Italy and Slovenia to the south and several other provinces of Austria on the other three sides: Tyrol to the west, Salzburg to the northwest, and Styria to the northeast. According to the recent statistics from City Population (2022), it had 564,513 people living on 9,536 km² land, resulting in a population density of 59.20 people/km². Carinthia consists of two statutory cities: Villach and the capital Klagenfurt, and eight districts: Spittal an der Drau, Feldkirchen, Sankt Veit an der Glan, Wolfsberg, Völkermarkt, Klagenfurt-Land, Villach-Land, and Hermagor. Klagenfurt is not only the capital but also the most populous city in Carinthia. Given that Carinthia is bounded by rich mountain ranges, such as the Carnic Alps, High Tauern, Großglockner, Gurktal Alps, and Karawanken Alps, many regions are geographically separated but are connected by major roads or railways. Such a physical barrier may impede people’s access to health care and subsequently affect their health outcomes. Therefore, it is crucial to measure spatial accessibility to acute hospitals that provide the most basic services on the front lines.
2.2. Population Across Census Blocks and 250-meter Grids

One important component of measuring spatial accessibility is health care demand. Since everyone need acute care, we use population as a proxy. To examine the potential impact of MAUP, we used the 2020 population data at the census block and 250-meter grid levels. Specifically, we downloaded the census block layer across entire Austria from OGD Austria (2022) and then joined the population collected from the same website to it. We collected the grid layer of Carinthia from WIGeoGIS (2022), a leading spatial data provider in Europe. To examine edge effects, we created a 15-mile buffer around the boundary of Carinthia, a common criterion used in prior studies (Luo and Wang 2003; Shao and Luo 2022). We then extracted all
grids and census blocks inside Carinthia plus the 15-mile buffer area. As shown in Table 1, we
gained 607 census blocks and 23,880 grids with populations of 562,089 and 561,628 inside
Carinthia. With the buffer area, there were 1,036 census blocks and 40,145 grids with total
populations of 892,034 and 891,308, respectively. Grids and census blocks with zero populations
were then removed in the following analysis. It should be noted that the differences in
populations between two units (461 and 726) are very small and negligible.

Table 1. Summary of data and data sources, for the Austrian province of Carinthia with and
without buffer area, 2020

<table>
<thead>
<tr>
<th>Study area</th>
<th>Data layer</th>
<th>Number of records</th>
<th>Spatial scale/format</th>
<th>Data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carinthia</td>
<td>Census block population</td>
<td>607 (562,089 people)</td>
<td>Polygon</td>
<td>OGD Austria</td>
</tr>
<tr>
<td>Grid population</td>
<td>23,880(^a) (561,628 people)</td>
<td>250-meter grid/polygon</td>
<td>WIGeoGIS</td>
<td></td>
</tr>
<tr>
<td>Acute hospital</td>
<td>13 (3,436 beds)</td>
<td>Point</td>
<td>50plus.at</td>
<td></td>
</tr>
<tr>
<td>Road network</td>
<td>-</td>
<td>Polyline</td>
<td>OpenStreetMap (OSM)</td>
<td></td>
</tr>
<tr>
<td>Carinthia and a 15-mile buffer area</td>
<td>Census block population</td>
<td>1,036 (892,034 people)</td>
<td>Polygon</td>
<td>OGD Austria</td>
</tr>
<tr>
<td>Grid population</td>
<td>40,145(^b) (891,308 people)</td>
<td></td>
<td>WIGeoGIS</td>
<td></td>
</tr>
<tr>
<td>Acute hospital</td>
<td>20 (5,018 beds)</td>
<td>Point</td>
<td>50plus.at</td>
<td></td>
</tr>
<tr>
<td>Road network</td>
<td>-</td>
<td>Polyline</td>
<td>OpenStreetMap (OSM)</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) refers to 154,774 grids in total, of which 23,880 grids have a nonzero population.
\(^b\) refers to 285,961 grids in total, of which 40,145 grids have a nonzero population.

