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Article

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

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Abstract: Health care accessibility studies are well established in the US but lacking in Austria, even though both experience high costs and have hospital care as the largest contributor to health care spending. This study aims to examine multiscale spatial accessibility to acute hospitals in Carinthia, Austria. Using the most recent data at census block and 250 meter grid levels, we refine proximity and generalized two-step floating catchment area (G2SFCA) methods while accounting for the modifiable areal unit problem (MAUP) and edge effects. For census blocks and 250 meter grids, the mean travel times to the nearest acute hospitals are 16 and 21 min, respectively, covering 58.8% and 76.2% of the population, which, however, increases to 25 and 31 min to the three nearest hospitals with similar populations. People bypassing the nearest hospital to seek hospitals at a longer distance, termed "bypass behavior", is more influential, as 20% more of the population living in mountainous or rural areas need to travel 30 min longer. The G2SFCA method with a more pronounced distance decay results in a more decentralized polycentric structure of accessibility and identifies poorer access areas. While urban advantage is most evident in Klagenfurt and Villach, not all areas near hospitals enjoy the highest accessibility. A combination of the proximity and G2SFCA methods identifies less accessible areas. The MAUP overestimates accessibility at a coarse level and in less populous areas. Edge effects occur at the border when using proximity only, but they are more sensitive when considering bypass behavior or a weak distance decay effect. This study contributes to our understanding of acute hospitals' accessibility in Carinthia and highlights the need to improve low-accessible areas in addition to universal health coverage. Cautions need to be exercised when using different geographic units or considering edge effects for health care planning and management.

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

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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 [1] and adverse health outcomes [2]. 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) [3] 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 to reduce disparities and improve 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 [4] which is close to the US, having spent 18.3% of its GDP [5]. One of the major reasons for such high costs is the persistent disparities in access to care and health outcomes [6]. Moreover, both Austria and the US have hospital care as the largest contributor to health care spending, accounting for 33.8% in 2019 [7] and 31.1% in 2021 [5], 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 [1,2,6]. 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 [7]. 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 an 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 [8]. 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 [7]. 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) [7]. Thus, it is important to understand how accessible they are to the public so that the services can be better delivered to cope with increasing costs and health disparities.

Access to health care can be conceptualized into five dimensions: availability, accessibility, accommodation, affordability, and acceptability [9]. 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 and uses it to examine health disparities, inequities, or the effectiveness of an existing health care system, such as measuring access to primary care [10–16], cancer care [17,18], pharmacies [19], hospitals or clinics [20–22], daycare centers [23], and emergency medical services [24,25]. However, very few studies are based in Austria, and there is a lack of examinations of access to acute hospitals. Most of them use travel time to measure access. For instance, Bauer et al. [21] examined 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 min. Hafner and Mahlich [13] measured access to physician care and found that the mean travel time of physician visits was 9.83 min in Vienna, Austria. Fritze, Graser, and Sinnl [24] estimated the realistic travel times of patients to optimize emergency medical service stations in Lower Austria.

Centered on the topic of access, there has been much debate about which method is more accurate in estimating access to health care [11,12,15,18,19,26]. 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 care, and some of them even bypass it. The G2SFCA method overcomes these issues, and it has become a popular measure in accessibility studies [26] (p. 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 [6,10,15,20,23,27]. 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 spatial accessibility to acute hospitals.

Both methods need an accurate estimate of travel time or distance 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 [27–29], and their travel time estimations are shown to be largely consistent [28]. Because of the merits of OSM (e.g., free, no limits of requests, high-quality, and up-to-date road network data [27]), this study will use it to estimate the travel time of people to acute hospitals.

Another issue is the selection of reliable geographic units at 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) [30]. As a classic geographic issue, MAUP has scale effects and zoning effects. As explained by Kwan [31], the scale effect refers to 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 [32]. Though largely intractable, MAUP can be mitigated through some potential solutions. For example, Mu and Wang [33] developed a scale-space clustering method that accounts for attributes 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 [18,34,35]. This study will examine spatial accessibility to acute hospitals at census block and grid levels to identify the possible influence.

In addition, health care accessibility may be subject to the classic edge effect [36,37]. The 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 [38]. While some studies argue that the impact of edge effects may not be significant and should be examined on a case-by-case basis [39], others claim that overlooking the edge effect can result in an underestimation of accessibility [36,40]. To avoid its potential impact, previous studies often create a buffer zone around the study area to measure accessibility [14,27,39,41]. In other words, they assume the presence of edge effects rather than directly examining their existence. This study will fill this gap by comparing 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 spatial accessibility to acute hospitals in Carinthia, Austria. The comprehensive assessment will be implemented by improving two popular methods: proximity method and G2SFCA method with varying parameters. Both will be applied to the most recent data at two geographic levels: census block and 250 meter grid. 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 sample data from Google Maps [42], this study will apply OSM, a high-quality, up-to-date, and free road network data provider, to estimate the travel time from patients to providers. Furthermore, in comparison with the official road network data, known as graph integration platform (GIP) from Austria's official traffic reference system, high-quality OSM data overcome their shortcomings in including disconnected or missing road segments.

