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Identifying spatiotemporal transit deserts in Seoul, South Korea

Hye Kyung Lee [a], Junfeng Jiao [b,*], Seung Jun Choi [b]

[a] School of Urban Planning and Real Estate Studies, Dankook University, Gyeonggi 31116, South Korea
[b] Urban Information Lab, The University of Texas at Austin, TX 78712, USA

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ABSTRACT

Transit deserts can result from the inequitable distribution of resources and services, and people living in transit deserts have limited access to transportation system. The aim of this study was to perform spatiotemporal data analysis to identify transit desert areas in Seoul in three steps. First, the transit gap between peak and off-peak hours is evaluated and various spatial changes in each temporal transit desert area are identified. Second, a spatial analysis is conducted to identify transit desert and transit oasis areas that emerge during peak hours. Lastly, an independent T-test is conducted to identify how the socio-economic characteristics of transit deserts and transit oases are statistically different. Our analysis show that, transit deserts changed across space and over the time in Seoul. Furthermore, transit deserts in general appear to be associated with socio-economically vulnerable residential areas.

1. Introduction

Rapid urbanization in many cities resulted in many urban issues such as spatial imbalances between the supply and demand of services in cities (Zhang et al., 2019). Spatial imbalance is considered as one of the critical factors that contribute to social inequity (Foth et al., 2013; Lucas, 2012; McCray and Brais, 2007; Zuo et al., 2020), and it restricts underrepresented populations' accessibility to resources and places. Public transportation has become a popular method to solve urban transportation issues by providing more accessibility to a wider socio-economic range of the population (Tribby and Zandbergen, 2012). Disparities in transit accesses may lead to socio-economic inequalities, to avoid such problem, it is necessary to evaluate the spatiotemporal accessibility of public transportation in cities and plan for more balanced and accessible transit services.

The term "desert" has been used extensively to describe the spatial disparities in accessibility to resources such as food, transit services, jobs, education, and childcare in cities (Aman and Smith-Colin, 2020; Cai et al., 2020; Kim and Park, 2020; Kim and Wang, 2019; Páez et al., 2010). "Transit desert" is defined as an area where existing transit services are not sufficient compared to its residents' travel demand (Jiao and Dillivan, 2013). Previous studies have identified transit deserts in cities by considering three variables: transit demand, transit supply, and transit gap. The transit gap is evaluated to show relative gaps between transit supplies and transit demands in specific areas. A transit desert is identified when transit demand far outweighs the transit supply in a given area (Jiao and Cai, 2020). Conversely, a "transit oasis" refers to an area where transit supply is far greater than transit demand; "in contrast to transit deserts." (Jiao, 2019). Transit deserts can result from the inequitable distribution of resources and services in a city, causing the people living in transit deserts to experience limited accessibility and inefficient transportation (Aman and Smith-Colin, 2020).

Despite previous research on transit deserts since 2013, little empirical research has considered wide ranges of spatial big data to explore spatial and temporal patterns of transit deserts in cities. The major objectives of this research are four-fold: First, it considers spatial and temporal analysis to identify how transit deserts are spatially distributed in cities, and how these transit deserts change over time. Second, it utilizes real-time dynamic spatial information such as telecommunication floating population and metro, bus, and micro mobility ridership data. Using these real-time spatial big data, we measure how transit deserts vary between peak and off-peak hours and consider mobile-based floating population to find transit demand and transit gaps in cities more accurately. Third, the socio-economic characteristics of transit deserts are identified to show spatial differences of these environments between transit deserts and transit oases. Lastly, this study analyzes Seoul, South Korea, which is one of the major Asian cities with dense urban development and transportation infrastructure.

The remainder of this article is structured as follows. Section 2 reviews relevant previous literature. Section 3 and 4 explains the study

* Corresponding author.
E-mail address: jjiao@austin.utexas.edu (J. Jiao).

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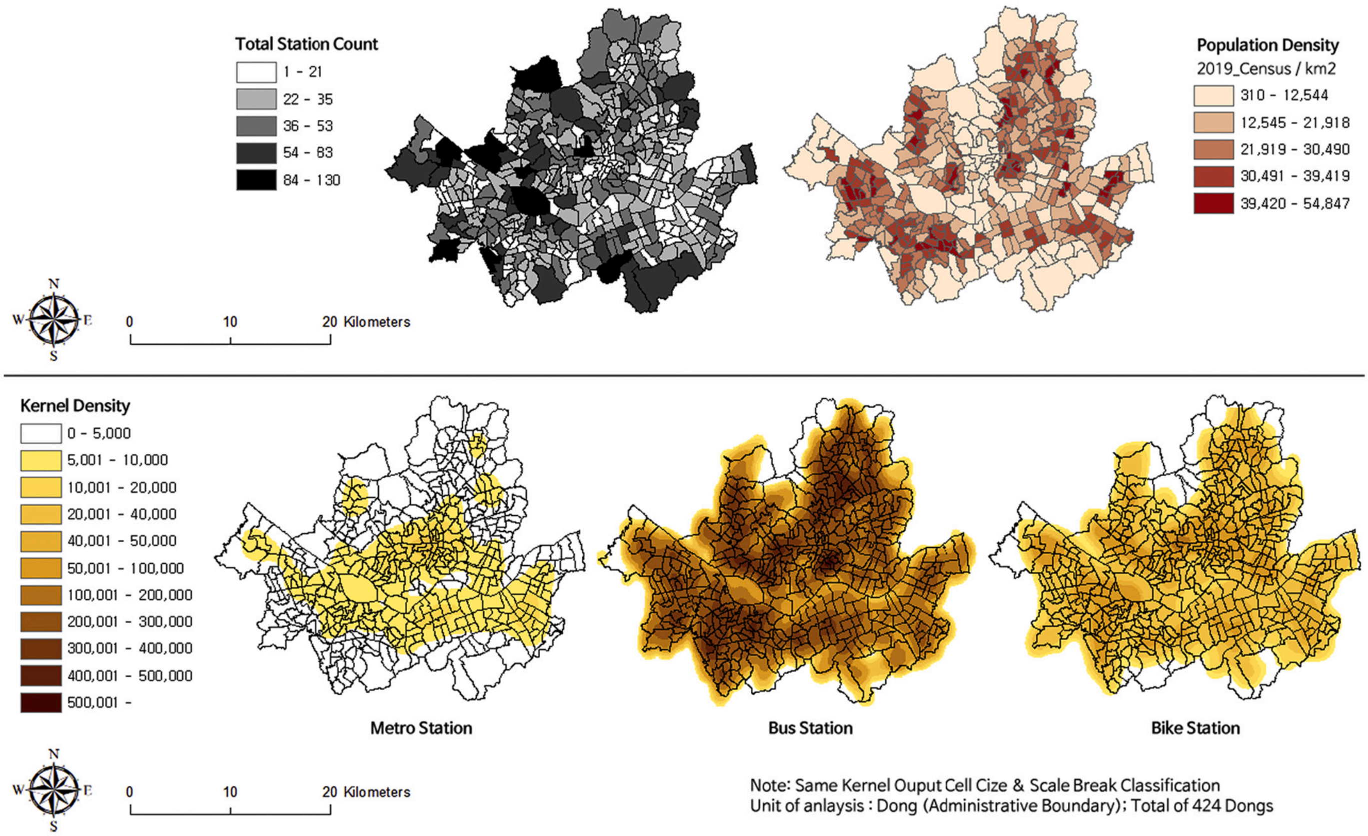

Fig. 1. Spatial characteristics of Seoul, South Korea.

area, data collection, measurement, and data analysis strategy. Section 5 presents the key findings of our descriptive statistics, spatial-temporal analysis, and *t*-test analysis. Finally, Section 6 and 7 conclude this empirical research by explaining the contribution of this study, discussing its limitations, and suggesting future research.

