Health Care Accessibility:

A Comparative Study Between Carinthia and Louisiana

The Marshall Plan Scholarship Paper

by

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Abstract

Austria and the United States are two countries that value equal access the most and invest so much in achieving this goal. However, health care needs are not always met, and health care disparity persists. There has been a large body of literature measuring accessibility to various health care due to the advances in geographic information systems (GIS). However, very limited research has been conducted on examining accessibility to acute care across different countries. Given that acute (care) hospitals dominate, and hospital care is the largest payer of total health care spending in the two countries, it is important to examine the access to these services in Austria and Louisiana. This study examines the accessibility to acute (care) hospitals in two pilot areas: Carinthia in Austria and Louisiana in the United States with the most recent data at the finest geographic scales in 2020. Both use the supply-demand ratio, proximity method, and the popular two-step floating catchment area (2SFCA) method to measure accessibility in GIS. While the supply-demand ratio refers to the acute (care) hospital bed-to-population ratio in a geographic area, and the proximity method purely captures patients' travel time to the nearest hospital, the 2SFCA is a match ratio of supply and demand with their interactions captured by a threshold travel time.

The study finds Carinthia has almost doubled the bed-to-population ratio than Louisiana (61 vs 33 per 10,000 people). However, the average travel time to the nearest acute (care) hospitals is twice longer than that in Louisiana (21 vs. 9.4 minutes). The proximity method shows people living around hospitals and along major roads in two states enjoy shorter travel time of 20 minutes while those who live farther, in mountainous areas, or close to farmland and water areas experience longer travel time of more than 1 hour, suggesting an urban advantage in accessing acute care. The different threshold travel times used in the 2SFCA methods could significantly shrink the areas with zero accessibility scores. In Carinthia, the spatial patterns of accessibility change from a

polycentric structure with the peaks scattered around acute hospitals, to a monocentric structure that is centered in the triangular regions of Villach, Klagenfurt, and southern Sankt Veit an der Glan District. In Louisiana, the spatial patterns change from a small polycentric structure to a large polycentric structure, and then to a decentralized structure but with the highest accessibility scores found in the northern areas of Louisiana. This study also observed not all areas close to the acute (care) hospitals have higher accessibility scores, which is different from those detected by the proximity method. Together, the three methods capture different profiles of accessibility to acute (care) hospitals in Carinthia and Louisiana.

The study has some impacts on health care communities that are engaged in GIS-based health care accessibility studies and health care planning in improving access. Possible policies may target the mountain areas in Carinthia and cities like Baton Rouge and New Orleans in Louisiana for improving the accessibility to acute care.

Keywords: Health care accessibility; acute care hospital; travel time; two-step floating catchment area method (2SFCA); Carinthia, Louisiana

Chapter 1. Introduction

Austria and the United States are two developed countries that have high-ranking health care systems (Ireland 2021). However, their health care systems are run in different ways. Austria adopts a social insurance model that both the employees and employers pay into the fund and the government retains regulatory control over the costs (McAlister and Helton 2021). In contrast, the United States adopts a mixed model that consists of different health care insurance, including private, Medicare, and Medicaid with little control of the cost by the government. Despite significant differences in the two systems, both value equal access to high-quality health care the most and have high health care spending. A recent report from Federal Ministry Labour, Social Affairs, Health and Consumer Protection (FMLSAHCP 2019) found that in 2017, Austrian health care spending shared 10.4% of GDP and the per capita was €4,373, lower than that of the United States which shared 17.9% of GDP and the per capita was $10,739 in the same year (Anne B. Martin 2019). In 2020, the U.S. health care spending even reached $12,530 per capita with $4.1 trillion that shared 19.7% of GDP (Centers for Medicare & Medicaid Services (CMS) 2020). Although significant progress has been achieved in the two countries, the health care needs of their people are not always met, and health care disparities may persist. To identify where the health care services need to be improved, an essential task is to accurately measure health care accessibility in both countries and guide more effective health care policies to be implemented for improving overall health outcomes without unnecessary costs.

Health care accessibility refers to the relative ease of reaching health care services at a given location (Wang 2015, 93). It reflects the extent to which patients and service providers match in terms of the characteristics and expectations (McLaughlin and Wyszewianski 2002). As a policy relevant concept, health care accessibility has been conceptualized into five aspects: availability, accessibility, accommodation, affordability, and acceptability (Penchansky and Thomas 1981). Based on whether patients potentially or truly utilize the services, some studies classify health care accessibility into potential accessibility and revealed accessibility. Given the limited availability or accessibility of the actual utilization data of health care services, most studies focus on potential accessibility to evaluate the effectiveness of the existing health care system and identify strategies for improvement (Wang 2015, 93).

Because health care accessibility involves patients as demands, health service providers as supplies, and their complex interactions across space, the geographic locations of both sides and their interactions with spatial impedance are key components of Geographic Information Systems (GIS). GIS has been defined as computer-based systems to describe, analyze, and predict patterns of spatial and attribute data (Cromley and McLafferty 2011; Kirby, Delmelle, and Eberth 2017). In the past two decades, a growing body of literature has used GIS to measure geographic access to health care, such as primary care (Del Conte et al. 2022; Demitiry et al. 2022; Guagliardo 2004; Luo and Wang 2003; Luo and Qi 2009; Wang, Vingiello, and Xierali 2020), cancer care (Onega et al. 2008; Shalowitz, Vinograd, and Giuntoli 2015; Wang and Onega 2015), pharmacies (Ikram, Hu, and Wang 2015), hospitals or clinics (Alford-Teaster et al. 2021; Cheng et al. 2020; Wang et al. 2020; Weiss et al. 2020), and daycare centers (Fransen et al. 2015). The research findings provide valuable guidance for targeting public health interventions in improving access to health care, especially for socially disadvantaged population. However, to my best knowledge, there has been not much research examining the geographic accessibility to acute care hospitals in Austria and the United States simultaneously.

Centered on these topics, there are debates on which method is more accurate to measure health care accessibility. While the provider-to-population ratio across a geographic area is simple, it omits the interactions between and the variations of patients and providers, and the fact that patients may cross borders to seek health care. Another method captures the proximity between demand and supply in measuring the travel time or distance from patients or providers. However, this method assumes that patients would reach to the nearest facility which may not be the real case as some of them may bypass it because of various reasons. Moreover, the proximity method does not account for the characteristics of two sides. Because of the rapid development of GIS in public health, the two-step floating catchment area (2SFCA) method overcomes the above issues and becomes a popular measure in health care accessibility studies. However, new concerns are raised in terms of the selection of the catchment size, the measure of travel time or distance by which transport modes, and the characteristics of patients and providers. Therefore, many studies develop 2SFCA's variants (Alford-Teaster et al. 2021; Del Conte et al. 2022; Fransen et al. 2015; Luo and Qi 2009; Shao and Luo 2022; Wang 2012). These methods, accounting for specific scenarios to capture the complexity of the real-world access; however, rely on the availability and accessibility of the datasets. This study will examine the three methods simultaneously to generate a picture of health care accessibility in Austria and the United States for public awareness.

Either for the proximity method or the 2SFCA method and its variants, all need an accurate estimate of travel time or distance from patients to service providers to capture the travel burden or mobility of patients. In geographic literature, the travel measure ranges from simple estimates such as Euclidean (straight-line) or geodesic (great circle) distance to complex estimates such as road network distance by a predefined speed limit, and the accuracy increases because most human movements generally travel along the physical road rather than point to point distance. While network-based distance (or travel time) could be estimated through static road networks or online network data providers, such as Google Maps, Bing Maps, or ArcGIS Online, there are concerns in terms of data timeliness, computation costs, service request limits, and consideration of traffic conditions. A recent popular online network provider, OpenStreetMap (OSM) solves these problems. It offers routing services which can be accessed in various free packages in Python and up-to-date network data for downloading. Moreover, it has been proven to be highly consistent with the aforementioned online road network providers in travel time estimates (Delmelle et al. 2019). Therefore, this study will use OSM to measure the travel time from population to acute (care) hospitals for two methods.

Another issue on health care accessibility is the selection of geographic units on which the measurement and analysis could be conducted. The reason is how data aggregated on these units would affect the validity of the findings thus the policy and planning strategies. In other words, it may suffer the modifiable areal unit problem (MAUP) (Fotheringham and Wong 1991). As a well-known geographic problem, MAUP has scale effects and zoning effects that refer to the variations in results generated at the different levels of spatial resolution and from the regrouping of zones at a given scale, respectively (Kwan 2009). To mitigate the MAUP, an acceptable way in health care accessibility is to select multiple geographic units at finer scales, which would be used in this study.

This study aims to examine health care accessibility in Austria and the United States with two pilot studies measuring geographic accessibility to acute care hospitals in two states of each country: Carinthia (German: Kärnten) and Louisiana. The acute (care) hospital refers to a hospital that provides short-term patient care for illness, disease, injury, or surgery. In Austria, it is termed as acute hospital. While in the United States, it is termed as acute care hospital. There are several reasons to select the geographic accessibility to acute (care) hospitals in two states as a research objective:

(1) Hospital care is the largest payer of total health care spending in Austria (33.8%) (FMLSAHCP 2019) and the United States (33%) (CMS 2020).

(2) The number of acute (care) hospitals and their capacities dominate in Austria (45% of total hospitals and 70% of total beds) (FMLSAHCP 2019) and the United States (64% of total hospitals and 97% of total beds) (American Hospital Association (AHA) 2022a; American Hospital Directory (AHD) 2022).

(3) Carinthia and Louisiana are located on the southern border of Austria and the United States and are bordered by other states of each country in three facets. Their geographic locations are similar.

(4) To my best knowledge, this is the first study to examine the geographic accessibility to acute (care) hospitals in two countries simultaneously and highlight their differences.

In these contexts, the study will apply OSM data to estimate the travel time from the residence of population to acute (care) hospitals. After comparing the bed-to-population ratio and other indicators, such as population density, it will use two popular accessibility measures in GIS: the proximity method that captures people's travel burden, and the 2SFCA method that considers population demand, acute (care) hospital supply, and their complex interactions because of services' scarcity. Using the most recent data, this study will measure the accessibility of acute hospitals at the grid and census tract levels in Carinthia and address the MAUP problem. In Louisiana, this study will only examine the accessibility to acute care hospitals at the census tract level because of data limitations. In short, the study will answer the following questions:

(1) How to use more advanced GIS technologies to measure geographic accessibility quantitatively and more accurately in Carinthia of Austria and Louisiana in the United States?

(2) What are the geographic accessibilities to acute hospitals in Carinthia? Which areas do people experience inadequate access?

(3) What are the geographic accessibilities to acute care hospitals in Louisiana? Which areas do people experience inadequate access?

(4) What are the similarities or differences between the geographic accessibilities in the two states?

(5) Could the research findings from two study areas shed new light on health care policies or strategies for mitigating the problem of inadequate access in two states?

The research will be structured in the following chapters:

Chapter 2 reviews the literature about recent development and applications of accessibility methods in health care.

Chapter 3 introduces two study areas, data sources, and data preparations for analyses. In Carinthia, major data sources include demographic population data at the grid (250m*250m) and census block levels, and acute hospitals from the 50plus platform. In Louisiana, major data sources include demographic population data at the census block level from the US Census Bureau and acute care hospitals from the Cecil G. Sheps Center for Health Services Research. Both use road network data from OSM to estimate travel time. All data are from 2020.

Chapter 4 describes analytic methods of accessibility measure which includes the proximity method as a baseline and the 2SFCA method as a refined approach.

Chapter 5 presents and analyzes the results in Carinthia including the travel time to the nearest acute hospital and spatial accessibility scores for all populations in Carinthia at two levels.

Chapter 6 presents and analyzes the results in Louisiana including the travel time to the nearest acute care hospitals and accessibility scores for all populations and population by race to examine the disparities among vulnerable populations in Louisiana.

Chapter 7 discusses the major findings and conclusions. It highlights the contributions and describes the limitations and future work of this research. It also lists the references used in this study and is followed by the author's vita.

Chapter 2. Literature Review

This chapter will review three popular measures of accessibility, the supply-to-demand ratio in a geographic area, the proximity method that measure travel time to health care services, and the more recent two-step floating catchment areas (2SFCA) method and its variants. It will systematically review prior studies on health care accessibility in two states or countries.

2.1. Supply-Demand Ratio Method for Health Care Accessibility Measurement

In health care studies, the supply-demand ratio has been conceptualized into physician-to-population ratio, oncologist-to-population ratio, and hospital bed-to-population ratio to capture the accessibility of health care services. For instance, the Association of American Medical Colleges (AAMC) uses the physician-to-population ratio to predict physician shortages in the next 15 years (IHS Markit Ltd 2021). Some states publish maps of primary care the physician-to-population or oncologist-to-population ratios to identify physician (oncologist) shortage areas (Alabama Rural Health Association 2022b; Lin et al. 2015). World Health Organization (WHO) releases the maps of hospital bed-to-population and physician-to-hospital ratio to state the accessibility of hospitals across different countries (WHO 2020, 2022). As a simple measure, the supply-demand ratio neglects the geographic variation in an area and the interactions between the supply and demand sides. Although this has been remedied by using a geographic area that represents the actual utilization patterns of patients in health care markets (Lin et al. 2015; Onega et al. 2008) so that most patients would be expected to seek care in the area, the variation within the unit is not captured, especially when the area is large.

2.2. Proximity Method for Health Care Accessibility Measurement

The proximal method measures the travel time or distance to the closest health care facility without considering the competition for services. It emphasizes the physical proximity to the health care supply locations because it assumes that residents will only use the nearest supply (Ghosh and McLafferty 1987). Although this assumption is not always the real case (Alford-Teaster et al. 2016), the measure is still adopted by many health care studies (Ikram, Hu, and Wang 2015; Onega et al. 2008; Shalowitz, Vinograd, and Giuntoli 2015; Wang et al. 2008; Weiss et al. 2020) when health care data is limited or the propose is to measure the number of populations within a range of an expected distance. Moreover, proximity has been demonstrated to be an important component for a community (Ikram, Hu, and Wang 2015). For these studies, the theme is primarily focused on estimating the minimal travel time (or distance) to pharmacies, cancer care, hospitals, or clinics. Few studies use the proximity method to measure the minimal travel time to acute (care) hospitals.

There are several approaches to estimating travel time (or distance). The simple measure is Euclidean (straight-line) or geodesic (great circle) distance. In absence of road network data, these two measures have been widely used in health care studies to capture patients' travel burden. With the growth of the availability of transportation network data and GIS software, many studies use more complex but more accurate road network data to measure travel time (or distance) by a predefined speed limit as most human movements travel along physical roads. However, preparing road network data involves extensive efforts, such as pre-processing topological errors in the road segment, incorporating speed limits, restrictions, and turn penalties, and snapping each location of patients or providers to a road segment (Delmelle et al. 2019). More importantly, it requires high-performance computers to store large data and calculate travel estimates of numerous pairs from patients to their service providers without the crash of desktop GIS software.

To remove the obstacles, an option is to use the routing services provided by online network data providers such as Google Maps, Bing Maps, or ArcGIS Online because their up-to-date network data incorporate dynamic traffic conditions, restrictions, and connectivity of road segments. When it comes to sizeable travel estimates, these routing services generally limit the number of requests due to the costs (Delmelle et al. 2019; Wang and Xu 2011). An alternative is OpenStreetMap (OSM), an online GIS platform that provides a free geographic database worldwide, including routing services without limitations. Because a recent study finds a high agreement with using Google Maps, ArcGIS Online, and OSM for travel time estimates (Delmelle et al. 2019), this study will apply OSM to estimate the travel time from patients to their potential acute (care) hospitals.

2.3. Two-step Floating Catchment Area Method and its Variants

The rapid development of GIS has advanced the measurement of health care accessibility with increasingly available datasets and computational power. While the supply-demand ratio and proximity method only consider one or two aspects of supply, demand, and their interactions, the two-step floating catchment area (2SFCA) method considers all three aspects. Its idea is to compute the supply-to-demand ratio within a floating catchment area at a supply location as the first step, and then sum the supply-to-demand ratio within a floating catchment area at a demand location as the second step. The first step is a measure of supply availability, and the second step is a measure of residents accessing at least one supply location. Thus, it considers the interactions between supply and demand within the floating catchment areas as a match ratio of supply and demand. The accessibility varies at different locations (Wang 2015, 97).

Since the inception of the 2SFCA method (Luo and Wang 2003), there is an increasing body of literature using it to measure the spatial accessibility to various health care services, such as primary care (Bissonnette et al. 2012; Del Conte et al. 2022; Luo and Qi 2009; McLafferty and Wang 2009; Wang et al. 2008; Wang et al. 2018; Wang, Luo, and McLafferty 2010; Wang, Vingiello, and Xierali 2020), hospitals or clinics (Alford-Teaster et al. 2021; Cheng et al. 2020; Delamater et al. 2013; Wang et al. 2020), pharmacies (Ikram, Hu, and Wang 2015), daycare centers (Fransen et al. 2015; Kim and Wang 2019), cancer care (Dai 2010; Shi et al. 2012; Xu et al. 2017; Wan et al. 2012), and dialysis service centers (Yang, Goerge, and Mullner 2006). In terms of the accessibility to hospitals that is related to this study, Alford-Teaster et al. (2021) examined the census track level accessibility to all hospitals in Vermont of the United States to identify the health disparities in healthcare access in rural and urban areas. Cheng et al. (2020) measured the spatial access of seniors to multi-tier, including primary, secondary, and tertiary hospitals to assess the inter- and intra-district disparities in Nanjing Province of China. Wang et al. (2020) examined the potential and revealed hospital accessibilities in Beijing city of China. Delamater et al. (2013) used Roemer's law to explore the association of hospital bed accessibility with the hospitalization rate in Michigan state of the United States.

Because the 2SFCA method assumes that health care services within the floating catchment area is accessible while those beyond are inaccessible, and no variability within the catchment, a large body of literature attempt to develop its variants to be more specifically accommodating the characteristics of the supply side, demand side, and their interactions. For instance, Wang (2015, 101) conceptualized the distance decay effect into different distance decay functions and applied them to floating catchment areas. The distance decay effect refers to the interaction between supply and demand declines with increasing travel time or distance between them. Thus, the travel time or distance is gradually decayed in the floating catchment areas. There are power, exponential, Gaussian, and log-normal distance decay functions (F. Wang and C. Wang 2022). Dai (2010) and Shi et al. (2012) incorporated Gaussian function into the 2SFCA method to examine the accessibility to primary or cancer care. Luo and Qi (2009) applied weights to different travel time zones within the floating catchment areas to account for distance decay and developed the enhanced 2SFCA method. Any improvements in setting reasonable catchment size and using the best-fitting distance decay function are not achievable without analyzing the real-world spatial behavior of patients.

In terms of the travel estimate, Del Conte et al. (2022) added different travel modes, such as car driving, bus, bicycle, and walking into the 2SFCA method and developed the multimodal commuter-based version with a case study of Milwaukee County in Wisconsin state of the United States. Based on the more specific consideration of the supply and demand sides, Shao and Luo (2022) allocated doctor's resources to the insurance plans on the supply side and adjusted the population's need by age and gender to develop the supply-demand adjusted version of the 2SFCA method. Recently, Alford-Teaster et al. (2021) incorporated broadband durability into the 2SFCA method and developed its virtual version to measure the accessibility to telehealth services in hospitals in Vermont of the United States. All these improvements rely on the availability and accessibility of data.

2.4. Health Care Accessibility in Austria

There is very limited research examining health care accessibility in Austria. Part of the reason is the author's primary language (English speaking) is not German so that the related literature in German is not searched. For the related work in English, Bauer et al. (2020) applied a supply-to-demand ratio and proximity method to high-resolution data to examine the access to intensive care (ICU) beds in 14 European countries. The study found national-level differences in the access to ICU beds: Germany ranked the highest in the accessibility score (35.3), followed by Estonia (33.5) and Austria (26.4). The travel time to the nearest facility with ICU beds was 12.7 minutes. Hafner and Mahlich (2016) used the travel time to the physician practice locations and other variables extracted from survey data to examine their association with physician visits in Austria. Fritze, Graser, and Sinnl (2018) applied the realistic travel times of patients to hospitals to optimize the locations of emergency medical services in Lower Austria. No studies are found to examine the geographic accessibility to acute hospitals at the finest geographic scales in Austria.

2.5. Health Care Accessibility in the United States

There has been fruitful research on health care accessibility in the United States given more challenges in its health care system. But this section will systematically review those focusing on the geographic accessibility to hospital care across the whole country or accessibility to health care services in Louisiana.

For the former theme, section 2.3 has already reviewed some related to the 2SFCA method, this section will review others related to the supply-to-demand ratio or proximity method. To list a few, Hung et al. (2018) quantified the drive distance to the nearest hospital that provides obstetric services and advanced neonatal care to examine the disparities across rural-urban areas and by their insurance types. The study found socioeconomically disadvantaged women faced increasing and substantial travel burdens in accessing those services. Henneman et al. (2011) estimated the minimal travel distance from the population to the emergency department visits and used it and other variables to examine their impact on emergency department visits. They found travel distance was significantly associated with acuity, and daytime, and resulted in admission, indicating both geography and travel distance matter in accessing these services. Smith et al. (2015) used GIS to estimate the travel distance from a patient's home address to the hospitals and found that long distance was associated with those who were younger and underwent pancreatic and esophageal resections in a Mid-Atlantic regionalized setting. Compared to other racial and/or ethnic groups, African American patients traveled shorter.

In terms of the health care accessibility in Louisiana, Ikram, Hu, and Wang (2015) applied GIS to measure people's accessibility to pharmacies at the census block level in Baton Rouge city and examine the disparity in pharmacy access across age and race. The study found that although most African Americans experienced shorter travel time than the White group in accessing the pharmacies, they suffered from poor accessibility when considering the population demand, supply capacities, and their interaction. Wang, Vingiello, and Xierali (2020) examined the disparities in spatial access to primary care physicians at the census block group level in Baton Rouge Metropolitan Statistical Area and found African Americans and poorer populations enjoyed shorter travel time and higher accessibility scores measured by the 2SFCA method. However, the "reversed racial advantage" may not capture the nonspatial obstacles related to financial and other socioeconomic factors. Prigozhina (2020) applied the 2SFCA method and others to examine the accessibility of HIV testing at the census tract and census block group levels in the Baton Rouge Metropolitan Statistical Area. However, there has been no research examining the geographic accessibility to acute care hospitals at the finest geographic scale-census block in the whole state of Louisiana.

