International Journal of Geo-Information

MDPI

Article

Decomposing Spatial Accessibility into Demand, Supply, and Traffic Speed: Averaging Chain Substitution Method

Kyusik Kim [1] and Kyusang Kwon [2,*]

[1] Department of Geography and Anthropology, Kennesaw State University, Kennesaw, GA 30144, USA; kkim84@kennesaw.edu
[2] Department of Urban Engineering, Chungbuk National University, Cheongju 28644, Republic of Korea
* Correspondence: kyusang.kwon@chungbuk.ac.kr

Abstract

Spatial accessibility to healthcare services is commonly determined by three core components: demand, supply, and traffic speed. Although understanding which factors contribute to accessibility changes can help prioritize interventions to enhance accessibility in underserved areas, limited research has examined the extent of their individual contributions. To better capture the local dynamics that shape healthcare accessibility, this study decomposes spatial accessibility to primary healthcare services using the chain substitution method (CSM), which quantifies the impact of each component by substituting them one by one. By examining how the order of factor substitution affects the relative impact of each factor on spatial accessibility, we analyzed the importance of substitution order in the CSM. This study found that the order of factor substitution plays a significant role in measuring the relative contribution of each factor. To mitigate the effects of substitution order, we proposed an averaging CSM that uses the average value across all possible substitution combinations. Based on the averaging CSM, our findings offer insight for healthcare policymakers and urban planners by clarifying how demand, supply, and traffic speed interact in determining accessibility, ultimately supporting targeted interventions in underserved areas.

Keywords: healthcare accessibility; generalized two-step floating catchment area; chain substitution method; averaging chain substitution method; order of factor substitution

Check for updates

Academic Editors: Wolfgang Kainz, Lan Mu and Jue Yang

Received: 26 October 2025
Revised: 23 December 2025
Accepted: 16 January 2026
Published: 18 January 2026

Copyright: © 2026 by the authors. Published by MDPI on behalf of the International Society for Photogrammetry and Remote Sensing. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

As a critical component of quality of life, access to necessary healthcare services and resources should be available to everyone. While access to healthcare (i.e., the ease with which people can reach medical services) depends on many factors, including socioeconomic and demographic factors (e.g., income level, language, culture) and financial resources (e.g., medical support, insurance) [1], geographers and urban planners have paid more attention to the geographical distribution of supply and demand and the role that traffic conditions play in that distribution [2,3]. In this regard, measuring place-based spatial accessibility and identifying blind spots has emerged as a necessary research and policy intervention.

Spatial accessibility is determined by three components: demand, supply, and traffic conditions. Changes in any of these components affect the level of spatial accessibility. For example, the size of the population or the number of patients determines the demand for healthcare services. The availability of physicians or operating hours affects the amount of care that can be delivered. Lastly, traffic conditions, such as travel speed, transportation infrastructure, and network connectivity, shape the extent to which patients can physically

reach healthcare providers. As these three components are interrelated in determining accessibility, understanding how each one contributes to accessibility changes is critical for setting policy priorities. To distribute limited resources effectively, it is essential to know which components should be addressed first to improve accessibility.

A few scholars have investigated the effect of temporal variations in demand, supply, and travel conditions on spatial accessibility to healthcare services. These three factors tend to be temporally dynamic rather than fixed [4,5]. Existing accessibility measurements assume that residents in a given location (i.e., demand) are spatially fixed. In reality, measuring the demand for healthcare services depends on the de facto population [6] for the geographical distribution of demand changes due to shifts in activity. The supply of healthcare services also changes within a 24 h period based on operating hours and temporal variation in resources [7]. In addition, traffic conditions and travel modes can vary dramatically within a day [8–10]. Recently, Kim and Kwon [11] demonstrated that a time-varying model, which incorporates spatiotemporal variations in the three components, can identify vulnerable areas that a time-static model may overlook.

However, the individual impacts of components on accessibility changes have received little attention. To the best of our knowledge, few studies have investigated this issue. Yang and Mao [12] decomposed the individual contributions of components using the Chain Substitution Method (CSM). Yet, because CSM assumes independence between factors, the order of factor substitution becomes critical in cases where independence is not guaranteed. This is particularly important in the context of the widely used 2SFCA, where variations in demand, supply, and traffic conditions are unlikely to be independent of one another. Similarly, Chen et al. [13] applied the same CSM and, following García-Vidal et al. [14], suggested that researchers determine the order of factor substitution based on the factors they consider most important. These efforts demonstrated the potential of CSM to decompose the effects of individual factors that constitute accessibility quantitatively, but they also revealed its limitations.

The goal of this paper is to quantitatively test the importance of factor substitution order and to propose averaging CSM as a way to address the limitations of the standard CSM. The averaging CSM is straightforward, as it calculates the mean of contributions by all possible combinations of factor substitution orders. This approach provides a consistent method for decomposing the contributions of factors by reducing deviations caused by order effects, while ensuring that the total contributions of each factor equal the total variations.

To demonstrate the variations resulting from the order of factor substitution and the utility of averaging CSM, we decomposed the accessibility scores to healthcare services in Seoul between 8 a.m. and 9 a.m. into demand, supply, and traffic factors. Specifically, demand factors were represented by the time-specific residential population, supply factors by the operating hours of medical facilities, and traffic factors by time-specific observed segment travel times. We then analyzed the effects of these factors on accessibility changes between the two time periods. By quantitatively evaluating the relative impacts of demand, supply, and traffic, this study aims to provide more reliable evidence for setting policy priorities in healthcare accessibility.

The rest of this study is structured as follows. In the next section, we describe the study area, data collection, and methodology, including accessibility measures and CSM. Then, we present accessibility results of how relative impacts vary by the order of factor substitution in CSM and introduce the averaging CSM. Lastly, in the discussion and conclusion sections, we discuss our findings and suggest policy implications and limitations to be addressed in future research.

https://doi.org/10.3390/ijgi15010044

2. Materials and Methods

2.1. Study Area

The variations caused by the order of factor substitution were demonstrated in Seoul, the capital of South Korea. As a center of business, shopping, and culture, Seoul attracts large numbers of commuters and shoppers. In 2021, the average daily population influx from surrounding cities was approximately 1.6 times the number of Seoul's residents, indicating that demand for healthcare services can change on an hourly basis.