2. Literature review

2.1. Transit desert

The term “transit desert” has been used to define areas with gaps between transit service supplies and transit-dependent population demands. Transit-dependent population tend to live in areas with inadequate public transit service and have a likelihood of being overlooked by society (Jiao and Dillivan, 2013). People in low-income neighborhood who rely heavily on public transportation often have limited accessibility to transit services. Due to the imbalance between their transit demands and supplies, low-income population often suffer long commute times, high transportation costs, and limited access to job opportunities (Shen, 2000; Nelson, 2013; Ahmed et al., 2008). Since 2013, studies on transit desert have been conducted mostly for American cities. This research explains that as transit demands exist not just in central cities, but also in surrounding areas, more thoughtful planning strategies to provide public transit for transit deserts in all parts of a metropolitan region should be considered (Jiao, 2017; Jiao and Dillivan, 2013). Transit deserts in four major U.S. cities, Charlotte, NC, Chicago, IL, Cincinnati, OH, and Portland, OR are analyzed by quantifying the gaps between transit demand and supply. Jiao and Dillivan (2013) also explain that areas adjacent to historic downtowns tend to have higher numbers of transit desert neighborhoods. A comprehensive set of public transit accessibility measurements was applied to evaluate transit deserts in the City of Dallas, TX (Aman and Smith-Colin, 2020). This study considered a diverse set of spatial and temporal factors including connectivity to the network, connectivity to destinations, service frequency, flexibility, and time efficiency. Beyond major American cities, research on transit deserts in Cape Town, South Africa have been geographically modeled. The Cape Town study identifies transit deserts based on formal public transport supply (bus rapid transit, traditional buses, and trains), and shows that similar to U.S. Cities, excess transit supply is mostly distributed near Cape Town’s city center. They propose that informal transit services such as unscheduled minibus-taxi might reduce transit gaps (Vanderschuren et al., 2021). Recently, a few transit desert studies on major developing Asian cities have been conducted to assess the concept of transit gaps in different environments. Research on the Wuhan Metropolitan Area, China explores the characteristics of transit deserts and low-income commuters. This research teases out the factors that explain why transit deserts occur in low-income neighborhoods, and potential planning strategies to reduce the gaps between public transit services and transit demand of commuters (Cai et al., 2020).

2.2. Open source data

To solve diverse urban issues, some smart cities have implemented a wide range of information and communication technology (ICT) and real-time spatial bigdata. Much of these related to transit demands and supplies have been offered as open source data. Advances in telecommunication technologies have allowed people use mobile devices for daily life, with mobile phones or smartphones having become the most dominant devices. The real-time spatial bigdata gleaned from these devices is useful to researchers seeking to collect information regarding how transit demands and supplies change across time and location (Lee and Kim, 2019; Williams et al., 2015). For quantifying transit demands, mobile phone signal-based population represents much more accurate information on spatiotemporal changes of people in cities compared to the conventional census-based population, which is usually collected every 5–10 years (Yun et al., 2020; Baker et al., 2017). As the limitations of a static population dataset has been indicated, the spatiotemporal analysis considering the mobile-based floating population are required in accessibility research (Kwan, 2013). Floating population is defined as a population that stays temporarily and moves around from at a given point in time and place to the other (Engbersen, 2016; Lee et al., 2017). It includes residential populations living in the region and the populations that temporarily stay in the region (Lee et al., 2020). Similarly, the mobile phone-based floating population is an active phone user who transmits mobile signals, which can be applied to measure the accessibility to public transit (Lee et al., 2018). The mobile phone signal-based population is sometimes referred to as "service population", "human activity", "human dynamics", and "temporary population" since these population volumes exist in a particular area for specific periods (Jo et al., 2020; Jung and Nam, 2019).

With the advantages of using mobile phone-based population data to describe the daily spatiotemporal changes of the population, Ryan (2011) argued that spatial big data can be used to dynamically measure people's access to public transit. Lee et al. (2018) used this method to identify areas with less spatial access to public transit in Seoul, South Korea. Cai et al., (2020) also used Spatial Big Data derived from Baidu search (Equivalent Google in China) to identify the spatial patterns of the transit systems and commuter flows in Wuhan Metropolitan Area. Results showed that real-time spatial population data could provide reliable and accurate estimation for public transit accessibility. However, there is limited studies on using real-time bigdata to measure transit demands and supplies in major Asian cities, this study seeks to fill these gaps through identifying spatiotemporal transit deserts in Seoul, South Korea.

3. Materials and methods

3.1. Study area

Seoul (37.34° N and 126.59° E) is the capital city of South Korea. The total area of Seoul is 605 km^2. The city is located along the banks of the Han River, which flows horizontally across Seoul and divides the city into North and South. There are 25 districts ("gu" in local terms) and 424 administrative boundaries ("dong" in local terms) within the assigned care of the 25 districts. The total population of Seoul in 2019 was 10,025,927, which serves as home to almost 20% of people in South Korea. Seoul's population density in 2019 is 16,571 people per square kilometers, which is about 2.4 times that of New York City. Considering the population who commute from surrounding areas to their work, education, and other essential places in Seoul, the number of floating human dynamics, or population movement, is much higher than the census records. The population density of 424 administrative boundaries ranges from 310 to 54,847 people per square kilometers, and public transportation infrastructure – metro, bus, micro mobility – is distributed across all administrative boundaries (Fig. 1). As of 2020, the total number of metro, bus, and micro mobility stations are 298, 11,269, and 2079, respectively. The total length of the nine lines that make up the metro system in Seoul is 327.1 km, and the percentage of land devoted to surface roads is 22.2%. According to Seoul Metropolitan Government, share of mode of transportation in 2015 consisted of 65.8% of public transportation, 23.0% of car, 6.8% of taxi, and 4.4% of others (Seoul Metropolitan Government, 2019). Compared to 51% public transit ridership of Tokyo, Japan in 2018 (Cao et al., 2020), Seoul shows relatively high public transportation usages.

Since 2004, public transportation system in Seoul has been improved by implementing different types of policies such as: reorganization of public bus services, introduction median bus lanes, integration of transit-fare cards. These changes resulted in positive outcomes and solved many public transportation issues in Seoul. Moreover, the city has implemented IoT and bigdata-based smart city strategies to manage real-time traffic flow, supply information on traffic congestion, adapt bus operations in real-time, and so on. Seoul has tried continuously not only to implement sustainable transit services, but also to provide balanced transit services to meet the needs of vulnerable people in the city. However, due to the rapid development of the city and its public transportation systems, Seoul has experienced new issues that disproportionately affect its built environments differently (Kim and Park, 2020). The kernel density analyses show that public transportation is especially concentrated mostly in the central parts of Seoul, which links to spatial imbalance issues in public transportation infrastructure (Fig. 1). Despite of diverse improvement of Seoul's public transportation infrastructure over the years, some of administrative "dongs" still have less accessibilities.

Bigdata of the public transit-fare cards system in 2019 shows that daily commuters using public transportation to move from adjacent cities in the MSA region to Seoul is about 1.3 million. 15.9% out of total public transit ridership to Seoul was departed from surrounding areas near Seoul, whereas each day over 7 million (84.1%) people have used public transportation to move inside Seoul administrative boundary. Also, floating population dataset in 2017 based on KT, one of major mobile companies in South Korea explains that the daily floating population in Seoul is about 20 million and about 9% out of total floating population in Seoul comes from surrounding cities. Seoul's higher public transit ridership compared to other big cities in the world, active implementation of diverse transportation policies over the years, and bigdata-based smart city strategies have improved transportation issues in the densely populated city. However, Seoul has spatial disparity issues in transit system, and it is meaningful to find the areas with inequalities and what factors in Seoul are related to these issues. This will be helpful to provide policy implementations that could be applied for other cities with spatial imbalance issues. As 84.1% of high rates of public transit ridership and 91% of floating population were made inside Seoul, the study on spatiotemporal imbalance issues in Seoul will be helpful to further analyze public transportation issues in adjacent cities.

3.2. Conceptual methods

3.2.1. Transit demand & transit supply

To identify transit desert areas in Seoul, this study considers two transit demand variables and thirteen transit supply variables. To measure transit demand, we include both the census population information of Seoul and the human dynamics captured by telecommunication signal data. The term "transit desert" refers to areas where transit supplies are not sufficient compared to residents' travel demand. Demand for public transit is largely driven by transit-dependent populations who do not own a personal vehicle and need public transit. Previous research on transit desert have used a methodology developed by the US Department of Transportation to measure transit-dependent population (Jiao and Cai, 2020). Transit-dependent populations was measured by subtracting the number of private vehicles from potential household drivers. According to bigdata from the national traffic survey of South Korea in 2018 shows the rate of single occupancy vehicle whose only occupant is the driver was 82.5%. Also, we assume the population between ages 20 and 84 to be potential drivers, since people of 20 years and older are qualified to get a driver's license in South Korea. Therefore, to find potential transit-dependent populations, we subtracted the number of registered vehicles from the census population between the ages of 20 and 84. Moreover, 9.5% out of 3.7 million registered drivers are people of ages 65 or older in 2018 (Han et al., 2020). This share of elderly drivers is estimated to increase, and the Korea Road Traffic Authority states that people age over 75 are required to get their licenses renewed every three years (Korea Road Traffic Authority, 2021).

This study also employs real-time "human dynamics" data to quantify the transit-dependent population. These data are offered by the Seoul Metropolitan Government, which has released open-source datasets since March 2018 (Seoul Metropolitan Government, 2021; Seoul Metropolitan Government and KT BigData, 2018). Human dynamics

Table 1
Descriptive statistics of demand and supply variables.

