INVESTIGATION ON VISITING PATTERN CHANGE IN COMMERCIAL AREAS DURING COVID-19: A CASE STUDY OF 21 CITIES IN JAPAN

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ABSTRACT:

During the COVID-19 pandemic, the patterns of visiting commercial areas have changed due to numerous factors, including the risk of infection and the government's state of emergency. This study investigated human mobility changes in commercial areas of 21 cities in Japan by applying time-series clustering of mobile big data during the COVID-19 pandemic. First, the analysis revealed that the human mobility changes were found to be area-specific and were classified into five patterns according to population change captured by mobile data: decreased cluster, slightly decreased cluster, no change cluster, slightly increased cluster, and increased cluster. There were some commercial areas, which were visited by more people, compared with the pre-COVID-19 period. Second, the increased clusters revealed a high proportion of commercial facilities that provide essential services. This finding suggests that the local-scale commercial areas were essential for supporting everyday life during the COVID-19 pandemic. Third, human mobility in commercial areas was temporarily altered, but ultimately returned to the pre-COVID-19 level. Overall, the proposed method and results provide basic information for resilient urban structures in Japan.

1. INTRODUCTION

The coronavirus disease 2019 (COVID-19) pandemic is a major threat to global health, which has substantially disrupted the social, economic, and healthcare systems of all countries worldwide. As COVID-19 is characterized by a long incubation period, high infectivity, and is difficult to detect, physical distancing is deemed to be the most effective measure for controlling the disease (Petersen et al., 2020). Despite the widespread use of vaccination, a reduction in human mobility is an effective measure as well. To date, numerous countries have limited travel activities by enacting lockdowns and emergency statements. Even without such limitations, people change their behavioral patterns related to the use of public transportation and visiting stores, restaurants, and public facilities to reduce the infection risk.

Commercial areas contain numerous facilities and services, which play essential roles in supporting daily life. However, these areas are characterized by the high risk of infection because many people interact in these areas. Some studies have revealed the risk of infection in commercial areas (Li et al., 2021), thereby highlighting the behavioral changes within commercial areas. For instance, Shaer et al. (2021) reported that the proportion of walking and biking for shopping increased after the COVID-19 pandemic, while good destination accessibility exhibited a positive relationship with biking and walking distance. Regarding these changes, that polycentric development is regarded as a resilient urban structure to decrease the risk of infectious disease (Malik and Zdyb, 2021).

In this context, it is essential to understand how the patterns of the commercial area are changed for comprehending the future of a city. This can facilitate the spatial control of pandemic. Some studies have already investigated how travel behaviors have been altered during the COVID-19 pandemic through various approaches, such as developing theories (van Wee and Witlox, 2021) and conducting surveys (Parady et al., 2020; Shamshiripour et al., 2020). Many previous studies have used mobile big data to capture human mobility changes during COVID-19 to investigate the changes in human mobility from a spatial perspective (Eom et al., 2021; Hu et al., 2021). However, these analyses were limited to the administrative boundary spatial scales and, therefore, cannot identify the changes at micro-level in commercial areas. Even though several studies focus on micro-level (Arimura et al., 2020; Nishihori et al., 2021; Trasberg and Cheshire, 2021), their analyses were limited to specific cities and short period.

This study investigated human mobility changes in commercial areas by applying time-series clustering with mobile big data in 21 cities in Japan to understand how the patterns of visiting commercial areas changed during the COVID-19 pandemic. Note that visiting patterns can be defined in various ways, such as frequency, destination, and transportation mode. From a methodological perspective, this study focused on the quantity of human mobility change at a destination, given the available information from the applied data. The remainder of this paper is organized as follows. Section 2 describes the study area and the data used in this study, Section 3 describes the methodology of this study, Section 4 presents the results, Section 5 contains conclusions, drawn from the results.