Chapter 3. Study Area and Data

This study selects Carinthia in Austria and Louisiana in the United States as two pilot study areas. Both states are on the southern border of their countries and are bordered by other states in three facets. They are also the bases of Carinthia University of Applied Sciences in Villach and Louisiana State University in Baton Rouge, respectively. The following sections will introduce the data in two study areas.

3.1. Data Sources and Preparations in Carinthia of Austria

Carinthia is the southernmost state of Austria and is named Kärnten in German. It is bordered by Italy and Slovenia to the south and several Austrian states including Tyrol (Tirol in German) to the west, Salzburg (Salzburg in German) to the northwest, and Styria (Steiermark in German) to the northeast. As the fifth largest state in Austria, Carinthia has 2 statutory cities (Statutarstädte) and 8 districts (Bezirke), which are the capital Klagenfurt city, Villach city, Spittal an der Drau District, Feldkirchen District, Sankt Veit an der Glan District, Wolfsberg District, Völkermarkt District, Klagenfurt-Land District, Villach-Land District, and Hermagor District (see Figure 3.1). Carinthia is well known for its rich mountains, such as the Carnic Alps (Karnischen Alpen) in the west, and the massif of the High Tauern, Großglockner, Gurktal Alps (Gurktaler Alpen) in the north or northwest, and Karawanken Alps (Karawanken) in the south. In 2022, Carinthia has 564,513 people with an area size of 9,536 km² and population density of 59.20 persons/km² (City Population 2022).

Table 3.1 reports all data used in Carinthia. All data are from 2020. The 250-meter grid layer is obtained from XXX. There are 154,334 grids with a total population of 561,237 in Carinthia. The census block layer is obtained from Open Data Austria and XXX which covers all census blocks in Austria. The acute hospitals are identified from the 50plus.at platform which contains hospital names, types, addresses, bed counts, specialists, and contact information. The address is used to geocode the geographic location of each acute hospital through Google Maps. There are 13 hospitals with 3,436 beds in Carinthia.

The road network data is obtained from OSM (2020). The travel time from the geographic centroid of each grid or census block to the location of each acute hospital is estimated using the Open Source Routing Machine (OSRM). OSRM is a high-performance routing engine running the shortest paths on OSM data. It provides a Python package that can automatically adjust parameters, such as speed and road restrictions based on the attributes of OSM data rather than manually process road segments that miss related information. Because most people prefer car driving (65%) for commuting in Austria (Statista 2022), this study uses driving time as the travel time. I am aware that a considerable amount of people prefers public transportation (33%). But because of data limitations and a short research period, this study only considers driving as a transport mode for people to access acute hospital resources.

One concern in measuring accessibility is the edge effect (Ikram, Hu, and Wang 2015). In this study, the edge effect refers to people living in Carinthia visiting the acute hospitals in the neighboring states and vice versa, and thus the results are less reliable near their edges (boundaries). This study only considers the edge effect at the census block level as it covers data in the neighboring states of Carinthia. A 15-mile buffer is created around the boundary of Carinthia (see Figure 3.2). Thus, the 15-mile buffer and Carinthia contain 1,036 census blocks with a total population of 892,034 and 20 acute hospitals with total beds of 5,018. Similarly, the OSRM is used on the OSM data to estimate the driving time from each census block to each acute hospital.

Figure 3.1 shows the distribution of the population at 250-meter grids and acute hospital beds in Carinthia. The population is distributed along the physical road and concentrated in Villach and Klagenfurt. Also, these two cities have the most hospital beds, followed by Sankt Veit an der Glan District, Spittal an der Drau District, and Wolfsberg District. Note that the northwest of Spittal an der Drau District and Feldkirchen District, the whole Völkermarkt District, Klagenfurt-Land District, and Villach-Land District do not have acute hospitals, suggesting residents need to travel outside for acute care.

Figure 3.2 shows the distribution of population density of each census block and acute hospital beds in Carinthia and the 15-mile buffer. Similarly, Villach and Klagenfurt have higher population densities than other districts, so as the acute hospital beds. Note that there are at least 7 acute hospitals in the buffer, which may affect the accessibility scores.

Table 3.1. Summary of data used in Carinthia, Austria, 2020

<table>
<tr><th>Study area</th><th>Data layer</th><th>Number of records</th><th>Spatial scale/format</th><th>Data source</th></tr>
<tr><td rowspan="4">Carinthia</td><td>Grid population</td><td>154,334[a]
(561,237 people)</td><td>250-meter grid/polygon</td><td>Ask Dr. Paulus</td></tr>
<tr><td>Census block population</td><td>607
(562,089 people)</td><td>Block/polygon</td><td>Open Data Austria and XXX (refers to the table of population gave by Dr. Paulus)</td></tr>
<tr><td>Acute hospital</td><td>13
(3,436 beds)</td><td>Point</td><td>50plus.at</td></tr>
<tr><td>Road network</td><td>-</td><td>Polyline</td><td>OpenStreetMap (OSM)</td></tr>
<tr><td rowspan="3">Carinthia and a 15-mile buffer</td><td>Census block population</td><td>1,036
(892,034 people)</td><td>Block/polygon</td><td>Open Data Austria and XXX</td></tr>
<tr><td>Acute hospital</td><td>20
(5,018 beds)</td><td>Point</td><td>50plus.at</td></tr>
<tr><td>Road network</td><td>-</td><td>Polyline</td><td>OSM</td></tr>
</table>

[a] refers to that there are 23,852 grids with a nonzero population.

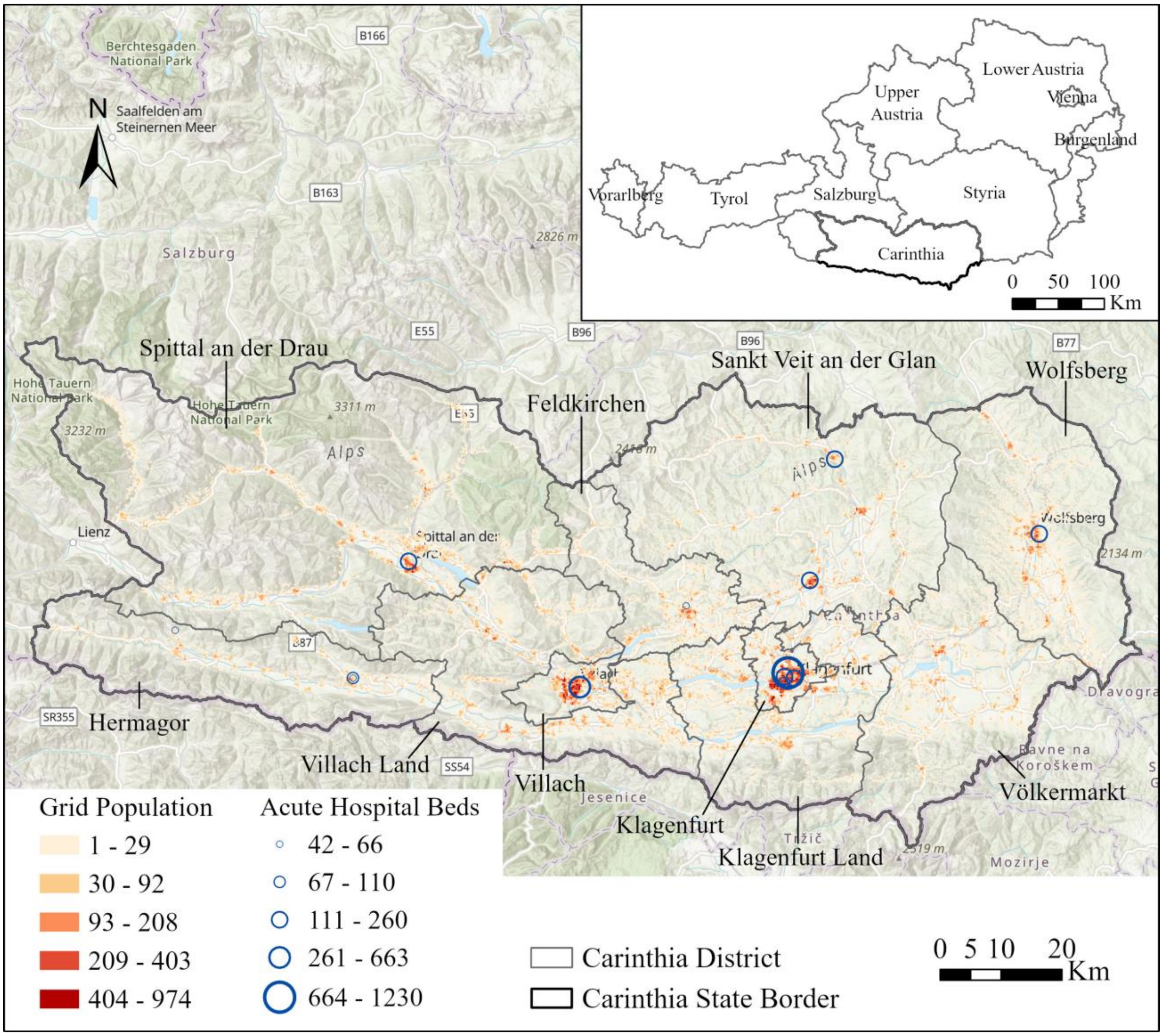

Figure 3.1. Population at the 250-meter grid level and acute hospital beds in Carinthia

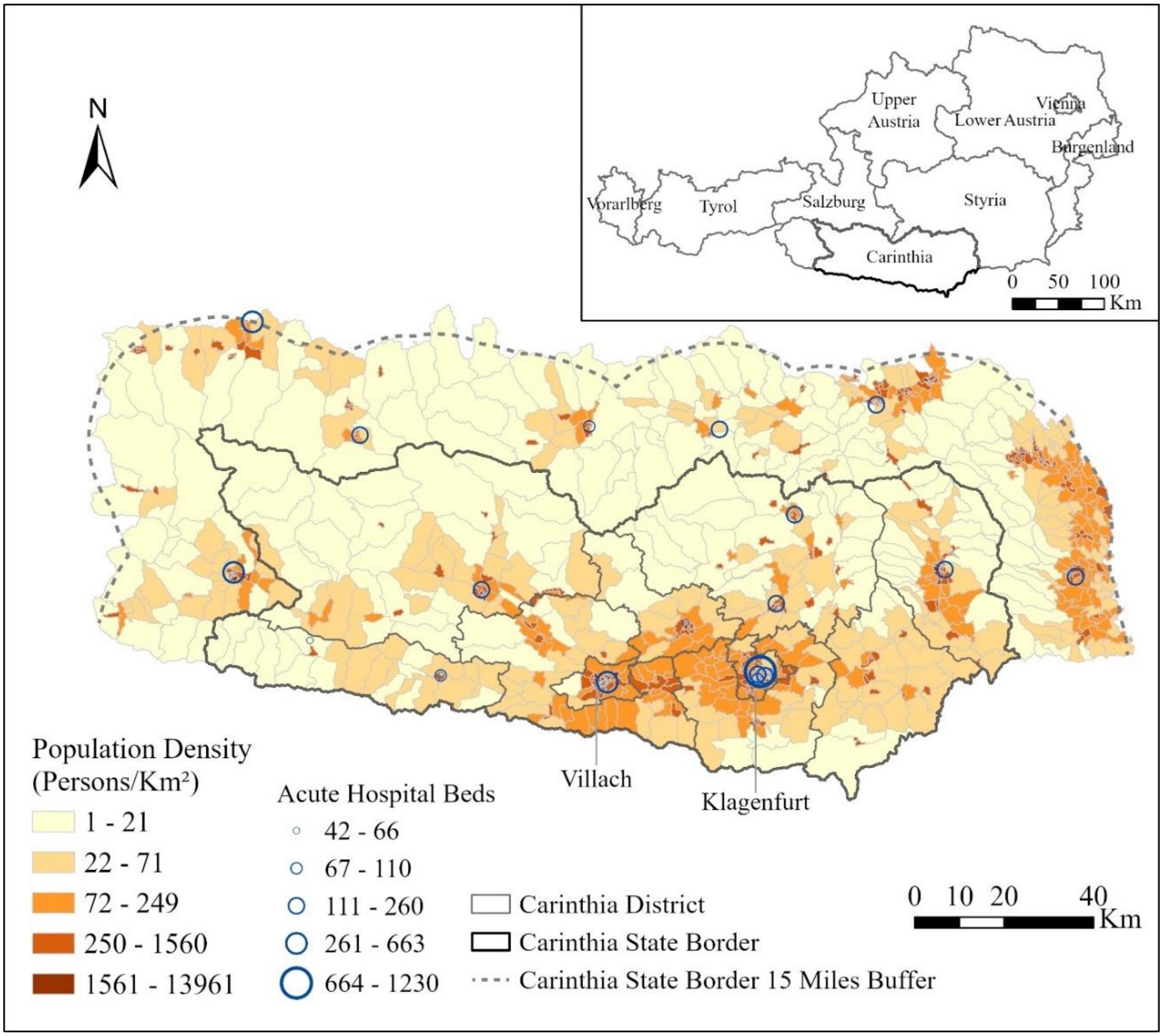

Figure 3.2. Population density of census blocks and acute hospital beds in Carinthia

3.2. Data Sources and Preparations in Louisiana of the United States

Louisiana is a southern state in the Deep South and South Central regions of the United States. It is bordered by the Gulf of Mexico to the south, Texas state to the west, Arkansas state to the north, and Mississippi state to the east. Both the east and part of the west boundaries are demarcated by the Mississippi River and Sabine Lake. Louisiana has 64 parishes (counties equivalent), among which Baton Rouge is the capital city residing in the East Baton Rouge Parish and New Orleans in the Orleans Parish is the largest city in terms of population. According to a recent report from the Louisiana Department of Health (2021), Louisiana has expanded health insurance coverage up to 91.4% in 2020, but it ranks the highest in the rates of heart disease and stroke, obesity, and diabetes, and low birthweight infants, sexually transmitted infections, and cancer incidence across the country. All highlight the importance of studying and understanding health-related issues, including the accessibility to acute care hospitals.

Table 3.2 reports all data used in Louisiana in 2020. The census block layer, as the finest geographic scale in the United States is obtained from the US Census Bureau (2020). There are 92,180 census blocks with a total population of 4,657,679. The list of acute care hospitals is downloaded from the website of the Cecil G. Sheps Center for Health Services Research which is affiliated with The University of North Carolina at Chapel Hill. It contains hospital name, address, state, and bed counts. Using Google Maps, the study geocodes all acute care hospitals in a point layer. There are 111 hospitals with 15,496 beds in total in Louisiana.

Similar to the Carinthia study area, this study uses OSM data and OSRM to estimate the travel time from the geographic centroid of each census block to the location of each acute care hospital in Louisiana. The driving mode is also chosen for travel estimate as the recent statistics from the US Department of Transportation (2020) report that 76.8% of Americans prefer driving alone or carpooling, and only 3.22% use public transportation for commuting. To mitigate the edge effect, a 15-mile buffer is also created around the state border of Louisiana, related census blocks, acute care hospitals, and OSM data are also processed and listed in Table 3.2.

Table 3.2. Summary of data used in Louisiana, USA, 2020

Study area	Data layer	Number of records	Spatial scale/format	Data source
Louisiana	Census block population	92,156[a] (4,657,679 people)	Block/polygon	U.S. Census Bureau
	Acute care hospital	111 (15,496 beds)	Point	Cecil G. Sheps Center for Health Services Research
	Road network	-	Polyline	OSM
Louisiana and a 15-mile buffer	Census block population	109,830[a] (5,267,725 people)	Block/polygon	U.S. Census Bureau
	Acute care hospital	127 (17,294 beds)	Point	Cecil G. Sheps Center for Health Services Research
	Road network	-	Polyline	OSM

[a] refers to the number of census blocks with nonzero populations after excluding 24 census blocks (population = 78) that are in farmlands and do not have road networks to be reached by driving.

Figure 3.3 shows the population density of each census block and acute care hospitals with beds in Louisiana and its 15-mile buffer. Areas with higher population density and hospital beds are concentrated around the city centers of Baton Rouge, New Orleans, Shreveport, Lake Charles, and Lafayette. The acute care hospitals are more evenly distributed in Louisiana but with varying bed counts in comparison to those in Carinthia. Several parishes near Baton Rouge do not have acute care hospitals, suggesting the potential travel of patients beyond these areas for utilizing acute care.

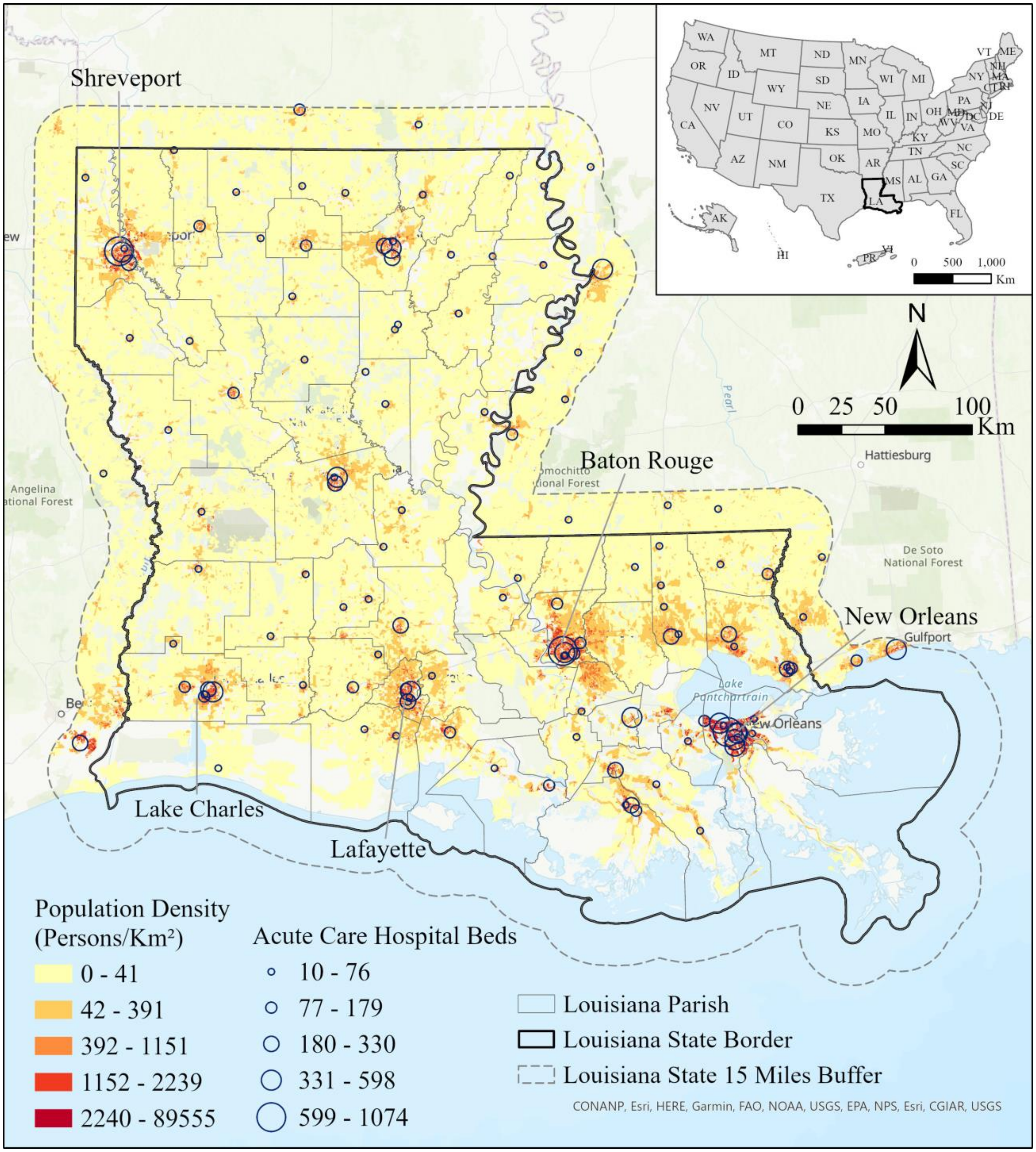

Figure 3.3. Population density of census blocks and acute care hospital beds in Louisiana. Note that the white fragmented patches are unpopulated areas and water bodies.

3.3. Data Summary in Carinthia and Louisiana

Table 3.3 summarizes the basic information at the census block level in Carinthia and Louisiana. While Carinthia has fewer census blocks with less population, area size, and acute (care) hospitals, it has a higher percentage of the population in Austria (6.2% vs. 1.4%), almost double the population density (59 persons/km^2 vs. 34 persons/km^2), and bed-to-population ratio (61 beds vs. 33 beds per 10,000 people) than Louisiana.

Table 3.3. Summary of basic information in Carinthia and Louisiana

Item	Number in Carinthia	Number in Louisiana
Census blocks	607	92,156
Population	561,237 (6.2% of Austria)	4,657,679 (1.4% of the USA)
Area size (km^2)	9538.01	135651.67
Population density (persons/km^2)	59	34
Acute (care) hospitals	13	111
Hospital beds	3,436	15,496
Bed-to-population ratio (in 10,000)	61	33

Chapter 4. Analytic Methods

This chapter will illustrate the proximity method and 2SFCA method to measure the geographic accessibility to acute (care) hospitals in Carinthia and Louisiana.

4.1. Geographic Proximity Method

In Carinthia, this study will use the geographic proximity method to measure travel time from the geographic centroid of a grid or census block to the location of its nearest acute hospital through the online routing service of OSM. In Louisiana, it will use the geographic proximity method to measure travel time from the geographic centroid of a census block to the location of its nearest acute care hospital through OSM routing service. Since the grid and census block are finer geographic scales in two study areas, it is reliable to use their geographic centroid.