As shown in Figure 1, we labeled several key areas for readers' reference. Although Seoul is a mix of business and residential districts, the CBD, YBD, and GBD are recognized as the city's major business districts and are common commuter destinations in the morning. In contrast, areas such as Nowon, Eunpyeong, Gangdong, and Gangseo are primarily residential. In addition, several major express highways run along the Han River, where heavy traffic frequently occurs during commuting hours.

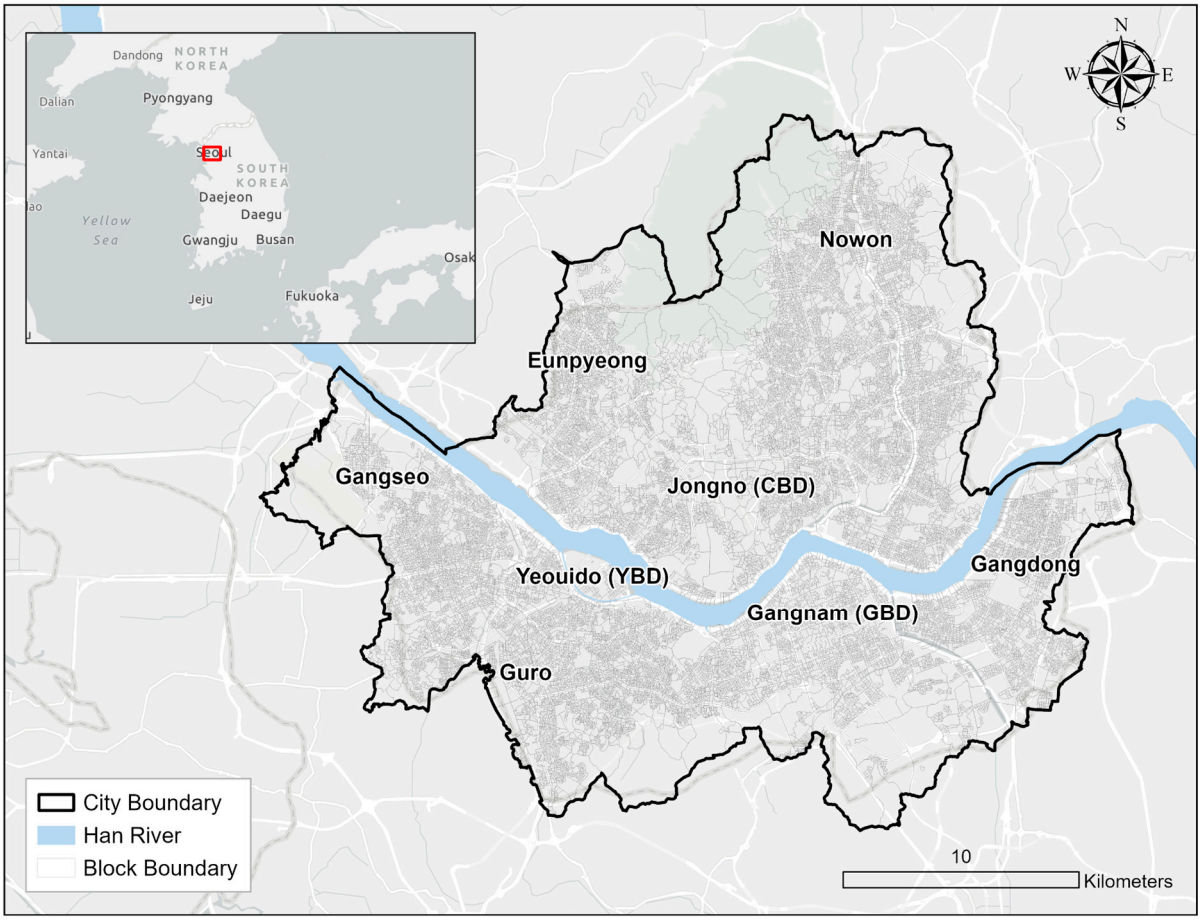


Figure 1. Illustration of the study area.

2.2. Data Collection

We collected data from weekdays in April 2021, a month with no national holidays or national events, to minimize fluctuations in demand, supply, and traffic conditions from one day to the next. In addition, compared to other months, April 2021 had less rain, which can have less impact on traffic conditions. Weekdays included Monday through Thursday; we excluded Fridays due to the possibility of distinct commuting and traffic patterns.

The three components (i.e., demand, supply, and traffic conditions) were collected from mobile phones, web scraping, and publicly available government data (Figure 2). Specifically, de facto population was obtained from mobile phone data [15] based on the

Jipgyegu, a spatial unit equivalent to a census block in the United States. Healthcare facilities were collected from Kakao and Naver, web-based map services, yielding 2827 primary healthcare facilities. Travel times were calculated along road network segments using road speed data from Seoul Transport Operation and Information Services, the city's traffic control agency.

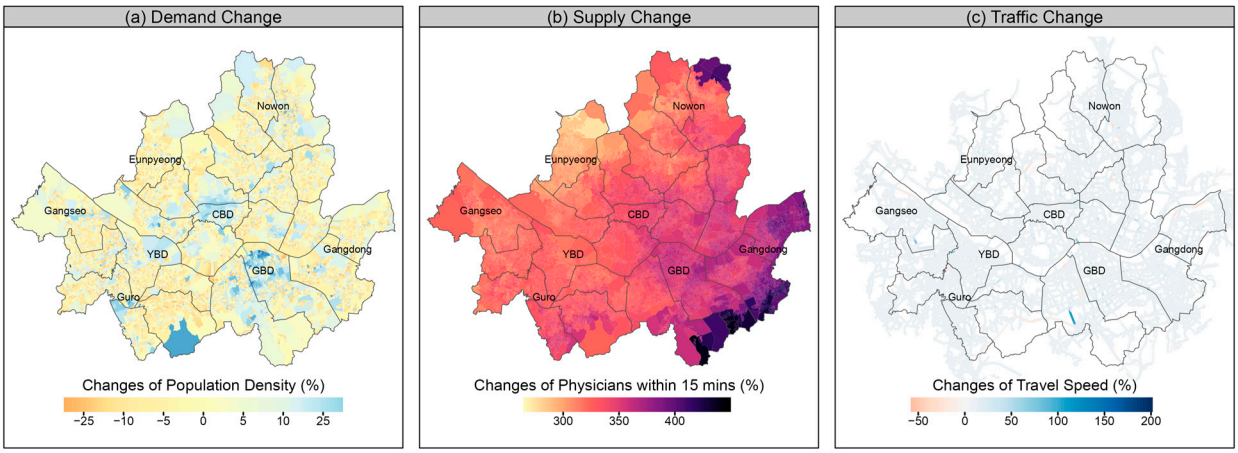


Figure 2. Spatial variations of three components between 8 a.m. and 9 a.m.