Variables (Units)		Sum	Min	Max	Mean	Std
Transit Demand	Human Dynamics (Counts)	170,692,833,397	69,021,750	1,888,366,000	402,577,400	219,748,500
	Census Population between age 20 and 84 - Registered Vehicle Number (Counts)	5,248,236	158	29,349	12,378	5027
Transit Supply	Bus Station (Counts)	11,269	1	111	27	15
	Metro Station (Counts)	298	0	5	1	1
	Public Bike Station (Counts)	2079	0	35	5	4
	Parking lot (Counts)	315,108	13	3467	743	553
	Area of Parking lot (km^2)	4.2399	0.0004	0.0534	0.01	0.0067
	Length of Driver Route (km)	1457.6	0.1	10.4	3.4	1.4
	Length of Bike Route (km)	686.6	0.1	5.6	1.6	0.9
	Number of Bike Road (Counts)	775	1	5	2	1
	Number of Taxi (Counts)	121,425	6	970	286	196
	Number of City Bus (Counts)	7636	0	86	18	16
	Public Bike Ridership (Counts)	27,779,484	0	919,809	65,518	74,971
	Bus Ridership (Counts)	5,866,778,760	313,291	77,742,630	13,836,740	10,300,470
	Metro Ridership (Counts)	6,435,773,170	20,252,380	306,708,900	15,178,710	28,980,600

data is based on KT telecommunication company's 4G LTE network system and is measured by an average unit of a 0.0026km^2 radius from each telecommunication station. As the second major telecommunication company in South Korea, KT has 17,408,108 subscribers, which covers one-quarter of all mobile users in South Korea as of November 2020. KT's LTE signal records an individual's location as long as the mobile is turned on regardless of whether people use their phone or not. Utilizing the mobile phone signal data to track human dynamics can measure people's movement highly accurately and can show more kinds of travel patterns compared to analysis using census population (Song et al., 2010). However, as concerns of the utilization of GPS-based datasets involving algorithmic uncertainties have been raised, this may affect the results (Kwan, 2016). To identify transit deserts, this study considers transit supply variables measured from transit infrastructure such as transit stops for metro, bus and docked public bike share, transit route, transit service volumes as described (Table 1).

3.2.2. *Transit gap*

To analyze spatiotemporal transit gaps in Seoul, transit demand and supply for each of the 424 administrative boundaries ("dong" in local terms) are measured. Different types of measurement in previous studies were conducted to examine the disparity in access to resources or public services. For example, two-step floating catchment area (2SFCA) method was applied to measure the spatial accessibility to daycare and kindergarten by calculating a ratio between supply and demand (Kim and Wang, 2019). The availability of any supply within the catchment from a demand location were considered to measure its accessibility and the catchment area size acted as a critical parameter for this measurement. However, using buffers based on the catchment distance or calculating usage ratio by measuring distance for individual locations overlap to each other, and 2SFCA has possibilities to skew the analysis results. Due to these limitations of 2SFCA method, transit gap measurement by subtracting *Z*-scores of demand from supply was applied for this study, and this method better keeps its statistical means. Also, this study used human dynamics to capture real time transportation demand and even beyond the registered boundary.

For this study, transit demand and supply variables are evaluated, and the value was divided by the area of each administrative boundary to get the density value. Then, each variable is subtracted by the average value and divided by the standard deviation to estimate the *Z*-score for standardizing each variable (Jiao and Cai, 2020). A Z-score statistically explains a value's relationship to the average of a group of values and

Table 2
Off peak and peak.

Criteria	Off peak	Peak
Time frames	0 to 7, 10 to 12, 15 to 18	7 to 10, 12 to 15, 18 to 24
Total	12 h	12 h

indicates how many standard deviations is away from the mean (Vanderschuren et al., 2021). To measure the conditions of transit supply in each administrative boundary, Z-score of transit supply was calculated by aggregating the thirteen transit supply criteria, then weighted these variables equally (Jiao and Cai, 2020). By subtracting the standardized Z-score of transit demand from the Z-score of transit supply, the transit gap of each area is analyzed. A negative value of transit gap indicates transit demand exceeds supply, while a positive value means transit demand is less than supply (Steiss, 2006). If the transit gap is less than one, the area is considered a transit desert, while if the result is greater than one, the area is considered a transit oasis. The transit gap for each administrative boundary is calculated using the following equation:

$$\text{Transit Gap} = \text{Transit Supply } (Z-\text{score}) - \text{Transit Demand } (Z-\text{score})$$

4. Data analysis/calculation

The data to identify spatiotemporal transit deserts are analyzed in four parts. First, descriptive statistics of transit demand and supply for 424 administrative boundaries in Seoul and transit gap by subtracting standardized z-score of transit demand from z-score of transit supply was analyzed (Table 1). Second, the transit gap between peak and off-peak hours is evaluated and various spatial changes in each temporal transit desert area are identified. As variables that affect transit demand or supply change depending on when, and where people use transit services (Choi et al., 2012; Bai and Jiao, 2020; Jiao, 2018), we define peak hours and off-peak hours considering people's activities in daily life for the analysis. The total number of hours for peak hours and off-peak hours are the same at 12 h each, and time frames for peak hours consist of 3-h intervals – morning (7 to 10), lunch (12 to 15), afternoon (18 to 21), and night (21 to 24) (Table 2).

Third, a spatial analysis is conducted to identify transit desert and transit oasis areas that emerge during peak hours. All transit deserts and transit oases in the four peak-hour time frames are merged. Then, if

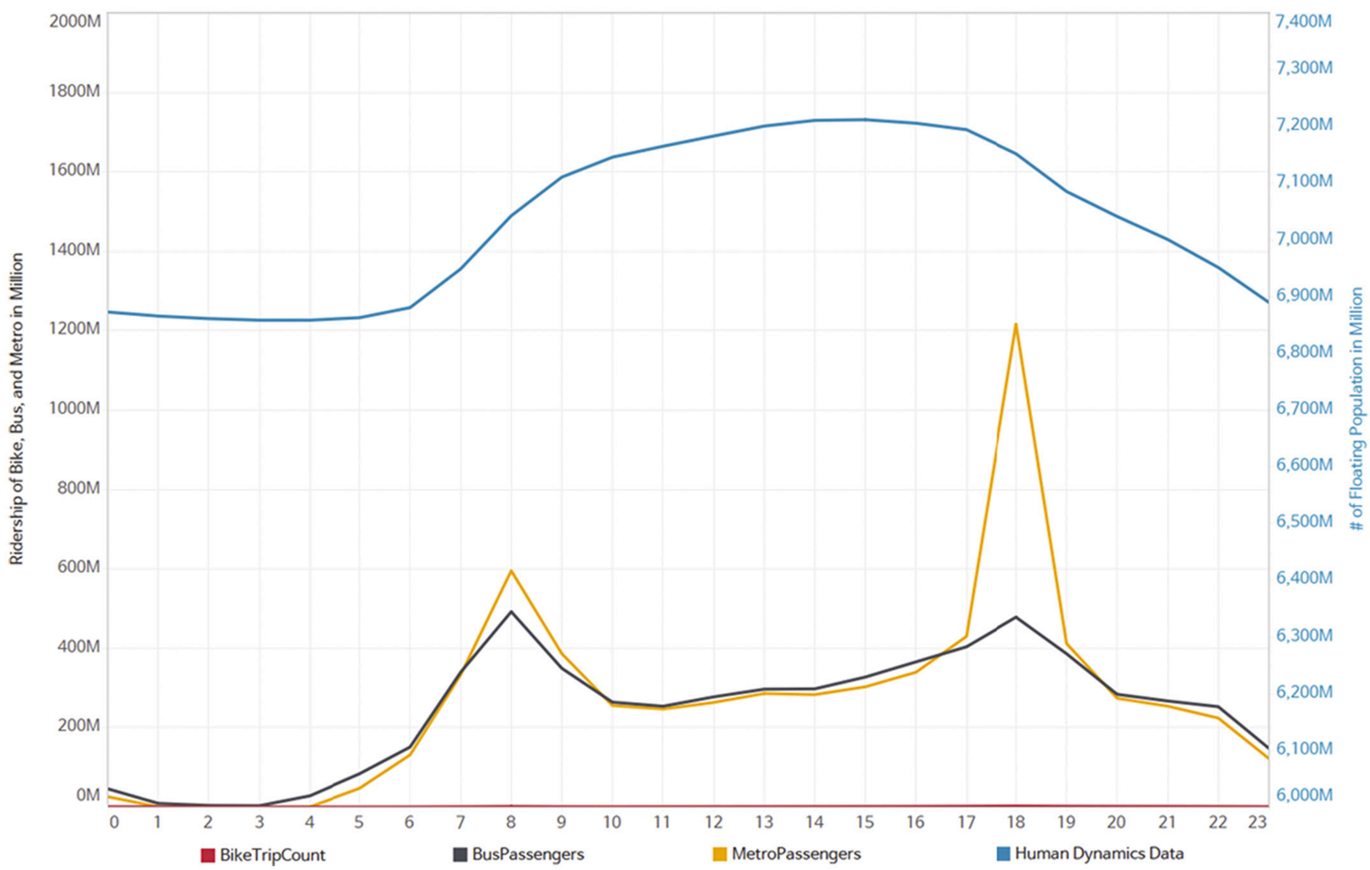

Fig. 2. Hourly patterns of human dynamics and transportation ridership in Seoul between January 1, 2019 and October 31, 2020.

transit desert and transit oasis areas during off-peak hours overlap, these areas are excluded from the set. The remaining areas spatially represent transit desert and transit oasis areas in Seoul that emerge during peak-hours only.