As shown in Figure 2a, areas with high population densities are concentrated in the
centers of districts or cities and less obvious along major roads. Interestingly, the triangle area
between Villach, Klagenfurt, and Feldkirchen has the highest population densities. A similar
pattern is found at the grid level but with some differences. The grid population is mainly
distributed along the major roads connecting different districts and cities and is concentrated in
the two largest urban areas of Klagenfurt and Villach, followed by Spittal an der Drau, Sankt Veit an der Glan, and Wolfsberg.

Figure 2. (a) Population density of census blocks and acute hospital beds in Carinthia.
2.3. Acute Hospital Capacity

The second component of measuring accessibility is health care supply. Prior research has often adopted hospital beds as a capacity measure (Alford-Teaster et al. 2021; Jing et al. 2023; Mao and Nekorchuk 2013; Wang et al. 2018), which was used in this study. We obtained all hospitals from the 50plus.at platform (2022). It is a local and popular website that provides health care, music, food, travel, and other information. On the website, each hospital has a name, address, bed counts, contacts, and specialties. We identified acute hospitals and geocoded their addresses in Google Maps to create a point layer. Table 1 reported 13 acute hospitals with 3,436 beds.
beds in Carinthia and 20 acute hospitals with 5,018 beds in Carinthia plus the 15-mile buffer area. Overall, the hospital bed ratio is 6 per 1,000 people, slightly lower than that for the entire Austria (7 beds per 1,000 people).

As shown in Figure 2, the capital Klagenfurt has more acute hospitals with more beds, followed by Villach, Sankt Veit an der Glan and Spittal an der Drau. No acute hospitals are in the northwest of the map, including Spittal an der Drau, Feldkirchen, the entire Völkermarkt district, Klagenfurt-Land, and Villach-Land. This implies that residents from these districts need to travel across district boundaries to acute hospitals.

2.4. Travel Time Estimation through OpenStreetMap

Our third component is estimating travel times from the demand (O) to the hospital supply (D). Travel time is a preferable measure, especially in service accessibility studies because it is more relevant and accurate than pure travel distance that often omits traffic conditions, speed limits, and means of transportation (Luo 2004). Moreover, most Austrians (65%) commute by car (Statista 2022). Although a considerable proportion of people take public transportation (34%) and the remaining 1% ride bikes, in the absence of such data and given that sick people may not be able to take them, we used car driving as the transport mode. Unlike most prior research using static road networks (Luo and Wang 2003; Mao and Nekorchuk 2013; Ikram, Hu, and Wang 2015), we used OSM to measure the driving time from the geographic centroids of census blocks and grid cells to each acute hospital, respectively. OSM offers up-to-date network data and routing services for public free use. The accuracy is proved to be similar to other network data providers (Delmelle et al. 2019). We used the Open Source Routing Machine (OSRM), a high-performance routing engine to find the shortest path along the roads with pre-set
speed limits, turn restrictions, and other topologies. We obtained two large driving time matrices with a total of 802,900 OD pairs for the 250-meter grid (= 40,145 * 20) and 20,720 OD pairs for the census block data (= 1,036 * 20). To evaluate the accuracy of travel time matrices, we sampled small numbers of OD pairs and estimated their travel times using Google Maps API. Their travel times were largely consistent with high R-square of 0.99 and 0.97, respectively, similar to those reported by Delmelle et al. (2019).