To demonstrate the importance of substitution order in CSM, we selected a time range that reflected variations across all three components. Specifically, we examined accessibility changes between 8 a.m. and 9 a.m., when demand, supply, and traffic conditions showed clear differences (Figure A1). This time range enables us to highlight how factor substitution order in CSM influences the variation in the relative impacts of each component on accessibility changes.

2.3. Generalized Two-Step Floating Catchment Area

Since Luo and Wang [16] proposed the two-step floating catchment area (2SFCA) method, one of the most common ways to measure spatial accessibility of healthcare, many scholars have tried to improve its ability in the aspects of demand, supply, and traffic conditions [17]. On the demand side, scholars have suggested several modified versions of 2SFCA, including the three-step FCA [18] and the conditional logit model-based FCA [17], to address some unrealistic demand allocation assumptions inherent in the original method. On the supply side, scholars have proposed methods for measuring supply levels given suboptimal configurations of suppliers [19], for classifying the size and characteristics of healthcare service providers [20], and for considering a hierarchical medical service supply system [21,22]. One notable exception is Kim and Kwon [11], who simultaneously considered all three components (i.e., demand, supply, and traffic conditions) to measure time-varying accessibility and addressed temporal variations in these factors.

In this paper, we applied the G2SFCA method [23], a generalized version of the 2SFCA that incorporates a Gaussian distance decay function and has been widely used in healthcare accessibility studies, e.g., [11,21]. The form of the G2SFCA used in this study is as follows:

$$A_i^t = \sum_{j\in\{d_{ij}\le d_0\}} \frac{s_j^t f\left(d_{ij}^t\right)}{\sum_{k\in\{d_{kj}\le d_0\}} P_k^t f\left(d_{kj}^t\right)}, t \in \{8 \text{ a.m. and } 9 \text{ a.m.}\} \quad (1)$$

where A_i^t is the accessibility value of zone i at time t, P_k^t denotes the population of zone k at time t, S_j^t means the number of available physicians of facility j at time t, d_{kj}^t indicates

the travel time from demand location k to supply location j, and d_0 is the catchment size. The distance decay function $f\left(d_{ij}^t\right)$ follows a Gaussian form with an impedance parameter of 50, yielding a weight of 0.01 at the 15 min threshold, where the impedance effectively approaches zero [24]. Accessibility was calculated at both 8 a.m. and 9 a.m. to analyze the impact of factor substitution order on accessibility changes between these two time windows.

2.4. Chain Substitution Method

We used CSM [12,25] to quantify the relative impact of temporal changes in demand, supply, and traffic conditions on accessibility between 8 a.m. and 9 a.m. The functions for the three factors are the following:

$$A_{i,8} = f(D_{i,8}, S_{i,8}, T_{i,8}) \tag{2}$$

$$A_{i,9} = f(D_{i,9}, S_{i,9}, T_{i,9}) \tag{3}$$

where D_i, S_i, and N_i represent demand, supply, and traffic conditions at location i, and subscripts 8 and 9 denote the time at 8 a.m. and 9 a.m., respectively. f is a function of the accessibility measure; thus, $A_{i,8}$ and $A_{i,9}$ denote accessibility at 8 a.m. and 9 a.m.

As the name CSM implies, we quantified the impact of each component by substituting three components, one by one, from the static model as follows:

$$I(\Delta D_i) = f(D_{i,9}, S_{i,8}, T_{i,8}) - f(D_{i,8}, S_{i,8}, T_{i,8}) \tag{4}$$

$$I(\Delta S_i) = f(D_{i,9}, S_{i,9}, T_{i,8}) - f(D_{i,9}, S_{i,8}, T_{i,8}) \tag{5}$$

$$I(\Delta T_i) = f(D_{i,9}, S_{i,9}, T_{i,9}) - f(D_{i,9}, S_{i,9}, T_{i,8}) \tag{6}$$

where $I(\Delta D_i)$, $I(\Delta S_i)$, and $I(\Delta T_i)$ denote changes in the impacts of demand, supply, and traffic conditions, respectively, at location i between 8 a.m. and 9 a.m. Because we could not directly compare these impacts, we standardized them as follows:

$$STD(I(\Delta D_i)) = \frac{I(\Delta D_i)}{|I(\Delta D_i)| + |I(\Delta S_i)| + |I(\Delta T_i)|} \times 100 \tag{7}$$

$$STD(I(\Delta S_i)) = \frac{I(\Delta S_i)}{|I(\Delta D_i)| + |I(\Delta S_i)| + |I(\Delta T_i)|} \times 100 \tag{8}$$

$$STD(I(\Delta T_i)) = \frac{I(\Delta T_i)}{|I(\Delta D_i)| + |I(\Delta S_i)| + |I(\Delta T_i)|} \times 100 \tag{9}$$

where $STD(I(\Delta D_i))$, $STD(I(\Delta S_i))$, and $STD(I(\Delta T_i))$ are percentages that represent the standardized impacts of demand, supply, and traffic conditions on accessibility changes between 8 a.m. and 9 a.m. As a result, the impact was either positive or negative. For instance, a positive value of $STD(I(\Delta D_i))$ would indicate that a change in demand led to higher accessibility at 9 a.m. A negative value of $STD(I(\Delta T_i))$, on the other hand, would indicate that a change in traffic conditions led to lower accessibility at 9 a.m.

3. Results

3.1. Changes in Accessibility

Figure 3 shows accessibility calculated by G2SFCA at 8 a.m. and 9 a.m., along with their difference (9 a.m.−8 a.m.). To make it easy to compare them, we fixed the same class classification. Access at 9 a.m. was greater than that at 8 a.m., and no blocks experienced a decrease in access level. This is clear in Figure 3c, where the percentage of changes ex-

ceeded 60%. Despite an increase in demand and traffic that could have reduced accessibility, we can infer that supply led to an improvement in accessibility, as accessibility increased across all blocks. We can use the CSM to examine how each factor influences accessibility and how that influence varies locally. However, as Yang and Mao [12] pointed out, the order of factor substitution may be significant in calculating the relative impacts. In this analysis, we examined the significance of the factor substitution order in determining the relative impacts.