Fourth, this study conducts an independent T-test to identify how the socio-economic characteristics of transit deserts and transit oases are statistically different in Seoul, and to show spatial differences between these environments. The independent T-test is a methodology that calculates two groups' average values and evaluates whether their differences are statistically significant (Kim et al., 2019). To run an independent *t*-test, transit desert and transit oasis areas that are analyzed during off-peak hours, peak hours, and peak-hours only. The independent T-test is calculated using the following equation.

$$t = \frac{\underline{X_o} - \underline{X_d}}{SE_{\underline{X_o} - \underline{X_d}}}$$

where $\underline{X_o}$: Average of Transit Oasis; $\underline{X_d}$: Average of Transit Desert;$SE_{\underline{X_o}-\underline{X_d}}$: Standard Error of Transit Oasis & Transit Desert

The unit of analysis for this study is the Seoul city administrative boundary. Our study area, which includes all of Seoul, includes a total number of 424 administrative boundaries or 'dongs' (in local terms). We collected and preprocessed hourly datasets between January 2019 to October 2020 for this study. To run our spatiotemporal analysis, Python, ArcMap 10.8, Stata 11, and Tableau Desktop programs were used. Major urban big datasets were preprocessed using following steps. First, all the transit stations' geographic information is obtained from the Seoul Metropolitan government. The metro, bus, and public shared bike stations were imported to ArcGIS and grouped by their corresponding administrative boundary or 'dongs' for analysis. Also, human dynamics from telecommunication datasets were rearranged to an hourly basis for each of the administrative boundary units. Second, since the transit usage data is assigned with the unique station ID code, we could pre-process and merge it with its corresponding administrative unit by using its ID code. The bigdata sets used in this study were imported into Python and using the Pandas and NumPy packages, and we merged the administrative boundary information obtained from ArcGIS into the transit usage data. Third, metro, bus, and public shared bike ridership were reorganized in Python, and 22 months of bigdata were accumulated hourly per administrative boundary.

5. Results

5.1. Descriptive statistics

5.1.1. Human dynamics & transit service usage in Seoul

The resulting descriptive statistics for human dynamics in Seoul based on hourly accumulated data for the study period showed that the floating population increases during the daytime and decreases after the night rush hour period around 18 pm. For this descriptive statistical analysis, we accumulated human dynamics and transit service usages for each hour between January 2019 to October 2020 (670 days). It could be understood that people come to Seoul during the morning rush hour from adjacent areas and spend their time in the city until the evening rush hour period. Meanwhile, transportation usage of metro and bus showed different patterns compared to human dynamics. Steep increases in usage occurred between 7 am to 8 am and 5 pm to 6 pm, and big drops in usage took place between 8 am to 9 am and 6 pm to 7 pm. The total bus ridership during morning peak hours and evening peak hours showed similar patterns, while metro use in the evening rush hour had much higher volumes than the morning rush hour. In the middle of the night between 12 am to 4 am, Seoul night bus also known as the "Owl Bus" is operated. Nine routes of nigh bus system are operated, and

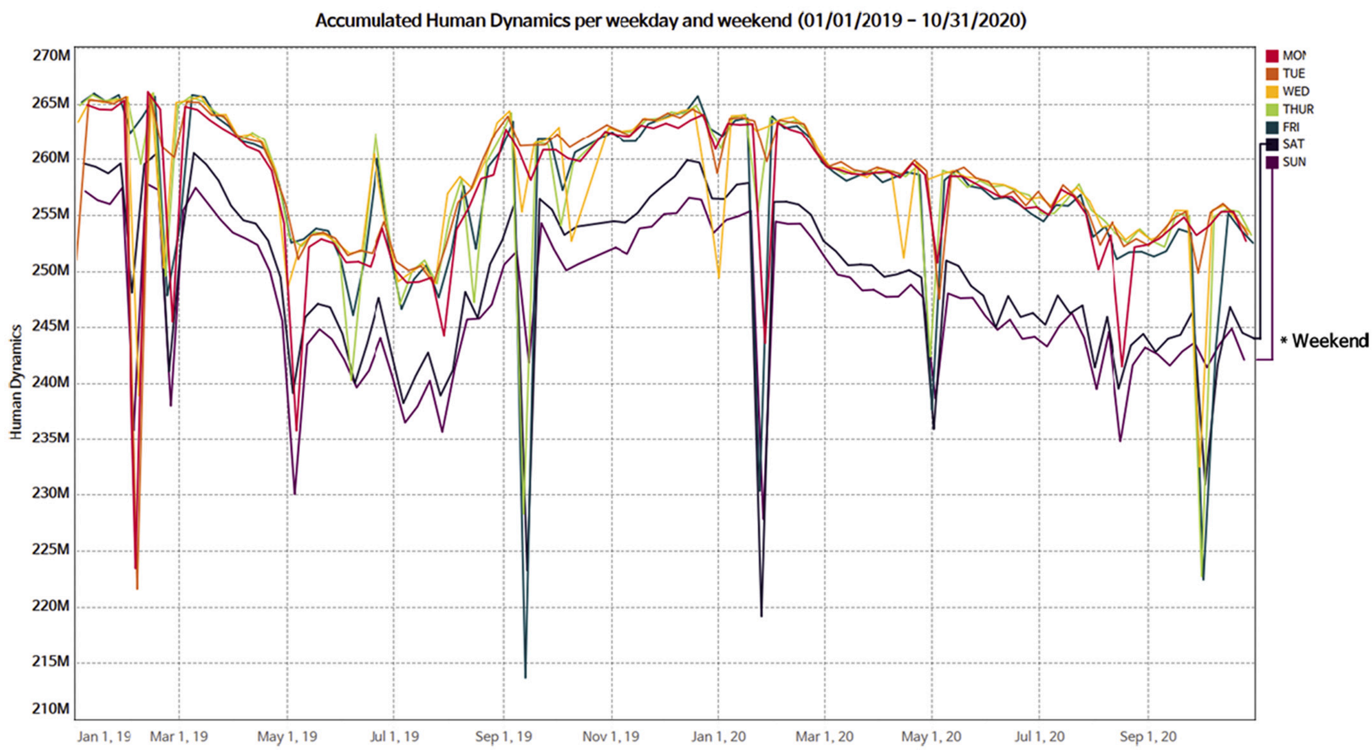

Fig. 3. Daily patterns of human dynamics in Seoul.

each bus line runs usually every 30 min. Compared to other time periods, bus and metro riderships between 12 am to 4 am are relatively low. For the study period, total number of bus ridership between 12 am to 4 am were 91,831,978, which was 2% of total bus ridership. Though the total volume of bike ridership was smaller than the use of bus and metro and hardly visible, more users were using it during night rush hour than the morning rush hour. In addition, 9% of bike users used public bikes in the middle of the night between 12 am to 4 am as an alternative transit service in addition to the night owl bus service to move around during this time (Fig. 2).

Human dynamics data of Seoul were also analyzed to reveal daily patterns, and the results show that higher volumes of human dynamics exist during weekdays compared to the weekend (Saturday and Sunday). The cumulative gap in human dynamics between weekday and weekend volumes ranges between five to ten million. For national holidays such as Thanksgiving in September and Lunar New Year in January, most people in Seoul leave Seoul to visit their hometown. Therefore, a sudden, large drop in human dynamics volume is identified during these holiday periods, and the annual patterns of human dynamics are shown to be similar between January 2019 and October 2020 (Fig. 3). The descriptive statistics show that the human dynamics volume decreased in 2020 compared to the numbers in 2019. This may be due to the impact of the COVID-19 pandemic. The first positive confirmed COVID-19 cases in Seoul were reported on January 19, 2020 (Ministry of Health and Welfare, 2021). As the number of confirmed COVID-19 cases increased and national social distancing measures were implemented, in-person gatherings reduced and policies for working or studying remotely were enforced to reduce transmission of the virus and to decelerate the progression of the pandemic.

5.2. *Transit desert & transit oasis analysis for off-peak and peak hours*

Transit gaps for peak and off-peak hours were analyzed and the spatial changes in temporal transit desert areas were identified. Dividing the total number of human dynamics by the total number of hours of the study period showed that Seoul has 10,615,225 human dynamics per hour, which is higher than the registered census population: 10,010,983. For this study, we defined peak hour and off-peak hour periods by considering people's daily activities. For this analysis, peak hour time frames consisted of 3-h intervals – morning (7 to 10), lunch (12 to 15), afternoon (18 to 21), and night (21 to 24). The descriptive statistics of the variables used to estimate transit gaps in Seoul showed that there were more human dynamics during peak hour periods compared to the volumes in off-peak hours. People use more public bikes, buses, and metro during peak hours. During peak hours, public bus ridership was almost two times higher than off-peak hours. Moreover, there were over 2.5 times more metro users during peak hours than off-peak hours.