3. Methods of Measuring Spatial Accessibility

3.1. GIS-based Proximity Method

The GIS-based proximity method is a globally popular approach to measure health care accessibility. It assumes that residents only use the closest facility. However, there has been much debate as patients may bypass the closest facility to seek their care (Wang, Onega, and Wang 2022). Moreover, most people tend to travel farther to seek high-quality or specialized care (McLafferty 2003), such as hospitalization for cancer patients (Wang, Wang, and Onega 2021b). Through the comparison of travel times to the closet and actual facility, Alford-Teaster et al. (2016) found that a small proportion of the population frequented the closest facility and the majority traveled to the facility within a 30-minute range of the closest facility. In the absence of actual trips, we refined the proximity method by estimating travel times from each census block and grid to the nearest, second nearest, and third nearest acute hospitals. We then computed average travel times to the three nearest and to all acute hospitals to compare their differences.
3.2. GIS-based Generalized Two-Step Floating Catchment Area (G2SFCA) Method

For the past decades, the 2SFCA method has been widely employed in measuring spatial accessibility, disparity, and inequality to inform health policies for improving access and reducing inequity. Essentially, the 2SFCA method measures the ratio of health care supply and demand accounting for their complex interactions. It can be implemented in two steps: (1) for each acute hospital location \( i \in (1, 2, 3, ..., n) \), it searches all population centroids of grids or census blocks \( j \) within a predefined threshold travel time \( (d_o) \) from location \( i \) (or catchment area \( i \)), and then computes the bed-to-population ratio \( R_i \) within the catchment area in Equation (1):

\[
R_i = \frac{S_i}{\sum_{j \in \{d_{ji} \leq d_o\}} D_j}
\]  

where \( S_i \) is the hospital beds at location \( i \), \( D_j \) is the population at location \( j \) within the catchment area, \( d_{ji} \) is the travel time from population centroid \( j \) to acute hospital \( i \); (2) for each population centroid of grids or census blocks \( k \in (1, 2, 3, ..., m) \), it searches all beds at hospital location \( i \) within the same threshold travel time \( (d_o) \) from location \( k \) (or catchment area \( k \)), and sums up the bed-to-population ratio \( R_i \) to compute accessibility \( A_k \) in Equation (2):

\[
A_k = \sum_{i \in \{d_{ki} \leq d_o\}} R_i = \sum_{i \in \{d_{ki} \leq d_o\}} \sum_{j \in \{d_{ji} \leq d_o\}} \frac{S_i}{\sum_{j \in \{d_{ji} \leq d_o\}} D_j}
\]

the first step measures the availability of hospital services at the supply location and the second step measures the total values of supply-demand ratios at the demand location. Therefore, a large \( A_k \) suggests a better accessibility.

However, the choice of catchment area has raised some major debates. It assumes that all people within a catchment area have equal access, but those outside the catchment have no
access to care (Luo and Wang 2003). Also, selecting different catchment sizes may introduce
uncertainty to accessibility scores. Both issues can bias the estimate. For this reason, many
studies have attempted to address the limitations, such as incorporating distance decay to develop
different accessibility measures (Guagliardo 2004; Luo and Qi 2009). As summarized by Wang
(2012), all these methods can be generalized into one framework, termed G2SFCA model, which
is expressed as:

\[
A_k = \sum_{i=1}^{n} \frac{S_i f(d_{ki})}{\sum_{j=1}^{m} D_j f(d_{ji})}
\]  \hspace{1cm} (3)

where \(f(d_{ki})\) and \(f(d_{ji})\) are distance decay functions captured by the travel time from
population locations \(k\) or \(j\) to acute hospital location \(i\). All other variables are identical to those
explained in Equations (1) and (2).