(4) Since the edge effect is unknown, this study will compute spatial 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 not been a study leveraging advanced GIS-based accessibility methods to examine spatial accessibility to acute hospitals in Austria. This study will improve the proximity and G2SFCA methods and account for two classic geographic issues: the MAUP and edge effects to measure multiscale accessibility at coarser census block and finer-grained grid cell levels, using the Austrian province of Carinthia as an example. In addition to enriching the accessibility literature, this study will contribute to our understanding of how accessible acute hospitals are 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. Materials and Methods

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 recent statistics from City Population (2022), it has 564,513 people living on 9536 km^2 land, resulting in a population density of 59.20 people/km^2. 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, 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. Data

One important component of measuring spatial accessibility is health care demand. Since everyone needs acute care, we use population as a proxy. To examine the potential impact of the MAUP, we used the 2020 population data at census block [43] and 250 meter grid [44] levels which represent coarser- and finer-grained data available to conduct this study. Specifically, we downloaded the census block layer across the whole of Austria from OGD Austria [43] and then joined the population collected from the same website to it. We collected the grid layer of Carinthia from WIGeoGIS [44], 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 [14,27]. We then extracted all grids and census blocks inside Carinthia plus the 15-mile buffer area. As shown in Table 1, we obtained 607 census blocks and 23,880 grids with populations of 562,089 and 561,628 inside Carinthia. With the buffer area, there were 1036 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 the two units (461 and 726) are very small and negligible.

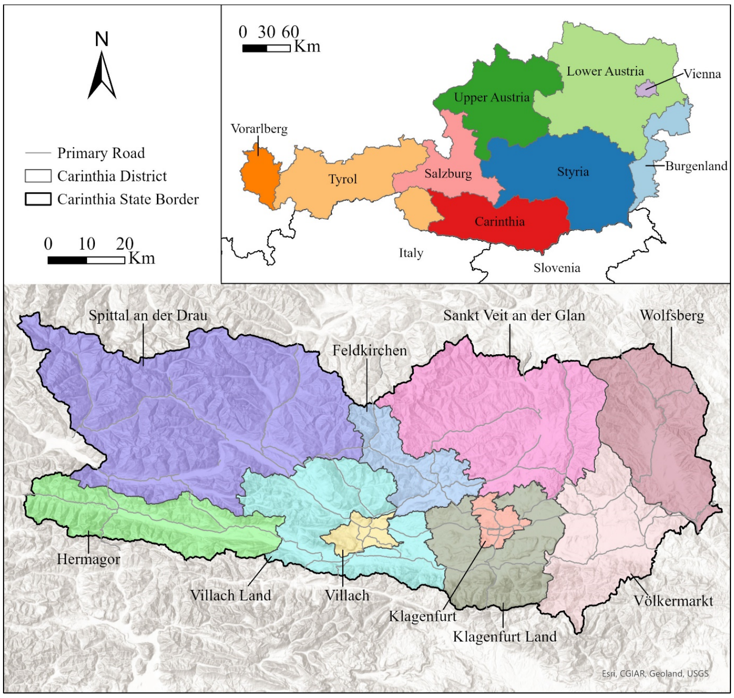

Figure 1. The study area: The Austrian province of Carinthia located in southern Austria.

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

Study Area	Data Layer	Number of Records	Spatial Scale/Format	Data Source
Carinthia	Census block population	607 (562,089 people)	Polygon	OGD Austria
	Grid population	23,880 [1] (561,628 people)	250 meter grid/polygon	WIGeoGIS
	Acute hospital	13 (3436 beds)	Point	50plus.at
	Road network	-	Polyline	OpenStreetMap (OSM)
Carinthia and a 15-mile buffer area	Census block population	1036 (892,034 people)	Polygon	OGD Austria
	Grid population	40,145 [2] (891,308 people)		WIGeoGIS
	Acute hospital	20 (5018 beds)	Point	50plus.at
	Road network	-	Polyline	OpenStreetMap (OSM)

[1] refers to 154,774 grids in total, of which 23,880 grids have a nonzero population. [2] 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 are less obvious along major roads. Interestingly, the triangle area between Villach, Klagenfurt, and Feldkirchen has the highest population density. 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.

