Time-varying spatial accessibility of primary healthcare services based on temporal variations in demand, supply, and traffic conditions: A case study of Seoul, South Korea

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Research Article

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Abstract

Background: Although demand, supply, and traffic conditions are interdependent, scholars have considered them separately when measuring the accessibility of healthcare services. Additionally, the temporal variations in these three factors is given relatively less attention in healthcare accessibility research, which mislead the wise policy decisions of healthcare planners. This study aims to examine the spatiotemporal variability of accessibility to primary healthcare services and identify areas with spatial discrepancy between time-varying and static accessibility models in Seoul, South Korea.

Methods: Using the generalized two-step floating catchment area method, we measure time-varying spatial accessibility with *de facto* population from hourly-collected mobile-based data, available healthcare facilities, and actual traffic conditions in Seoul, South Korea. Additionally, the bivariate Local Moran's I allowed for the identification of the areas with discrepancy between the two accessibility models.

Results: The results show that a geographical pattern of time-varying accessibility significantly differs with that of static accessibility. Time-varying accessibility is lower in commercial areas and higher in residential areas, compared with static accessibility, whose accessibility is higher in central Seoul. The result of the bivariate Local Moran's I analysis highlights that ignoring time variations of the three factors will result in overestimation in commercial areas and underestimation in residential areas. Based on the discrepancy between the two models, we typified overestimated areas and underestimated areas as attention needed and false attention areas, respectively.

Conclusion: We suggest areas in which the healthcare policy needs to pay more attention by identifying areas with spatial discrepancies between time-varying accessibility and static accessibility. Considering the time variations will provide a more realistic impression of spatial accessibility to primary healthcare.

Background

Examining the accessibility levels to healthcare can help policymakers improve public health and promote quality of life [1] Urban geographers and planners have examined the geographical distribution of supply and demand and the role of traffic conditions in that distribution [2, 3] to better evaluate accessibility to healthcare. Although the three factors (i.e., demand, supply, and traffic condition) are temporally not fixed [4–8], the temporal variations have been given relatively less attention in healthcare accessibility research. Furthermore, given that an accessibility model that does not consider the temporal variations is more likely to overestimate (or underestimate) accessibility levels [9], which mislead the wise policy decision of healthcare planners, measuring the realistic spatial accessibility of healthcare is crucial for monitoring the effectiveness of a healthcare system and ascertaining policy measures that minimize spatial disparities [10].

As an effort to measure reasonable place-based accessibility of healthcare, the development of the two-step catchment area (2SFCA) method has facilitated the application of 2SFCA-based methods to healthcare accessibility research. Many studies have further attempted to enhance its ability of demand, supply, and traffic conditions. For example, the three-step FCA [11] and the conditional logit model-based FCA [12] accounted for the demand side, the modified 2SFCA [13], Seoul enhanced 2SFCA [14], hierarchical 2SFCA [15, 16], and grid-to-level 2SFCA [15, 16] tackled supply dimension, and the enhanced 2SFCA [17] and multi-modal 2SFCA [18] considered traffic conditions in the models.

While studies that use person-based accessibility have considered the temporal variations [19, 20], it is only recently that studies on place-based accessibility have attempted to include the temporal variations in accessibility measures. This is because measuring place-based spatiotemporal accessibility with the variations requires large-scale data on demand, supply, and traffic conditions between locations. Recent advancements in big data and enhanced computing power have made the examination of place-based spatiotemporal accessibility more feasible [8] with various applications, such as, jobs [e.g., 21,22], grocery stores [e.g., 23,24], electric vehicle charges [e.g., 25], and healthcare [e.g., 7–9,26,27]. However, there are very few studies that consider the three factors simultaneously [23, 25].

In healthcare accessibility research that uses the 2SFCA-based method, considering the temporal variations of all the three factors is critical as the accessibility outcome achieved from the 2SFCA-method is determined by demand, supply, and catchment area by distance/time. Furthermore, in reality, the geographical distribution of population varies owing to shifts in activities [8]; the availability of healthcare services further depends on opening hours [7, 23], and varying traffic conditions by congestions [4–6]. In this regard, the static accessibility model that ignores the temporal variations of demand, supply, and traffic conditions is likely to fail to estimate the temporal changes in geographical accessibility patterns.

However, to the best our knowledge, there is no study that considers all the three factors in the place-based accessibility of healthcare. Moreover, previous studies on healthcare accessibility have considered one or two of the three factors. For example, Xia et al. [8] evaluated real-time population distribution using GPS trajectory data but used travel time based on the Euclidean distance and constant travel speed. Hu et al. [5] examined the effect of traffic congestion on the spatial accessibility of emergency medical services in China without considering temporal changes in demand and supply. Zhang et al. [9] measured the walk accessibility of older adults to general practitioners in London, United Kingdom, and evaluated vertical equity between older adults and other age groups. However, they only considered a temporal variation of opening hours. Regarding the nature of the 2SFCA-based method, researchers need to consider the three factors simultaneously. Moreover, given that accessibility levels can be overestimated (or underestimated) when ignoring temporal variations [4, 9], measuring accessibility more realistically is crucial for helping healthcare planners make wise decisions.

Accordingly, this study aims to (1) explore the areas with high or low levels of time-varying accessibility and (2) identify spatial discrepancy between time-varying and static accessibility. We further use the generalized 2SFCA (G2SFCA) method with *de facto* population from hourly-collected mobile-based data, available healthcare facilities, and actual traffic conditions in Seoul, South Korea, to evaluate the time-varying accessibility of primary healthcare services. To achieve these goals, time-varying accessibility patterns are visualized in relative manners. Areas in which the two accessibility models differ significantly are identified using bivariate Local Moran's *I* statistic. Therefore, this study contributes to capturing spatiotemporal variations in the accessibility to primary healthcare and better knowledge for the decision making of healthcare planners.

This paper proceeds as follows. The next section describes the study area, data collection, and methodology, including an accessibility measure and bivariate Local Moran's *I*. We further present and compare the accessibility results of the static and time-varying models. In conclusion, we discuss our findings and suggest policy implications and limitations to be addressed in future research.