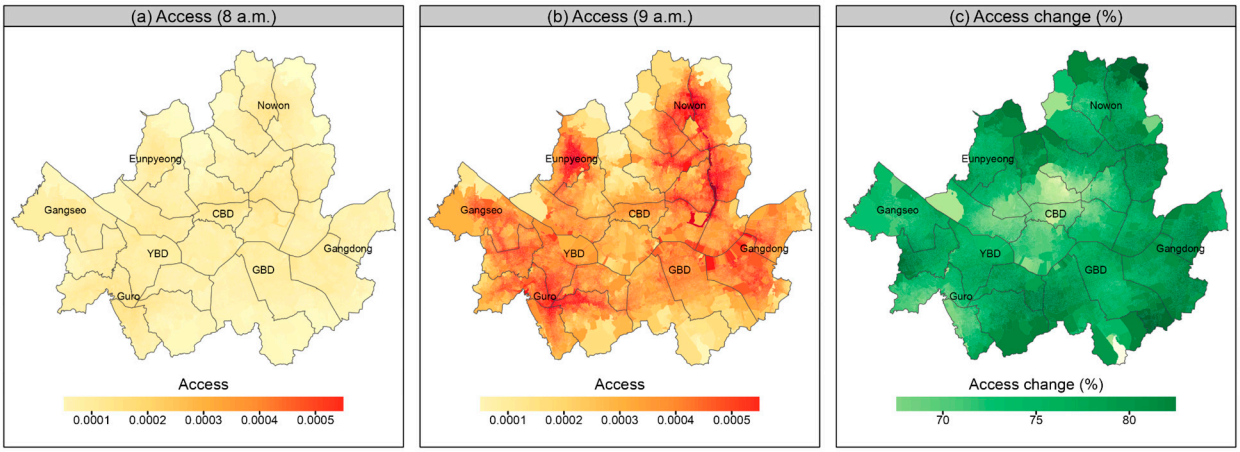


Figure 3. Changes in accessibility between 8 a.m. and 9 a.m.

3.2. Difference in the Relative Impacts by the Order of Factor Substitution

The size of the relative effects varies by the order of factor substitution (Figure 4). For demand, the third-order substitution shows a wider range of variation compared with the first-order substitution. Traffic impacts showed a similar pattern to demand impacts. In contrast, for supply, the third-order impacts exhibited less variation than the first-order impacts.

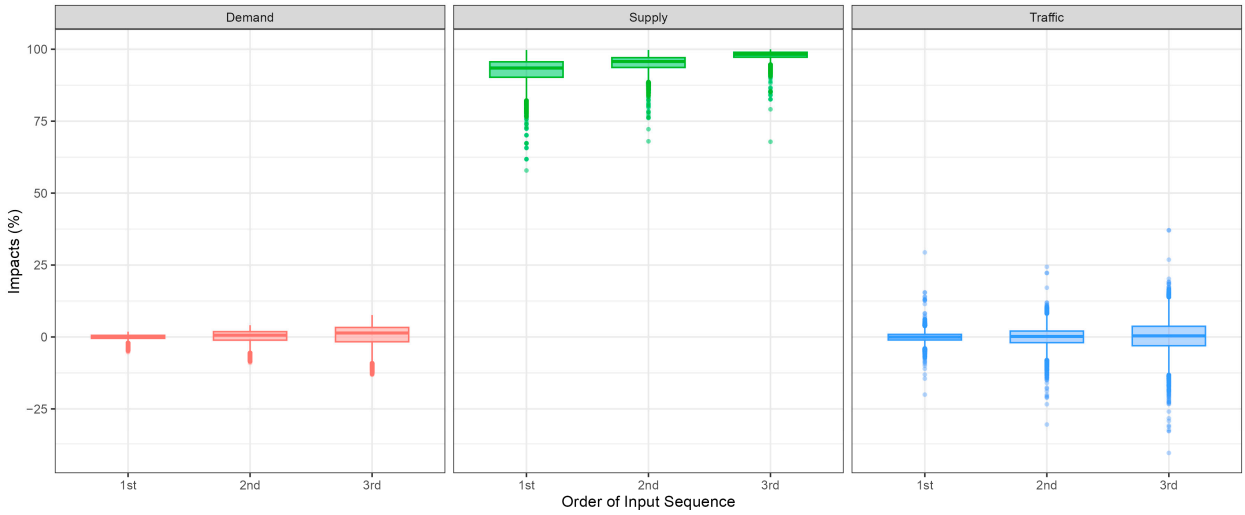


Figure 4. Variations in relative impacts by the order of factor substitution.

The Kruskal–Wallis test confirmed that mean impacts differed across factor substitution orders (Table 1). All combinations of factor substitution orders were statistically significant at the 0.001 level. This suggests that the relative impacts of components on accessibility may be unreliable if they depend on arbitrary factor substitution orders. In

other words, an appropriate justification for determining the order of factor substitution is essential for effective policymaking.

$$MAD_i = \frac{1}{n}\sum_{j=1}^{n}|x_j - \overline{x}| \quad (10)$$

MAD_i = mean absolute deviation of the ith block;
x_j = relative contribution correpsonding to the jth order of factor substitution;
$\overline{x}$ = average contribution across all possible orders of factor substitution.

Table 1. Kruskal–Wallis test and pairwise comparisons.

Component	Comparison	p Value
Demand	1st vs. 2nd	<0.001
	1st vs. 3rd	<0.001
	2nd vs. 3rd	<0.001
Supply	1st vs. 2nd	<0.001
	1st vs. 3rd	<0.001
	2nd vs. 3rd	<0.001
Traffic	1st vs. 2nd	<0.001
	1st vs. 3rd	<0.001
	2nd vs. 3rd	<0.001

Figure 5 shows that the mean absolute deviation (MAD) varies locally. MAD represents the magnitude of variation in impacts caused by the order of factor substitution (Equation (10)). The larger the MAD, the greater the effect of factor substitution order. For demand, overall MAD values were small but blocks around the CBD and GBD showed up to 5% variation depending on factor substitution order. The range of MAD for supply was wider than that for demand, with some blocks, including those near the CBD and GBD, showing values approaching 15%. For traffic, MAD around the CBD and GBD was not substantial, but relatively large values appeared in several outskirt blocks.