Table 3
Descriptive statistics of the variables in off-peak and peak hours.

Criteria	Off-Peak	Peak
Human Dynamics for the Study Period (22 months/ 670 days)	84,890,075,688	85,802,758,326
Transit Dependent Census Population	5,248,236	5,248,236
Public Bike Ridership for the Study Period	10,085,336	17,694,148
Bus Ridership for the Study Period	1,959,982,667	3,906,796,093
Metro Ridership for the Study Period	1,782,582,123	4,653,191,047
Number of Bus Station	11,269	11,269
Number of Metro Station	298	298
Number of Public Bike Station	2079	2079
Number of Parking lot	315,108	315,108
Area of Parking Lot (km^2)	4.2	4.2
Length of Driver Route (km)	1458.6	1458.6
Length of Bike Route (km)	687.6	687.6
Number of Bike Route	775	775
Number of Taxi	121,425	121,425
Number of City Bus	7636	7636

The transit service usages shown in Table 3 are cumulative values for the study period, 22 months. To analyze daily patterns and the differences between peak and off-peak hours, the cumulative values were divided by the total numbers of days in the study period, 670 days. From this calculation, we found that there were on average 5,831,038 daily bus passengers and 6,945,061 daily metro passengers during peak hours,

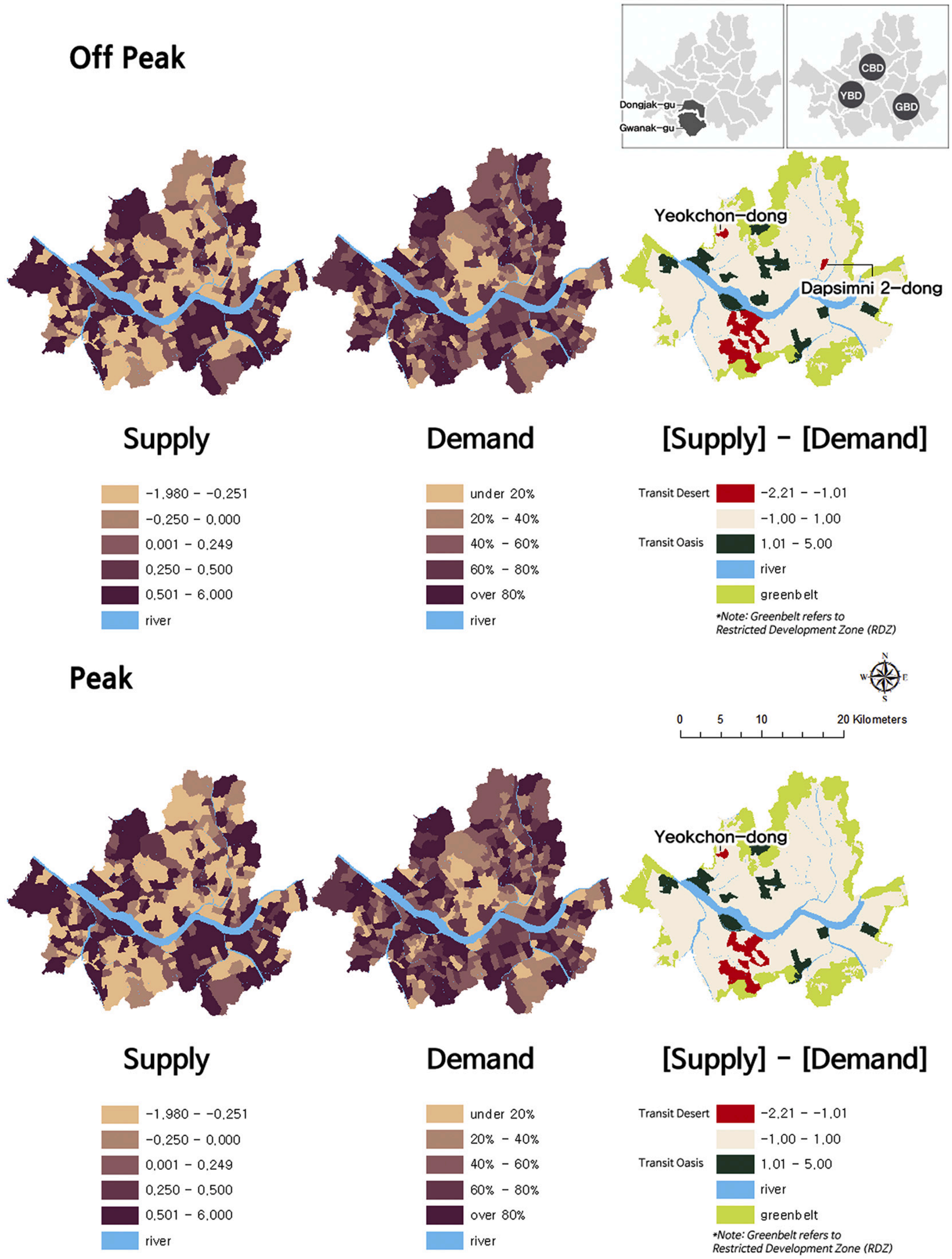

Fig. 4. Transit gap in off-peak and peak hours.

and an average of 2,925,347 daily bus riders and 2,660,570 daily metro riders during off-peak hours. When we divided these volumes by 12 h to evaluate hourly usage for peak and off-peak periods, we found an average of 1,064,675 transit users used bus and metro during one-hour peak periods, while an average of 465,493 people used bus and metro during a one-hour off-peak periods. The results indicate that there were over two times more transportation services used during peak hour periods compared to off-peak hours. Additionally, on a daily average, there are 26,409 public bike riders during peak hours and 15,053 riders during off-peak hours (Table 3).

Transit supply and demand variables for each of the 424 administrative boundaries ("dong" in local terms) were measured and the spatiotemporal patterns of transit gaps in Seoul were evaluated. Fig. 4 shows the spatial distribution of transit supply, demand, and gaps for each 'dong' in Seoul. Greenbelt as one of policies for restricting urban land development is overlaid to the results of transit gap analysis for better understanding the urban development pattern in Seoul (Jeon, 2019). These results show that different dongs were identified as transit deserts and transit oases over time, and there were different spatial patterns between peak and off-peak time frames. The descriptive statistics, explained above, indicate that, overall, the amount of transit ridership is smaller during off-peak hours, yet some dongs still have high transit demand and were identified as transit deserts during off-peak hours. This spatiotemporal analysis showed that during both peak and

Table 4
Characteristics of peak hour in four periods.

Criteria	Morning (7–10)	Lunch (12–15)	Afternoon (18–21)	Night (21–24)
Human Dynamics	21,325,894,834	21,864,350,024	21,547,149,947	21,065,363,521
Transit Demand Population	5,248,236	5,248,236	5,248,236	5,248,236
Public Bike Ridership	3,469,725	3,560,787	6,487,310	4,176,326
Bus Passengers	1,191,364,077	880,327,342	1,160,160,498	674,944,176
Metro Passengers	1,315,309,348	833,491,360	1,903,300,105	601,090,234
Bus Station	11,269	11,269	11,269	11,269
Metro Station	298	298	298	298
Public Bike Station	2079	2079	2079	2079
Number of Parking lot	315,108	315,108	315,108	315,108
Area of Parking lot (km^2)	4.2	4.2	4.2	4.2
Length of driver route (km)	1457.6	1457.6	1457.6	1457.6
Length of bike route (km)	686.6	686.6	686.6	686.6
Number of Bike Route	775	775	775	775
Number of Taxi	121,425	121,425	121,425	121,425
Number of City Bus	7636	7636	7636	7636

off-peak hours, the south-western part of Seoul (Donjak-gu and Gwanak-gu) had a cluster of transit desert areas and was simultaneously evaluated to be the most vulnerable area with insufficient transit services for residents. Some of three main business districts in Seoul – Central business area (CBD), Yeouido business district (YBD), and Gangnam business area (GBD) were identified as transit oases during both peak and off-peak hours.

For this study, we defined peak hour and off-peak hour periods by considering people's daily activities. The time frames for peak hours consist of 3-h intervals – morning (7 to 10), lunch (12 to 15), afternoon (18 to 21), and night (21 to 24). Spatiotemporal analysis of peak hour time frames, considering the different patterns of human dynamics, bike, bus, and metro usage, were conducted. Table 4 shows the characteristics of transit demand and supply variables for each of the four peak-hour time frames. Human dynamics gradually increased and hit their peak during the lunch peak hour period, with the cumulative sum of human dynamics reaching 21,864,350,024 during this period. However, as people head out of Seoul to their homes, the human dynamics decreased to 21,547,149,947 in the afternoon peak period and again to 21,065,363,521 during the night peak hours. On the contrary, transit ridership of bus, metro, and public bike showed quite different trends. During morning and afternoon peak hours, there were more users of these modes than in any of the other peak hour periods. Nevertheless, people used public bikes more during the afternoon peak hours, and they rode the bikes less in the morning peak hours. Depending on when, how, and why people use transit services, there are different impacts on the characteristics of transit services for each the four peak hour time frames.