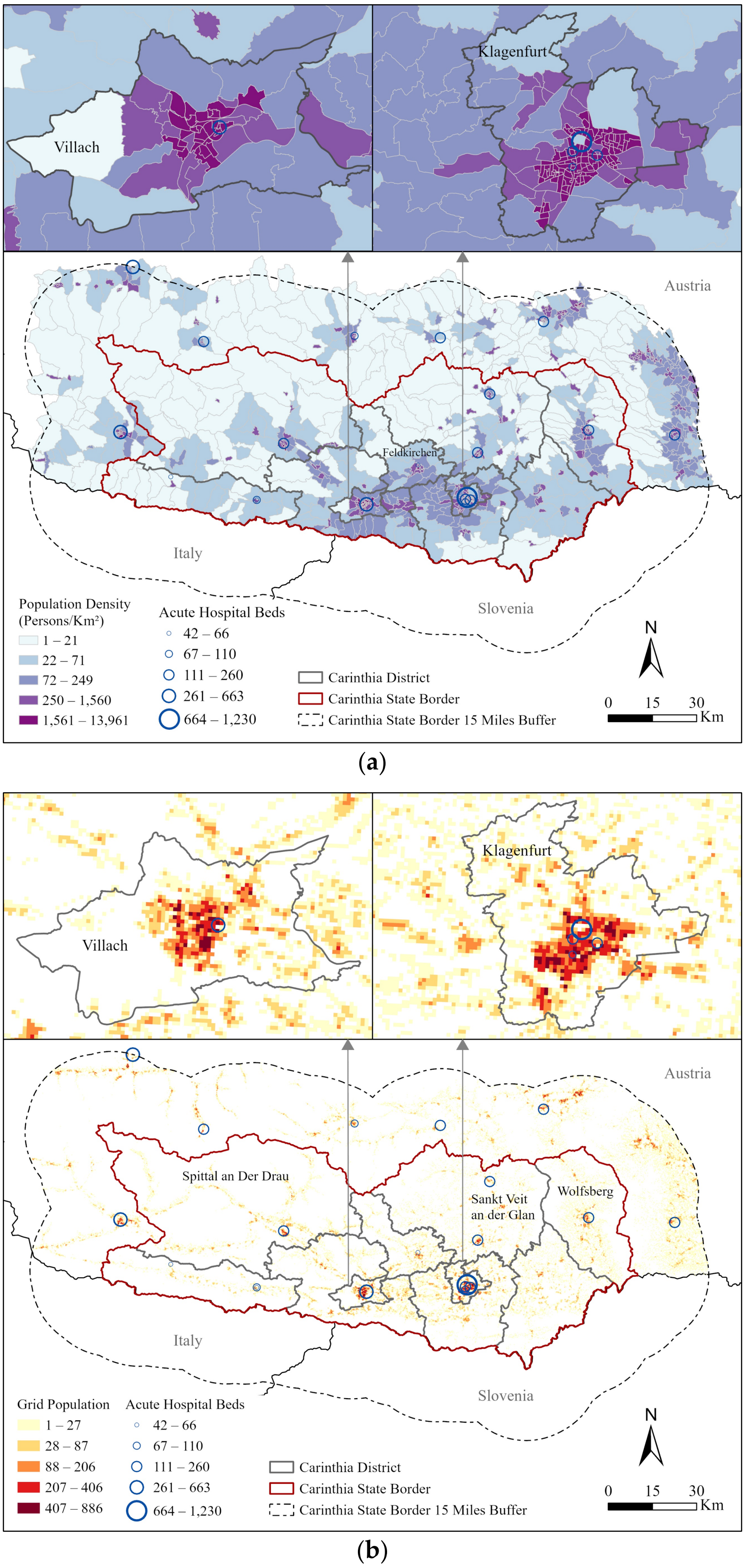

Figure 2. (**a**) Population density of census blocks and acute hospital beds in Carinthia; (**b**) 250 meter grid population and acute hospital beds in Carinthia.

The second component of measuring accessibility is health care supply. Prior research has often adopted hospital beds as a capacity measure [20,45–47], a method which was used in this study. After carrying out extensive searches in English and German languages, we could not find official hospital data, so we obtained the data of all hospitals from the 50plus.at platform [48]. It is a local and popular website that provides health care, music, food, travel, and other information. It includes a full list of hospitals. 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 3436 beds in Carinthia and 20 acute hospitals with 5018 beds in Carinthia plus the 15-mile buffer area. Overall, the hospital bed ratio is 6 per 1000 people, slightly lower than that for the whole of Austria (7 beds per 1000 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.

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 [49]. Moreover, most Austrian people (65%) commute by car [50]. 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 use them, we used car driving as the transport mode. Unlike most prior research using static road networks [14,19,46], we used OSM and the high-performance Open Source Routing Machine (OSRM) to measure the driving time from the geographic centroids of census blocks and grid cells to each acute hospital, respectively. Another reason to use OSM is because the road network data from Austria's official traffic reference system are disconnected or missing in some areas, leading to the failure of the travel time estimation. We obtained two large driving time matrices with a total of 802,900 OD pairs for the 250 meter grid (=40,145 $\times$ 20) and 20,720 OD pairs for the census block data (=1036 $\times$ 20). To evaluate the accuracy of travel time matrices, we sampled small numbers of OD pairs and estimated their travel times using Google Maps Distance Matrix API. The travel times from OSM and Google Maps were largely consistent with high R-square values of 0.99 and 0.97, respectively, similar to those reported by Delmelle et al. [28].

2.3. GIS-Based Proximity Method

The GIS-based proximity method is a globally popular approach to measure health care accessibility [22]. It assumes that residents only use the closest facility. However, there has been much debate as patients may bypass the closest facility to seek care [51]. Moreover, most people tend to travel farther to seek high-quality or specialized care [52], such as hospitalization for cancer patients [34]. Through the comparison of travel times to the closest and actual facility, Alford-Teaster et al. [53] found that 35% of the population frequented the closest facility and that the majority traveled to a facility within a 5 min 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 cell 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.

2.4. GIS-Based Generalized Two-Step Floating Catchment Area (G2SFCA) Method

As introduced previously, since the inception of the 2SFCA method [14], it has been widely employed in measuring spatial accessibility, disparity, and inequality to inform health policies for improving access and reducing inequity. Various forms have been proposed to address the issues in the original method, such as identical catchment size [14].

These forms can be generalized into one framework, termed the generalized 2SFCA (G2SFCA) method [6]. Its essence is still to measure the ratio of health care supply and demand while accounting for their complex interactions which is, however, more explicitly captured by a distance decay function $f(d)$. In brief, there are two steps in the G2SFCA method: (1) for each acute hospital location $i \in (1, 2, 3, \ldots, n)$, it searches all population centroids of grids or census blocks (j) with travel time d_{ji} decayed by a function $f(d_{ji})$ from location i, and then computes the bed-to-population ratio R_i in Equation (1):

$$R_i = \frac{S_i}{\sum_{j=1}^{m} D_j f(d_{ji})} \tag{1}$$

where S_i is the hospital beds at location i, D_j is the population at location j, d_{ji} is the travel time from population centroid j to acute hospital i; (2) for each population centroid of grids or census blocks $k \epsilon \{1, 2, 3, \ldots, n\}$, it searches all beds at hospital location i with travel time d_{ki} decayed by a function $f(d_{ki})$ from location k, and sums up the bed-to-population ratio R_i to compute accessibility A_k in Equation (2):

$$A_k = \sum_{i=1}^{n} R_i = \sum_{i=1}^{n} \frac{S_i f(d_{ki})}{\sum_{j=1}^{m} D_j f(d_{ji})} \tag{2}$$

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 better accessibility.