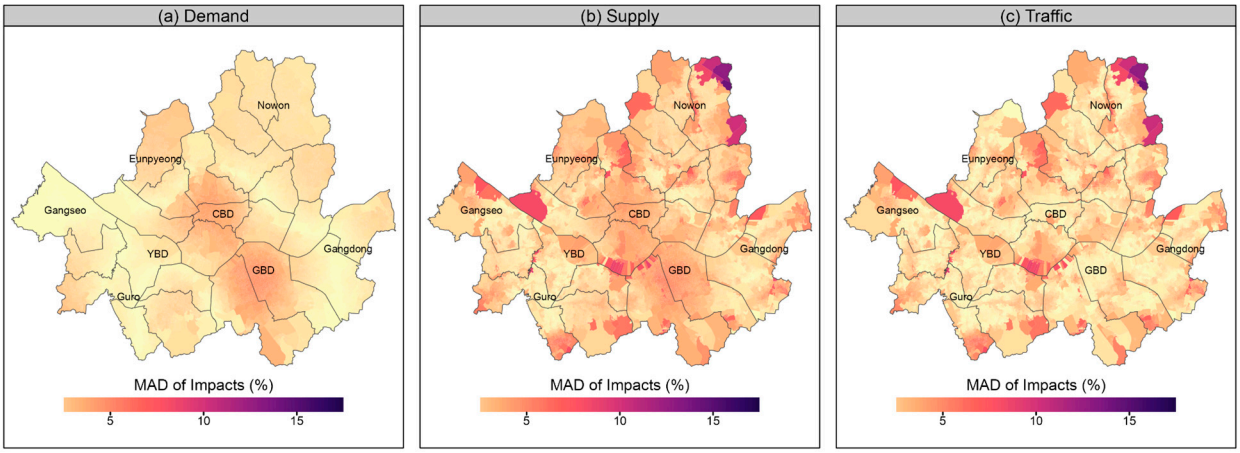


Figure 5. Mean absolute deviation of each component's impact on accessibility changes.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2\right]}{n-1}}} \quad (11)$$

where

G_i^* = Getis–Ord's G_i^* statistic for the ith block;

x_j = MAD of the jth block;

w_{ij} = Queen contiguity spatial weight between blocks i and j.

To highlight the blocks most affected and to show the spatial distribution of MAD, we identified MAD hot spots using Getis–Ord's G_i^* (Figure 6) [26]. These maps clearly display areas where factor substitution order significantly influenced accessibility. The hot spots demonstrated that factor substitution order is critical when applying CSM. In particular, demand and supply were highly sensitive to factor substitution order in the CBD and GBD. By contrast, traffic showed a different pattern, with its impact more locally dispersed.

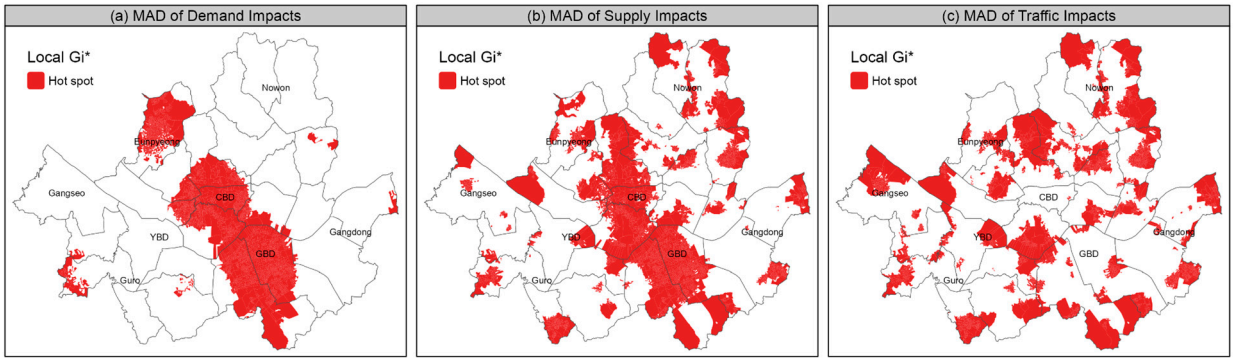


Figure 6. Hot spots of MAD from Getis–Ord's G_i^*.

By examining mean comparisons, variations in relative impacts, and hot spots of MAD, we found that the impacts of all three components were significantly influenced by the order of factor substitution in CSM. This leads us to conclude that decision-making based on CSM outcomes may be unreliable if the order is not evidence-based or properly justified.

3.3. Averaging CSM

For determining factor substitution when clear evidence or justification is lacking, we propose the averaging CSM to evaluate the effects of each factor and to support unbiased policymaking. For each block, we calculate the mean relative impact across all six input-sequence combinations and visualize these average effects.

As Figure 7a showed, changes in demand negatively affected accessibility around the CBD and GBD. Because these areas are major business centers, demand increased at 9 a.m. compared to 8 a.m., when commuting typically ends. By contrast, outskirt residential areas (e.g., Eunpyeong and Nowon) experienced a decrease in demand, which positively affected accessibility. In Figure 7b, the number of available physicians increased from 8 a.m. to 9 a.m., and supply impacts improved accessibility across all areas. Thus, no block experienced a negative supply impact on accessibility. For traffic, Figure 7c showed more complex patterns than demand and supply. Overall, traffic negatively affected accessibility around the Han River, where major express highways pass through.