Data And Study Settings

Study area

We conducted this study in Seoul, Korea's capital city, to demonstrate the temporal fluctuations and effects of three factors on the spatial accessibility of primary healthcare services. Seoul is the most densely populated city worldwide (9.64 million persons and 605 km² in 2019) and a commuting and shopping destination. In 2021, the daily average population influx from other cities was approximately 1.6 times the number of residents. This influx means that the demand for healthcare services can change over time even within the same zone. Furthermore, compared with other cities, Seoul has significant traffic congestion, with an average commuting time of 44.7 minutes in 2021.

Owing to variations in *de facto* population and traffic congestion, Seoul was the ideal location for this case study because (1) data about the three factors (i.e., *de facto* population, operation schedules of primary healthcare facilities, and travel time based on traffic congestion) are available, (2) a temporal variation in spatial accessibility by location is easy to capture owing to the high density of primary healthcare services, and (3) the greenbelt (i.e., restricted development zones) restrains expansion around Seoul, reducing the edge effect for spatial accessibility of primary healthcare facilities on the outskirts of the city (see Fig. 1).

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. Additionally, compared with other months, April 2021 had less rain; this can affect traffic conditions. Weekdays included Monday through Thursday; we excluded Fridays owing to the possibility of distinct commuting and traffic patterns.

We collected data about each factor from several sources. We calculated the *de facto* population of Seoul by the hour using location information from mobile phones (Seoul Open Data Plaza), based on a spatial unit known as a *jipgyegu* (hereafter, a census block), which is the equivalent of a census block in the United States. On average, the *de facto* population was lowest at 3 a.m. (10,214,039 people, M = 533.29, SD = 541.23) and highest at 3 p.m. (10,827,023 people, M = 565.30, SD = 1446.73), including commuters or shoppers arriving from surrounding cities. Moreover, some areas were more concentrated than others.

We used Kakao and Naver, web-based map services in Korea, to collect supply data. This study defines "primary healthcare services," in consideration of the context of the healthcare delivery system in Korea. In Korea, there are many medical specialists who do not belong to large hospitals and can easily open their own private hospitals and clinics and public health centers. Similar to primary healthcare services provided by general practitioners in the United Kingdom or family physicians in the United States, these private hospitals and clinics provide services for disease prevention and treatment of mild diseases (e.g., colds). Unlike in the United Kingdom, where patients make an appointment to see their doctor beforehand, patients in Korea can visit nearby hospitals for mild treatment or vaccination at any time without booking an advance appointment. In this context, it is important to measure time-varying access to healthcare services based on the *de facto* population rather than the home-based population.

We therefore considered clinics or hospitals that had 30 or fewer beds and offered medical services in any of the following areas: internal medicine, pediatrics, otolaryngology, and family medicine. Based on the definition, we split Seoul into grids and sought facilities within 1,000 meters of the centroid of each grid cell by iterating all grids using the Kakao map API, to further collect information about primary healthcare facilities (e.g., X and Y coordinates, name, and address). However, because the Kakao map API does not return operating schedules for facilities, we collected schedule information from Naver map, using the name and address of information gathered from Kakao map API; this procedure yielded 2,827 primary healthcare facilities.

We used the road speeds provided by Seoul's Transport Operation & Information Services (TOPIS), a traffic control agency, to estimate traffic conditions. TOPIS collects traffic information from many agencies involved in transportation in Seoul, including the bus management system, the public transit card system, and the Korea Expressway Corporation. We integrated TOPIS data that include daily and hourly speed information with road network data from the Korea Transport Database (KTDB). For roads missing speed information, we inputted the average speed of roads in Seoul into the roads, based on each time period, then calculated travel time (i.e., length of the road link divided by speed and multiplied by 60). To calculate travel times between census blocks and primary healthcare facilities, we used the OD cost matrix function of the network analyst in ArcMap 10.7.1 via Python's *arcpy* module.

Time selection

Because the extent of a change in accessibility may not be significantly large by an hour, we considered five time periods (i.e., 8 a.m., 10 a.m., 3 p.m., 6 p.m., and 8 p.m.) based on variations in population, traffic condition, and hospitals between 8 a.m. and 9 p.m., as primary healthcare services in Seoul do not operate 24 hours (Fig. 2). At 8 a.m., there exists 555 persons per census block on average (SD = 1,057), approximately 2.37 min/km of the average travel time (SD = 0.44), and 446 hospitals, which account for

15.8% of the total. At 10 a.m., there are 562 persons per census block (SD = 1,338), approximately 2.67 min/km of the average travel time (SD = 0.54), and 2,799 hospitals, which account for 99% of the total and is similar at 3 p.m. At 6 p.m., that is the afternoon rush hour, the average population decreases to 557 persons (SD = 1,120), the travel time is as high as 2.9 min/km (SD = 0.63), and operating hospitals also decrease to 48% of the total. Lastly, at 8 p.m., there are 546 persons per census block (SD = 856), 2.78 min/km travel time on average (SD = 0.57), and 73 hospitals, which account for 2.6% of the total.

The three components spatially vary by time as well. For example, the population density increases around CBD and GBD from morning to afternoon, then decreases after 6 p.m. The traffic congestion is worse in the afternoon rush hour than in the morning rush hour. Hospitals are less open at 8 a.m. and 8 p.m., while almost 99% of hospitals operate at 10 a.m. and 3 p.m.