In the context of health studies, distance decay describes the interaction between health
care demand and supply declines with longer travel times between them (Wang 2015). It has
been conceptualized as different functional forms such as inverse power \(f(d_{ji}) = d_{ji}^{-\beta}\) (Luo
and Wang 2003; Wang and Tang 2013; Wang et al. 2020), exponential \(f(d_{ji}) = e^{-\beta d_{ji}}\) (Jing
et al. 2023; Tang et al. 2017; Wang 2018), square root exponential \(f(d_{ji}) = e^{-\beta \sqrt{d_{ji}}}\) (Wang et
al. 2021b), Gaussian/normal \(f(d_{ji}) = e^{-\beta d_{ji}^2}\) (Dai 2010; Shao and Luo 2022; Shi et al. 2012),
and log-logistic \(f(d_{ji}) = \frac{1}{(1 + \frac{d_{ji}}{\alpha})^\beta}\) (Delamater et al. 2013). Ideally, the best-fitting distance
decay function \(f(d_{ji})\) and friction coefficient \(\alpha\) or \(\beta\) can be estimated by analyzing the real-
world patient-to-hospital flows. For example, Wang (2021) used them in Florida and found the
inverse power to be the best in capturing the travel behaviors of patients and the friction
coefficient \(\beta\) to be 1.3. Tao et al. (2020) used hospitalization data in Hubei, China, and found
that the inverse power outperformed all other distance decay functions and the corresponding $\beta$ fell into a range from 1 to 1.6. However, without actual trips, most studies opt for empirical functions. This study used the inverse power function to measure the accessibility and performed a sensitivity analysis using $\beta$ from 1 to 1.6 with an interval of 0.1.

4. Results and Discussions

4.1. Comparing Travel Time Across Census Blocks and Grids

Because our interest is the accessibility of people in Carinthia, our following analyses will mask out those in the 15-mile buffer zone. As shown in Figure 3, the travel times to the first three nearest acute hospital increase, but decrease when the values are averaged, and increase when averaging values to all acute hospitals at both the census block and grid levels. For all travel times at each level, they have almost identical mean and median values which however cover different percentages of population. For instance, 58.8% of the block population travel 16 minutes on average to reach the nearest acute hospitals, while 76.2% of the grid population averagely travel 21 minutes. Taking bypass behavior into account, 52.6% and 73.4% of the block- and grid-based populations need to drive 25 and 31 minutes on average to reach the three nearest acute hospitals. Although the population proportions drop a little, the extra 10 minutes can give patients two more choices of close acute hospitals. Between the two level, mean travel times across grids are longer but with less variability. This is understandable as a block is larger, using its geographic centroid underestimates the travel time to acute hospitals.
Figure 4 shows estimated travel times to the nearest and three nearest acute hospitals. For both spatial units, less than 60% of the population living around acute hospitals in urban areas enjoy the shortest travel time of 15 minutes to reach acute hospitals, followed by 32% and 33% traveling between 15 to 30 minutes (see Figure 4a-b). This suggests that half people benefit from the urban advantage. The remaining minorities (11% and 8%) need to travel longer than 30 minutes to reach the nearest acute hospital. Between the two units, the variability of travel times is smoothed across blocks but is revealed across grids as indicated by shorter times of grids along major roads that connect different districts or cities. Compared to blocks, a higher proportion of the grid population travel within 30 minutes to reach the closest acute hospital (89% vs 92%). When it comes to average times to three nearest acute hospitals, the patterns change significantly although they are similar at two levels. In Figure 4c-d, a peak occurs in Klagenfurt where 21% and 22% of the total population can reach three acute hospitals within 15 minutes on average. Longer travel times are observed for areas with acute hospitals connected by major roads in
southern Carinthia and the surroundings of Klagenfurt, where 45% and 49% of population drive 15 to 30 minutes. The remaining 34% and 29% of population reside in the periphery of Carinthia and need to travel exceeding 30 minutes. These percentages are higher than those who can reach the nearest acute hospital in more than 30 minutes (see Figure 4a-b).

To quantify differences in travel times and their respective population proportions between two units, we assigned the travel time of each block to each grid and mapped the results in Figure 5. Note that the negative (positive) values in red (green) color refer to travel times across grids being smaller (larger) than those across blocks. Areas with yellow color refer to similar travel times within a 10-minute range between the two units. Travel time differences to the nearest and three nearest acute hospitals exhibit similar patterns. For both units, most of the population (86% and 87%) residing near the centers of districts or cities travel similar times to reach one to three acute hospitals. Compared to blocks, the grid population along major roads and in peripheries of districts or cities tend to underestimate travel times. This implies that the MAUP is more likely affecting less or sparsely populated areas.
Figure 4. Travel times to the nearest acute hospital across (a) census blocks and (b) 250-meter grids, and average travel times to the three nearest acute hospitals across (c) census blocks and (d) 250-meter grids in Carinthia.
4.2. Comparing Accessibility Scores to Acute Hospitals Across Census Blocks and Grids