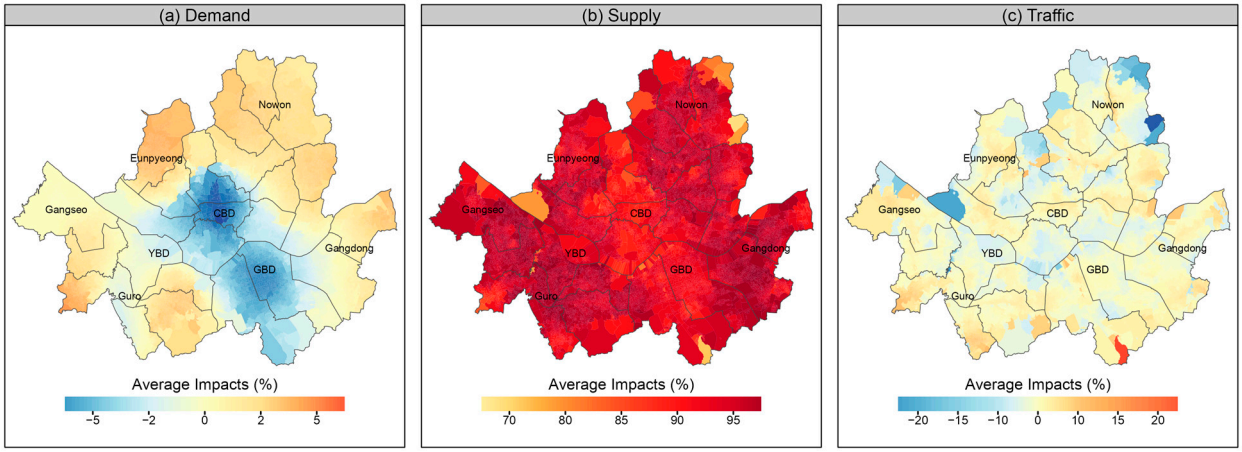


Figure 7. Averaging CSM through all combinations.

4. Discussion

As the first effort to explicitly quantify, statistically test, and spatially analyze the impacts of order dependency in the CSM on spatial accessibility measures, this study addressed the question of how important the order of factor substitution is for evaluating the relative impacts of components on accessibility changes. We also proposed the averaging CSM to reduce the uncertainty caused by order dependency. Using Seoul as a case study and considering three components of spatial accessibility (i.e., demand, supply, and traffic conditions), we evaluated how their relative impacts on accessibility changes varied between 8 a.m. and 9 a.m. and examined the reliability of the relative impacts calculated by CSM.

Highlighting the potential importance of factor substitution order in CSM, we demonstrated that significant variations in relative impacts arose depending on the order used. Our analyses using the Kruskal–Wallis test, MAD, and Getis–Ord's G_i^* confirmed that these variations are not negligible. Some areas exhibited significantly higher variation than others, which may mislead policymakers in interpreting the impacts of each component on accessibility. The relative impacts on accessibility differed by as much as 15%. In particular, the impacts were especially sensitive to factor substitution order in areas with large population shifts and increases in supply, such as the CBD and GBD.

There are two possible ways to reduce the misinterpretation caused by factor substitution order. First, as we suggested, one approach is to average the impacts across all possible factor substitution order combinations. This approach determines each factor's contribution by averaging the contributions obtained when joining all possible coalitions of the other factors, which may lead to a fairer allocation. Although the average may not be a perfect measure, we recommend that relative impacts be interpreted in conjunction with the spatial distribution of MAD across orders. Second, if the importance of factor substitution order is acknowledged, then the specific sequence should be explicitly justified [12]. For example, why is one component prioritized first and others are placed second or third?

While we proposed that the averaging CSM can be a way to reduce the uncertainty, it still has limitations in the context of the 2SFCA method, which is widely used in healthcare accessibility studies. The structure of the 2SFCA makes it difficult to evaluate the comprehensive impact of each component because it is determined by the interrelationships among demand, supply, and traffic factors. As a result, the final 2SFCA value is not well-suited for use in CSM. Specifically, in the 2SFCA method, demand variations at a given location affect the physician-to-patient ratio within its catchment area. This altered PPR then indirectly influences the accessibility of other demand locations outside the original area. That is, a CSM based only on changes in the final accessibility value cannot capture the sequential

impacts on accessibility. In addition, this study has focused only on the CSM and does not compare it with other methods. While the primary objective is to examine the effect of order dependency in the CSM, a comparative analysis could provide further insights into the limitations of the CSM beyond those identified in this study. Therefore, this study suggests that future research should develop a new decomposition method that accounts for both the direct and indirect impacts of each component in the 2SFCA framework. Last but not least, our results were derived from a single study area. While our findings clearly demonstrated that order dependency had a significant impact on factor decomposition, the robustness and generalizability of the results could be further strengthened through comparisons across multiple study areas. However, a multi-regional comparative analysis was not feasible in this study due to the limited available regions that provide a sufficiently high level of data granularity for all three required factors, including population movement, hospital operating hours, and traffic congestion times. Nevertheless, future research incorporating multiple study areas may further refine our conclusions.

Although the test we used can be applied to long-term changes in accessibility, our evaluation focused on a one-hour window. Within this short period, we did not observe negative impacts of supply, because no hospitals closed during the morning peak hour. As a result, supply consistently had a positive impact on accessibility changes. If the order of factor substitution were evaluated over a longer time frame, more dynamic supply impacts might be observed.

5. Conclusions

This paper demonstrates the uncertainty caused by the order of factor substitution in CSM, highlighting significant variations in the relative contributions of the three factors that determine spatial accessibility. We found substantial variation across all substitution order combinations, as well as areas where relative contributions varied more widely. These findings indicate that CSM is less applicable in contexts where demand, supply, and traffic factors are interrelated in the measurement of 2SFCA. Accordingly, we introduced averaging CSM, which considers all possible combinations.

Although averaging CSM is not a perfect solution, it serves as a practical alternative. However, to better evaluate relative contributions, future research should develop improved methods that address the uncertainties in calculation while accounting for the structure of the 2SFCA method. A more robust approach would enhance our ability to understand how hourly or yearly variations in the three factors affect spatial accessibility and provide policymakers with clearer guidance on where and how to improve spatial access by targeting specific factors.