Methods

Generalized two-step floating catchment area method

The 2SFCA-based approaches are effective for measuring spatial accessibility because they consider demand, supply, and traffic conditions simultaneously, and have extensive healthcare applications (e.g., Delamater, 2013; Kang et al., 2020; Kim et al., 2021; Langford and Higgs, 2006; Luo and Qi, 2009; Luo and Wang, 2003).

$$A_i = \sum_j \frac{S_j f(d_{ij})}{\sum_k P_k f(d_{kj})}$$

1

Wang [1] suggested a generalized two-step floating catchment area method as Eq. 1. Based on the equation, we computed time-varying accessibility with t for five time periods (i.e., 8 a.m., 10 a.m., 3 p.m., 6 p.m., 8 p.m.) as follows:

$$A_i^t = \sum_{j \in (d_{ij} \leqslant d_0)} \frac{S_j^t f(d_{ij}^t)}{\sum_{k \in (d_{kj} \leqslant d_0)} P_k^t f(d_{kj}^t)}, \quad t \in \{8 \text{ a.m., } 10 \text{ a.m., } 3 \text{ p.m., } 6 \text{ p.m., } 8 \text{ p.m.}\}$$

2

where {P}_{k} denotes the population of zone k within the catchment area of facility j, {S}_{j} denotes a primary healthcare facility, {d}_{kj} meansthe travel time from demand location k to supply location j, and {d}_{0} indicates a threshold of the catchment area. In this analysis, {S}_{j} counts as one facility. Therefore, {R}_{j} denotes the facility-to-population ratio at facility j. t includes 8 a.m., 10 a.m., 3 p.m., 6 p.m., and 8 p.m.

Here, $f\left({d}_{ij}\right)$ represents a distance/time impedance function that can be power, negative exponential, or gaussian function. In this analysis, we used the Gaussian function with 50 of the impedance parameter to get 0.01 at the 15-min threshold point, which makes an impedance weight approach zero at a certain threshold point [32]; this is consistent with other studies [e.g., 33,34]. Nevertheless, because the accessibility values are dependent on the parameter as Wan et al [33] tested, we adopted the spatial accessibility ratio (SPAR) that is less sensitive to variations of the parameters than the absolute accessibility value [33], because the accessibility value is relatively interpreted based on the regional mean. Hence, the SPAR is computed as ${A}_{i}^{t}$ and divided by the average of ${A}_{i}^{t}$for presenting our results consistently regardless of the parameter.

Bivariate Local Moran's I

To examine the spatial discrepancy in accessibility between time-varying and static accessibility models, we explored their spatial relationships using a bivariate Local Moran's *I* proposed by Anselin et al. [35], which yields typologies of the relationships. The bivariate Local Moran's *I* is described as follows:

$$I_{i}^{B}={x_i}\sum\limits_{j} {{w_{ij}}{y_i}} \tag{3}$$

where ${x}_{i}$ and ${y}_{i}$ denote the static and time-varying accessibility respectively, ${w}_{ij}$ denotes the spatial weight matrix with the first-order queen contiguity, and ${I}_{i}^{B}$ indicates the bivariate Local Moran's *I* in icensus block. As the equation indicates, the bivariate Local Moran's *I* in i census block is determined by the static accessibility value in i census block and the time-varying accessibility values in neighboring j census block.

The outcome includes five types of relationships: high static accessibility & high time-varying accessibility (High & High), high static accessibility & low time-varying accessibility (High & Low), low static accessibility & high time-varying accessibility (Low & High), low static accessibility & how time-varying accessibility (Low & Low), and no significant relationship. We implemented this using R [36] and reported the outcome at the 0.05 level based on 9,999 randomized permutations.

In this analysis, we focus on High & Low and Low & High types. These types can be considered evidence of a spatial discrepancy between the two accessibility models, as a census block that falls within either typology can be considered a high static access area or low time-varying access area, and vice versa. This discrepancy is likely to mislead the accessibility landscape of healthcare.

Results

Spatial pattern of time-varying accessibility of primary healthcare

This study calculates one static accessibility and five time-varying accessibilities (i.e., 8 a.m., 10 a.m., 3 p.m., 6 p.m., and 8 p.m.) and further compares them. Accessibility values are converted to SPAR based on the regional average of accessibility, to minimize the effect of time impedance weight and visualize consistent outcomes regardless of the impedance weight. SPAR is used to interpret accessibility values in a relative term based on one that is the average of the study area. Therefore, if an accessibility value of a census block is greater than 1, its accessibility is higher than the average in Seoul. Likewise, if it is less than 1, it can be assessed as lower than the average.

Figure 3 shows SPAR results. The dark green color indicates higher accessibility than average while the dark pink color indicates lower accessibility than average. In terms of time-varying accessibility, at 8 a.m., accessibility is 50% higher than the average in Gangseo and Guro, and 50% lower in the outskirts of Seoul. At 10 a.m., the number of highly accessible areas decreased. Moreover, most areas were similar to the average. This is similar at 3 p.m. At 6 p.m., areas around Gangseo and Guro have higher accessibility, and meanwhile, CBD has lower accessibility. In conclusion, at 8 p.m., residential areas such as Eunpyeong, Nowon, and Gangseo and areas around YBD and GBD have higher accessibility, but CBD still has lower accessibility.

For static accessibility, the accessibility levels of most census blocks are similar to the average given that the accessibility levels in most areas ranges between 0.5 and 1.5. Unlike time-varying accessibility, static accessibility is higher in central Seoul and along the Han River and lower in the outskirts. This landscape reflects a result that central Seoul has relatively higher accessibility where hospitals are densely located and road network connectivity is high, as hospital operating hours and traffic congestion are not considered in the static accessibility model.

Spatial variation of accessibility varies by time of the day. As seen in Fig. 4, the ridgeline plot illustrates SPAR distributions for the two accessibility models with the coefficient of variation (CV). From 8 a.m. to 6 p.m., SPARs are distributed around 1; SPAR at 8 p.m. is widely dispersed, and the static SPAR is slightly to the right of 1, which reflects on the CV. For instance, CV from 8 a.m. to 6 p.m. ranges between 0.252 and 0.288, but CV at 8 p.m. is 0.6, which means that many census blocks has higher and lower accessibility than the average accessibility. As can be seen from the map of Fig. 3 and the ridgeline of Fig. 4, the CV of the static SPAR is 0.201. This is because similar values are gathered around the average, indicating a smaller spatial variation of static accessibility compared with time-varying accessibility.