Table 2 reported block- and grid-based accessibility with different friction coefficients. To avoid too small values, all scores are inflated by multiplying by 1,000. Results are interpreted as acute hospital beds per 1,000 people.
Table 2. Descriptive statistics of block-based and grid-based accessibilities in Carinthia

<table>
<thead>
<tr>
<th>Travel friction coefficient</th>
<th>Block-based accessibility</th>
<th>Grid-based accessibility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>β = 1</td>
<td>6.73</td>
<td>5.27</td>
</tr>
<tr>
<td>β = 1.1</td>
<td>6.78</td>
<td>5.04</td>
</tr>
<tr>
<td>β = 1.2</td>
<td>6.82</td>
<td>4.74</td>
</tr>
<tr>
<td>β = 1.3</td>
<td>6.85</td>
<td>4.44</td>
</tr>
<tr>
<td>β = 1.4</td>
<td>6.88</td>
<td>4.09</td>
</tr>
<tr>
<td>β = 1.5</td>
<td>6.90</td>
<td>3.71</td>
</tr>
<tr>
<td>β = 1.6</td>
<td>6.92</td>
<td>3.38</td>
</tr>
</tbody>
</table>

SD refers to standard deviation.

Overall, the block-based accessibility is higher than the grid-based accessibility in terms of the mean and median values but with larger variations (4.14 – 12.06 vs 1.64 – 4.26), except for the last case (β = 1.6). Interestingly, each average block-based accessibility is slightly higher than the overall acute hospital bed ratio (= 6) while the average grid-based accessibility is much lower. For both units, the increase of the friction coefficient from 1 to 1.6 leads to a slight increase in the average block-based accessibility but to a larger decrease in its median values, and the mean and median values of the grid-based accessibility. It also results in higher standard deviations of accessibility at two units, implying a reduced spatial smoothing effect but the change is slower across grids. Another interesting finding is that the variability of the two-level accessibility is much more stable for the intermediate values of the friction coefficient, for example, when β = 1.3. This is consistent with the friction coefficient regressed from the real patient-to-hospital flows in Florida (Wang 2021).

To distinguish the differences of accessibility across two units, we visualize their scatter plots and spatial patterns in Figure 6. For each map, we symbolize the accessibility scores into five classes with the same interval for easy comparison. As the friction coefficient β increases, the goodness of fit between the block- and grid-based accessibility declines from 0.81 to 0.39. It
suggests that a stronger distance decay effect, indicative of a shorter travel time, is more likely to generate less consistent accessibility scores with a possible overestimation at the block level.

For all maps in Figure 6, major patterns of accessibility shown at the two geographic levels are largely consistent and stable at $\beta = 1.3$. The distribution of accessibility changes from a dual-nuclei structure based on Villach and Klagenfurt to a decentralized polycentric structure extending throughout the whole study area, with accessibility shrinking towards the centers of the districts. At both geographic levels, the accessibility peaked around acute hospitals in the urbanized areas of Klagenfurt and Villach (> 9 beds per 1,000 people), covering 19% or 20% of the total population, respectively, followed by Sankt Veit an der Glan, and other districts with larger $\beta$. The rise of $\beta$ results in a higher population proportion (2% to 44%) being least accessible to acute hospitals (see the range $\leq 3$ beds per 1,000 people). Most of them live in the Völkermarkt district, but also in the outskirts of Carinthia, and mostly in mountainous or rural areas. This rise also results in less population falling into the accessibility ranges of 3 – 5 (39% – 22% for blocks, and 41% – 21% for grids) and 5 – 7 (29% – 8% for blocks and 28% – 9% for grids). This shows that a larger friction coefficient only has a minor impact on the most accessible areas, but it tends to identify more areas or populations with the poorest accessibility, which is more obvious at a finer level. This fact may be exacerbated during the Covid-19 pandemic or the flu season, especially during winter. Some acute hospitals may become overcrowded, leading to longer wait times for appointments or visits. To mitigate this, health departments and agencies may need to plan ahead to provide or allocate additional mobile beds, physicians, nurses, or assistants in the acute hospitals located in those areas. Furthermore, most grid populations are distributed along physical roads, as is their accessibility. While this is more
realistic, given less availability of finer-scaled data, the grid-based accessibility can be a supplement to support acute care delivery.