4.2. Two-Step Floating Catchment Area Method

The 2SFCA method is developed by Luo and Wang (2003) to measure accessibility in GIS that involves two steps: one floating catchment of supply locations to calculate the supply-to-demand ratio and then one floating catchment of demand locations to sum the supply-to-demand ratio. In other words, it considers both the supply and demand and their complex interaction captured by the catchment. In terms of the accessibility to acute (care) hospitals in this study, the supply refers to the acute (care) hospitals, and demand refers to the population. First, for each acute (care) hospital, the method searches all population location (k) that are within a threshold travel time (d_0) from location j (or catchment area of C_j), and compute the hospital bed-to-population ratio R_j within the catchment area C_j in Equation (1):

$$R_j = \frac{S_j}{\sum_{k \epsilon C_j} D_k} \tag{1}$$

Where S_j is the hospital beds at location j, D_k is the population at location k that falls within the catchment area C_j.

Second, for each population location i, the method will search all beds at hospital location j within the threshold travel time (d_0) from i (or catchment area of Z_i), and sum up the hospital bed-to-population ratio R_j to compute accessibility A_i in Equation (2):

$$A_i = \sum_{j \epsilon Z_i} R_j = \sum_{j \epsilon Z_i} \frac{S_j}{\sum_{k \epsilon C_j} D_k} \tag{2}$$

A larger accessibility value A_i indicates better accessibility in the location.

Figure 4.1 illustrates the process of 2SFCA method using travel time to define catchment area. Suppose each hospital has 1 bed and each population location has 1 person. The catchment area *a* has 1 acute (care) hospital α and 8 people, and thus the hospital bed-to-population ratio is 1/8. Similarly, catchment area *b* has a ratio of 1/4, and the catchment area *c* has a ratio of 1/5. Within catchment area *a*, its population at census block 1 has access to hospital α only, so the accessibility at census block 1 equals the hospital bed-to-population ratio at catchment area *a* with a value of 1/8. Similarly, the population at census block 5 or 8 has access to hospital *b* only, and its accessibility is 1/4. However, the population at census block 4 has access to hospitals *a* and *b* (see the area overlapped by catchment areas *a* and *b*), so it enjoys a higher accessibility (i.e., 1/8+1/4 = 0.375).

The 2SFCA method has been developed in the ArcGIS toolbox (Wang 2015, 112). The study conducts all analyses in ArcGIS Pro and R software.

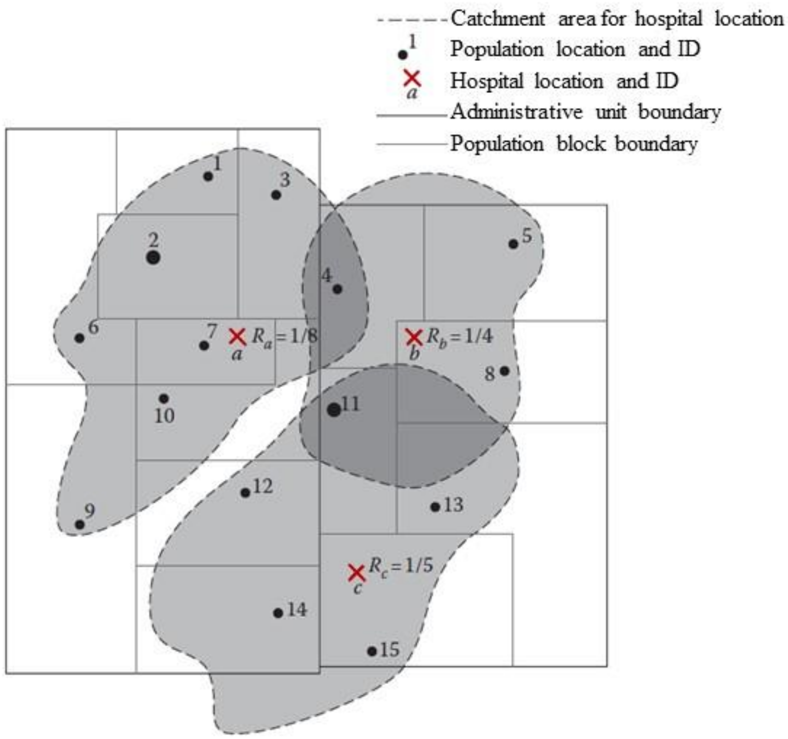

Figure 4.1. A schematic map of the 2SFCA method using road network-based travel time to define the catchment area (redrawn from Wang 2015, 98)

Chapter 5. Accessibility to Acute Hospitals in Carinthia

This chapter will report the accessibility scores by the proximity method which serves as a basic measure and the 2SFCA method which serves as an advanced method in GIS and analyze where low access areas are at the grid and census block levels in Carinthia. Both the MAUP problem and edge effect will be examined at two levels.

5.1. Minimal Travel Time Across Grids and Census Blocks

This section will examine the minimal travel times at the grid and census block levels and illustrate how they differ when considering the MAUP problem. Figure 5.1 shows the minimal travel time to the nearest acute hospital across the 250-meter grids in Carinthia. People living around hospitals and along the major roads connecting different districts enjoy shorter travel times within 20 minutes while those who live far from acute hospitals and in mountainous areas experience longer travel times which could reach 172 minutes (see yellow grids in the northwest and southeast regions of Carinthia). Such pattern displays an urban advantage.

As shown in Figure 5.2, the minimal travel time to the nearest acute hospital across the census blocks in Carinthia exhibits similar patterns to those at the grid level. There are some discrepancies as the areas that experience shorter travel time increase because of the large size of the census block compared to the 250-meter grid. In other words, the larger census blocks smooth the variabilities of access which; however, are revealed at the grid level. Another difference is that the census blocks are located in the northwest and southeast regions of Carinthia. Although people who live there experience the longest travel time to acute hospitals but still significantly less than the same areas at the grid level (62 minutes vs. 172 minutes). Such long travel times at both geographic levels may attribute to people living in Carinthia only accessing its own acute hospitals rather than traveling outside. The impact of the edge effect will be examined later.

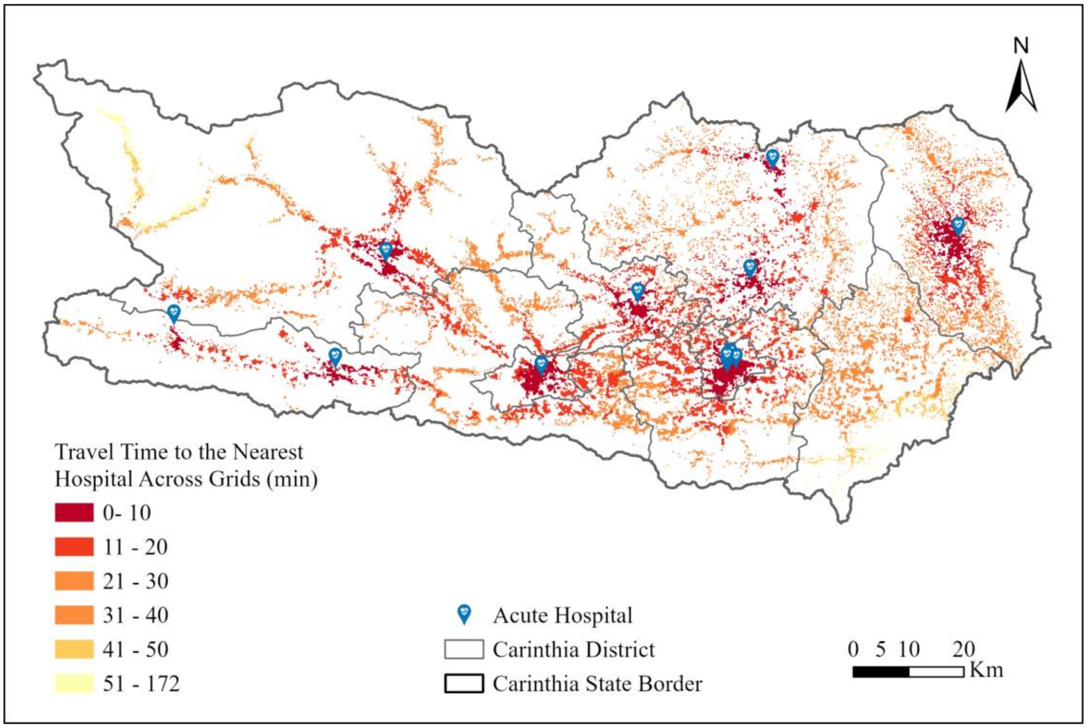

Figure 5.1. Minimal travel time to the acute hospital across 250-meter grids in Carinthia

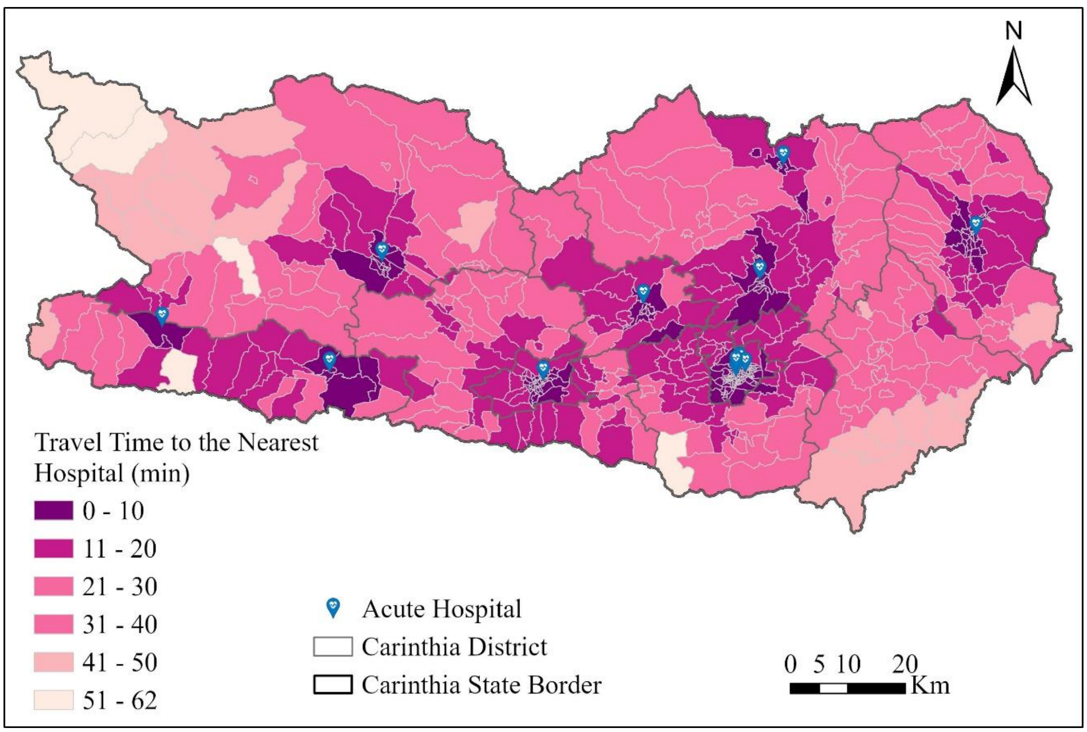

Figure 5.2. Minimal travel time to the acute hospital across census blocks in Carinthia

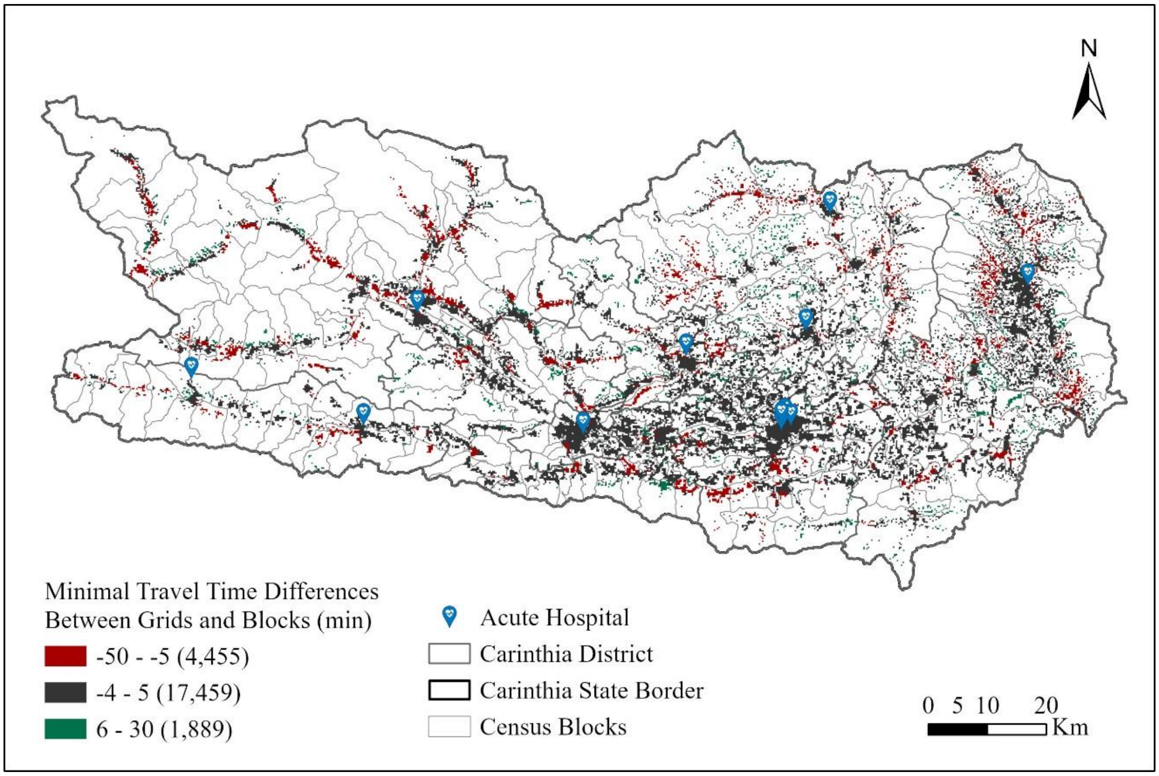

Figure 5.3. Minimal travel time difference to acute hospitals across blocks and grids in Carinthia. Note that the number in parenthesis represents the number of grids in the travel time range.

To quantify their differences, I use the "Spatial Join" tool in ArcGIS Pro to assign each census block to each grid and calculate the minimal travel time differences for the grids that have nonzero population and valid census blocks matched (some grids in the state border of Carinthia do not find the census blocks where they can fall into). The results are shown at the grid level in Figure 5.3.

The negative (positive) values in red (green) color represent the minimal travel time at the grid level is smaller (larger) than those at the census block level. The gray color represents the minimal travel time difference between the two levels in the 10-minute range. Most grids that cover 84% of the total population have a small minimal travel time difference from those at the census block level, and they are close to acute hospitals. The grids with minimal travel time less than blocks (see red color) are in the peripheries of the populous areas centered in the districts and along the major road networks, which cover 12% of the total population. In contrast, the grids with minimal travel time more than blocks (see green color) are scattered and less (1,889 vs. 4,455) with 2% of the total population. This suggests that a significant proportion of the population (14%) would be affected when selecting geographic scales to measure their access to acute care hospitals.

Figure 5.4 shows the percentage of the cumulative population across the minimal travel time at the grid and census block levels. The cumulative population across the two levels is largely consistent but with some minor differences when the minimal travel time ranges from 10 minutes to 50 minutes. 40% of the total population enjoy travel time to the nearest acute hospital within 10 minutes, and around 70%, 90%, and 95% of the population reach the acute hospital within 20, 30, and 40 minutes. These indicate that most people have good access to acute hospitals and only a small proportion of the population experience longer travel time (i.e., 10% need to travel more than 30 minutes). The average travel times are 21 and 16 minutes at the grid and block levels.

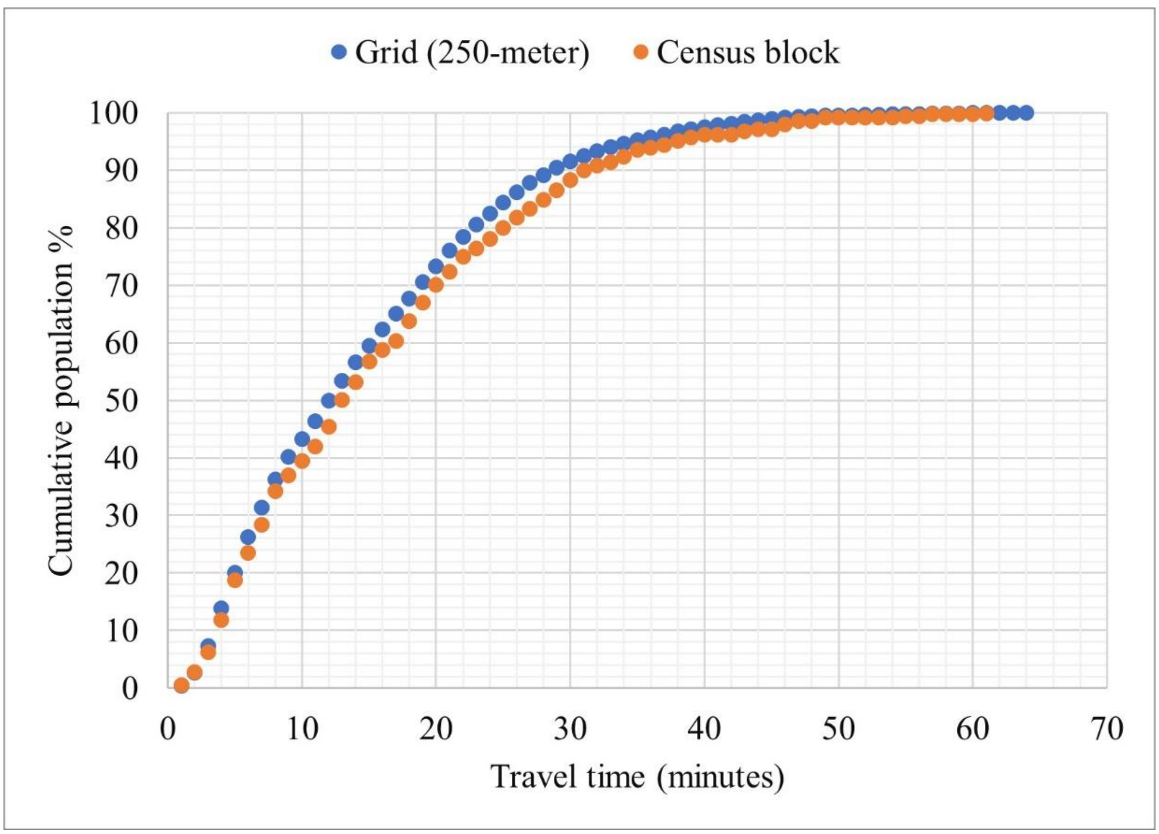

Figure 5.4. Cumulative population percentage by minimal travel time across grids and blocks in Carinthia

The edge effect is examined at the grid and census block levels in Figure 5.5-5.6. Both exhibit obvious edge effects on the north border of Carinthia (see the green grids and blocks) as some acute hospitals outside Carinthia are closer (see Figure 3.2), but it is stronger at the grid level.

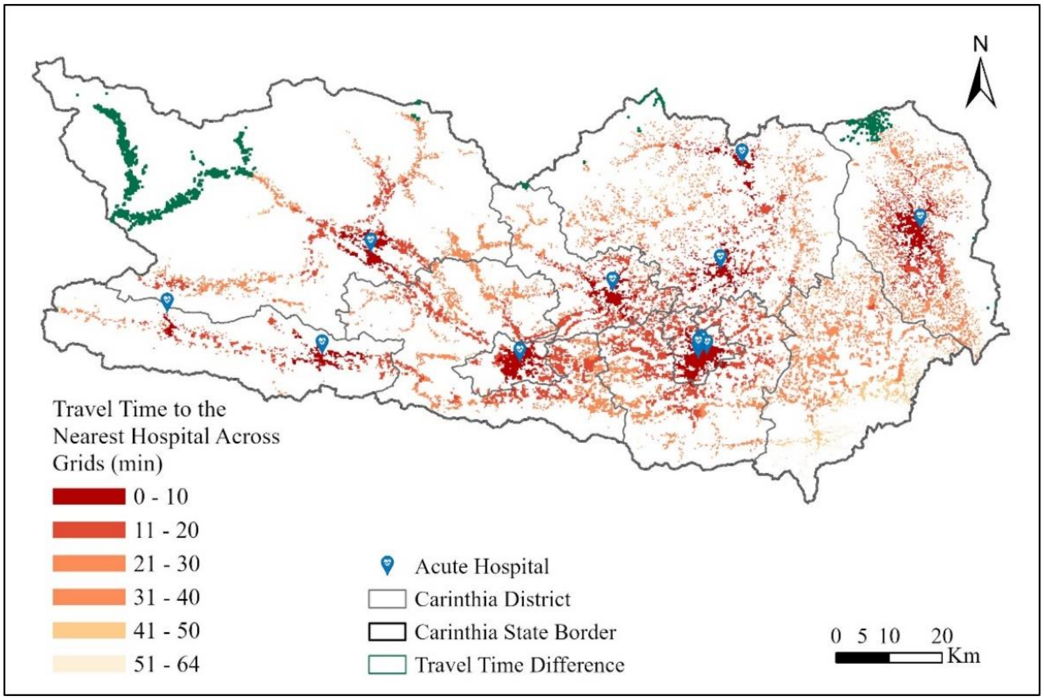

Figure 5.5. Edge effect at the grid level in Carinthia

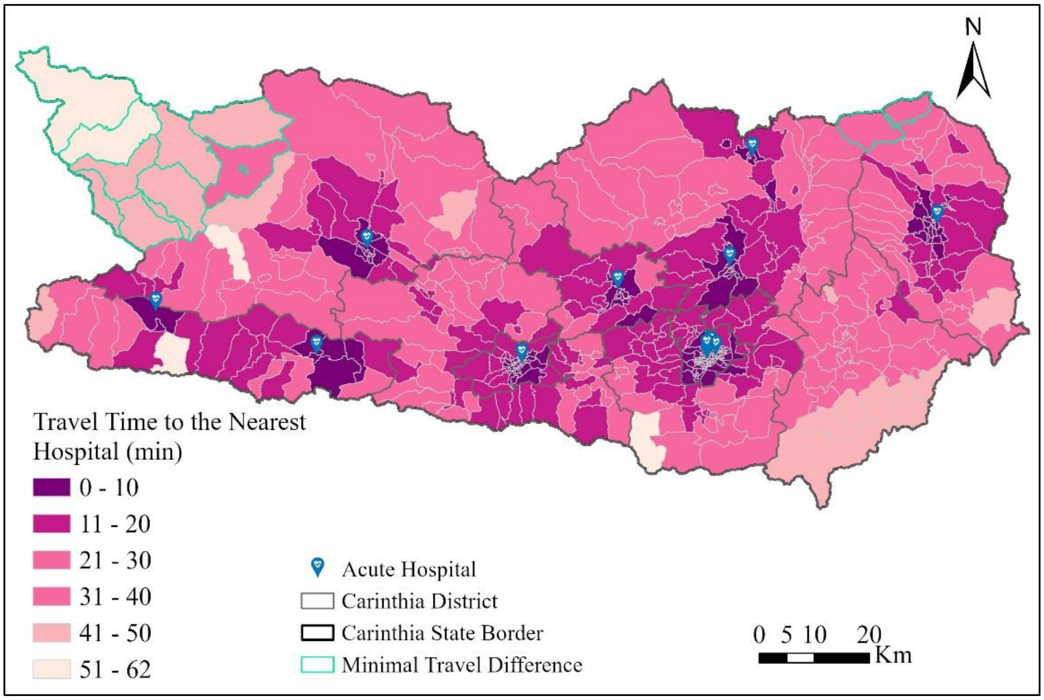

Figure 5.6. Edge effect at the census block level in Carinthia

5.2. Spatial Accessibility to Acute Hospitals Across Grids

This section will describe the accessibility scores derived by the 2SFCA method at the grid level. As introduced previously, the 2SFCA method is a match ratio of acute hospital beds and population summed twice within the floating catchment areas. One debate in accessibility studies is the definition of the floating catchment area. In absence of the actual utilization data of patients, it is impossible to account for the distance decay parameters and the appropriate function format. Therefore, this study will implement the 2SFCA method based on multiple travel time thresholds: 15, 20, 30, 40, 50, and 60 minutes. Figure 5.7-5.12 shows their accessibility scores with catchment sizes ranging from 15 to 60 minutes in the 2SFCA method at the grid level in Carinthia. I also calculate the accessibility scores by accounting for the 15-mile buffer for examining the edge effect. The results are largely consistent with minor differences and are not reported here. All accessibility scores are inflated by multiplying 10,000 to avoid too small values. Thus, the accessibility could be interpreted as the acute hospital beds per 10,000 people.