Figs. 5 and 6 show the spatial distribution of transit supply, demand, and gaps during morning, lunch, afternoon, and night peak hour periods. Again, a cluster of transit desert areas was identified in the south-western region of Seoul (Dongjak-gu & Gwanak-gu). Additional administrative dongs were identified as transit deserts as well, which were located to the north of the Han river – Yeokchon-dong, Songcheon-dong, and Dapsimni 2-dong – during the afternoon and night peak hours. This analysis shows that there are different changes in transit desert and oasis areas depending on specific peak hours. The highest number of transit oasis areas was identified during the night peak hour period. Similar to previous analyses, some of three main business districts in Seoul were identified as transit oases during the peak hour time frames.

5.3. *Transit desert & transit oasis only for peak hour periods*

To find which transit desert and transit oasis areas in Seoul emerge during peak hours only, combined peak hour period transit deserts and oases were overlaid onto peak hour transit deserts and oases, and off-peak hour transit deserts and oases were erased. We could then spatially identify where transit desert and transit oasis areas in Seoul emerge for peak-hour periods only. Fig. 7 shows the transit deserts and transit oasis identified only during the peak hours of the four time periods. The results show that there are more transit oases than transit deserts during peak hours in Seoul. Looking more in detail, three transit desert and six transit oasis areas remained apparent during peak hours only. The three transit deserts are Sillim-dong in Gwanak-gu and Sangdo 2-dong in Dongjak-gu, and Songcheon-dong in northern part of Seoul. The transit oases are Gasan-dong, Ogeum-dong, Jangji-dong, Jamsil 6-dong, Yeoksam 1-dong in the southern part of Seoul, and Myeong-dong in the northern part of Seoul.

5.4. *T-test to identify the significant socio-economic factors of transit desert and oasis*

Previous spatiotemporal analyses of transit deserts and transit oases show that there are different patterns in Seoul. Though transit gaps are analyzed considering transit demand and supply variables, the socio-economic characteristics of these areas could have impacts on these spatiotemporal patterns. To identify how the socio-economic characteristics of these transit desert and transit oasis areas are statistically different in Seoul and to show the spatial differences of these environments, an independent T-test was conducted. In addition to the socio-economic characteristics, transit-relevant variables for peak and off-peak period were examined to find statistical differences between temporal transit desert and oasis area. This will be helpful to understand the temporal differences of physical transportation infrastructure *between transit desert and oasis areas*. Transit desert and transit oasis areas that were identified during off-peak hours, peak hours, or peak-hours only were considered for the independent t-test.

In total we used 46 areas in this test, consisting of 23 transit desert and 23 transit oasis areas. Table 5 explains the socio-economic variables and transportation factors analyzed in the t-test. Transportation factors included human dynamics, metro users, bus users, and bike ridership during off-peak and peak hours. For socio-economic factors, we considered variables from spatial big datasets – average apartment transaction price, total number of transactions, the number of basic livelihood security recipients as measurements of vulnerable/low-income population, the number of senior residents older than age 64, and the number of residents with disabilities in each administrative boundary.

Table 6 shows the descriptive statistics of the variables used in the T-test. The apartment transaction records show that there were more transaction records with higher average transaction prices in transit oases than in transit deserts. Transit oases had a mean of 190 transaction records with an average transaction price of 99 billion Won (89 million USD). Meanwhile, transit deserts had a mean of 206 transaction records with an average transaction price of 61,545 million won. Surprisingly, there were more low-income residents receiving stipends in transit

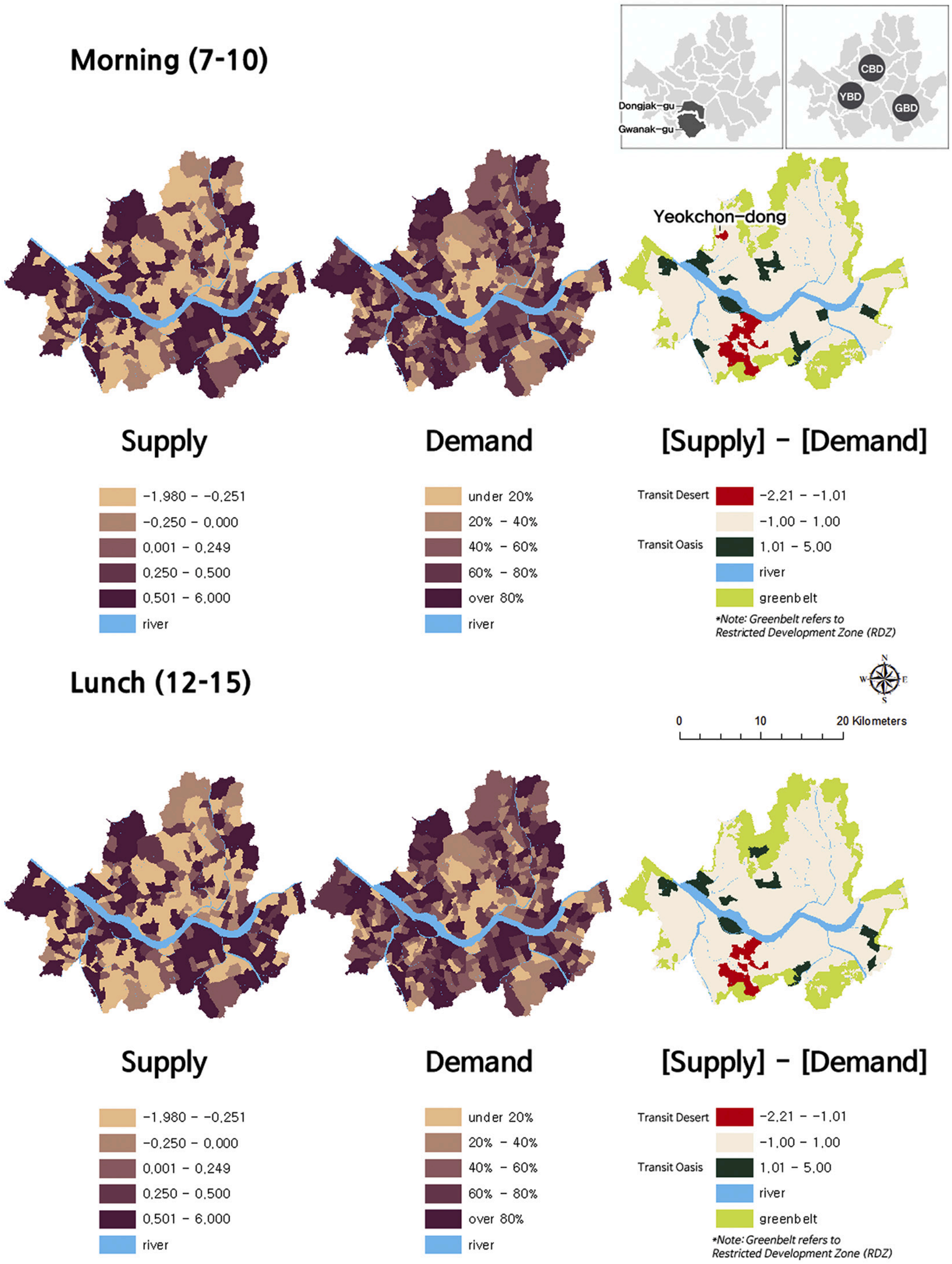

Fig. 5. Transit gap during morning and lunch peak hours.

deserts than in transit oases. The average number of residents receiving stipends in transit deserts was more than two times higher than the number of those receiving stipends in transit oases. Similarly, the average number of residents with disabilities were both high in transit deserts than in transit oases. However, transit oases have greater average number of senior residents older than age 64 compared to transit desert. Additionally, transit oases had better transit infrastructure with higher number of bus, metro, and public bike stations. Regardless of time frame, human dynamics, bus, metro, and bike ridership had higher values in transit oasis areas than transit desert areas.

Table 7 shows the results of our independent T-test. This test between transit oasis and transit desert areas shows that there were statistically significant differences in average apartment transaction price ($p < 0.05$), the number of residents receiving voucher, seniors, and residents with disabilities ($p < 0.001$). Also, the number of transit stations including bus, metro, and bike ($p < 0.001$), off-peak hour human dynamics ($p < 0.05$), bike ridership and bus users ($p < 0.05$), metro users ($p < 0.001$), peak hour human dynamics ($p < 0.05$), bike ridership and bus users ($p < 0.05$), and metro users ($p < 0.001$) are statistically significant between transit oasis and transit desert areas. The results of this T-test explain that the differences in average value for these indicators between transit desert and transit oasis areas were statistically significant.