Compared with static accessibility with higher accessibility in central Seoul, time-varying accessibility is lower in commercial areas and higher in residential areas. This observation indicates the risk of misinterpretation in the case only the static accessibility model is considered without time variation. Furthermore, the small spatial variation of static accessibility compared with time-varying accessibility would not be useful for identifying spatial disparity. As confirmed by the ridgeline plot, the extent of spatial variation is not fixed and varies by time. Moreover, its variation is the highest at 8 p.m. Based on this observation, we have attempted to explore the potential misunderstandings by the time they may occur when using the static accessibility model.

Spatial discrepancy

Figure 5 depicts the relationship between the static model and the time-varying model. We used the Spearman rank's correlation coefficient, given that a rank in a study area is more meaningful than a value as SPAR indicates a relative value compared to the average. All the values had statistically significant positive relationships at the 0.05 level. However, their magnitudes differed. For instance, the relationship at 8 a.m. was the strongest (i.e., \rho = 0.44), while the relationship at 8 p.m. was the weakest (i.e., \rho = 0.16), indicating that the result of the static model was likely unreliable as it did not consider time variation.

We further investigated where the spatial discrepancy occurred between the two models. The bivariate Local Moran's *I* shows their discrepancy in Fig. 6. Of the five typologies, we pay special attention to High & Low and Low & High types because they have different levels of accessibility between the two models. The identified discrepancy is defined in terms of policy implications, posing that time-varying accessibility is more realistic than static accessibility.

The High & Low types include census block with high static accessibility and low time-varying accessibility of their neighbors; we define this type as "attention needed." This type of census block has higher accessibility in the static model but has lower accessibility in the time-varying accessibility. Consequently, if healthcare policymakers or planners evaluate the primary healthcare situation with the static model, those High & Low census block would be overlooked, despite needing attention. In Fig. 6, the census block classified as "attention needed" are mainly found around CBD and GBD.

Unlike the High & Low type, the census block of Low & High can be defined as "false attention." These census blocks are observed as the area with low static accessibility and high time-varying accessibility of their neighbors. When assessing it with the static model, these areas might be identified as areas where additional healthcare services are needed. In contrast, if the time-varying model is used, these Low & High areas have sufficient high accessibility. In this case, healthcare resources would be able to be inefficiently allocated. The Low & High areas are mainly identified in Gangseo, Eunpyeong, and Nowon considered residential areas.

In terms of the extent of the spatial discrepancy, Fig. 7 shows the percentages of each typology. As the graph depicts, the number of discrepant census block (i.e., High & Low and Low & High) increased as time went by, from morning to afternoon. Particularly, High & Low areas at 8 a.m. accounted for just 1.73% of the total. However, the areas increased to 10.06% at 8 p.m. Considering Fig. 2, which illustrates the variations in the three components, we know this increase might be affected by the heavy traffic and small numbers of hospitals at 8 p.m.

Conclusion And Discussion

This study measured time-varying accessibility of primary healthcare in Seoul, Korea, compared the geographical patterns of accessibility from both static and time-varying perspectives, and identified areas with spatial discrepancy between the two models. We employed the G2SFCA method and found that the static model, based on home-based population demand, the same level of supply availability, and free-flow traffic conditions, tended to overestimate spatial accessibility in the business district areas and underestimate it in the residential area.

Our analysis shows the substantial importance of the consideration of temporal variations in measuring spatial accessibility of primary healthcare services. As shown in the figures (see Fig. 3 and Fig. 4), time-varying accessibility displayed different geographical patterns and variations by time. In addition, the finding from the bivariate Local Moran's *I* analysis corroborated the findings by previous studies [e.g., 4,9], which state that ignoring time variations of the three factors (i.e., demand, supply, and traffic conditions) will further result in overestimation or underestimation from the static accessibility model.

In our study area, Seoul, time-varying accessibility tended to be low in business areas (i.e., CBD, YBD, and GBD) and high in residential areas (i.e., Nowon, Eunpyeong, Gangseo, etc). Although primary healthcare hospitals are concentrated in the business areas, the low accessibility in those areas is most likely attributed to the population distribution and traffic congestion during the daytime. For example, for business purposes, the number of *de facto* populations in business areas increases, consequently increasing the demand compared with the number of hospitals. Similarly, heavy traffic congestion reduces the size of the catchment area in the 2SFCA method for the same travel time. Moreover, the number of available hospitals decreases. Consequently, business areas have lower accessibility level than residential areas, which have a small number of *de facto* population and relatively large size of the catchment area.

Compared to other studies that compared static and time-varying accessibility [e.g., 4,23], we also identified both the overestimation and underestimation of accessibility. From the discrepancy between the two models, we typified overestimated areas and underestimated areas as attention needed and false attention areas, respectively. If we do not consider these time variations, we shall not be able to detect these spatial discrepancies, and may end up giving a false sign to healthcare policymakers and planners. Hence, considering the time variations will provide more realistic impression of spatial accessibility to primary healthcare.

This study makes three significant contributions. First, we present more realistic geographic patterns of spatial accessibility to primary healthcare in Seoul, Korea, while considering the temporal variations in demand, supply, and traffic conditions simultaneously. Second, this analysis corroborates the importance of considering the temporal variations in measuring spatial accessibility. Third, we suggest areas that healthcare policy needs to pay more attention by identifying areas with spatial discrepancies between time-varying accessibility and static accessibility.

This study also has limitations that necessitate future research. First, we did not consider temporal differences in the accessibility of healthcare services by socioeconomic or demographic group. For example, population demand was concentrated in CBD during daytime hours. However, many of these people were workers who had difficulty accessing healthcare services. Second, in terms of supply, this paper did not contain sufficiently detailed information about all times of operation that might affect the availability of healthcare (e.g., lunchtime). Third, we focused on accessibility based on private vehicles and did not consider other modes of transport. For instance, public transport is also subject to traffic conditions and operating schedules during the day. Moreover, walking remains the most frequent mode of travel to healthcare facilities. If these limitations can be addressed in future research, we may be able to provide a complete impression of the accessibility of primary healthcare in Seoul.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Data are publicly available online. Readers can refer to Seoul Open Data Plaza (https://data.seoul.go.kr/) for de facto populations, the Korea Transport Database (https://www.ktdb.go.kr/) for road networks, and Transport Operation & Information Services (https://topis.seoul.go.kr/) for road speeds. Also, a document of Kakao developers provides information of Kakao API (https://developers.kakao.com/docs/latest/ko/local/common).