As shown in Figure 5.7 where a 15-minute catchment size is used, the highest accessibility scores (111-230) are in areas around acute hospitals in Klagenfurt city and Hermagor District, and northern areas of Sankt Veit an der Glan District, followed by the second highest around the borders of Feldkirchen District, Sankt Veit an der Glan District, and Klagenfurt city. Areas around hospitals in Villach city, Wolfsberg District, and southern Sankt Veit an der Glan District have the third highest accessibility score range (71-90), and then followed by areas around hospitals in Spittal an der Drau District and Feldkirchen District. A large proportion of grids in mountains have no accessibility scores. This suggests that for those areas, there are either no hospitals or not in a 15-minute driving range.

In Figure 5.8, using a 20-minute catchment size, the areas with nonzero accessibility scores are expanded. Areas around acute hospitals in Klagenfurt city, Hermagor District, and Sankt Veit an der Glan District still have the highest accessibility scores (111-255), so as the second and third highest areas. Compared to Figure 5.7, areas in the western Hermagor District, Spittal an der Drau District, and Wolfsberg District have accessibility decreased. This indicates that more populations are involved in competing for acute hospital care when increasing the driving time by 5 minutes.

In Figure 5.9, based on the 30-minute catchment size, the multiple monocentric patterns found in Figure 5.7-5.8 are smoothed out. The highest accessibility score significantly drops from 255 to 135, and the areas are shifted to those between Villach and Klagenfurt, and southern Sankt Veit an der Glan District. Although areas with nonzero accessibility scores are expanded, all have accessibility scores decreased. It is understandable as the driving range increases, the accessibility score around acute hospitals decreases because people living in the overlapping driving range will enjoy more choices to access more hospitals.

In Figure 5.10, when the driving range continues to increase (40 minutes), areas with zero accessibility scores shrink. Areas with higher scores are in the central southeast of Carinthia, such as Villach, Klagenfurt, and Sankt Veit an der Glan District. In Figure 5.11, using a catchment size of 50 minutes, the spatial pattern is consistent with those in Figure 5.10, but all accessibility scores decrease with more areas having nonzero scores. In Figure 5.12, the accessibility scores are smoothed out as large catchment sizes allow more population to compete for acute care.

From Figure 5.7-5.12, the accessibility scores are gradually smoothed out from high to low values. The spatial variabilities experience significant changes from a catchment size of 20 minutes to 30 and 40 minutes. Also, 90% of the total population can access the nearest acute hospital in 30 minutes, suggesting this is a suitable catchment size, which has been widely used in prior studies.

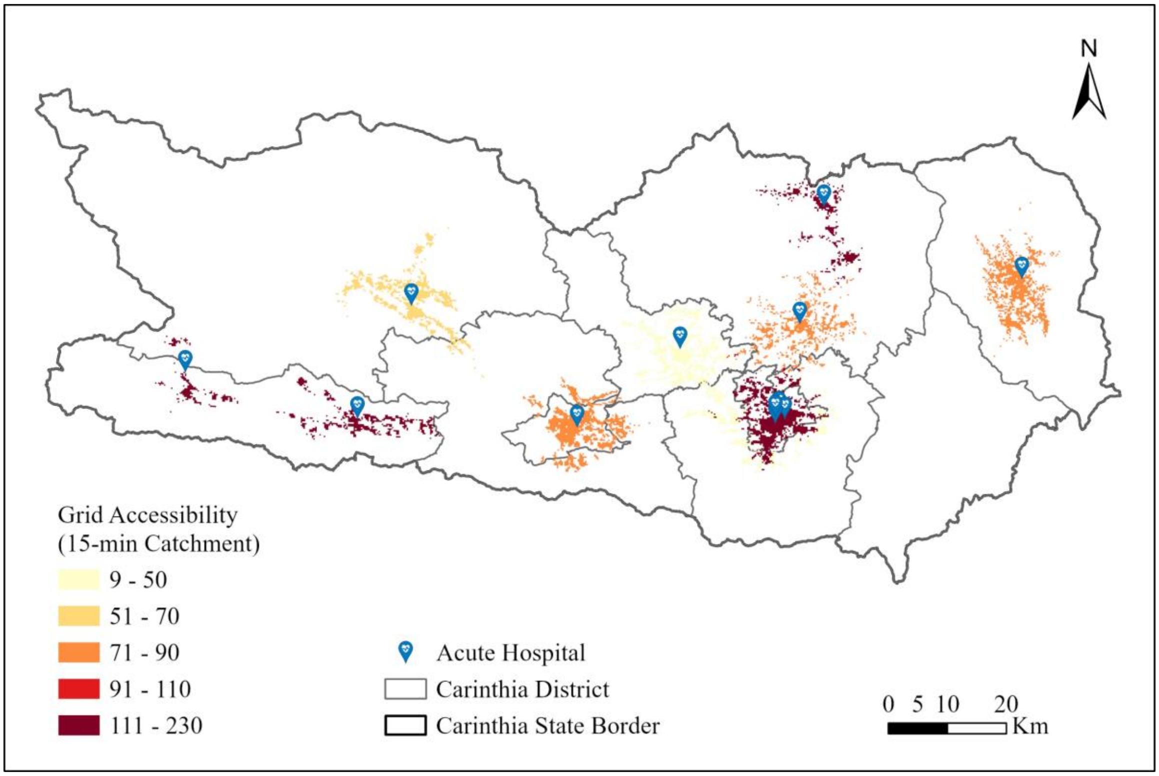

Figure 5.7. Grid-based accessibility scores by 2SFCA method (15-minute catchment) in Carinthia

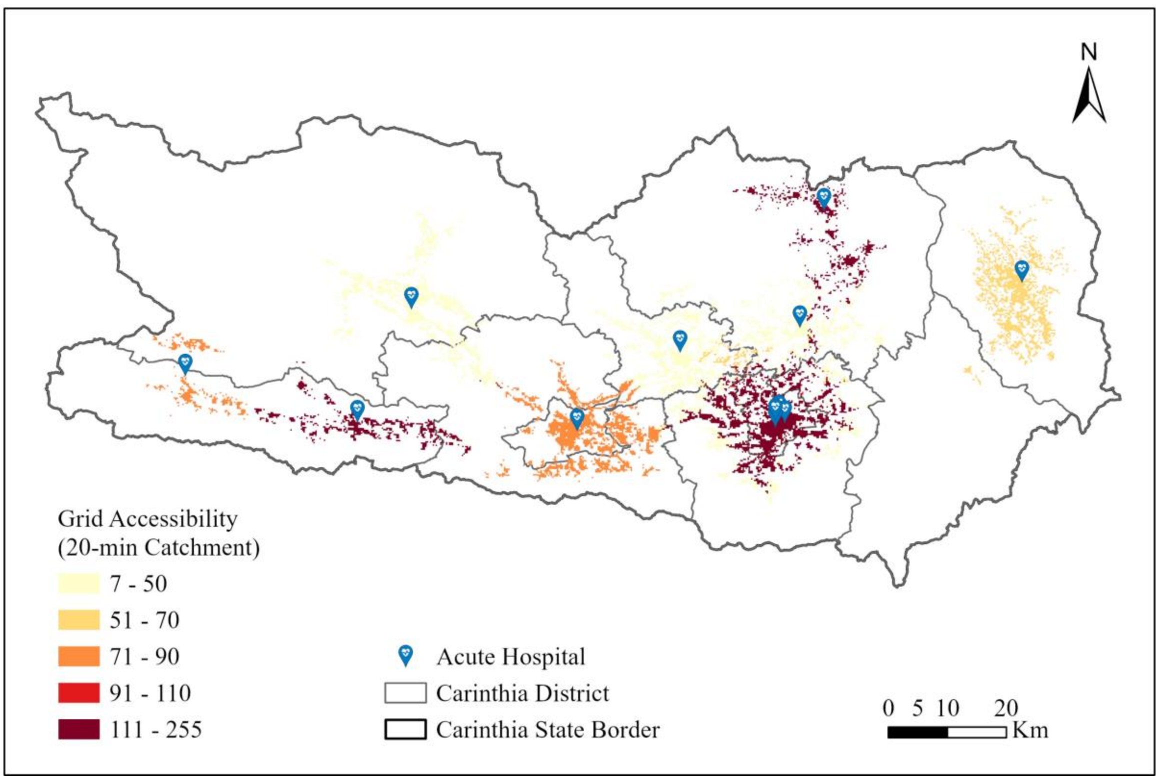

Figure 5.8. Grid-based accessibility scores by 2SFCA method (20-minute catchment) in Carinthia

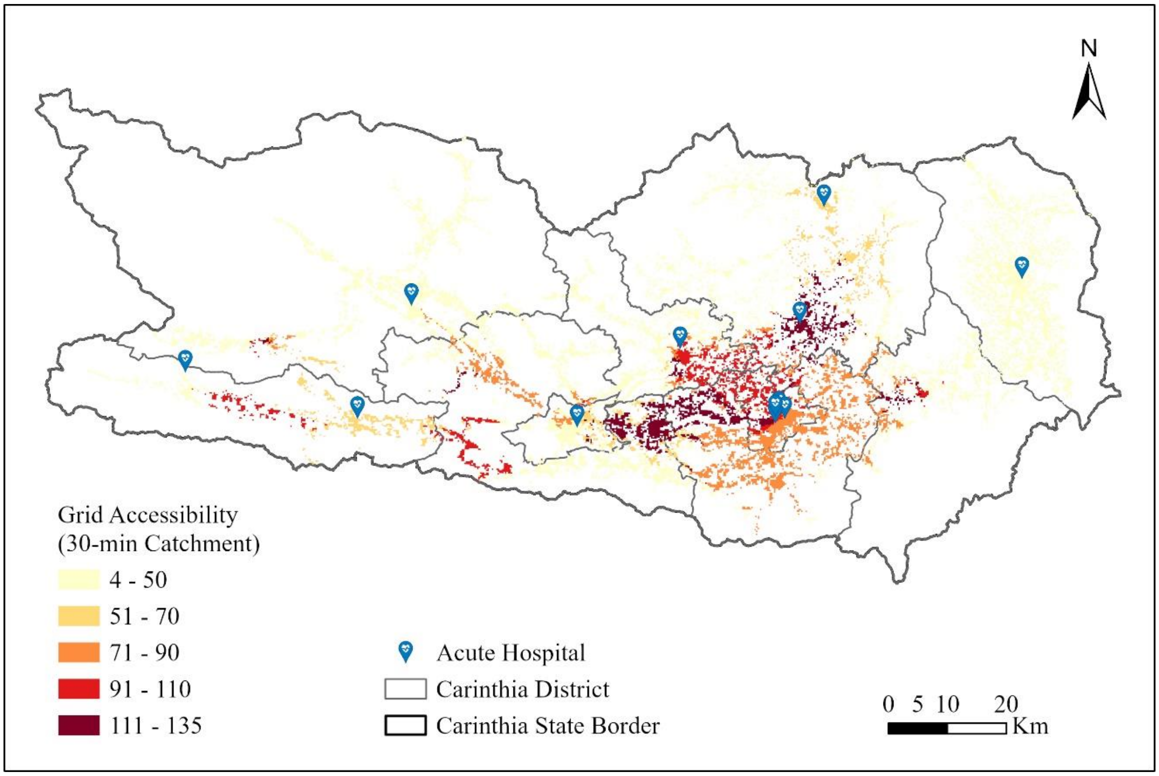

Figure 5.9. Grid-based accessibility scores by 2SFCA method (30-minute catchment) in Carinthia

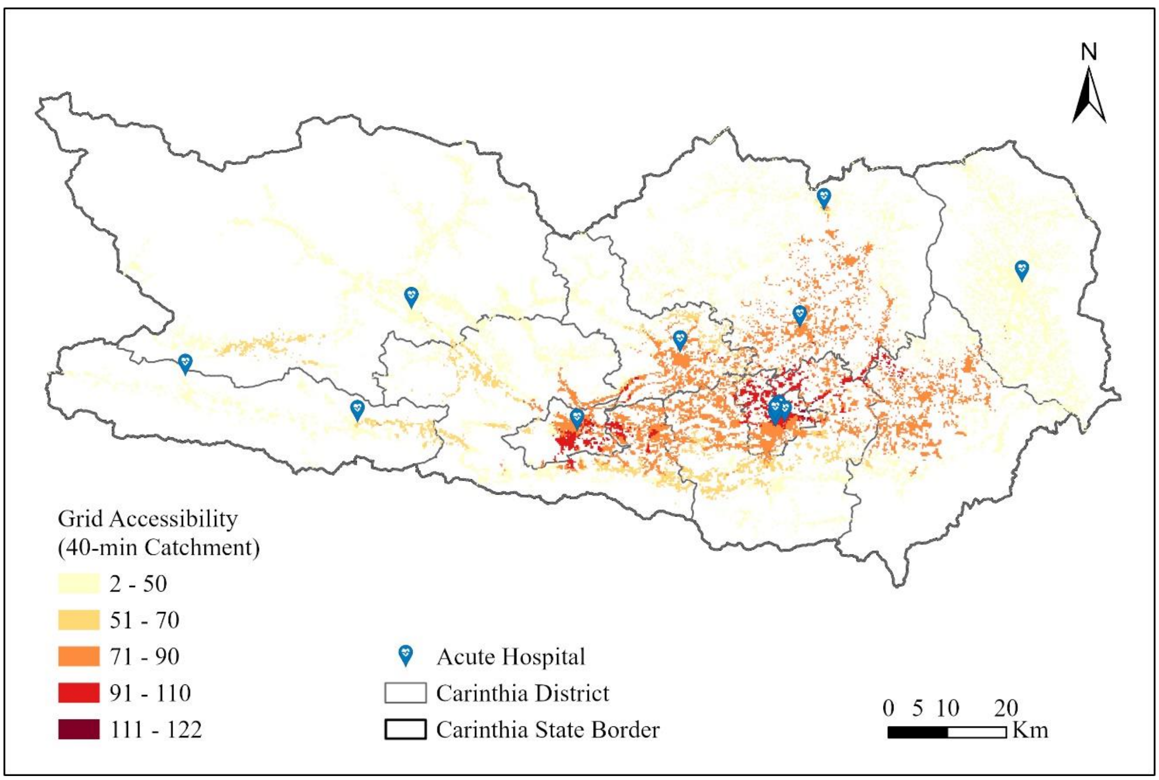

Figure 5.10. Grid-based accessibility scores by 2SFCA method (40-minute catchment) in Carinthia

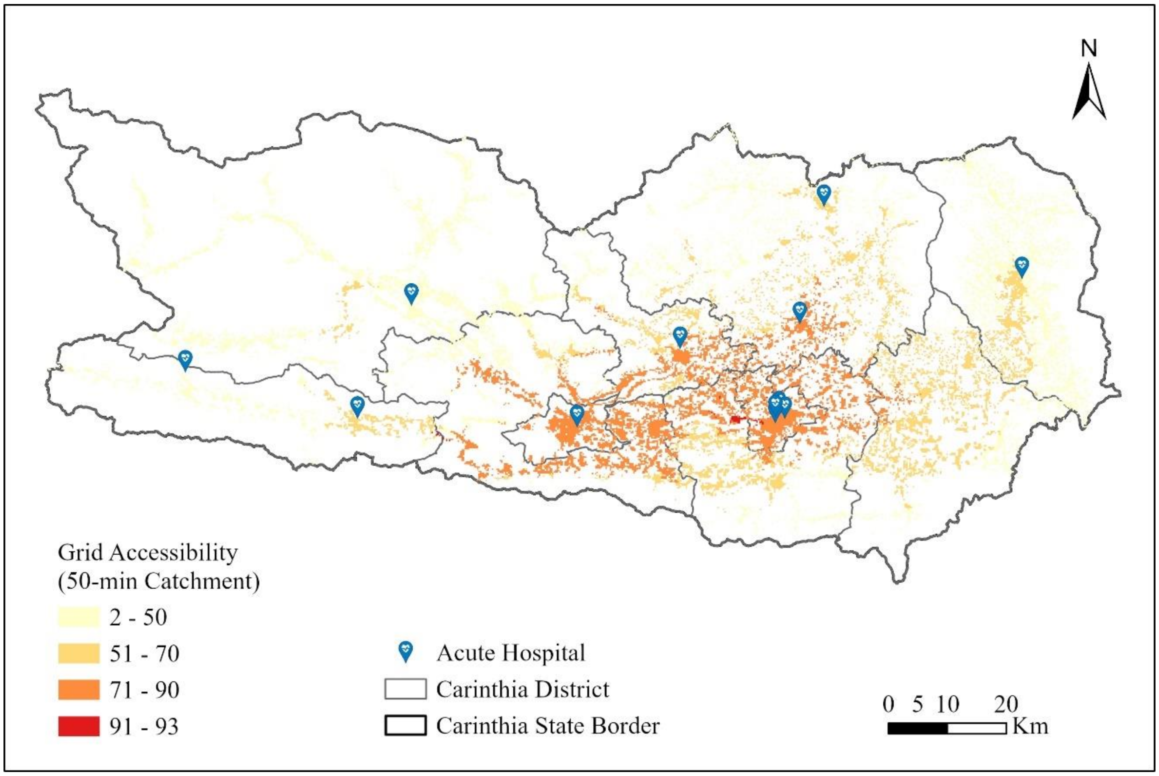

Figure 5.11. Grid-based accessibility scores by 2SFCA method (50-minute catchment) in Carinthia

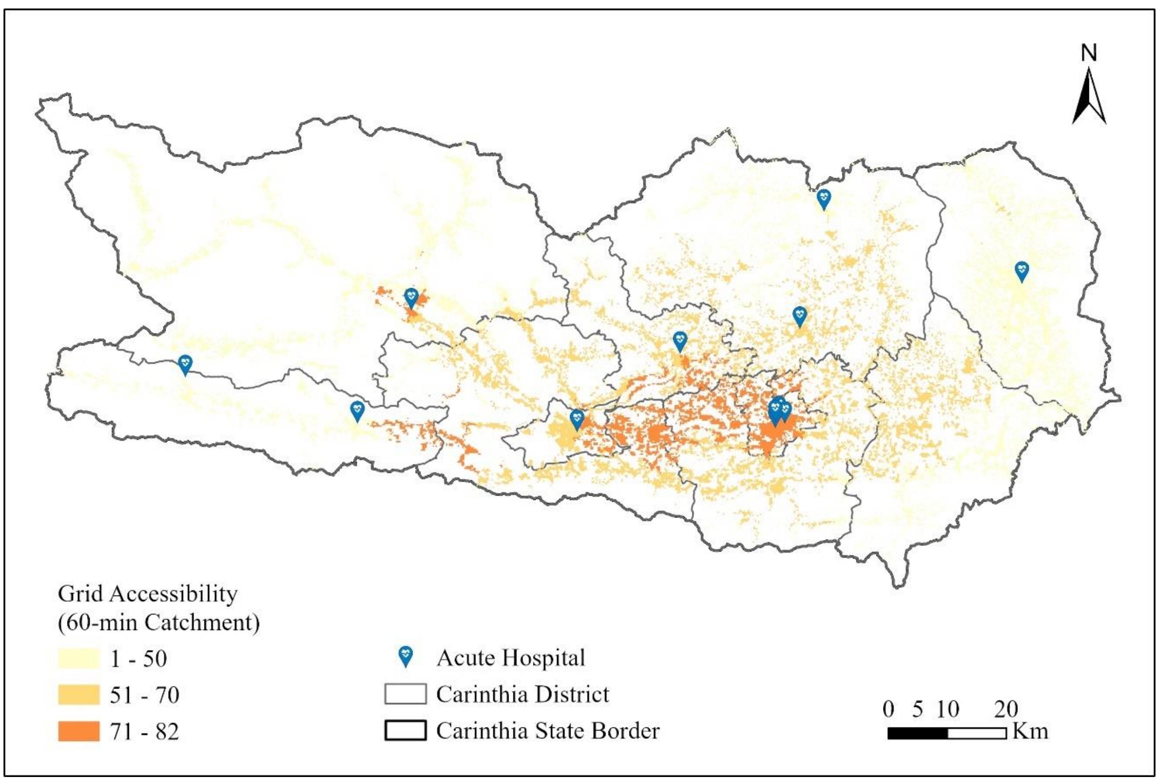

Figure 5.12. Grid-based accessibility scores by 2SFCA method (60-minute catchment) in Carinthia

5.3. Spatial Accessibility to Acute Hospitals Across Census Blocks

This section will describe the accessibility scores derived by the 2SFCA method at the census block level in Carinthia. For comparison with those at the grid level, the catchment sizes of 15, 20, 30, 40, 50, and 60 minutes are experimented in the 2SFCA method. The accessibility scores are also scaled by multiplying 10,000 to avoid small values. The edge effect is also examined by considering the 15-mile buffer, the results are largely consistent and only minor differences are found along the northern border. Therefore, only the accessibility scores without a 15-mile buffer are visualized in Figure 5.13-5.18. In each map, the number in the parathesis refers to the number of blocks in the range of accessibility scores.