In the context of health studies, distance decay describes the interaction between health care demand and supply declines with longer travel times between them [26]. It has been conceptualized as different functional forms such as inverse power ($f(d_{ji}) = d_{ji}^{-\beta}$) [14,54,55], exponential ($f(d_{ji}) = e^{-\beta d_{ji}}$) [45,56,57], square root exponential ($f(d_{ji}) = e^{-\beta\sqrt{d_{ji}}}$) [34], Gaussian/normal ($f(d_{ji}) = e^{-\beta {d_{ji}}^2}$) [27,41,58], and log-logistic ($f(d_{ji}) = \frac{1}{\left(1+\frac{d_{ji}}{\alpha}\right)^{\beta}}$) [59]. Ideally, the best-fitting distance decay function $f(d_{ji})$ and friction coefficient α or β can be estimated by analyzing real-world patient-to-hospital flows. For example, Wang [60] used them in Florida and found the inverse power to be the best for capturing travel behavior of patients and the friction coefficient β to be 1.3. Tao et al. [61] used hospitalization data in Hubei, China, and found that the inverse power outperformed all other distance decay functions, and the corresponding β fell into a range from 1 to 1.6. However, without actual trips, most studies opt for empirical functions. Additionally, we used access-related key words, such as "access to hospital", "travel time to hospital", "2SFCA, hospital" with "Austria" in English and German languages to search the literature, and there was no result. We discussed these parameters and functions with local researchers who worked in the GIS and public health. There is no consensus about parameter selection. Due to the limited research, it was recommended to conduct a sensitivity analysis using the common criteria, β from 1 to 1.6 with an interval of 0.1 in the inverse power function, to measure accessibility.

3. Results

3.1. Comparing Travel Time across Census Blocks and Grids

Because our interest is accessibility for people in Carinthia, our following analyses will mask out those in the 15-mile buffer zone. As shown in Figure 3, for the census block and grid levels, travel times increase from the first nearest, to the second nearest, and to the third nearest acute hospitals, but decrease when averaging travel times to the first three nearest acute hospitals (see the fourth group of boxplots), and then increase when averaging travel times to all acute hospitals. For all travel times at each level, they have almost identical mean and median values which, however, cover different percentages of populations. For instance, 58.8% of the block population travels 16 min on average to reach the nearest acute hospitals, while 76.2% of the grid population travels 21 min, on average. Taking bypass behavior into account, 52.6% and 73.4% of the block- and grid-based populations need to drive 25 and 31 min on average to reach the three nearest acute hospitals. Although the population proportions drop a little, the extra 10 min can give patients two more choices of close acute hospitals. Between the two levels, mean travel times across grids are longer but with less variability. This is understandable as a block is larger than a grid in terms of size, and they both use geographic centroids as a starting point to estimate travel time to acute hospitals; thus, blocks tend to underestimate travel time which is shorter than that across grids.

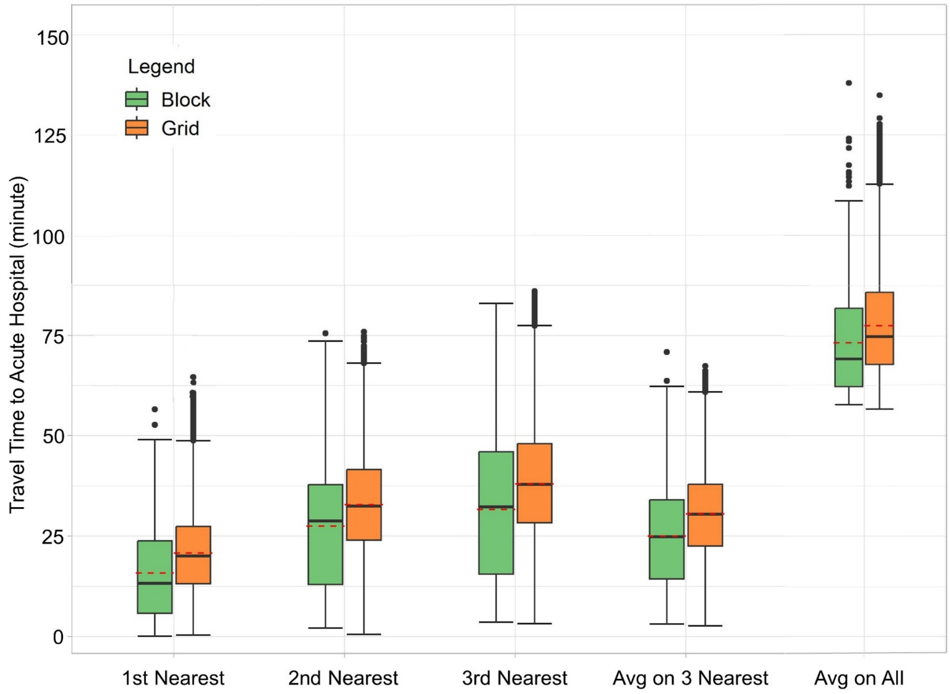

Figure 3. Boxplots of travel times to acute hospitals across census blocks and 250 meter grids. The horizontal red dash line represents the mean value of travel times in each category.