The spatial pattern of accessibility computed by the G2SFCA method differs from those estimated by the proximity method. Instead of being higher with shorter travel times to acute hospitals, the accessibility by the G2SFCA method is selectively higher around acute hospitals as it considers the competition and availability of acute hospitals. Thus, not all blocks or grids closest to acute hospitals enjoy the best accessibility, which is apparent, when analyzing areas around the acute hospital in Feldkirchen in Figure 6.
Figure 6. Scatter plots and maps of block- and grid-based accessibilities using different friction coefficients in the G2SFCA method.
4.3. Examining Edge Effects on Measuring Accessibility Across Census Blocks and Grids

This section examines edge effects on accessibility measured from the proximity and the G2SFCA methods at the census block and grid levels using data for Carinthia and data with an additional buffer zone. Due to the limited space, only the difference of travel times to the nearest and the three nearest acute hospitals are shown in Figure 7a – 7b, respectively. Differences in the two levels with friction coefficients equal 1 and 1.6 are shown in Figure 7c-d. Obviously, for both levels in Figure 7a-b, the edge effects only affect the accessibility of areas along the northern borders of Carinthia, which seem to be fairly consistent. Between the two methods, the differences in the travel time to the three nearest acute hospitals (see red color) are more sensitive as they cover more areas with higher populations.

In Figure 7c-d, we use a small range of -0.5 to 0.5 to indicate an acceptable difference of accessibility measured by the G2SFCA method. The negative (positive) values represent the accessibility obtained without the buffer zone to be smaller (larger) than those with the buffer zone. For both geographic levels with the same friction coefficient, their differences in accessibility exhibit similar patterns. The highly urbanized areas in darker purple and green colors or areas near provincial boundaries in light pink or green colors exhibit the largest difference in accessibility. Although urbanized areas are higher than provincial border areas, border areas are less populated (see Figure 7c-d), suggesting higher sensitivity of edge effects near provincial borders. The edge effect seems stronger at the grid level with more populations being affected, especially those living near the northern border (52% vs. 44% or 52% vs. 10%).

Furthermore, as the friction coefficient increases, more regions and populations at the bottom of the map fall into the acceptance range of accessibility differences, along with reduced populations in higher or lower differences. It shows that edge effects have less impact on
accessibility when a stronger distance decay effect is applied. This is understandable as the G2SFCA method uses a distance decay function without limits on the catchment size, and thus all blocks or grids close to or further away from the provincial border are involved in the calculation of accessibility. This also makes spatial patterns different from those shown in Figure 7a-b. The edge effect examined through the proximity method only applies to regions close to the provincial border while in the G2SFCA method, it affects more areas close to or further away from the border.
Figure 7. (a)-(b) Edge effect of travel time across census blocks and grids in Carinthia, and (c)-(d) edge effect of G2SFCA-based accessibility using two friction coefficients across census blocks and grids in Carinthia.
5. Conclusions

Studies on spatial accessibility to health care are well established in the US for examining disparities and inequities but lacking in Austria although both experience high health care spending and have hospital care as the largest payer. This study examines the multiscale spatial accessibility to acute hospitals in Austria with the most recent data in the province of Carinthia, as an example. The study refines the proximity method by considering bypass behavior and the generalized two-step floating catchment area (G2SFCA) method by incorporating inverse power distance decay to examine accessibility at the 250-meter grid and census block levels while accounting for the classic Modifiable Areal Unit Problem (MAUP) and edge effects. To our best knowledge, this is the first study systematically examining the spatial accessibility to acute hospitals for an Austrian province.