In Figure 5.13, based on a 15-minute catchment, the highest accessibility scores are in areas around acute hospitals in Klagenfurt city, Hermagor District, and northern areas of Sankt Veit an der Glan District, followed by the second highest in Villach city and areas around the borders of Feldkirchen District, Sankt Veit an der Glan District, and Klagenfurt city. Areas around hospitals in Wolfsberg District, and southern Sankt Veit an der Glan District, and Spittal an der Drau Distrcit have the third highest accessibility score (71-90) and are followed by areas in central Carinthia. A large proportion of grids in mountains have no accessibility scores. The areas with the lowest and zero accessibility scores suggest low hospital capacities or not in a 15-minute driving range.

In Figure 5.14, using a 20-minute catchment size, areas with zero accessibility scores are shrunk. Areas around acute hospitals in Klagenfurt city, eastern Hermagor District, and Sankt Veit an der Glan District still have the highest accessibility scores (111-220). Compared to Figure 5.13, areas in the western Hermagor District and Villach city have accessibility flatted outward, ranking the third highest. The accessibility scores in the southern Sankt Veit an der Glan District and

Feldkirchen District are flatted by the neighboring areas and jumped into the lowest range. As the catchment size increases, more populationa are included to compete for acute care in those areas.

In Figure 5.15, based on the 30-minute catchment size, the areas with higher accessibility scores are shrunk and expanded outward in the south of the study area. Areas in Villach city have the accessibility drop into the lowest range (4-50). The accessibility scores in the triangular region of Klagenfurt city, Feldkirchen District, and Sankt Veit an der Glan District increase although still lower than those in the city and two districts. Areas with zero accessibility scores have significantly reduced in comparison to the catchment size of 20 minutes in Figure 5.14.

In Figure 5.16, using the driving range of 40 minutes, areas with zero accessibility score are extruded and scattered around the state border. The southern Villach and areas on the right side of Klagenfurt city rank the highest range of accessibility score (111-125). Centered on them, their neighboring areas with lower accessibility score spread. When the catchment size extends to 50 and 60 minutes in Figure 5.17-5.18, the dual-nuclei structure fuses into a monocentric structure with the accessibility scores decreasing.

From Figure 5.13-5.18, when adjusting the catchment size, the accessibility scores are progressively smoothed from high to low values. The spatial structure of accessibility changes from a polycentric structure where their peaks are scattered around acute hospitals in the districts or cities to a monocentric structure that dominates in the triangular regions of Villach, Klagenfurt, and southern Sankt Veit an der Glan District. The variabilities of spatial accessibility experience a significant change from 30 to 40 minutes of driving range, which covers almost 90% to 97% of the total population in Carinthia (see Figure 5.4). Similar to the accessibility at the grid level, the 30-minute driving range is a suitable catchment size.

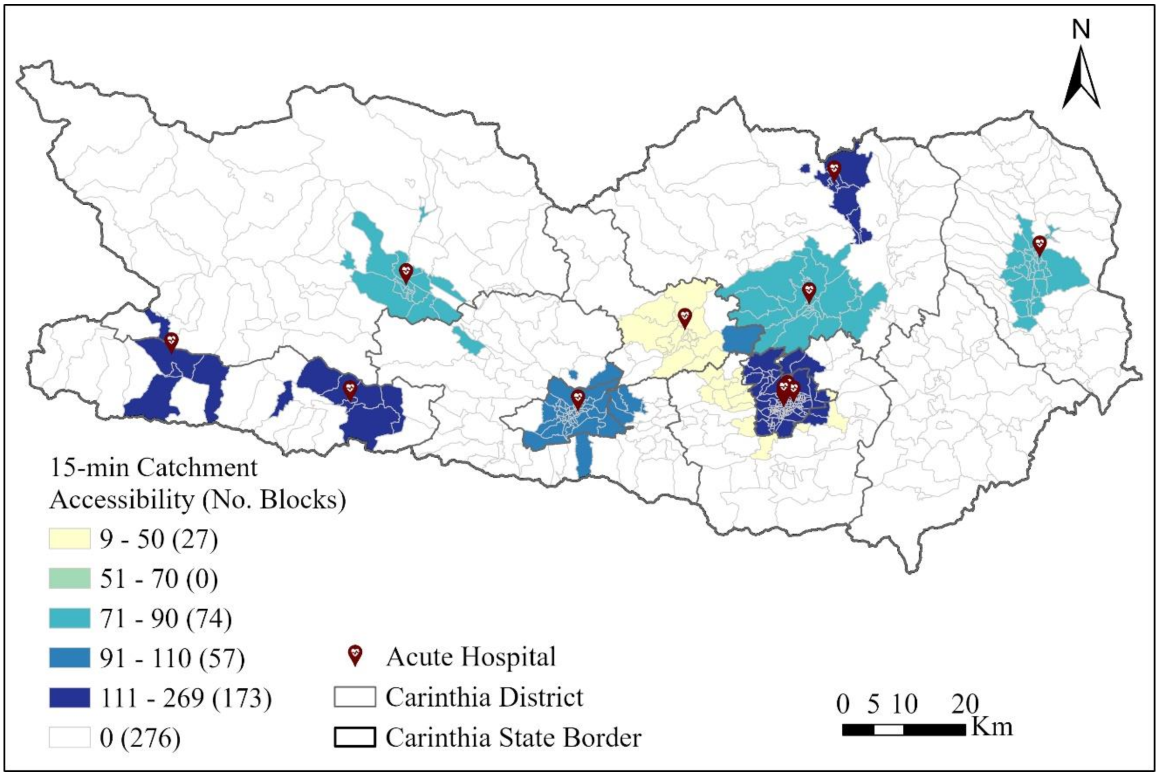

Figure 5.13. Block-based accessibility scores by 2SFCA method (15-minute catchment) in Carinthia

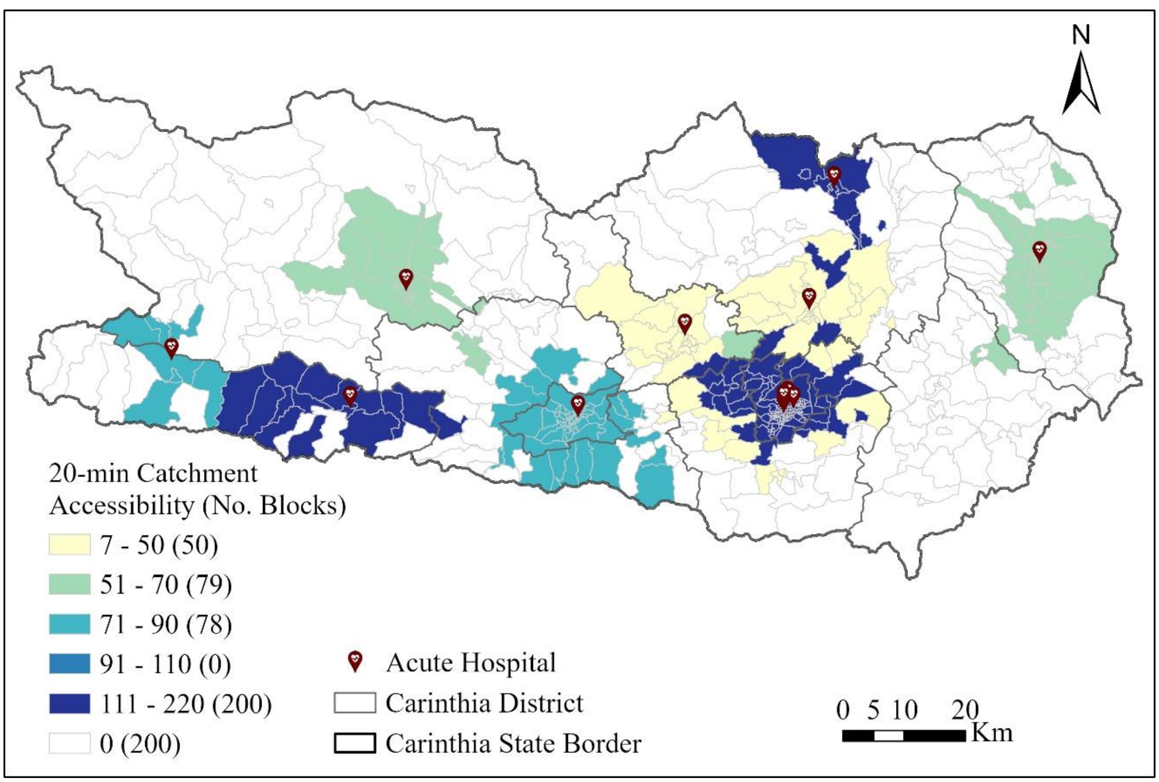

Figure 5.14. Block-based accessibility scores by 2SFCA method (20-minute catchment) in Carinthia

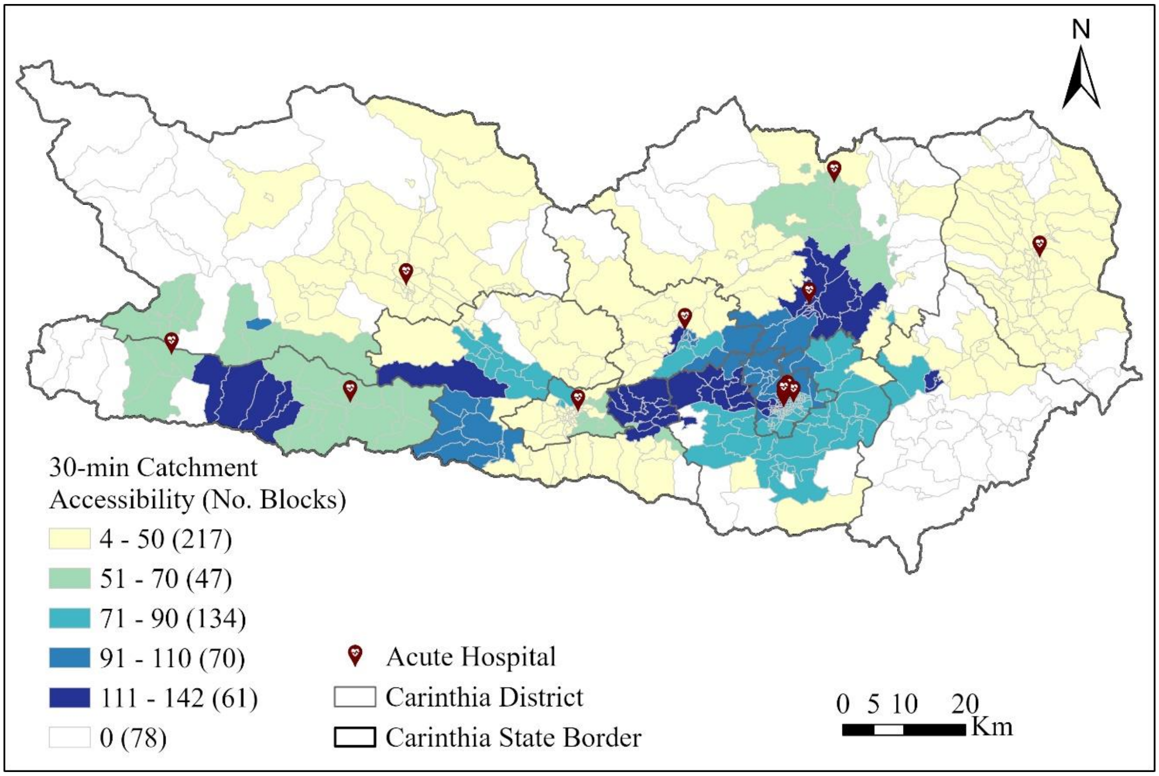

Figure 5.15. Block-based accessibility scores by 2SFCA method (30-minute catchment) in Carinthia

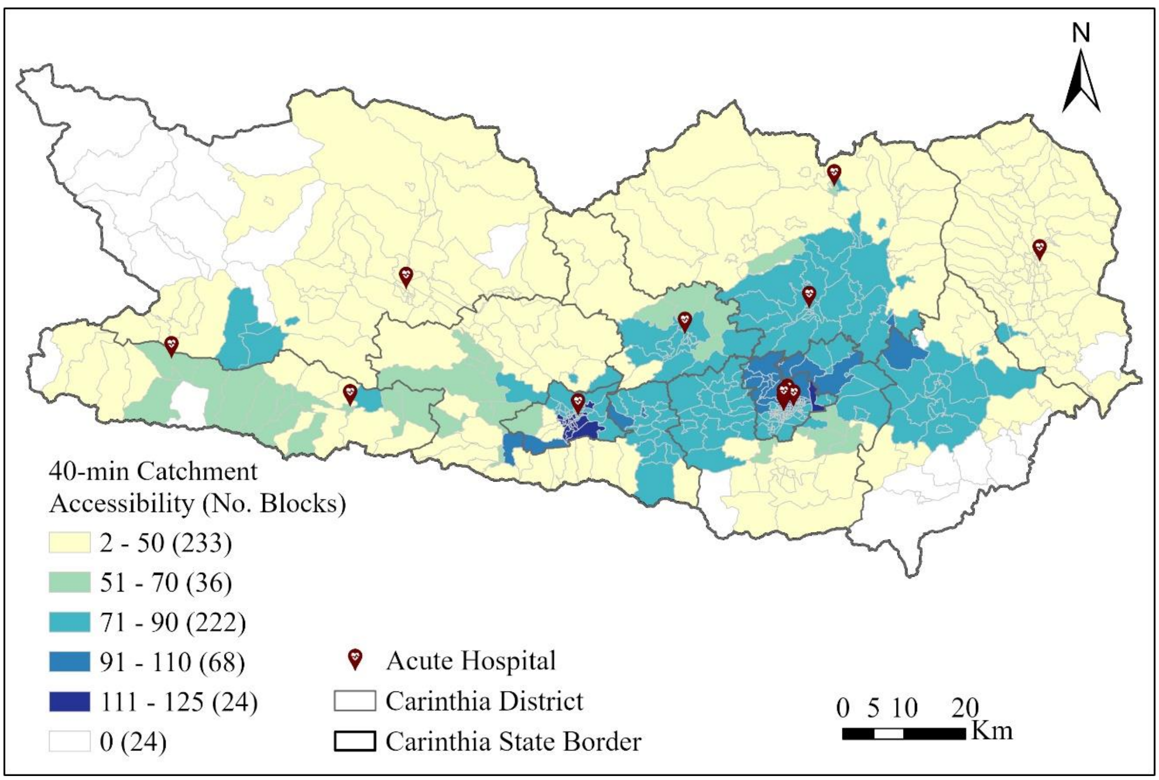

Figure 5.16. Block-based accessibility scores by 2SFCA method (40-minute catchment) in Carinthia

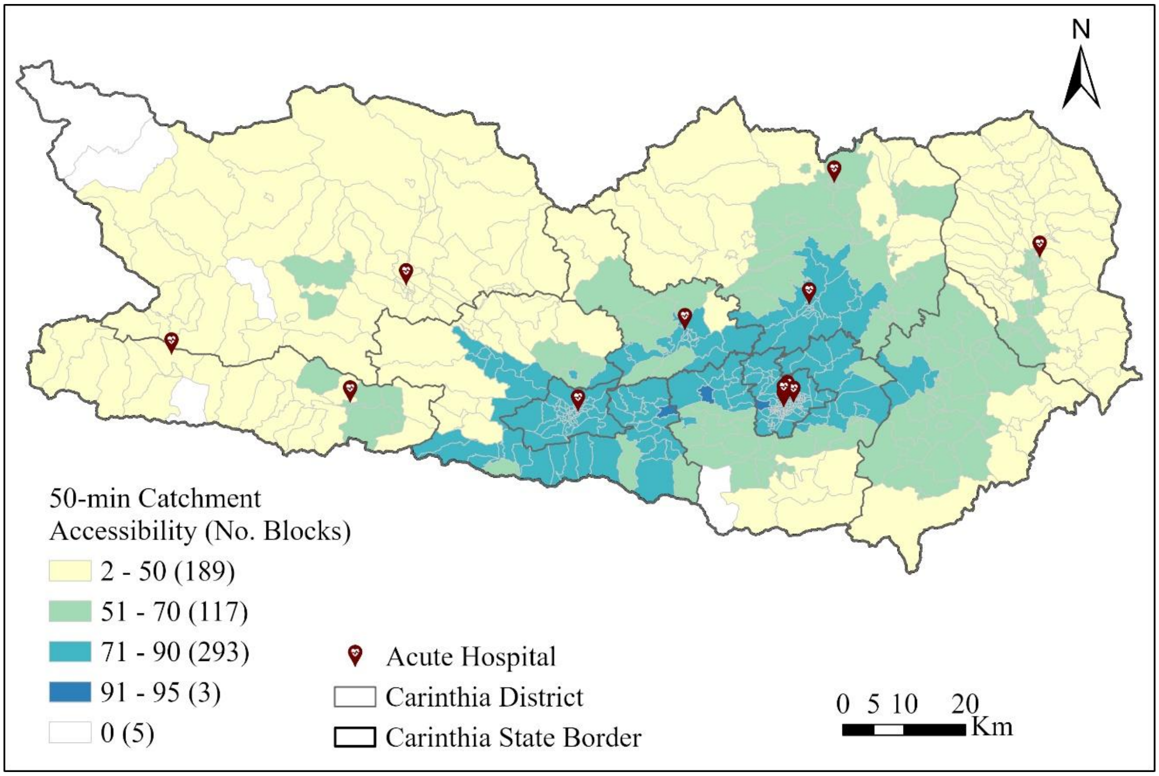

Figure 5.17. Block-based accessibility scores by 2SFCA method (50-minute catchment) in Carinthia

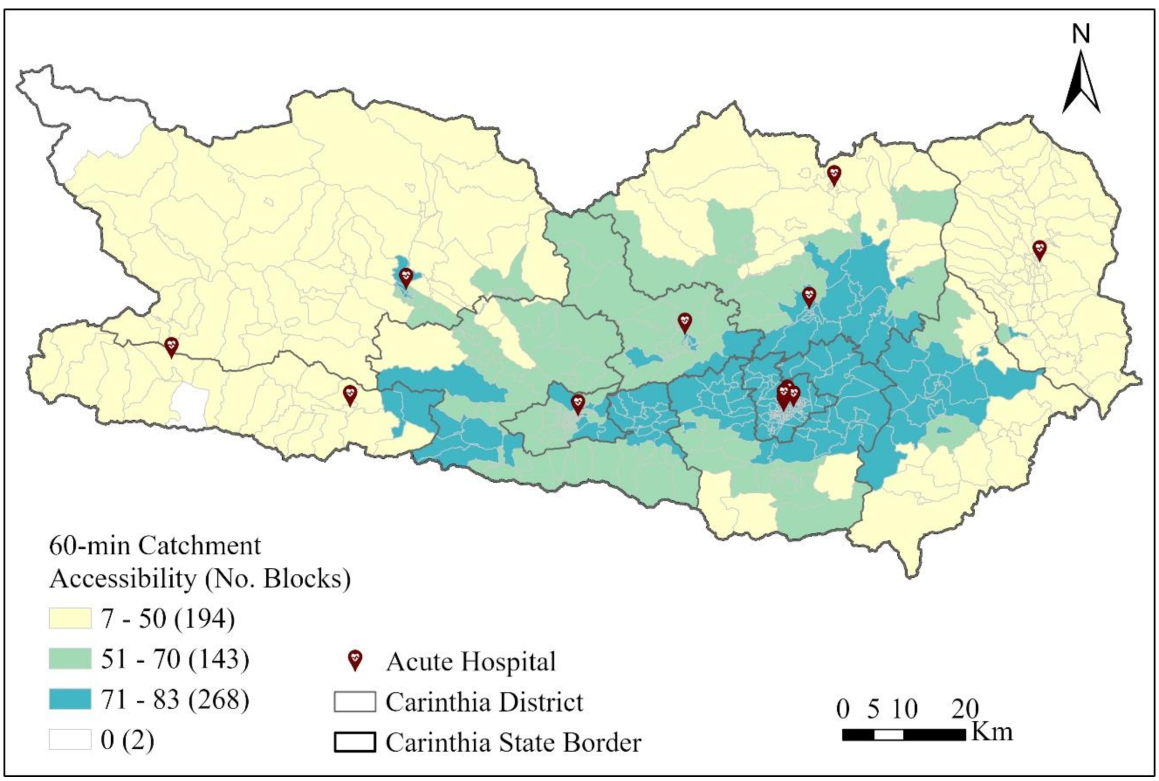

Figure 5.18. Block-based accessibility scores by 2SFCA method (60-minute catchment) in Carinthia

5.4. Comparison of Spatial Accessibility Across Grids and Census Blocks

The previous two sections have illustrated the accessibility scores of different catchment sizes at the grid and census block level, this section will examine their differences by joining each block to each grid and then minus their values to identify the (in)consistencies. The results are reported in Figures 5.19-5.23. In all maps, the red grids with negative accessibility scores represent the accessibility scores at the grid level are smaller than those at the census block level. The green grids with positive accessibility scores represent the accessibility scores at the grid level are larger than those at the census block level. The gray grids represent the differences in the accessibility scores at two levels are acceptable with a small range of -4 and 5. In other words, it is equally the same as the accessibility score is inflated with 10,000.