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 min to reach acute hospitals, followed by 32% and 33% traveling between 15 to 30 min (see Figure 4a,b). This suggests that half of the people benefit from an urban advantage. The remaining minorities (11% and 8%) need to travel longer than 30 min to reach the nearest acute hospital. Between the two units, the variability of travel time is smoothed across blocks but is revealed across grids, as indicated by shorter times for grids along major roads that connect different districts or cities. Compared to blocks, a higher proportion of the grid population travels within 30 min to reach the closest acute hospital (89% vs. 92%). When it comes to average times to the 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 min 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 the population drive 15 to 30 min. The remaining 34% and 29% of the population reside in the periphery of Carinthia and need to travel more than 30 min. These population percentages are higher than those who can reach the nearest acute hospital in more than 30 min (see Figure 4a,b).

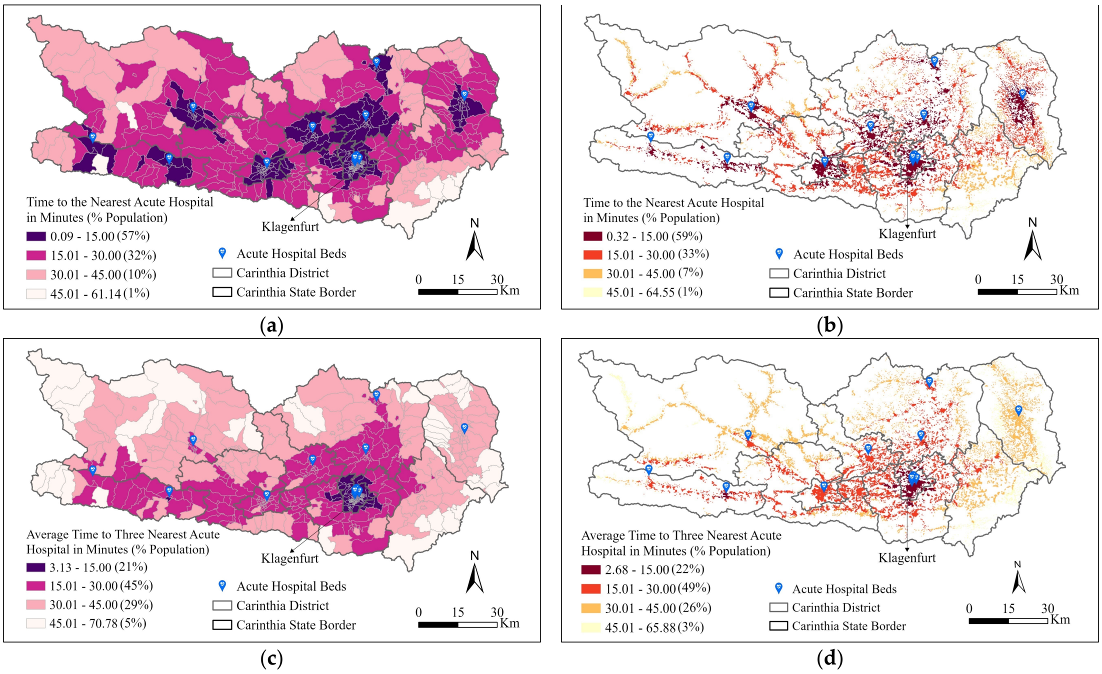

Figure 4. Travel times to the nearest acute hospital across (**a**) census blocks and (**b**) 250 meter grids; and average travel times to the three nearest acute hospitals across (**c**) census blocks and (**d**) 250 meter grids in Carinthia.

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 green (red) color refer to the travel times across grids being smaller (larger) than those across blocks. Areas with a yellow color refer to similar travel times within a 10 min 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 tends to underestimate travel times. This implies that the MAUP is more likely to affect less or sparsely populated areas.

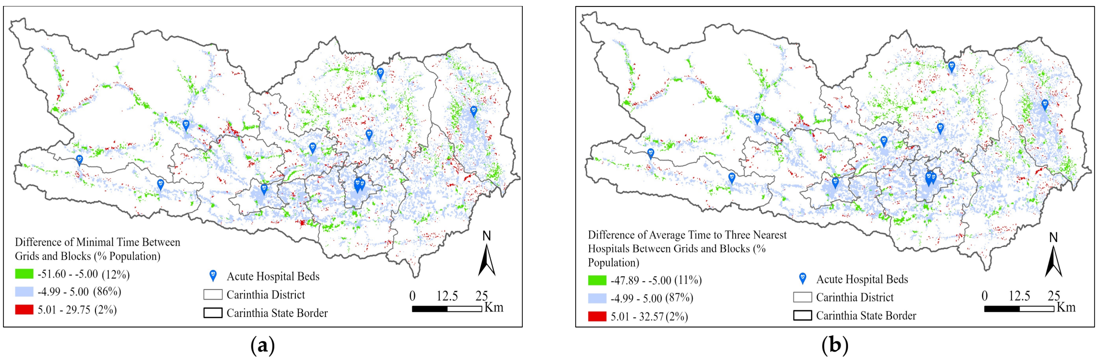

Figure 5. (**a**) Differences in travel time to the nearest acute hospital; and (**b**) differences in average travel time to the three nearest acute hospitals between grids and blocks.

3.2. Comparing Accessibility Scores to Acute Hospitals across Census Blocks and Grids

Table 2 reported block- and grid-based accessibility scores with different friction coefficients. To avoid too small values, all scores are inflated by multiplying by 1000. Results are interpreted as acute hospital beds per 1000 people.