This study yielded some interesting findings that will inform health interventions and contribute to our understanding of geographic issues in applying GIS to public health. Overall, most Carinthian can reach the nearest and three nearest acute hospitals within 30 minutes, and travel times for those living around acute hospitals, especially in urban areas, are much shorter. The bypass behavior is more influential as 20% more population living in mountainous or rural areas need to travel more than 30 minutes, suggesting the poorest access in these areas. However, not all areas close to acute hospitals enjoy the best accessibility, such as Feldkirchen. This may be attributable to hospital crowdedness captured by the G2SFCA method but is overlooked by the proximity method. Both methods capture different profiles of accessibility, and they complement each other by identifying areas that lack accessibility which will be a key priority for health policy to improve access.
Further, the consideration of bypass behavior in the proximity method only adds 10-minute travel time, providing more people with more choices to reach acute hospitals. This is especially true for those people living in Klagenfurt, followed by southern Carinthia, and the periphery of Carinthia. Also, bypass behavior results in a similar pattern at the two levels of analysis. For the G2SFCA method, a stronger distance decay is more likely to result in a decentralized polycentric structure of accessibility. While this method has a minor impact on most accessible areas, it tends to identify more areas with the poorest accessibility. Cautions may be taken as this situation may be exacerbated in these poorest accessibility areas during the flu season, or during a pandemic, such as Covid-19. Health departments and agencies may need to plan ahead to improve access in these areas. The variability in accessibility seems more stable when the friction coefficient equals 1.3. This is consistent with a previous study using real trips (Wang 2021). We thus recommend using this value in the inverse power function for accessibility measures in Carinthia.

The selection of geographic units affects accessibility. While the overall patterns are largely consistent, the larger blocks tend to overestimate accessibility with more variabilities, and the spatially finer grids seem to yield lower accessibility with higher stability. The consideration of bypass behavior may increase the variability of travel times at the grid level, particularly for those along major roads connecting different districts or cities. Also, less or sparsely populated areas are more susceptible to the MAUP. Therefore, when it comes to the health care management and planning, one should be careful about the selection of geographic units. However, as always, a trade-off exists between higher accuracy and longer computational time for finer-scale analysis.
The presence of edge effects relies on the method selected to measure accessibility and are more likely to occur when using the G2SFCA method. In the original proximity method, only areas along the northern border are affected, but when considering bypass behavior, the accessibility is more sensitive to the edge effects. In contrast, in the G2SFCA method, more areas are affected, especially those near the northern border and highly urbanized areas with acute hospitals nearby. However, when a stronger distance decay effect is applied, edge effects are less influential.

This study has some limitations that warrant discussion and call for future work. First, due to the limited data, the study only considers spatial accessibility to acute hospitals. Future studies should consider socioeconomic inequalities and rural-urban disparities that may affect hospital access. Second, this study applies OSM to measure travel times to acute hospitals while neglecting the time of leaving homes, waiting for doctors and admissions, which may underestimate the total time of receiving short-term acute care. Nevertheless, it is very challenging to take these additional times into consideration. Further, the nearest or the three nearest acute hospitals may not be the primary choices of patients due to the availability of beds, quality and scope of services, or patients’ preferences or familiarities. Future studies should consider using hospitalization data to estimate actual travel times or derive the best-fitting distance decay function to better measure accessibility by the G2SFCA method. Third, the study chooses car driving as the only means of transportation, given that almost 2/3 of Austrians prefer this type of transportation. However, since public transportation or bicycling are also very popular for commuting, future studies should incorporate multimodal accessibility when related transportation data are available.
References