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

K. Kim and K. Kwon designed the study. K. Kim collected data and implemented method. K. Kim and K. Kwon prepared the initial draft of the manuscript.

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Figures

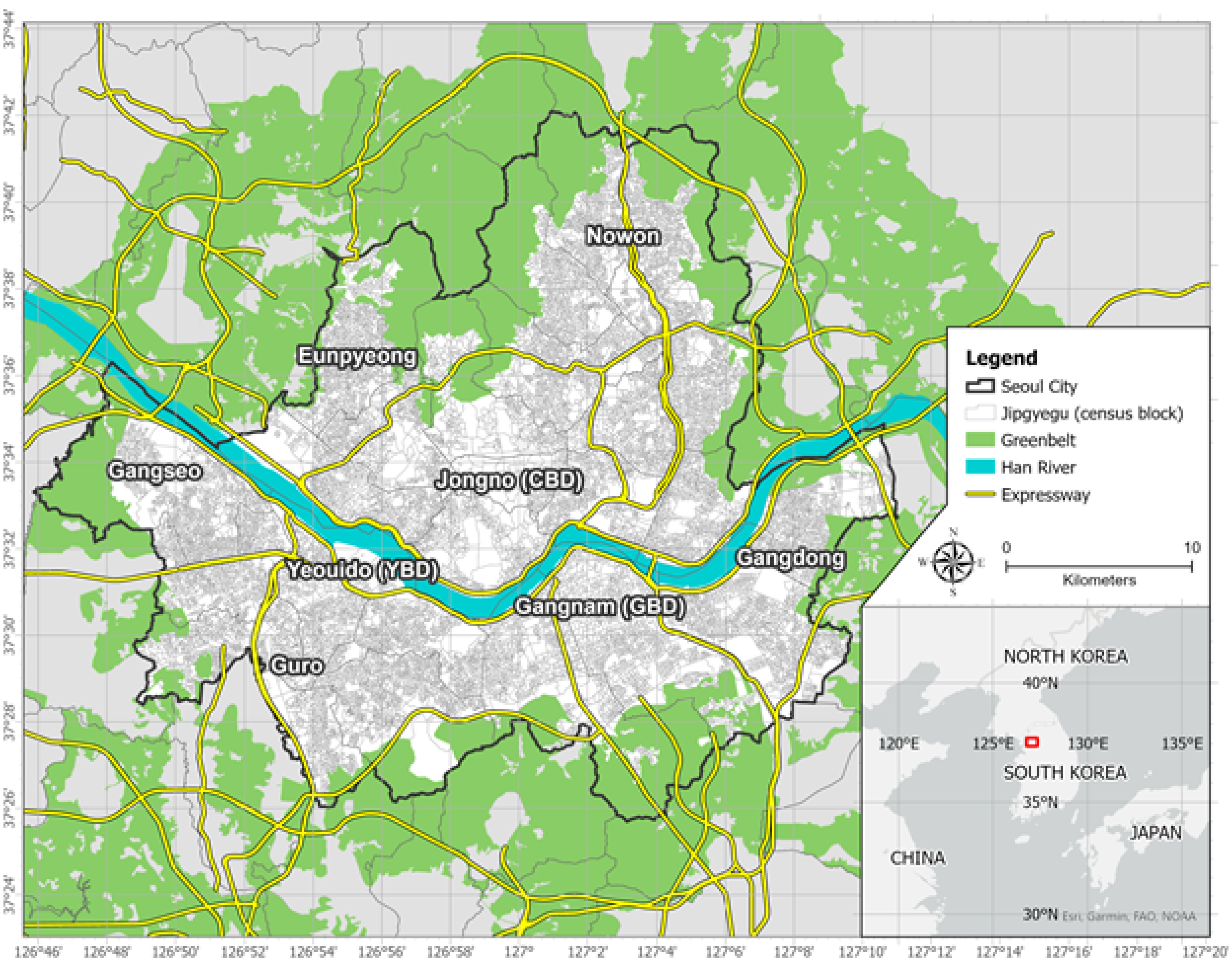

Figure 1

Illustration of the study area.