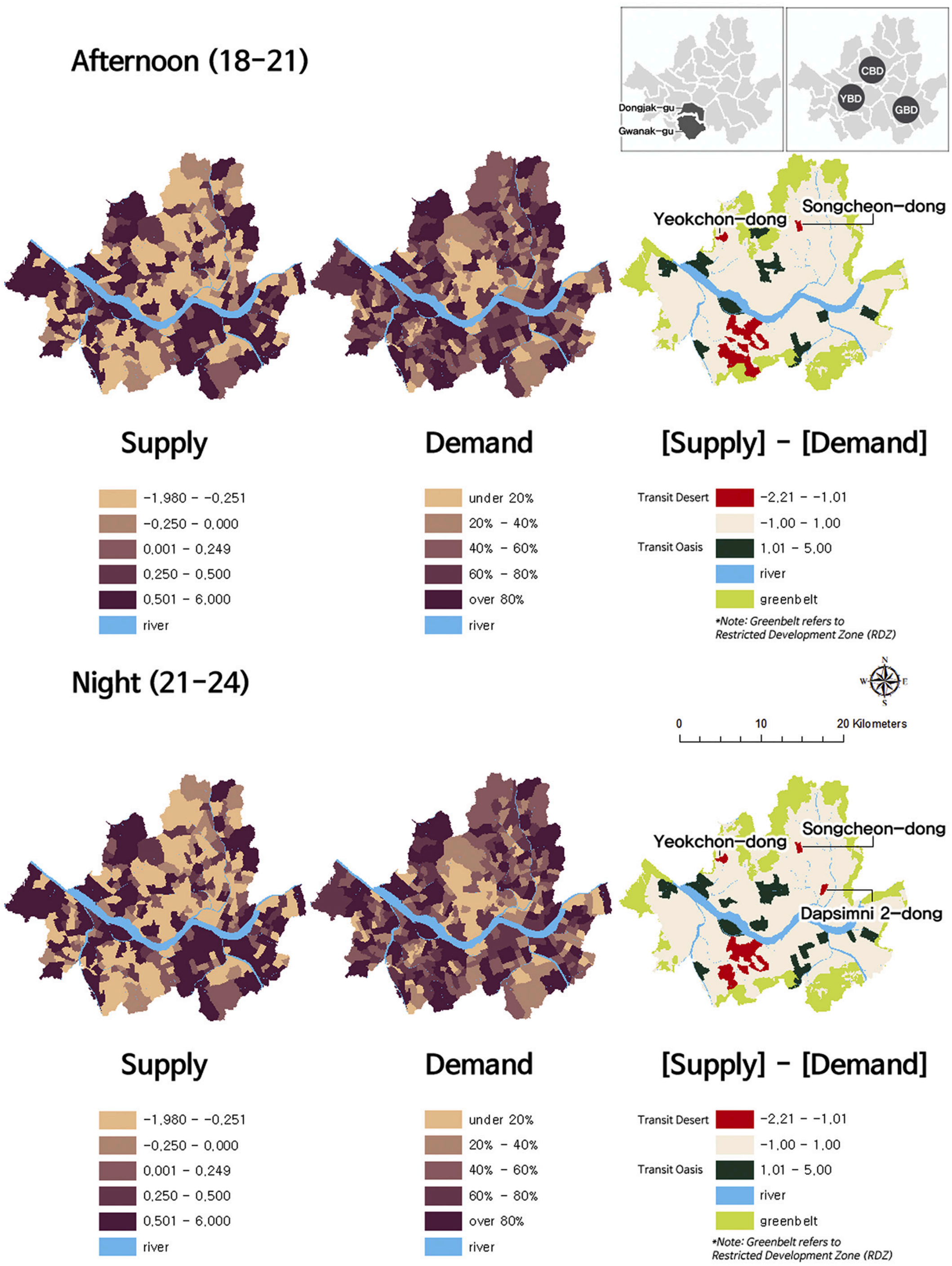

Fig. 6. Transit gap during afternoon and night peak hours.

6. Discussion

"Transit deserts" are areas where transit demand is greater than the supply. In the opposite case, the areas where transit supply is greater than the demand are defined as "transit oases". As cities continue to grow rapidly, some areas develop spatial imbalances between supply and demand of transit services. These spatial disparities in transit services can exacerbate socio-economic inequity issues in cities, and the gap between transit desert and transit oasis area will worsen without appropriate analyses and planning strategies. Therefore, it is important to identify where transit desert or transit oasis areas are in rapidly growing cities such as Seoul, South Korea in order to implement sustainable and balanced transit services for people. As transit demand and supply changes across locations and times, spatiotemporal analysis will help evaluate the different patterns of transit desert and oasis areas across time periods and places.

Three stages of spatiotemporal analysis for transit gaps were conducted in this study. First, the transit gaps between peak and off-peak hours were evaluated and the spatial changes of transit desert areas over time were identified. Second, spatial analysis to identify transit desert and transit oasis areas which emerge during peak hours only was conducted. Third, this study ran an independent T-test to identify whether the socio-economic characteristics of transit deserts and transit oases were statistically different in Seoul and how these socio-economic

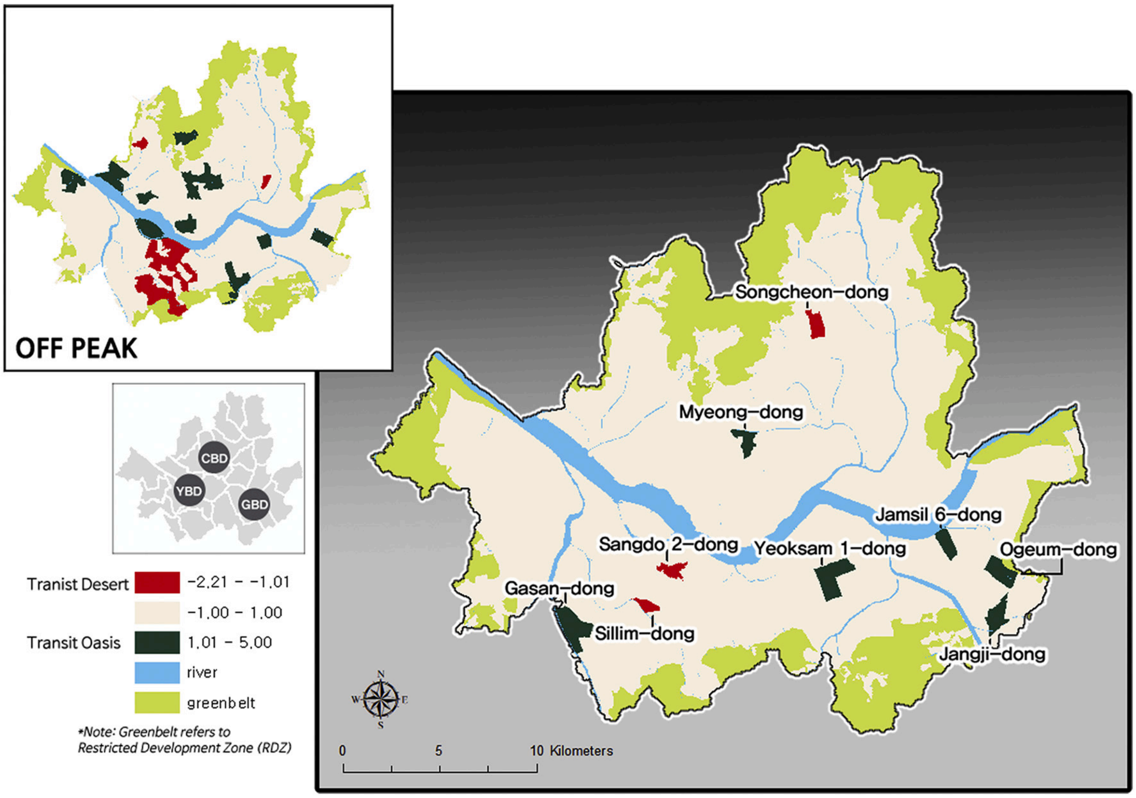

Fig. 7. Transit desert and oasis only apparent in peak hours.

Table 5
Independent *T*-Test variables.