Author Contributions: Conceptualization, Kyusik Kim and Kyusang Kwon; methodology, Kyusik Kim and Kyusang Kwon; formal analysis, Kyusik Kim and Kyusang Kwon; data curation, Kyusik Kim and Kyusang Kwon; writing—original draft preparation, Kyusik Kim and Kyusang Kwon; writing—review and editing, Kyusik Kim and Kyusang Kwon; visualization, Kyusik Kim. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2023S1A5A8078509) and the National Research Foundation of Korea (NRF) grant funded by the Korean Government (MSIT) (RS-2023-00246551).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

G2SFCA	Generalized two-step floating catchment area
CSM	Chain substitution method
MAD	Mean absolute deviation

Appendix A

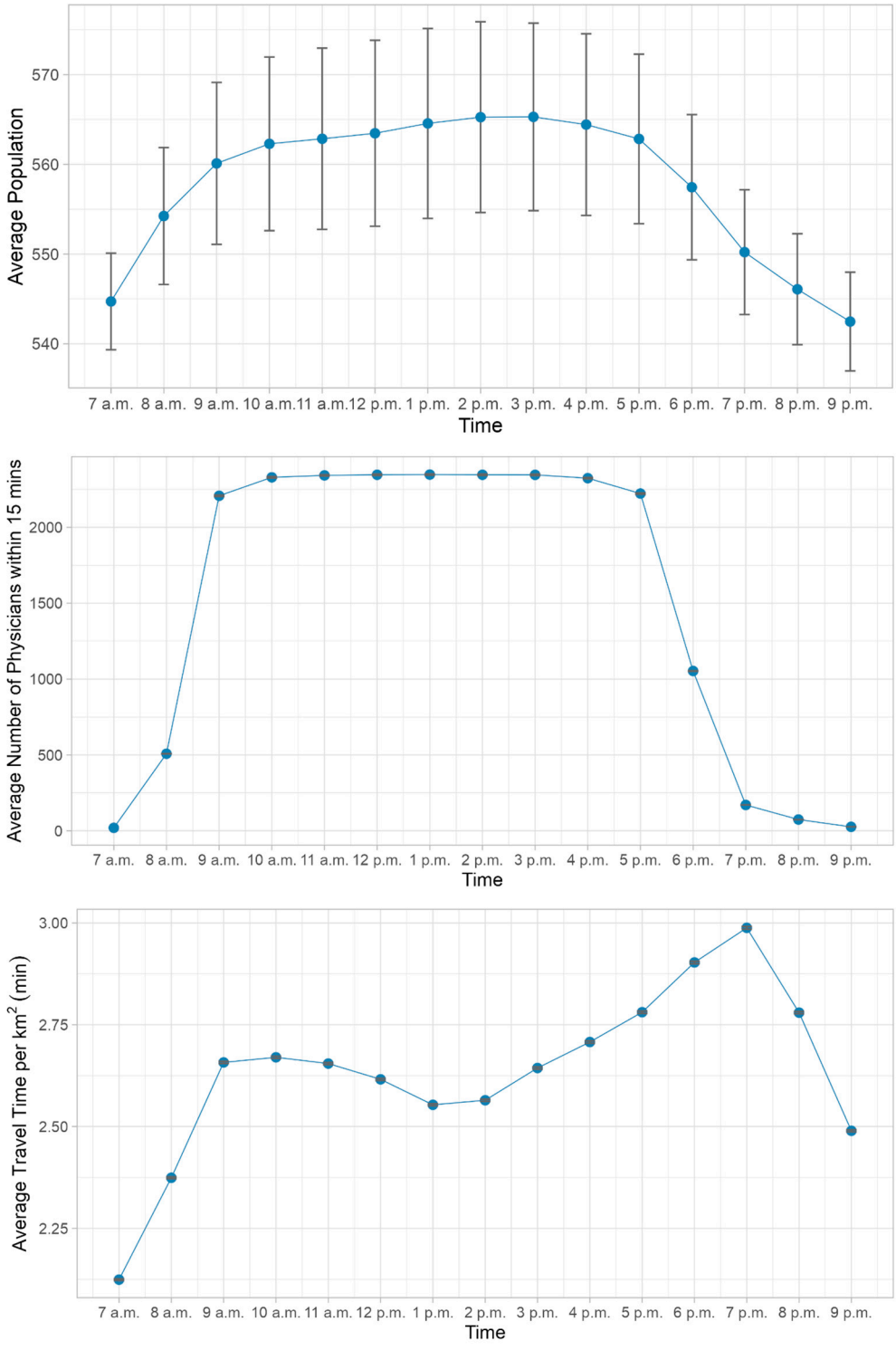


Figure A1. When considering the changes in the three components, the time range between 8 a.m. and 9 a.m. was suitable for comparing accessibility changes.

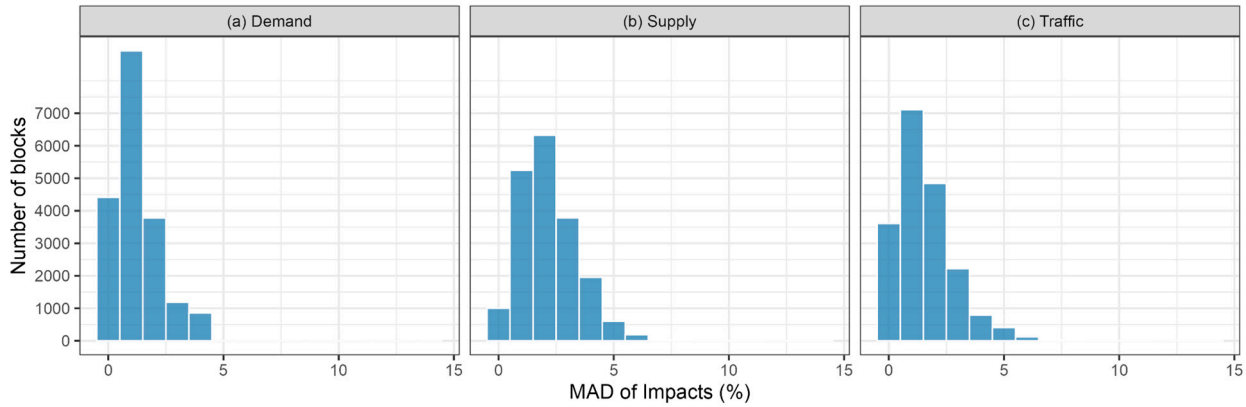


Figure A2. Histograms of MAD of the relative impacts.