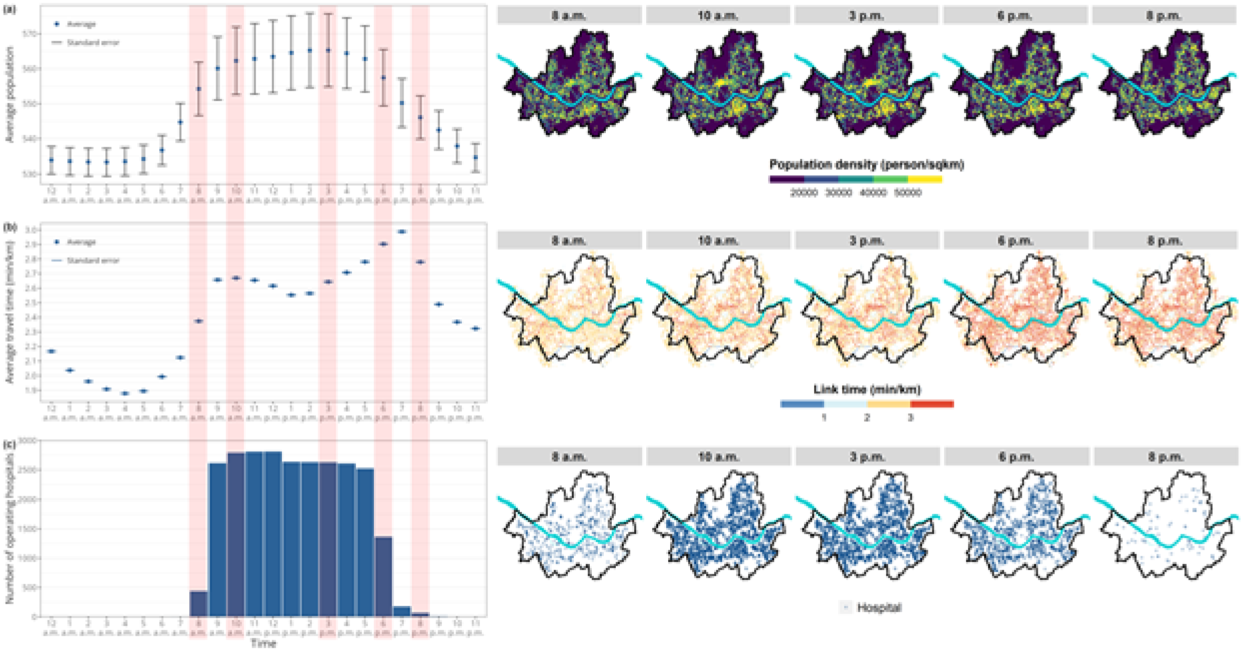

Figure 2

Illustrations of time-varying three components.

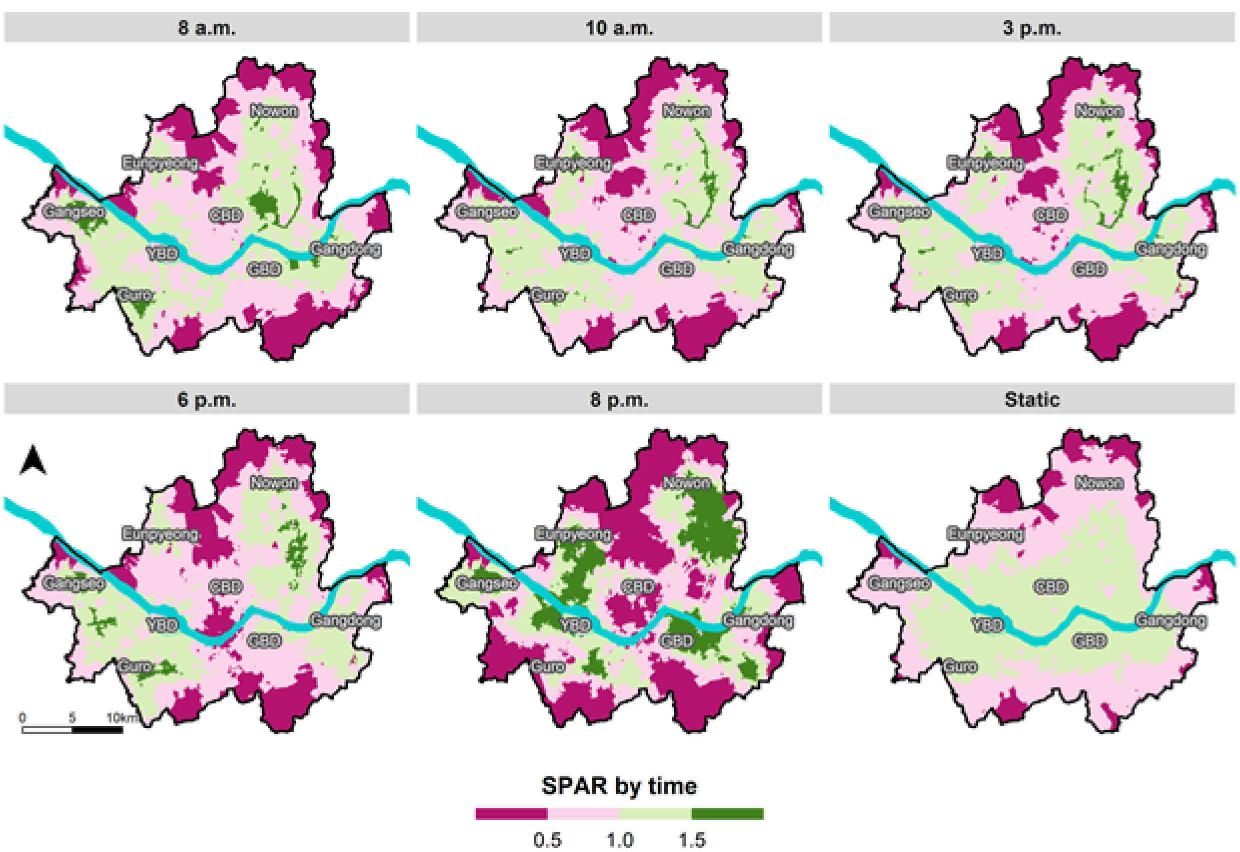

Figure 3

SPAR maps by time.