When the catchment size increases from 15 to 60 minutes, although the number of grids with equal values of accessibility at two levels decreases, their populations are all above 80%. This suggests the accessibility scores derived by the 2SFCA method at two levels are largely consistent but there are still some differences. For the grids (red color) with accessibility scores lower than those calculated from the census blocks, their spatial patterns change from polycentric structures around acute hospitals to fragmented structures scattered throughout the whole study area. While the change in their number is going down and up, their population decreases and significantly drops from 12.3% in the 40-minute catchment in Figure 5.22 to 4.9% in the 50-minute catchment in Figure 5.23. In contrast, the number of grids with accessibility scores higher than those at the census block level increase, so as their populations that range from 1.7% to 11.1%. Most of them are scattered in the study area along the physical road.

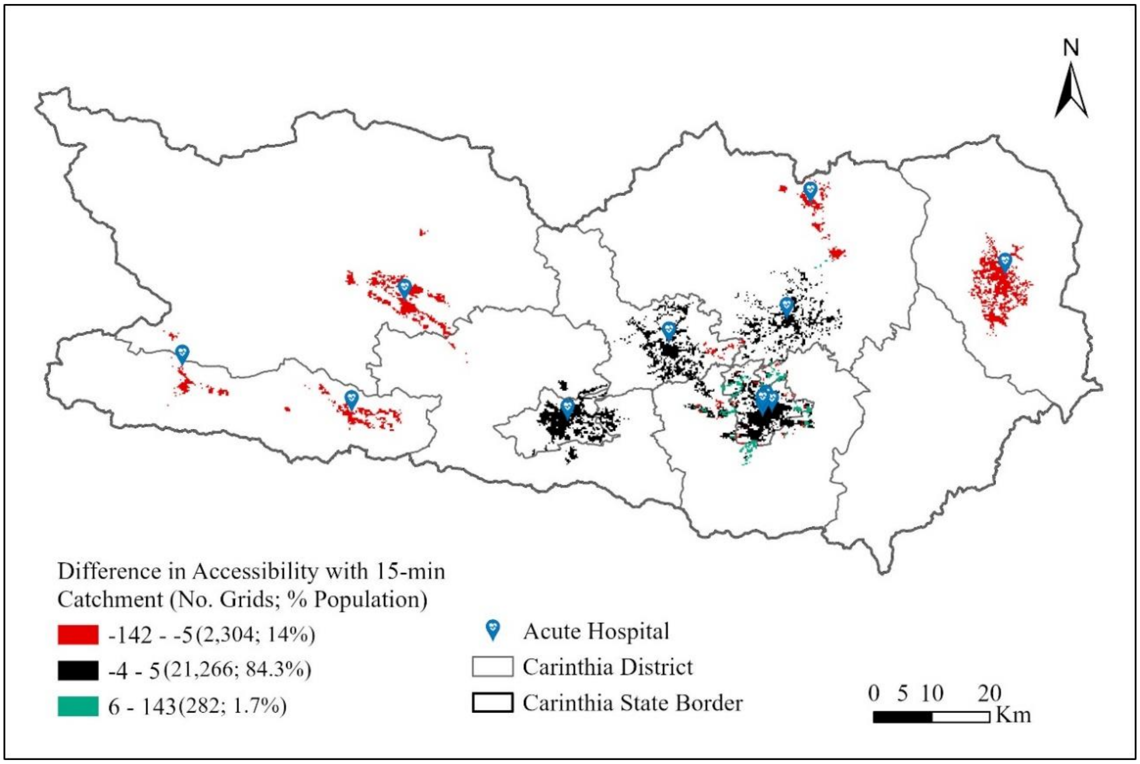

Figure 5.19. Differences of grid-based and block-based accessibility scores by 2SFCA method (15-minute catchment) in Carinthia

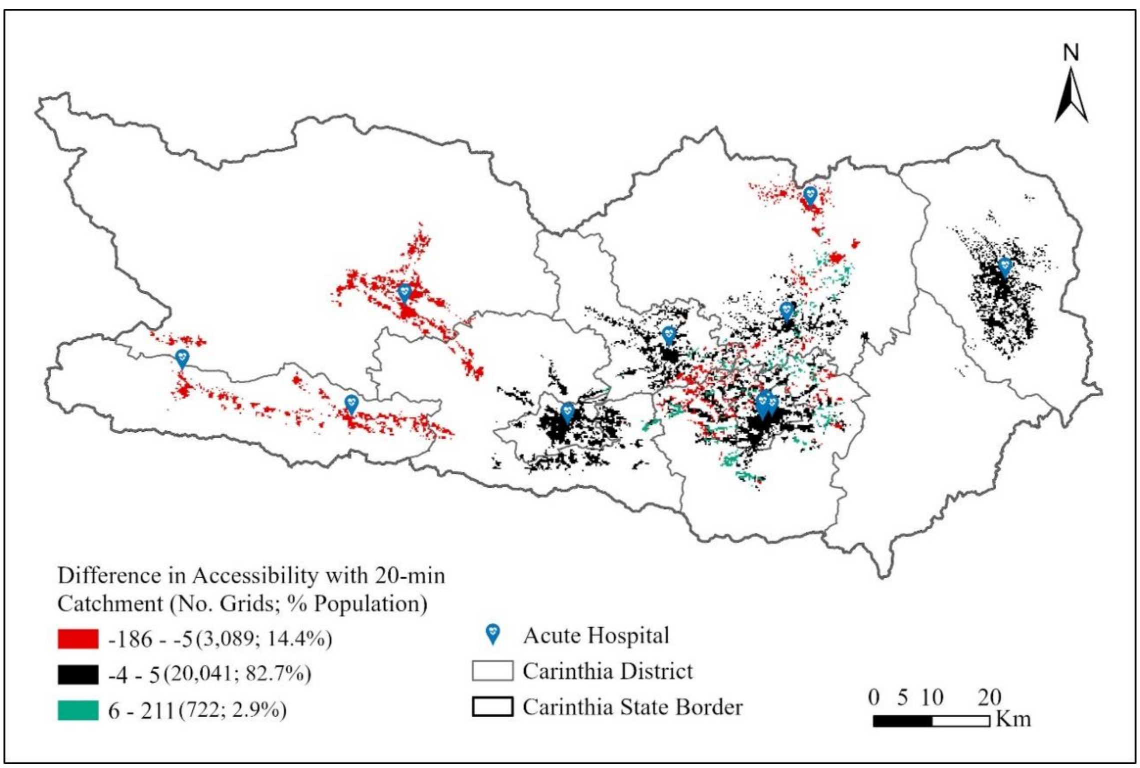

Figure 5.20. Differences of grid-based and block-based accessibility scores by 2SFCA method (20-minute catchment) in Carinthia

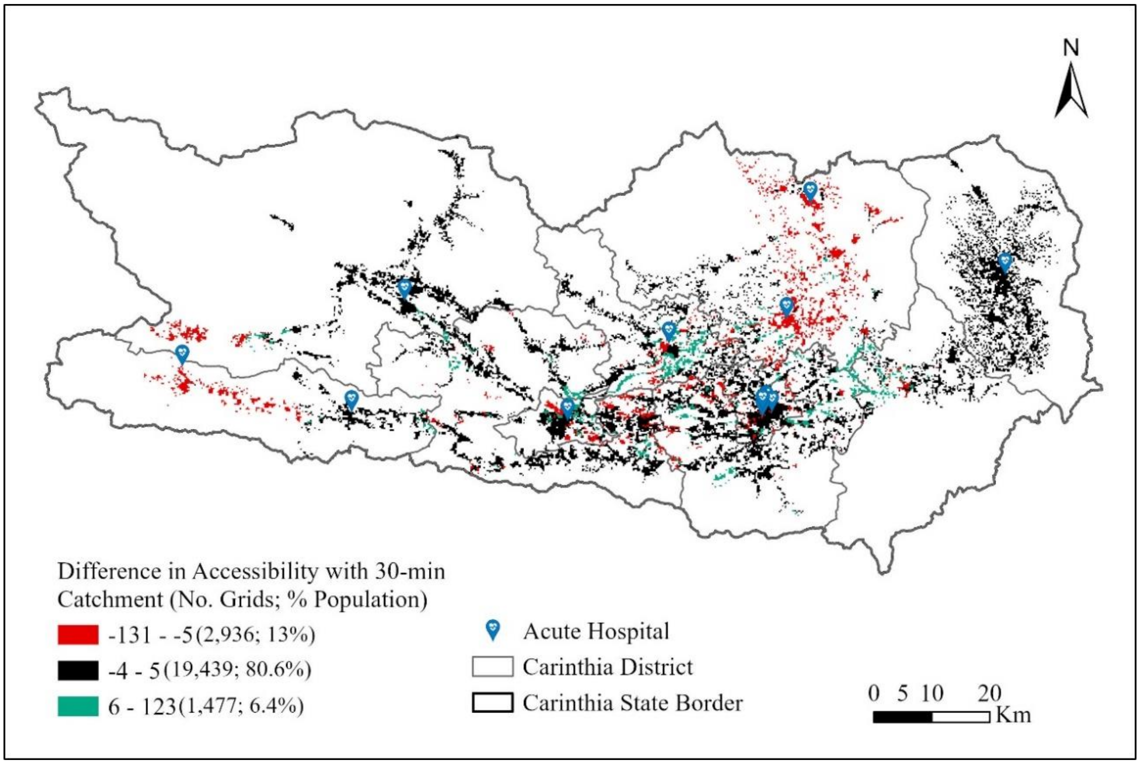

Figure 5.21. Differences of grid-based and block-based accessibility scores by 2SFCA method (30-minute catchment) in Carinthia

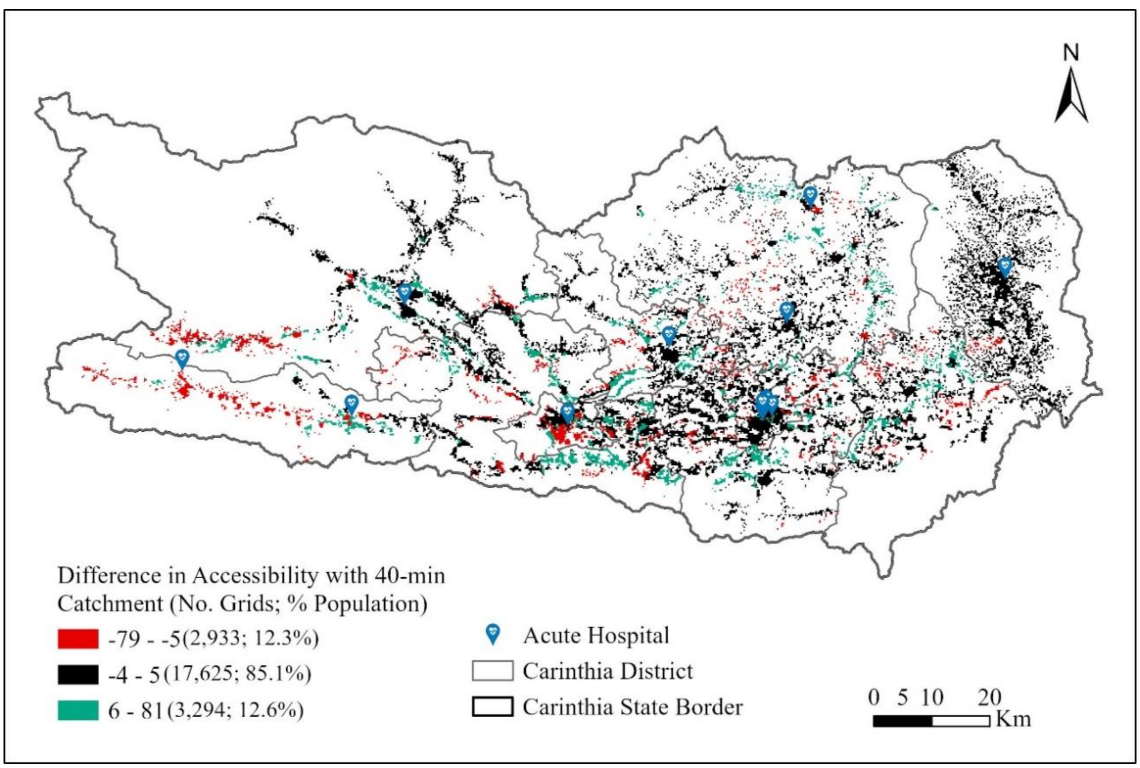

Figure 5.22. Differences of grid-based and block-based accessibility scores by 2SFCA method (40-minute catchment) in Carinthia

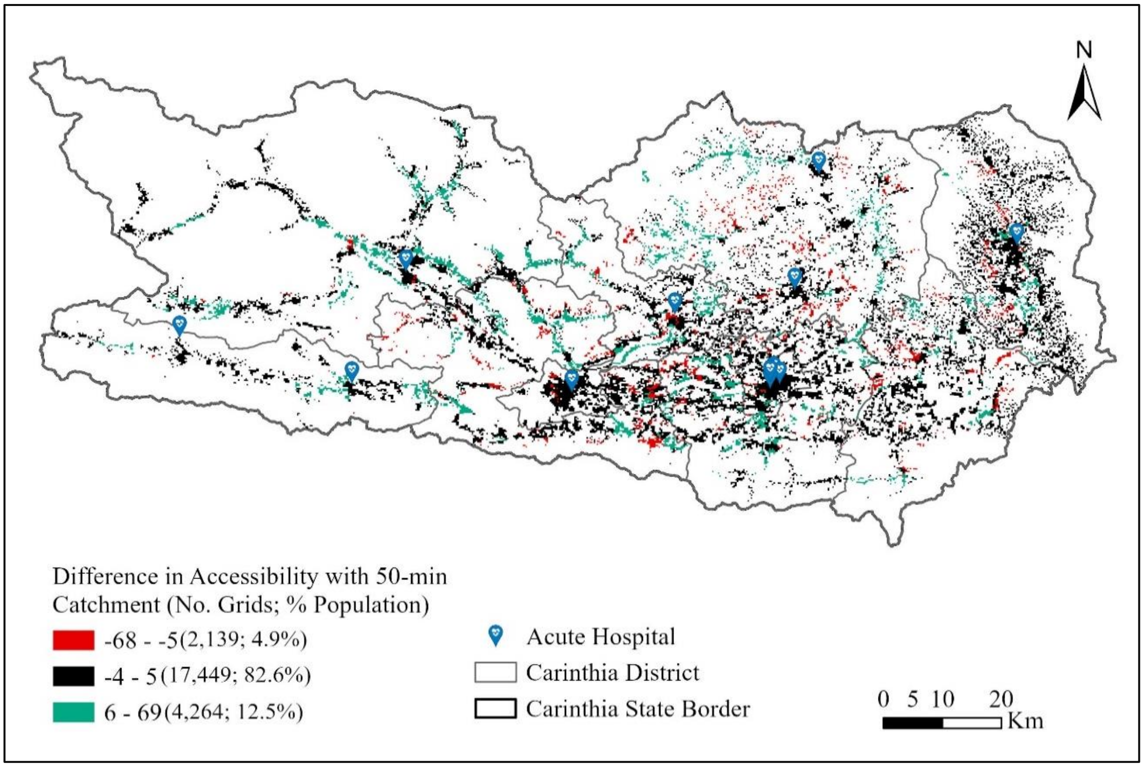

Figure 5.23. Differences of grid-based and block-based accessibility scores by 2SFCA method (50-minute catchment) in Carinthia

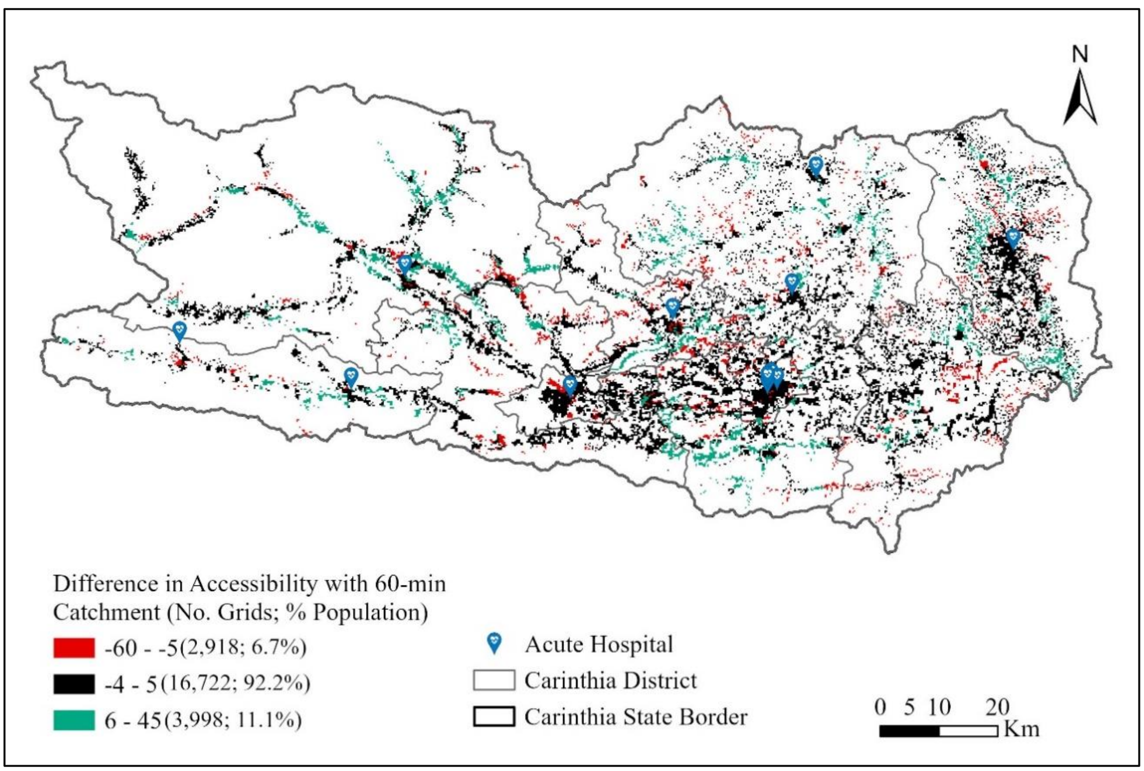

Figure 5.24. Differences of grid-based and block-based accessibility scores by 2SFCA method (60-minute catchment) in Carinthia

5.5. Summary

This chapter applied two methods: the proximity method that measure the travel time to the nearest acute hospitals, and the 2SFCA method that considers population demand, acute hospital bed supply, and their complex interactions captured in predefined catchment areas with varying driving times which can be interpreted as a match ratio of supply and demand. These two measures were evaluated at the 250-meter grid and block levels to illustrate how their accessibility scores were distributed for addressing the MAUP. The edge effect only affected the accessibilities along the northern borders but was more obvious at the grid level. For both levels, the proximity method suggested that most regions have similar accessibilities, so as their populations. However, some discrepancies were found as the accessibilities of 14% of the total population were affected by the selection of geographic scales. The study also found the grid-based population experienced shorter travel times to acute hospitals than the block-based population. The differences were more apparent in the northwest and southeast regions where people traveled 62 to 172 minutes.

In terms of the accessibility scores measured by the 2SFCA method, the major debate is the selection of catchment area size. In the absence of actual utilization data of acute hospitals, this study used different catchment sizes ranging from 15 to 60 minutes of driving time to calculate the accessibility scores at the grid and census block levels. The spatial pattern of accessibility scores changed from polycentric structures around acute hospitals to a monocentric structure around Villach and Klagenfurt cities. The increase in catchment sizes would significantly reduce the areas with zero accessibility scores which were distributed in mountain areas or far from centers of cities or districts. For both levels, the 30-minute travel time was demonstrated as a reliable catchment size. Between the two, their accessibility scores were largely consistent, but differences were also found along the physical roads.

Chapter 6. Accessibility to Acute Care Hospitals in Louisiana

This chapter will report the accessibility scores by proximity method and 2SFCA method and analyze where low access areas are in Louisiana. The edge effect is considered for each method. In other words, all accessibility scores are calculated within Louisiana and its 15-mile buffer.

6.1. Minimal Travel Time to Acute Care Hospital

This section uses the proximity method to calculate the minimal travel time to the acute care hospitals in Louisiana. As shown in Figure 6.1, people living around acute care hospitals and along the major roads connecting different parishes enjoy shorter travel times within 20 minutes while those who live farther, especially those living closer to farmland and water areas experience longer travel times which could be as high as 76 minutes (see yellow blocks along the middle right corridors and southern New Orleans), lower than grid-based minimal travel times (172 minutes) but higher than block-based travel times (62 minutes) in Carinthia. This might be attributable to a higher number of acute care hospitals more evenly distributed in Louisiana.

As shown in Figure 6.2, 66% of the total population enjoy 10 minutes to drive to the nearest acute care hospital, 90% and almost 100% of the total population need 20 and 30 minutes to reach the acute care hospital. Compared to Carinthia, Louisiana has more population enjoying shorter travel times to acute care hospitals, and thus higher accessibility. One possible reason is that Louisiana has eight times more hospitals than Carinthia (see Table 3.3). The average travel time is 9.4 minutes, which is shorter than that in Carinthia (21 and 16 minutes at the grid and block levels).