References

1. Penchansky, R.; Thomas, J.W. The Concept of Access: Definition and Relationship to Consumer Satisfaction. *Med. Care* **1981**, *19*, 127–140. [CrossRef] [PubMed]
2. Khan, A.A. An Integrated Approach to Measuring Potential Spatial Access to Health Care Services. *Socio-Econ. Plan. Sci.* **1992**, *26*, 275–287. [CrossRef]
3. Luo, W.; Whippo, T. Variable Catchment Sizes for the Two-Step Floating Catchment Area (2SFCA) Method. *Health Place* **2012**, *18*, 789–795. [CrossRef] [PubMed]
4. Järv, O.; Tenkanen, H.; Salonen, M.; Ahas, R.; Toivonen, T. Dynamic Cities: Location-Based Accessibility Modelling as a Function of Time. *Appl. Geogr.* **2018**, *95*, 101–110. [CrossRef]
5. Tenkanen, H.; Saarsalmi, P.; Järv, O.; Salonen, M.; Toivonen, T. Health Research Needs More Comprehensive Accessibility Measures: Integrating Time and Transport Modes from Open Data. *Int. J. Health Geogr.* **2016**, *15*, 23. [CrossRef]
6. Xia, T.; Song, X.; Zhang, H.; Song, X.; Kanasugi, H.; Shibasaki, R. Measuring Spatio-Temporal Accessibility to Emergency Medical Services through Big GPS Data. *Health Place* **2019**, *56*, 53–62. [CrossRef]
7. Paul, J.; Edwards, E. Temporal Availability of Public Health Care in Developing Countries of the Caribbean: An Improved Two-step Floating Catchment Area Method for Estimating Spatial Accessibility to Health Care. *Int. J. Health Plann Mgmt* **2019**, *34*, e536–e556. [CrossRef]
8. Chen, B.Y.; Yuan, H.; Li, Q.; Wang, D.; Shaw, S.-L.; Chen, H.-P.; Lam, W.H.K. Measuring Place-Based Accessibility under Travel Time Uncertainty. *Int. J. Geogr. Inf. Sci.* **2017**, *31*, 783–804. [CrossRef]
9. Hu, W.; Tan, J.; Li, M.; Wang, J.; Wang, F. Impact of Traffic on the Spatiotemporal Variations of Spatial Accessibility of Emergency Medical Services in Inner-City Shanghai. *Environ. Plan. B Urban Anal. City Sci.* **2020**, *47*, 841–854. [CrossRef]
10. Luo, W.; Yao, J.; Mitchell, R.; Zhang, X. Spatiotemporal Access to Emergency Medical Services in Wuhan, China: Accounting for Scene and Transport Time Intervals. *Int. J. Health Geogr.* **2020**, *19*, 52. [CrossRef]
11. Kim, K.; Kwon, K. Time-Varying Spatial Accessibility of Primary Healthcare Services Based on Spatiotemporal Variations in Demand, Supply, and Traffic Conditions: A Case Study of Seoul, South Korea. *J. Transp. Health* **2022**, *27*, 101531. [CrossRef]
12. Yang, J.; Mao, L. Understanding Temporal Change of Spatial Accessibility to Healthcare: An Analytic Framework for Local Factor Impacts. *Health Place* **2018**, *51*, 118–124. [CrossRef] [PubMed]
13. Chen, L.; Chen, T.; Lan, T.; Chen, C.; Pan, J. The Contributions of Population Distribution, Healthcare Resourcing, and Transportation Infrastructure to Spatial Accessibility of Health Care. *Inq. J. Health Care Organ. Provis. Financ.* **2023**, *60*, 004695802211460. [CrossRef] [PubMed]
14. García-Vidal, G.; Pérez-Campdesuñer, R.; Sánchez-Rodríguez, A.; Martínez-Vivar, R. Chain Substitution and Successive Approximation Method: Throughput Analysis at SMEs. *Int. J. Eng. Bus. Manag.* **2019**, *11*, 184797901983839. [CrossRef]
15. Seoul Open Data Plaza De Facto Population in Seoul at the Jipgyegu Level. Available online: https://data.seoul.go.kr/ (accessed on 6 February 2025).
16. Luo, W.; Wang, F. Measures of Spatial Accessibility to Health Care in a GIS Environment: Synthesis and a Case Study in the Chicago Region. *Environ. Plan. B Plan. Des.* **2003**, *30*, 865–884. [CrossRef]
17. Jang, H. A Model for Measuring Healthcare Accessibility Using the Behavior of Demand: A Conditional Logit Model-Based Floating Catchment Area Method. *BMC Health Serv. Res.* **2021**, *21*, 660. [CrossRef]
18. Wan, N.; Zou, B.; Sternberg, T. A Three-Step Floating Catchment Area Method for Analyzing Spatial Access to Health Services. *Int. J. Geogr. Inf. Sci.* **2012**, *26*, 1073–1089. [CrossRef]

19. Delamater, P.L. Spatial Accessibility in Suboptimally Configured Health Care Systems: A Modified Two-Step Floating Catchment Area (M2SFCA) Metric. *Health Place* **2013**, *24*, 30–43. [CrossRef]
20. Kim, Y.; Byon, Y.-J.; Yeo, H. Enhancing Healthcare Accessibility Measurements Using GIS: A Case Study in Seoul, Korea. *PLoS ONE* **2018**, *13*, e0193013. [CrossRef]
21. Tao, Z.; Cheng, Y.; Liu, J. Hierarchical Two-Step Floating Catchment Area (2SFCA) Method: Measuring the Spatial Accessibility to Hierarchical Healthcare Facilities in Shenzhen, China. *Int. J. Equity Health* **2020**, *19*, 164. [CrossRef]
22. Zhang, S.; Song, X.; Zhou, J. An Equity and Efficiency Integrated Grid-to-Level 2SFCA Approach: Spatial Accessibility of Multilevel Healthcare. *Int. J. Equity Health* **2021**, *20*, 229. [CrossRef]
23. Wang, F. Measurement, Optimization, and Impact of Health Care Accessibility: A Methodological Review. *Ann. Assoc. Am. Geogr.* **2012**, *102*, 1104–1112. [CrossRef]
24. Kwan, M.-P. Space-Time and Integral Measures of Individual Accessibility: A Comparative Analysis Using a Point-Based Framework. *Geogr. Anal.* **1998**, *30*, 191–216. [CrossRef]
25. Hu, L.; Zhao, C.; Wang, M.; Su, S.; Weng, M.; Wang, W. Dynamic Healthy Food Accessibility in a Rapidly Urbanizing Metropolitan Area: Socioeconomic Inequality and Relative Contribution of Local Factors. *Cities* **2020**, *105*, 102819. [CrossRef]
26. Ord, J.K.; Getis, A. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geogr. Anal.* **1995**, *27*, 286–306. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.