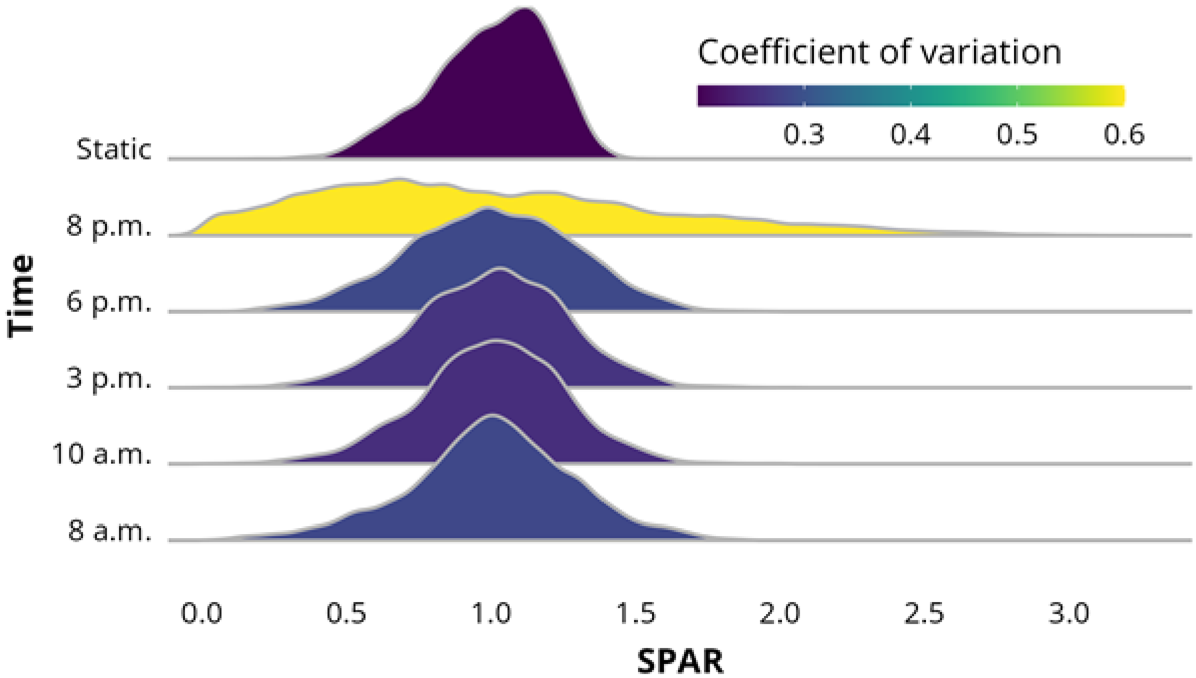

Figure 4

Distributions of SPAR by time.

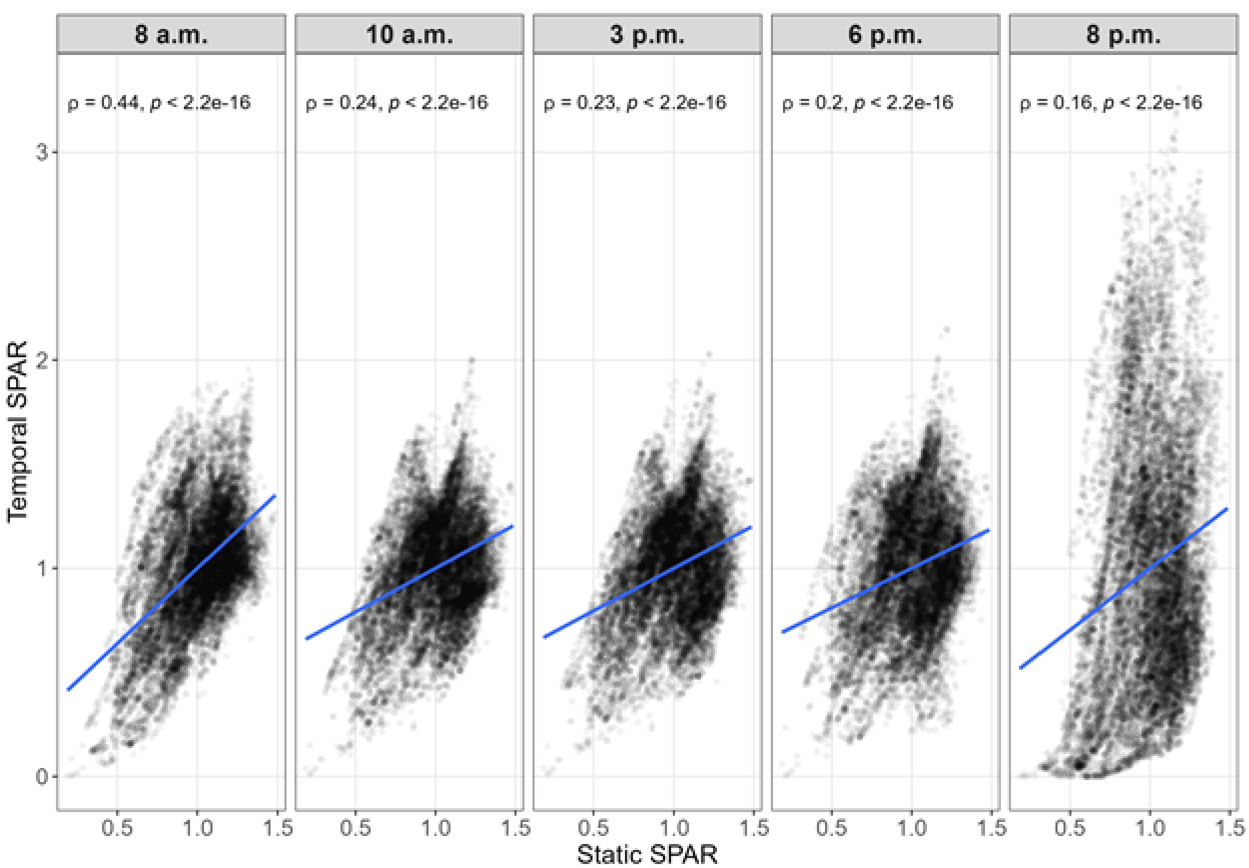

Figure 5

Spearman rank's correlation between the static SPAR and the time-varying SPAR.