Variables			Unit	Source
Socio-economic Factors	Housing	Average apartment transaction price	One million Won (in $1000)	Ministry of Land, Infrastructure, and Transport Korea (2019–20)
		Number of apartment transaction	count	
	Low income	Number of residents receiving government voucher	count	The Seoul Metropolitan Government (2019–20)
	Senior	Number of residents older than age 64	count	
	Disabilities	Number of residents with disabilities	count	
Transportation factors	Infrastructure	Number of stations (Bike + Bus + Metro)	count	
	Off-Peak	Human Dynamics	count	
		Metro users	count	
		Bus users	count	
		Bike ridership	count	
	Peak	Human Dynamics	count	
		Metro users	count	
		Bus users	count	
		Bike ridership	count	

differences result in spatial differences. Also, transit-relevant factors for peak and off-peak period were examined to find statistical differences between temporal transit desert and oasis area. The key findings of this study are as follows: First, there are more daytime than nighttime human dynamics in Seoul, and human dynamics are more active during weekdays than on weekends. Second, some of the areas in Seoul identified as transit deserts and oases were found to have different patterns of transit gaps across time periods and locations. Third, transit deserts usually form a cluster in the south-western part of Seoul, while transit oases clustered around the major business districts in Seoul. Fourth, the results of the independent T-test show significant differences between transit desert and oasis areas in terms of housing price, the number of marginalized groups, transportation infrastructure, human dynamics, and transit service usages. These findings explain that transit desert and oasis areas change spatially and temporally in Seoul. Therefore, more careful consideration of these spatial and temporal changes is necessary to ensure that sustainable plans to solve transit gap issues are implemented in cities.

7. Conclusion

This paper contributes to the existing literature in several ways. It identified not only how transit desert areas spatially distributed within the study area, but also how these transit desert areas changed over time. Second, this study utilized real-time spatial big data to collect telecommunication floating population, metro, bus, and micro mobility ridership to consider different demand patterns across time in Seoul. We measured how transit deserts vary between peak and off-peak hours and considered mobile-based floating population to find transit demand and transit gaps more accurately in cities. Third, the socio-economic characteristics and physical public transportation factors of transit desert and oasis areas were evaluated to explain the spatial differences between these environments. Finally, this study analyzed transit gaps in Seoul, South Korea, which is one of the major Asian cities with dense

Table 6
Descriptive statistics of the variables used in T-Test.

Category	Type	Mean	Max	Min	Median
Average APT transaction price	Oasis	99,014	236,100	20,610	86,695
	Desert	61,545	117,372	22,882	55,354
Number of APT transactions	Oasis	190	468	7	130
	Desert	206	512	22	173
Number of residents receiving vouchers	Oasis	503	2135	12	291
	Desert	1141	2206	518	1038
Number of residents older than age 64	Oasis	6895	8267	1934	4945
	Desert	2877	6813	300	2741
Number of residents with disabilities	Oasis	611	1965	32	489
	Desert	1217	2169	560	1155
Number of stations (Bike + Bus + Metro)	Oasis	62	130	21	49
	Desert	35	64	10	33
Off peak: Human Dynamics	Oasis	317,127,496	795,087,995	125,050,716	291,290,220
	Desert	228,546,014	385,527,706	138,665,494	210,935,829
Off peak: Metro users	Oasis	23,132,843	85,890,864	0	15,558,516
	Desert	3,174,137	18,667,724	0	0
Off peak: Bus users	Oasis	10,327,264	27,942,087	2,071,577	9,072,425
	Desert	6,082,268	11,991,915	1,269,811	5,490,804
Off Peak: Bike ridership	Oasis	72,979	358,427	1226	54,300
	Desert	30,114	117,565	0	19,302
Peak: Human Dynamics	Oasis	361,062,594	912,554,205	147,421,800	304,357,888
	Desert	220,800,168	364,450,502	123,734,282	200,559,651
Peak: Metro users	Oasis	59,394,388	220,818,035	0	40,633,424
	Desert	8,428,971	47,038,376	0	0
Peak: Bus users	Oasis	20,692,731	49,800,545	3,250,445	20,890,895
	Desert	12,575,639	26,694,366	2,580,318	10,908,609
Peak: Bike ridership	Oasis	124,301	561,382	1449	96,515
	Desert	30,114	117,565	0	19,302

Table 7
Independent T-Test result.

Category	Type	Mean	Standard deviation	t	p
Average APT transaction price	Oasis	99,014	52,253	3.172	**0.003**[**]
	Desert	61,545	21,889		
Number of APT transactions	Oasis	190	152	0.335	0.739
	Desert	206	165		
Number of residents receiving voucher	Oasis	503	552	−4.392	**0.000**[***]
	Desert	1141	424		
Number of residents older than age 64	Oasis	6895	1749	−4.386	**0.000**[***]
	Desert	2877	1343		
Number of residents with disabilities	Oasis	611	486	−4.748	**0.000**[***]
	Desert	1217	372		
Number of stations (Bike + Bus + Metro)	Oasis	62	31	3.791	**0.000**[***]
	Desert	35	16		
Off peak: Human Dynamics	Oasis	317,127,496	168,199,521	2.336	**0.026**[**]
	Desert	228,546,014	69,121,600		
Off peak: Metro users	Oasis	23,132,843	20,092,576	4.711	**0.000**[***]
	Desert	3,174,137	5,213,759		
Off peak: Bus users	Oasis	10,327,264	6,686,608	2.775	**0.009**[**]
	Desert	6,082,268	3,017,755		
Off Peak: Bike ridership	Oasis	72,979	73,844	3.544	**0.001**[**]
	Desert	30,114	16,652		
Peak: Human Dynamics	Oasis	361,062,594	199,079,663	3.181	**0.003**[**]
	Desert	220,800,168	71,185,363		
Peak: Metro users	Oasis	59,394,388	49,952,574	4.712	**0.000**[***]
	Desert	8,428,971	13,985,837		
Peak: Bus users	Oasis	20,692,731	13,200,106	2.656	**0.012**[**]
	Desert	12,575,639	6,360,438		
Peak: Bike ridership	Oasis	124,301	119,490	3.660	**0.001**[**]
	Desert	30,114	30,770		

P-values marked with bold indicate statistically significant p-values. ***, ** indicate significance at the 1% and 5% level, respectively.

urban development and transportation infrastructure. The results of this study can be used as a reference for crafting policy suggestions that deal with the imbalance between transit demand and supply, and for implementing sustainable and balanced transit service strategies in cities.

This study highlights possible transportation inequities in cities by utilizing real-time big data. As the difference between average housing prices and the number of marginalized groups like low-income households, seniors, and people with disabilities in transit desert and oasis areas proved to be statistically significant, this presents the possibility that more low-income residents live in transit desert areas with substandard housing conditions, and that transit deserts in general appear to be associated with socio-economically vulnerable residential areas. These findings are in line with Jiao and Dillivan's (2013) argument that those who experience inadequate transit services may be those most marginalized in society. To improve living conditions in transit deserts, the implementation of more shared mobility services could play a role. For example, in New York City shared mobility services are planned with the intention to improve transportation conditions for physically challenged and low-income populations (Jiao and Wang, 2021). Then, identifying the authentic needs of the population living in transit desert is in need. Perhaps, a participatory mechanism based on crowdsourcing can provide promising insights (Griffin and Jiao, 2019) because the voluntary expression of real users is expressed, for installation of transportation.

However, this study has several limitations. First, the present study used spatially and temporally aggregated data, which may link to methodological limitation. For example, ridership datasets for discrete geographic data was aggregated into administrative boundaries and hourly datasets was also aggregated into each day. This adjustments to the datasets may involve the Modifiable Area Unit Problem (MAUP) or the Modifiable Time Unit Problem (MTUP) (Cheng and Adepeju, 2014) in the results. If possible, using other additional factors with individual location information that may have impacts on transit gaps should be more accurate for future studies. Second, as this study focused on Seoul as the study area, many important transit desert issues such as 15.9% out of total transit ridership to Seoul were overlooked. To analyze the transit demand from the adjacent areas, this study utilized mobile-based floating population to measure people into Seoul. However, for better understanding inter-region transit demand issues, further strategies should be followed. Third, this study analyzed transit desert and oasis areas based on standardized *Z*-score of transit demand and supply. However, it did not fully consider spatial mismatch issues between jobs and housing locations of each people. Therefore, further studies to find whether transit systems fulfill desired destinations, to consider spatial mismatch for transit desert analysis, and spatial imbalance issues of inter-region should be followed. Fourth, since the independent T-test only shows significant differences between transit desert and transit oasis areas, additional statistical analysis should be conducted to find what factors have strong relationships with transit deserts and transit oases in cities in general. Also, other socio-economic factors should be examined further to address the important issues in transit desert. Fifth, the use of a geographical unit (e.g. dong) to confine transit accessibility is inevitable due to the nature of our proposed transit gap methodology, which can limit the results. To address this limitation, as a future direction, it is recommended to use a utility-based measure to capture passengers' perceptions of impedance when travelling by transit systems. Finally, since the human dynamics data used in this study are based on KT Corporation service signals, analyses that use other telecommunication records may result in a different outcome. Future studies should consider these limitations by embracing more indicators and collecting more real-time spatial bigdata for transit gap research.

Declaration of competing interest

The authors confirmed there is no conflict of interest.

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