Table 2. Descriptive statistics of block-based and grid-based accessibilities in Carinthia.

Travel Friction Coefficient	Block-Based Accessibility					Grid-Based Accessibility				
	Mean	Median	Min	Max	SD [1]	Mean	Median	Min	Max	SD [1]
$\beta = 1$	6.73	5.27	2.07	56.74	4.14	4.67	4.30	2.28	29.54	1.64
$\beta = 1.1$	6.78	5.04	1.78	78.87	5.12	4.41	3.97	1.98	39.69	1.87
$\beta = 1.2$	6.82	4.74	1.51	106.19	6.32	4.13	3.62	1.69	55.98	2.14
$\beta = 1.3$	6.85	4.44	1.27	136.83	7.70	3.84	3.26	1.42	80.20	2.48
$\beta = 1.4$	6.88	4.09	1.05	167.79	9.18	3.54	2.89	1.18	112.61	2.93
$\beta = 1.5$	6.90	3.71	0.86	196.11	10.66	3.25	2.53	0.96	163.58	3.51
$\beta = 1.6$	6.92	3.38	0.7	219.85	12.06	2.97	2.18	0.77	245.22	4.26

[1] SD refers to standard deviation.

Overall, each average block-based accessibility is slightly higher than the overall acute hospital bed ratio (=6), while average grid-based accessibility is much lower, suggesting overestimation from a coarse geographic level. For both units, an increase in β leads to higher standard deviations of accessibility at two units, implying a reduced spatial smoothing effect. Another interesting finding is that the variability of 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 [60].