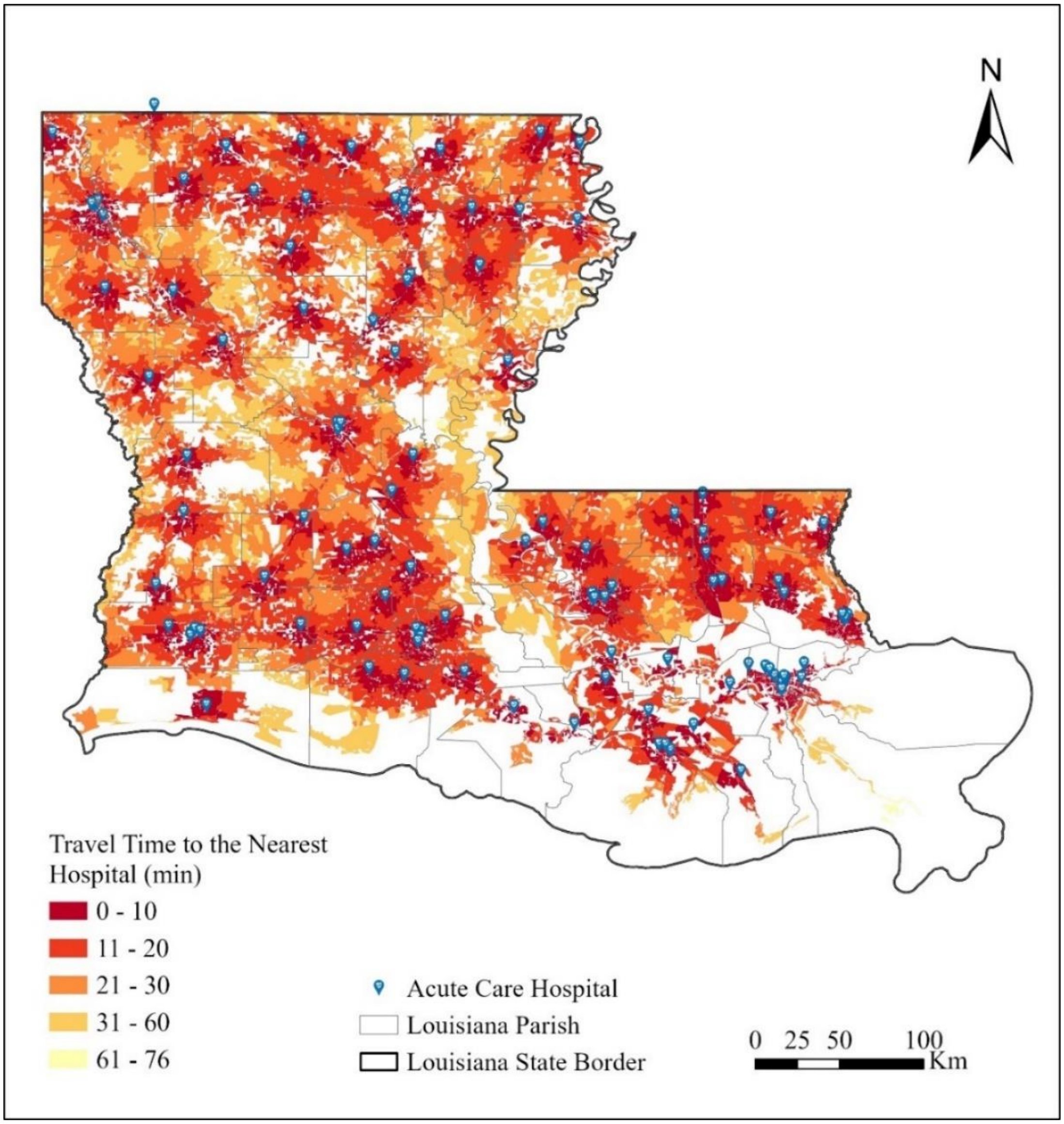

Figure 6.1. Travel time to the nearest acute care hospital across census blocks in Louisiana

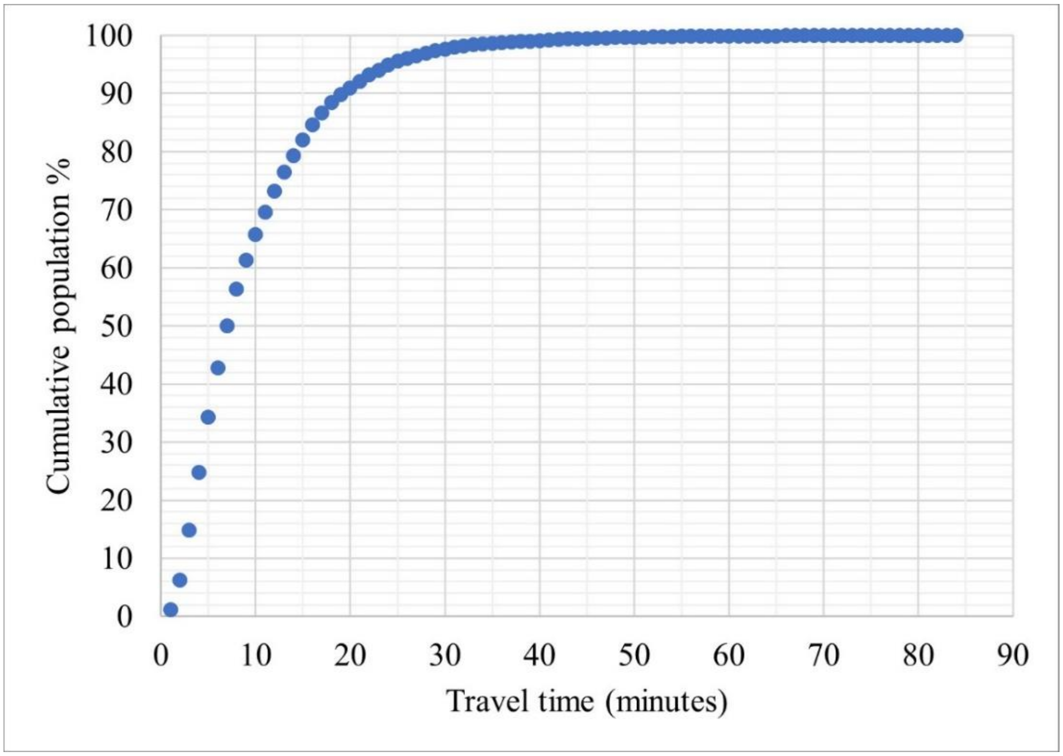

Figure 6.2. Percentage of cumulative population by travel time across census blocks in Louisiana

6.2. Spatial Accessibility to Acute Care Hospital

This section implements the 2SFCA method based on multiple travel time thresholds: 10, 20, 30, 40, 50, and 60 minutes at the census block level. All accessibility scores are inflated by multiplying 10,000 to avoid too small values. Thus, the accessibility could be interpreted as the acute hospital beds per 10,000 people. The accessibility scores for each catchment size are mapped in Figure 6.3-6.8.

In Figure 6.3, using the 15-minute catchment, a significant proportion of census blocks have zero accessibility (see the white areas). This may attribute to low hospital beds or not being in a 15-minute driving range. Although New Orleans and Baton Rouge have a minimal travel time of 10 minutes to acute care hospitals, their accessibility scores derived by the 2SFCA method are not the highest. Instead, the highest accessibility scores are in areas around acute care hospitals in the northwest and central southwest regions of Louisiana. Note that some census blocks around hospitals have the lowest accessibility scores (1-20). A possible reason is that more population competes with the lower number of hospitals within the catchment area (see Figure 3.3), which is generally not captured by the minimal travel time.

In Figure 6.4, based on the 20-minute catchment size, areas with zero accessibility scores are significantly shrunk. Areas around acute care hospitals in central regions of northern Louisiana, Lake Charles at the bottom-left corner of the map, western regions of New Orleans, and some other scatted regions have the highest accessibility scores (81-541). In comparison to Figure 6.3, the spatial patterns of accessibility scores spread around acute care hospitals, and the scores decrease.

In Figure 6.5, when the 30-minute catchment is used, areas with zero accessibility scores continue to shrink with the accessibility covering more areas. People living in Lake Charles and some scattered regions still enjoy the highest accessibility scores (dark red color) with a range of 81-236, followed by people residing in the central regions, and two big clusters in the north of the map. Areas with the third and fourth highest accessibility scores are primarily distributed in four big clusters in the south, and north of the central cluster and Lake Charles of the map.

In Figure 6.6, using the driving time of 40 minutes, the highest accessibility scores significantly drop compared to those with a 30-minute driving range (76 vs. 236). The increase in the catchment areas generates three big clusters in the north of the map and several small clusters in the south that rank the highest accessibility score range (61-76). Five big clusters in the third highest rank of accessibility scores are also found (see the orange color blocks) in the northwest of the central region (N = 1) and south of the map (N = 4, see Baton Rouge and New Orleans). When the catchment size increases to 50 and 60 minutes in Figure 6.7-6.8, the polycentric structures are dissolved but with a little higher accessibility score (100 and 82 vs. 76). The highest accessibility scores are primarily in the northern regions of Louisiana.

From Figure 6.3-6.8, the change of the catchment sizes from 15 to 60 minutes results in the accessibility scores being more smoothy from high to low values, and more areas being detected with nonzero accessibility scores. The spatial patterns of accessibility change from small polycentric structures to large polycentric structure, and then to decentralized structures but with the highest accessibility scores dominate in the northern areas of Louisiana. Significant changes are observed from 15 to 40 minutes, and then the major patterns become stable. Therefore, it recommends the driving time of 30 to 40 minutes as a suitable catchment size for measuring the geographic accessibility to acute care hospital by the 2SFCA method.

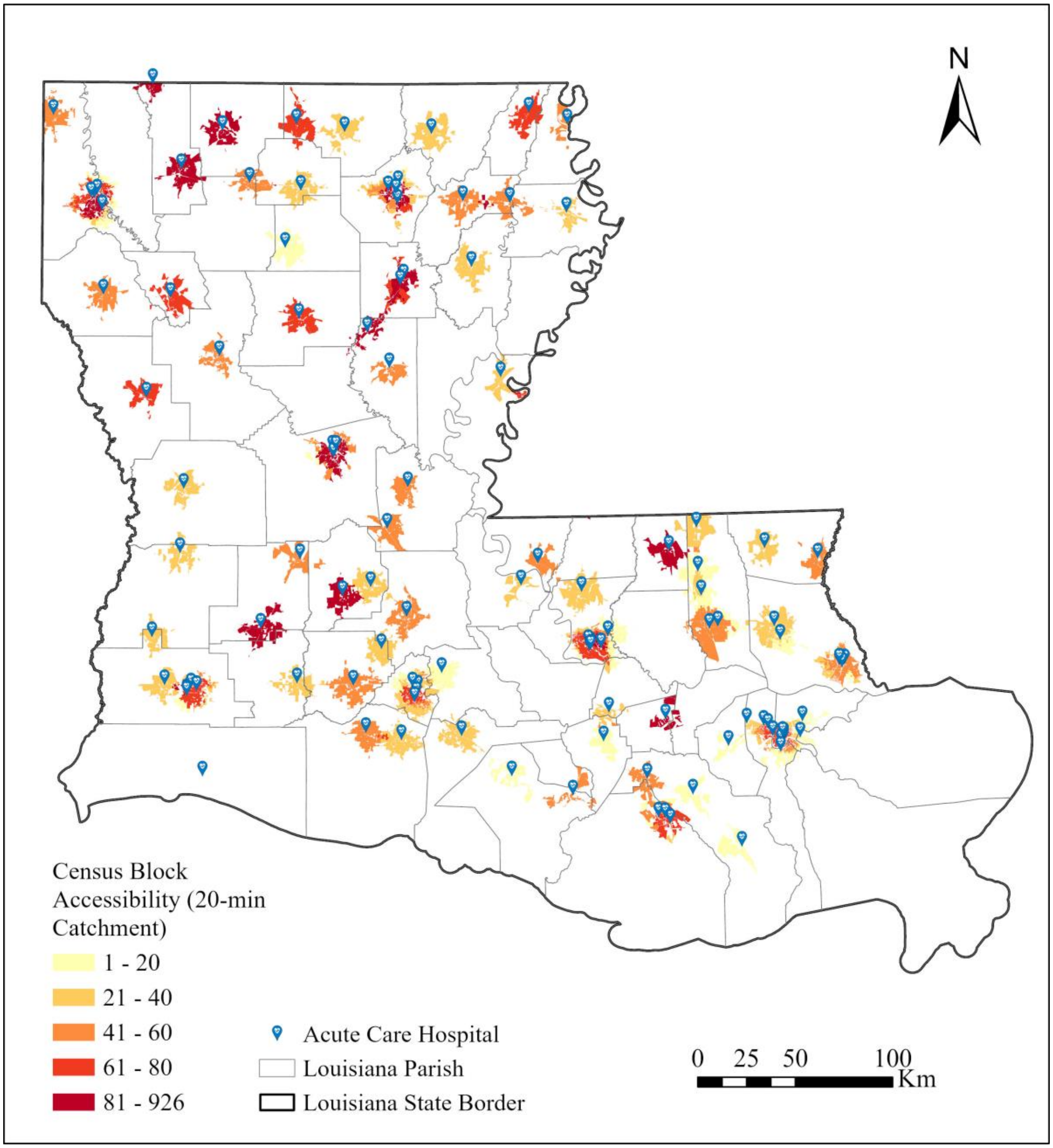

Figure 6.3. Block-based accessibility scores by 2SFCA method (10-minute catchment size) in Louisiana

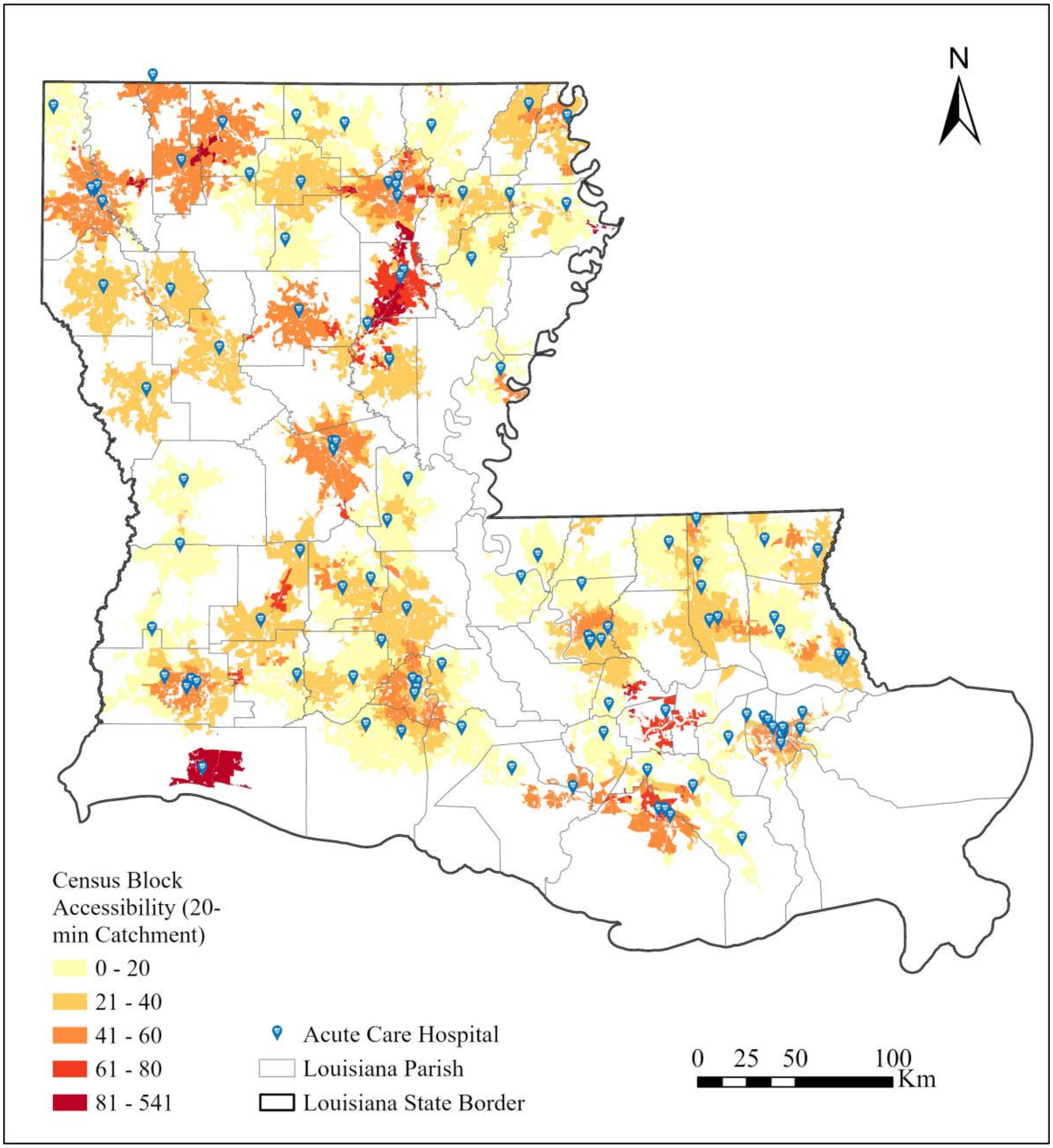

Figure 6.4. Block-based accessibility scores by 2SFCA method (20-minute catchment size) in Louisiana

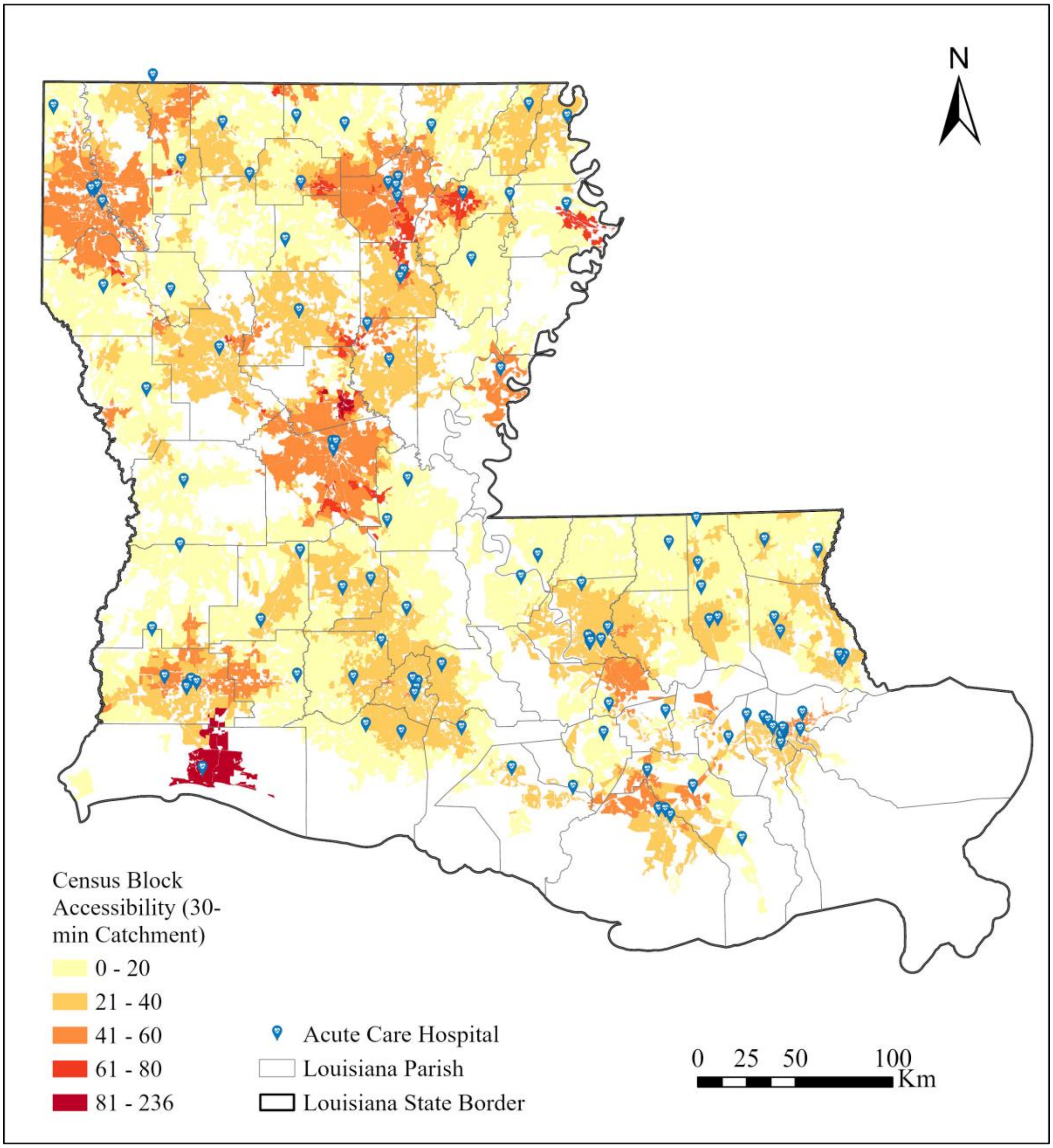

Figure 6.5. Block-based accessibility scores by 2SFCA method (30-minute catchment size) in Louisiana