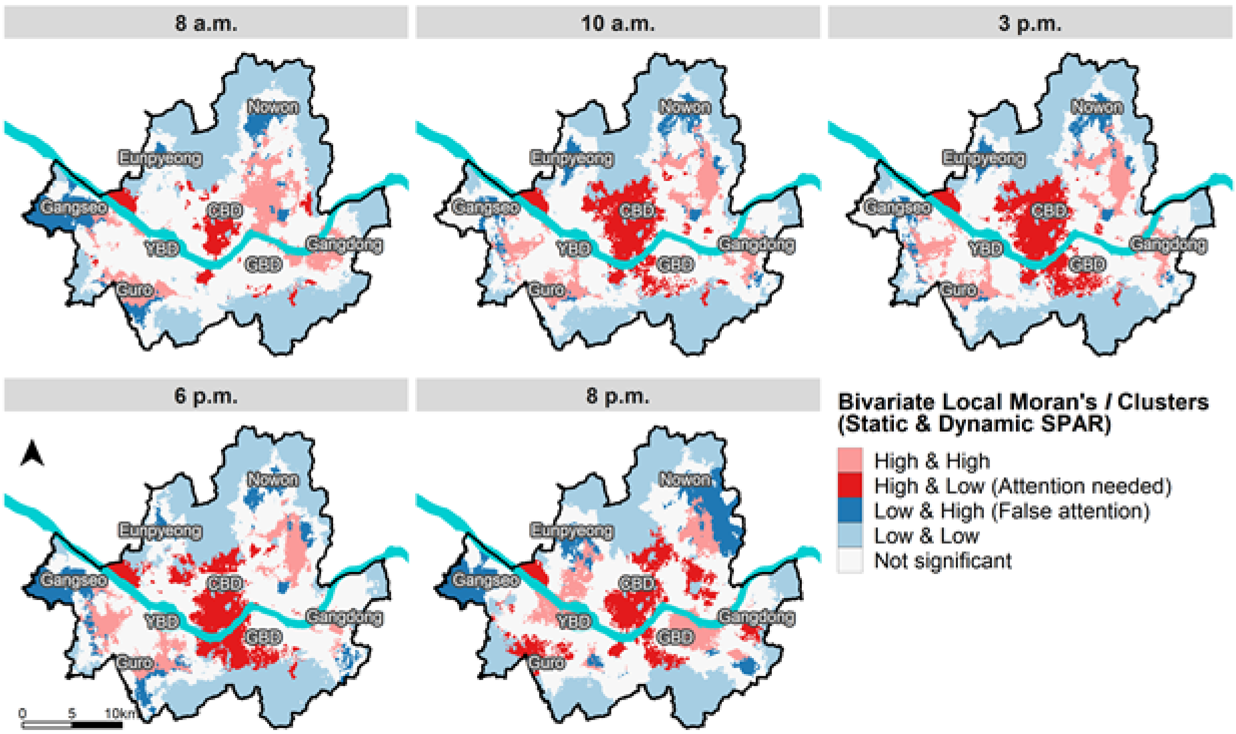

Figure 6

Bivariate Local Moran's *I* maps between the static SPAR and the time-varying SPAR

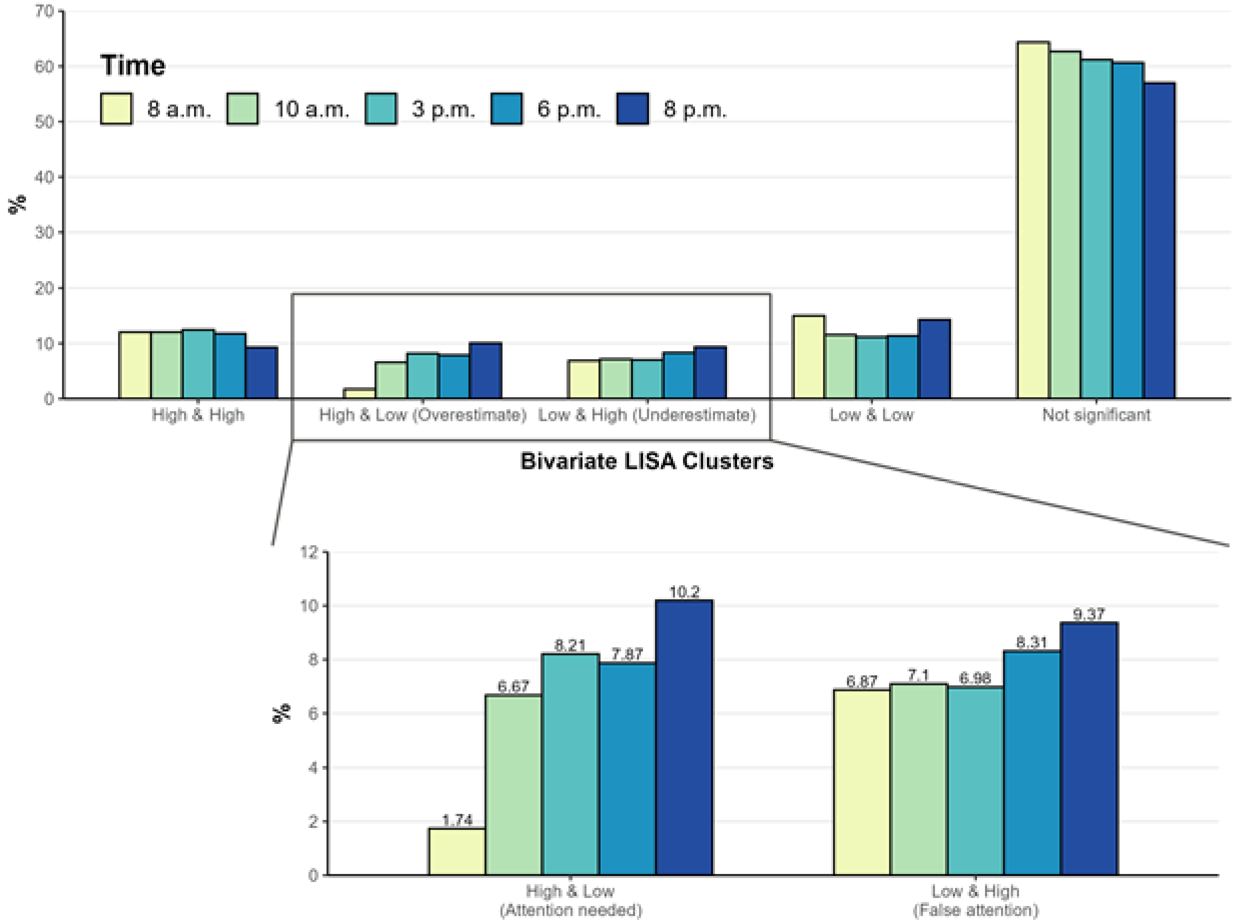

Figure 7

Percentages of spatial discrepancy by time.