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

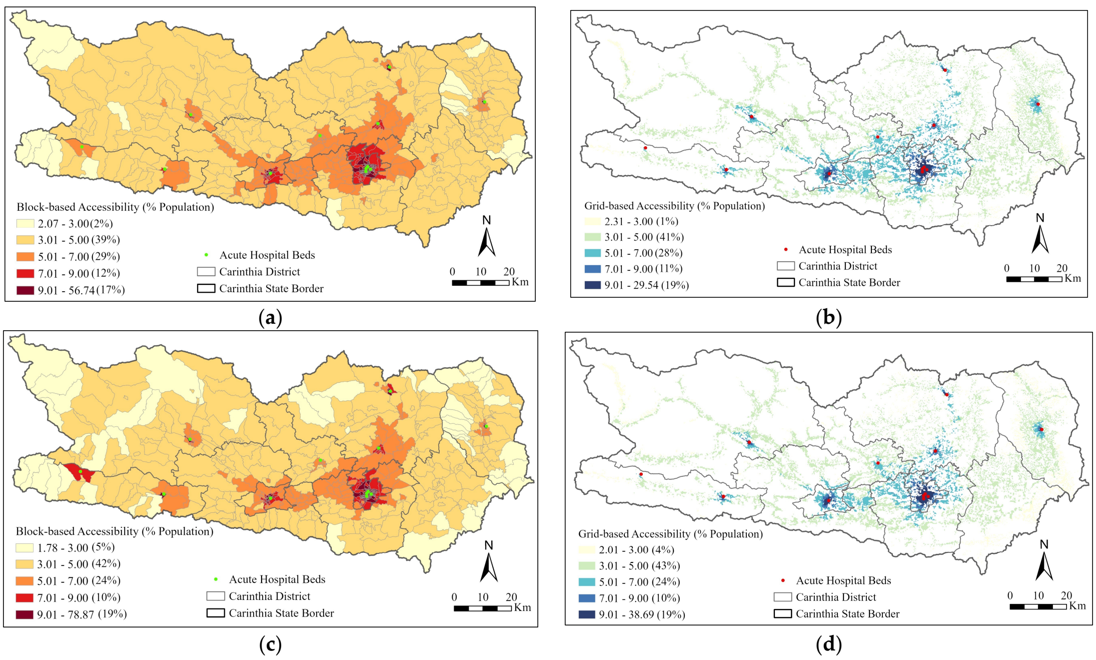

Figure 6. *Cont.*

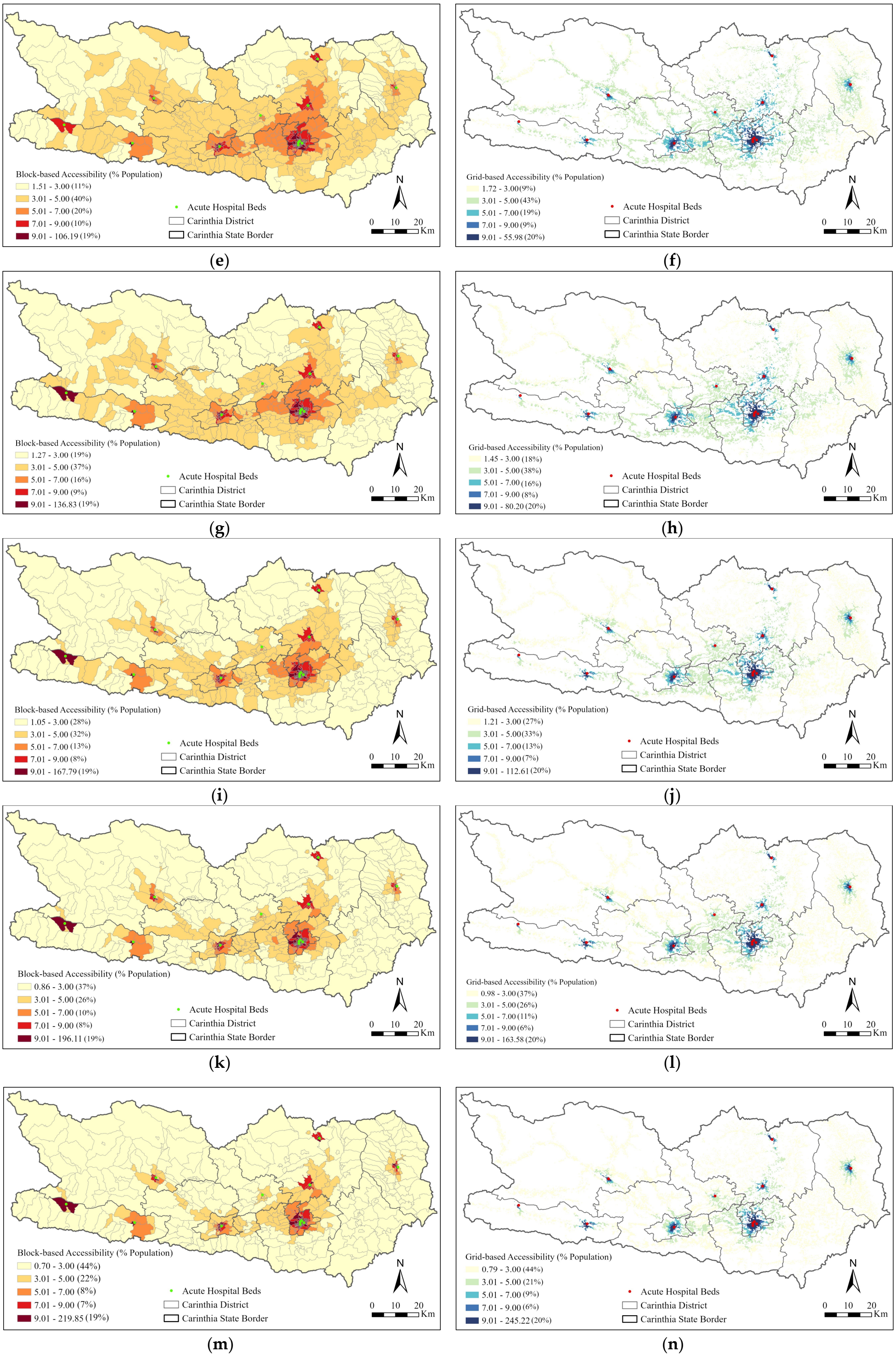

Figure 6. Scatter plots and maps of block- and grid-based accessibilities using (**a**,**b**) β = 1; (**c**,**d**) β = 1.1; (**e**,**f**) β = 1.2; (**g**,**h**) β = 1.3; (**i**,**j**) β = 1.4; (**k**,**l**) β = 1.5; (**m**,**n**) β = 1.6 in the G2SFCA method. Note: all district names from Carinthia can be found in Figure 1.

For all maps in Figure 6, major patterns of accessibility shown at the two geographic levels are largely consistent and stable at β = 1.3. The distribution of accessibility changes from a dual-nuclei structure centered at 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, accessibility peaked around acute hospitals in the urbanized areas of Klagenfurt and Villach (>9 beds per 1000 people), covering 19% or 20% of the total population, respectively, followed by Sankt Veit an der Glan, and other districts with larger β. The rise in β results in a higher population proportion (2% to 44%) being least accessible to acute hospitals (see the range $\leq$ 3 beds per 1000 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 of the population falling into the accessibility score's 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 finding may be exacerbated during the COVID-19 pandemic or 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 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 the lack of availability of finer-scaled data, grid-based accessibility can be a supplement to support acute care delivery.

The spatial patterns 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, accessibility measured by the G2SFCA method is selectively higher around acute hospitals as it considers the competition for 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.

3.3. Examining Edge Effects on Measuring Accessibility across Census Blocks and Grids

This section examines edge effects on accessibility measured using the proximity and G2SFCA methods at census block and grid levels using data for Carinthia and data with an additional buffer zone. Due to the limited space, only the differences in travel times to the nearest and the three nearest acute hospitals are shown in Figures 7a and 7b, respectively. Differences in the two levels with friction coefficients equal to 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 travel times to the three nearest acute hospitals are more sensitive as they cover more areas with higher populations.

In Figure 7c–f, we use an arbitrary small range of −0.5 to 0.5 to represent an acceptable difference in accessibility measured by the G2SFCA method. The negative (positive) values represent accessibility values obtained without the buffer zone to be smaller (larger) than those obtained 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–f), 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.