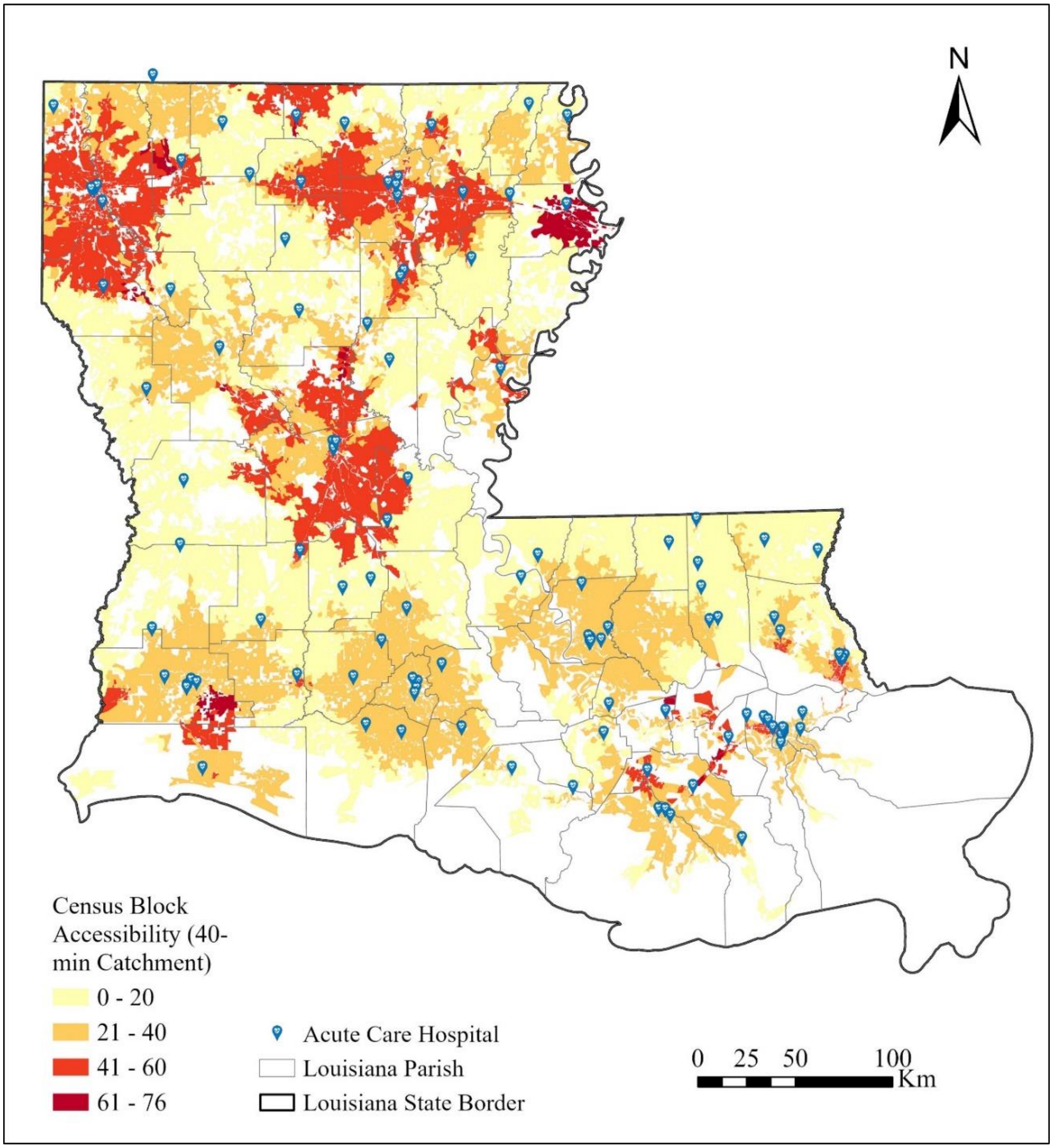

Figure 6.6. Block-based accessibility scores by 2SFCA method (40-minute catchment size) in Louisiana

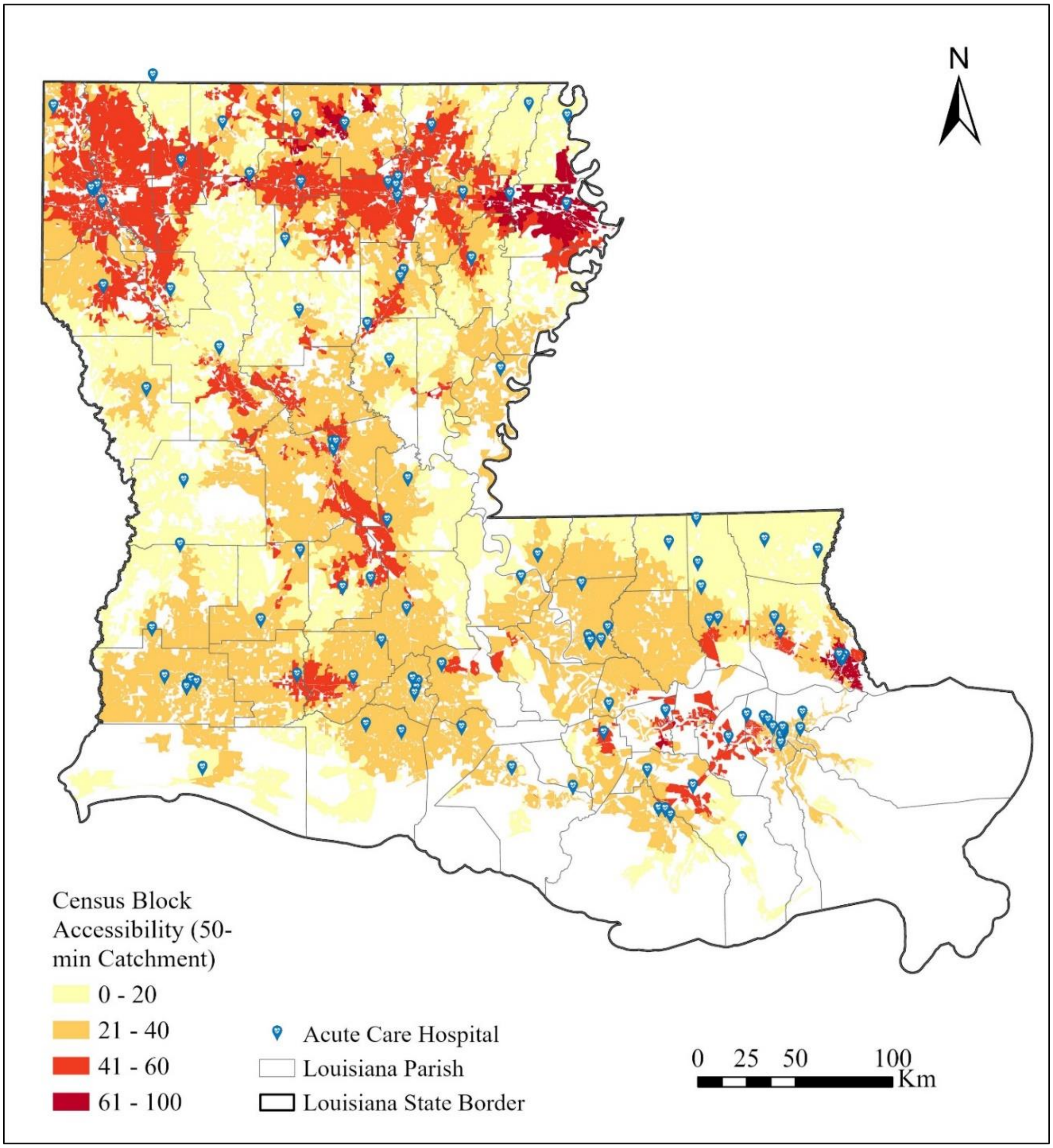

Figure 6.7. Block-based accessibility scores by 2SFCA method (50-minute catchment size) in Louisiana

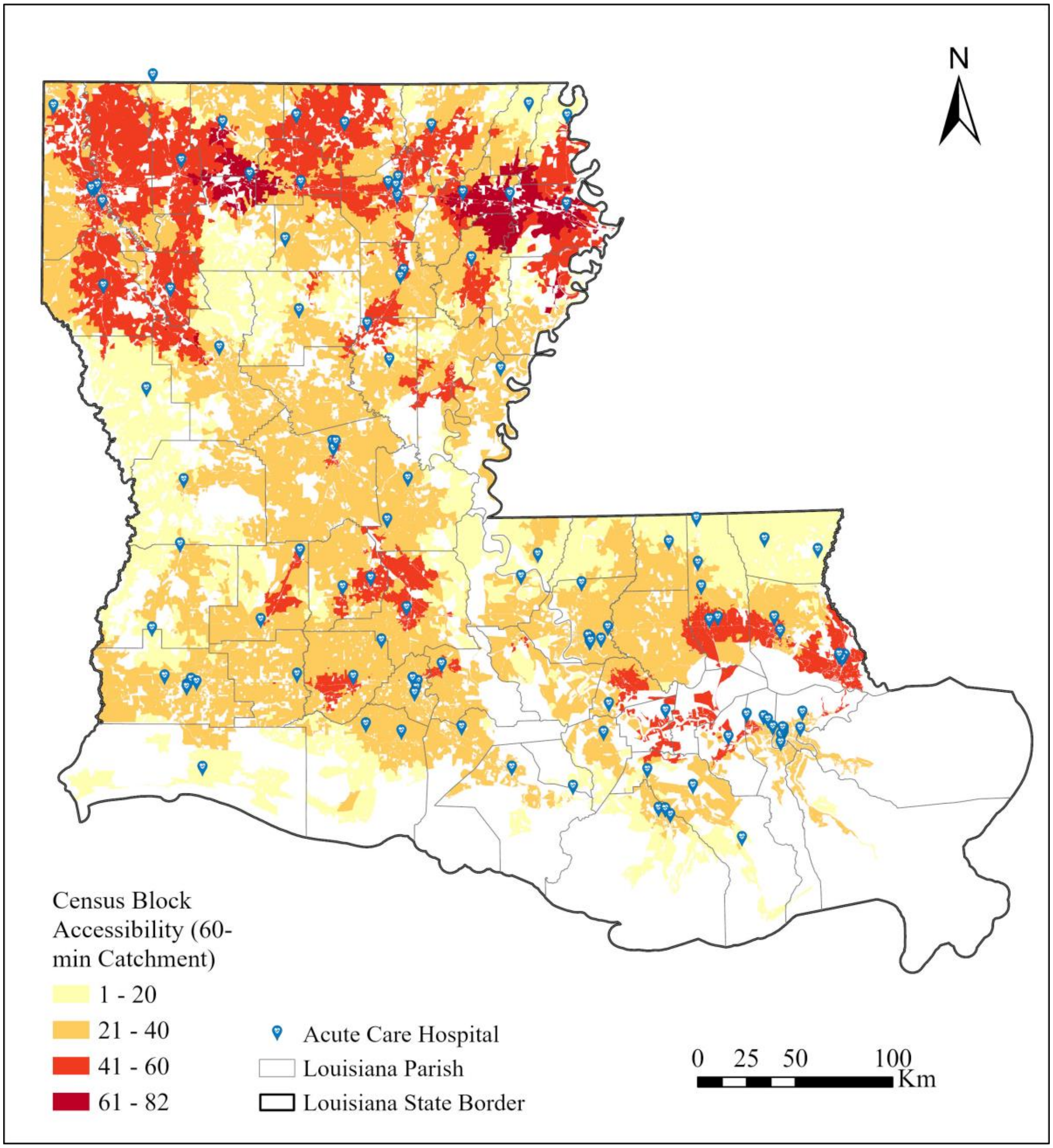

Figure 6.8. Block-based accessibility scores by 2SFCA method (60-minute catchment size) in Louisiana

6.3. Summary

This chapter also applied proximity method and 2SFCA method to examine the geographic accessibility to acute care hospitals at the census block level in Louisiana. The proximity method found that people living around acute care hospitals and along major roads connecting different parishes enjoyed shorter travel times of 20 minutes while those living farther, closer to farmland

and water areas experienced longer travel times of 76 minutes. It also detected that 90% to 100% of the state population enjoyed 20 to 30 minutes to drive to the nearest acute care hospital for the care. The average travel time was 9.4 minutes, which was lower than that in Carinthia.

For the accessibility scores derived from the 2SFCA method, different catchment sizes ranging from 15 minutes to 60 minutes were chosen to examine the changes of their spatial patterns. The increase of catchment sizes significantly reduced the number of blocks with zero accessibility scores. It also resulted in changes of the spatial patterns which ranged from a small polycentric structure to a large polycentric structure, and then to a decentralized structure with the highest accessibility scores peaked in the northern Louisiana. The changes also demonstrated that a driving time of 30 to 40 minutes can be used in the 2SFCA method as a suitable catchment size to measure the geographic accessibility to acute care hospitals in Louisiana.

Chapter 7. Conclusions

Austria and the United States are two countries that value equal access the most and invest so much in achieving this goal because access is the first step toward a large goal of improving overall population health. However, health care needs are not always met, and health care disparity has been long been persisted. Given that acute (care) hospitals dominate in two countries in terms of their numbers and capacities, and hospital care is the largest payer of total health care spending, it is important to examine people's access to these services in two countries. This study examines the accessibility to acute (care) hospitals in two pilot areas: Carinthia (German: Kärnten) in Austria and Louisiana in the United States with the most recent data in 2020. Both use the supply-demand ratio, proximity method, and the popular two-step floating catchment area (2SFCA) method which are commonly used in health care studies to measure accessibility.

The supply-demand ratio is measured as the acute (care) hospital beds divided by the population in Carinthia and Louisiana respectively. The purpose is to give readers some general ideas of access in these two states. The proximity method assumes residents are more likely to use the nearest acute care hospitals which is measured by travel time derived from OpenStreetMap. The 2SFCA method considers the match ratio of acute (care) hospital beds, population, and their interactions captured by a threshold of travel time catchment. The accessibility score can be interpreted as acute (care) hospitals per 10,000 people. In Carinthia, the latter two methods are both implemented at the 250-meter grid and census block levels to address the modifiable areal unit problem (MAUP) and examine the possible edge effect. Both are classic issues in Geography. In Louisiana, because of data limitations, the latter two methods are only conducted at the census block level, the finest geographic scale used by the U.S. Census Bureau. To my best knowledge, this is the first study to examine health care accessibility simultaneously in Austria and the United States.

This chapter will summarize major findings and conclusions, highlight the contributions and significance, and points out the limitations and future work.

7.1. Major Findings and Conclusions

This research has several interesting findings in two study areas of Carinthia and Louisiana. The study summarizes them as follows:

In terms of acute (care) hospital bed-to-population ratio measured by the supply-demand ratio method across the whole study areas in two states, Carinthia has almost doubled ratio than Louisiana (61 vs 33), so as the population density (59 persons/km^2 vs. 34 persons/km^2) although the number of acute hospitals is 13, remarkably less than that in Louisiana (13 vs 111). However, the average travel time to the nearest acute (care) hospitals is twice longer than that in Louisiana (21 vs. 9.4 minutes). This demonstrates using two measures would be better to estimate people's access to acute care in two areas.

In terms of the minimal travel time to acute (care) hospitals in Carinthia, the spatial patterns of the grid and census block levels are largely consistent. Both find that people living around hospitals and along the major roads connecting different districts or cities enjoy shorter travel time of 20 minutes while those who live farther or in mountainous areas experience longer travel times which could reach more than 1 hour. This pattern demonstrates an urban advantage. Moreover, the populations within different travel times at the two levels are similar. Both have 70%, 90%, and 95% of the population reach the nearest acute hospitals within 20 to 40 minutes. It indicates most people have good access to acute care, and only a small proportion of the population (5%)

experience longer travel time (i.e., more than 40 minutes). For two levels, the differences are found along the major roads that are far from acute hospitals, and 14% of the population is affected.

In terms of the minimal travel time to acute (care) hospitals in Louisiana, similar to the findings in Carinthia, people living around acute care hospitals and along major roads connecting different parishes enjoy shorter travel times of 20 minutes while those who live farther, especially live closer to farmland and water areas experience longer travel times which could be as high as 76 minutes. Once again, it demonstrates the urban advantage in accessing acute care. However, the study finds that 90% and almost 100% of the total population drive 20 and 30 minutes to use the nearest acute care hospitals in Louisiana, which is shorter than those in Carinthia (70%-87%).

For the accessibility scores measured by the 2SFCA method in Carinthia and Louisiana, their spatial patterns vary when adjusting the catchment sizes. For grid and block levels used in Carinthia and Louisiana, when increasing catchment sizes, areas with nonzero accessibility scores increase, the accessibility scores are progressively smoothed from high to low values, and not all areas close to acute (care) hospitals have higher accessibility because of the competition of acute care, which is not captured by previous two methods. However, some differences are found across the geographic levels in Carinthia and the two study areas. For example, in Carinthia, while 80% of the population enjoys similar accessibility at two levels, 20% of the population is affected by the selection of geographic levels and they are scattered in areas along the physical roads. The grid-level accessibility shows more variabilities. Between two study areas, in Carinthia, the spatial patterns of accessibility change from a polycentric structure with the peaks of accessibility scores scattered around acute hospitals, to a monocentric structure that is centered in the triangular regions of Villach, Klagenfurt, and southern Sankt Veit an der Glan District. In Louisiana, the spatial patterns of accessibility change from a small polycentric structure to a large polycentric structure, and then to a decentralized structure but with the highest accessibility scores found in the northern areas of Louisiana. Moreover, while the 30-minute driving time is found to be a suitable catchment size in Carinthia, 40-minute of travel time is more suitable for measuring accessibility in Louisiana.

In sum, the three methods capture different profiles of accessibility in two study areas. Their results are not consistent as each emphasizes different aspects of accessibility measurement. Both the proximity method and the 2SFCA method demonstrate the urban advantage and poor access of people who live far from acute (care) hospitals. However, lower accessibilities are still found around hospitals because of the scarcity of acute care resources. Health care policies may targe the areas with lower accessibility, such as mountain regions in Carinthia, and cities like Baton Rouge and New Orleans in Louisiana.

7.2. Contributions and Significance

This study will contribute to the methodological frontier and applications of GIS in public health, and policy implementation and strategies to improve health care access in two states of two countries. For the methodology, it leverages the supply-to-demand ratio, proximity method, and 2SFCA method to examine the accessibility to acute care hospitals in Carinthia and Louisiana and illustrate how different methods depict the accessibility profile. Very few studies have done so. It also addresses two classic geographic issues that concern researchers: modifiable areal unit problem (MAUP) and edge effect. The research in Carinthia shows the selection of different geographic units has impacts on the estimations of accessibility scores. While the overall patterns are largely consistent, the accessibility scores at the finer geographic unit (250-meter grid) exhibit more variabilities which are smoothed at the coarse unit (census block). Cautions may be needed when it comes to management and planning purposes. Both the grid and census block levels only detect minor edge effects along the northern border of Carinthia. In addition, both studies in

Carinthia and Louisiana use OpenStreetMap as a data source to estimate the travel time to the nearest acute (care) hospitals at finer geographic scales. In comparison with the static road network data from the census, OpenStreetMap is more advantageous as the data is free, the geo-computation is faster, the data processing is less labor-intensive, the package is free, and it accommodates traffic conditions.

The recent advances of GIS have demonstrated its advantages of and great potential in addressing geographic issues in public health. This study uses acute (care) hospitals in Carinthia and Louisiana as an example to examine health care accessibility by GIS. In fact, acute (care) hospitals dominate hospital markets in the two states, and their costs are among the cohort of hospital care that is the largest payer of total health care spending in the two countries. Given that no studies have been conducted, this research opens the door to embracing the field.

In terms of the health policy implementation and strategies, both the minimal travel time to the nearest acute (care) hospitals and accessibility scores measured by the 2SFCA method at the grid and census block levels in Carinthia and census block level in Louisiana help identify which areas have higher accessibility, which areas have lower accessibility, and how many populations are covered in two categories. The findings shed light on public health interventions for decision-makers or stakeholders in allocating or delivering more care (adding more beds or building new acute (care) hospitals) to the areas and populations with lower accessibility.

7.3. Limitations and Future Work

This study has some limitations that merit discussion and call for future work. First, for the study areas in Carinthia and Louisiana, it only considers the spatial accessibility measured by the supply-demand, proximity method, and the popular 2SFCA method, nonspatial factors, such as sociodemographic and rural-urban characteristics of the population and their insurance status are not considered because of the limited accessibility and availability of those data. Future studies will consider these together as prior studies found they also have some impacts on people's access. Second, in measuring the geographic proximity to the acute (care) hospitals, this study selects the nearest acute (care) hospital as the first choice of populations which; however, may not be the real case as people bypass it for various reasons, such as waiting time, availability of the beds, quality and scope of services, insurance coverage, or patient's preference or familiarities. Future studies may consider using the actual utilization data of patients in accessing acute (care) hospitals to estimate their travel times. Third, for the 2SFCA method, this study assumes patients within the catchment area can equally access the acute (care) hospital while those beyond are not. Future studies will consider using the actual utilization data to derive the best-fitting distance decay function and apply it to the 2SFCA method or its variants to measure the accessibility scores. In addition, two studies both choose car driving as the only mode of transport, given that a large proportion of Austrian prefers public transportation or bicycle for commuting, future studies will estimate their travel times and examine their accessibilities when related data are available.

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Vita

Changzhen Wang was born in Hong’an County, Hubei Province, China. She received her B.S. degree in Geographic Information Systems (GIS) from Southwest Jiaotong University in Chengdu, Sichuan Province, China, in 2010. In 2013, she received her M.E. degree in Cartography and Geographic Information Engineering from the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing at Wuhan University, China. While working on her M.E. degree, she was a visiting scholar at the University of Michigan, Ann Arbor, and conducted her thesis project funded by the Henry Luce Foundation under the supervision of Dr. Shuming Bao. In 2014-2018, she worked as a GIS project manager and developer at the Wuhan Land Use and Urban Spatial Planning Research Center, and served as a consultant for UN-Habitat in Nairobi, Kenya.

Since the fall of 2018, Changzhen has been a Ph.D. student in geography in the Department of Geography and Anthropology at Louisiana State University under the direction of Dr. Fahui Wang. Her research focuses on the development and applications of GIS, computational methods, spatial network modeling and analysis, and geovisualization in public health, transportation, and urban studies. She has received several awards, most recently the 2021 AAG Health Data Visualization Award, the 2021 CPGIS Best Student Paper Award, and the 2022 AAG Peter Gould Student Paper Award. She has published one book and seven peer-reviewed articles listed under the section of Publications.

Publications

1. Book

Wang, F., and **C. Wang**. 2022. *GIS automated delineation of hospital service areas*. Boca Raton, FL: CRC Press.

2. Selected peer-reviewed articles (total = 7)

Hu, Y., **C. Wang**, R. Li, and F. Wang. 2020. Estimating a large drive time matrix between ZIP codes in the United States: A differential sampling approach. *Journal of Transport Geography* 86:102770.

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