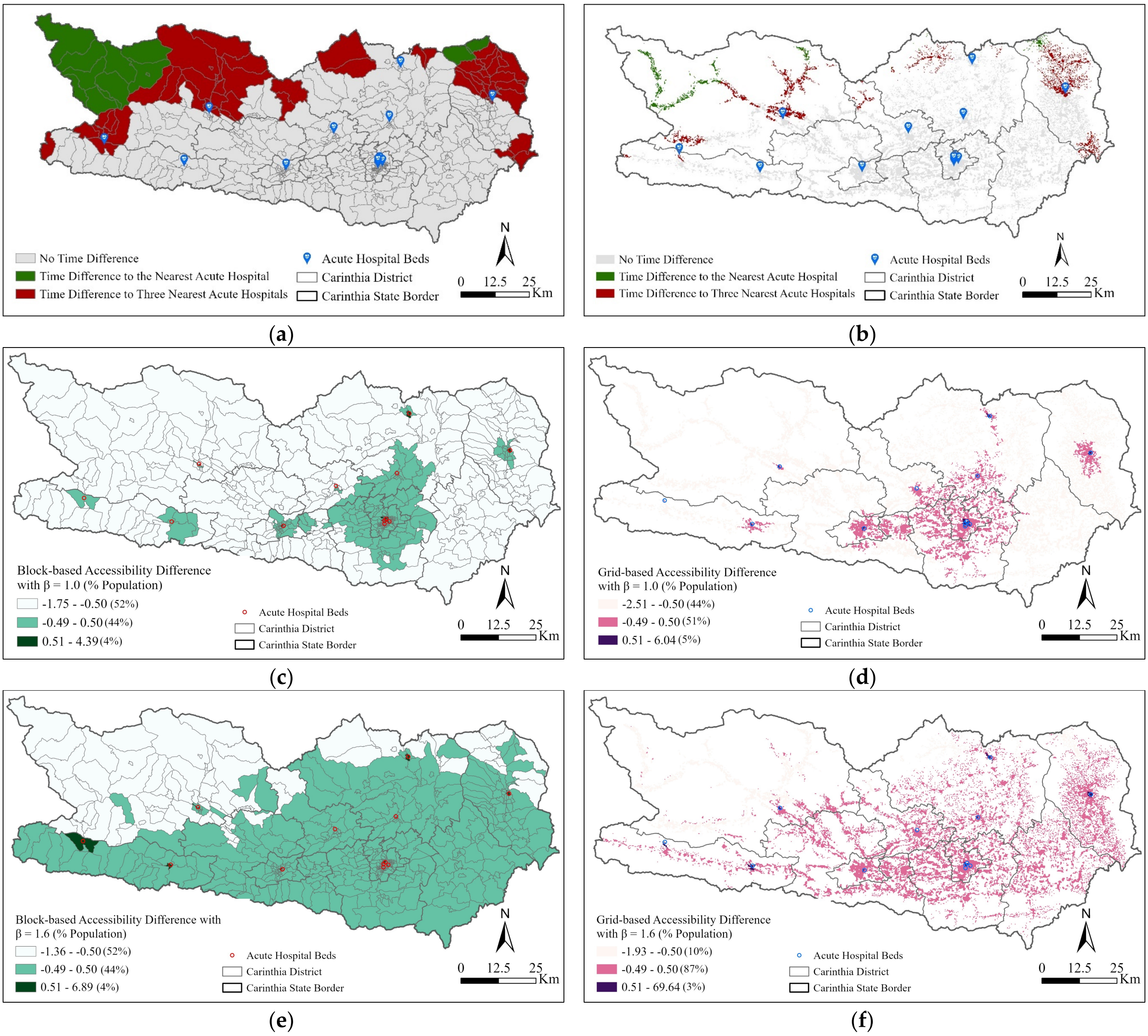

Figure 7. (**a**,**b**) Edge effect of travel time across census blocks and grids in Carinthia; (**c**,**d**) edge effect of census block-based and block-based accessibility by G2SFCA using β = 1; and (**e**,**f**) edge effect of census block-based and block-based accessibility by G2SFCA using β = 1.6 in Carinthia.

4. Discussion

Studies on spatial accessibility to health care are well established in the US for examining disparities and inequities, but they are lacking in Austria, even though both experience high health care spending and have hospital care as the largest contributor. This study examines 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 to systematically examine spatial accessibility to acute hospitals with advanced GIS technology in an Austrian province. When related data become available, it can be extended to the whole country to inform more effective policies in health care delivery, management, and planning.

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 residents can reach the nearest and three nearest acute hospitals within 30 min, and travel times for those living around acute hospitals, especially in urban areas, are much shorter. Bypass behavior is more influential as 20% more of the population living in mountainous or rural areas need to travel more than 30 min, suggesting the poorest access in these areas. Perhaps, these nearest acute hospitals can improve the quality of their acute care by collaborating with other well-known acute hospitals or by seeking more support and resources from local governments to meet the acute care needs of local communities. Therefore, residents would not need to travel for a much longer time. 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 overlooked by the proximity method. Similarly, more resources or support are needed in these areas to reduce the waiting time for a health care procedure. A common finding from these two methods is that people living in the Völkermarkt district and in the most remote areas of Carinthia have very poor access, as these areas do not have acute hospitals. Local authorities and health departments should build new acute hospitals or satellite hospitals, provide emergency medical services to those communities, or allocate more resources to the existing nearby hospitals to increase their access and reduce crowdedness. 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 a 10 min 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 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. In addition to building new or satellite hospitals for those areas, the existing hospitals could optimize their triage and treatment strategies to increase efficiency. The variability in accessibility seems more stable when the friction coefficient equals 1.3. This is consistent with a previous study using real trips [60]. We thus recommend using this value in the inverse power function for accessibility measures in Carinthia if related hospital flow data are not readily available.

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 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 is 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, accessibility is more sensitive to 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 for leaving homes and waiting for doctors and admissions, which may underestimate the total time of receiving short-term acute care. Nevertheless, it is very challenging to measure these additional times. A possible solution may be conducting surveys in the local communities in Carinthia. Further, the nearest or the three nearest acute hospitals may not be the primary choices of patients due to 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 Austrian people prefer this type of transportation. However, since public transportation and cycling are also very popular for commuting, future studies should incorporate multimodal accessibility when related transportation data are available. In addition, this study uses some common criteria to define the distance decay function in the G2SFCA method and examines the edge effects. These criteria may be more suitable for the US, as very limited research has been found in Austria. Thus, future studies will conduct local surveys or use local data to obtain parameters that are more practical and suitable for measuring accessibility in Austria.

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