2. STUDY AREA AND DATA

2.1 The study area

The study area of this study included 20 ordinance-designated cities (Sapporo, Sendai, Saitama, Chiba, Yokohama, Kawasaki, Sagamihara, Niigata, Shizuoka, Hamamatsu, Nagoya, Kyoto,

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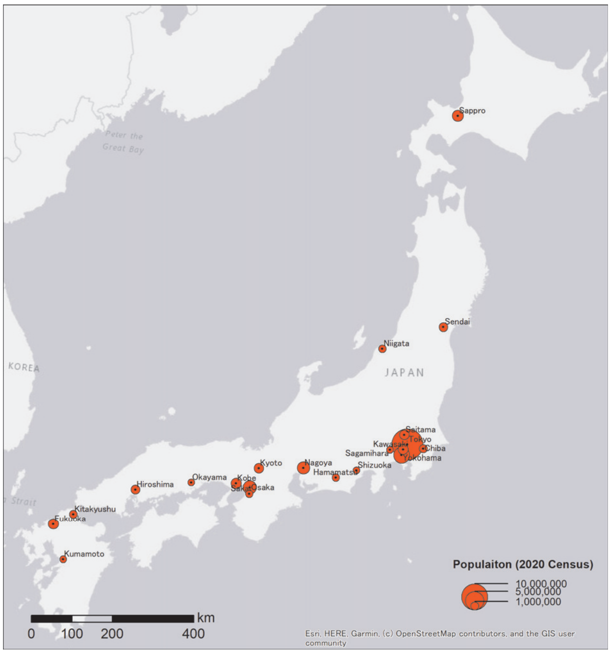


Figure 1. The study area with the location of analyzed cities

Osaka, Sakai, Kobe, Okayama, Hiroshima, Kitakyusyu, Fukuoka, and Kumamoto) and the Tokyo Metropolitan Special Ward Area. The location and the population statistics are both shown in Figure 1.

2.2 Data

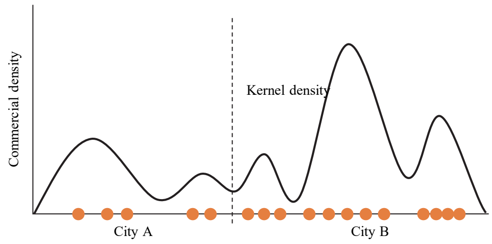
2.2.1 Human mobility data: Human mobility was determined by using mobile spatial statistics, obtained from the DOCOMO Insight Marketing, Inc. Mobile spatial statistics were built based on the population distribution with 1-h resolution. These data include information on the actual population in Japan based on the mobile terminal network operational data from NTT DOCOMO mobile phones (Terada et al., 2013). Notably, NTT DOCOMO stands out with > 82 million customers in Japan. The population in the present study was determined as the number of people estimated in a 500 m square grid cell at a specific time. However, for privacy protection, residential area information was considered at the city scales, not at the grid scales.

2.2.2 Commercial facility data: The distribution of commercial facilities was determined by using “Tele-Point-Pack!” (ZENRIN InterMap Inc., 2020). Note that “Tele-Point-Pack!” was constructed by using ~25 million items, listed in nationwide telephone directories in Japan. In addition, the postal code, industry category, address, and location (longitude and latitude); all were added.

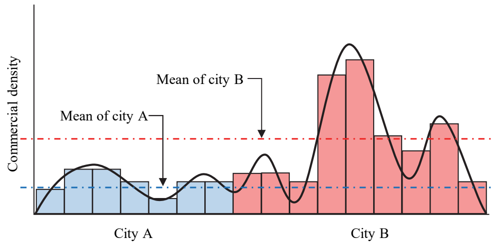
3. METHODOLOGY

3.1 Commercial area extraction

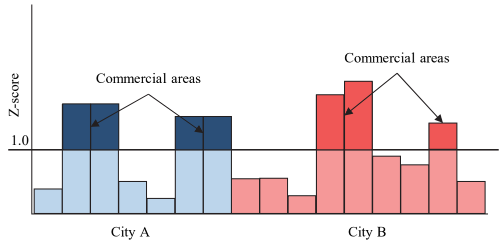
In general, the commercial area represents the geographic concentration of retail stores, restaurants, and offices. Commercial areas provide various services in urban areas, and many people visit such areas to use these services. Although the definitions of commercial areas are plentiful (Hu et al., 2019; Wang et al., 2016), we defined a commercial area as the relative geographic accumulation area of retail and firms compared to the surrounding area. This implies that both central and neighborhood-level commercial areas were included.



(a) Step 1: Kernel density estimation



(b) Step 2: Aggregation of density to grid level



(c) Step 3: Extraction of commercial area based on Z-score

Figure 2. Process for extracting a commercial area

Methodologically, we selected ~340 categories to extract the commercial area based on a previous study from commercial facility data (Akiyama et al., 2011). The selected data include the categories, closely related to daily commercial activities such as grocery stores, clothing stores, household and general shops, hair salons, drug stores, restaurants, sporting-goods stores, amusement facilities, medical clinics, real estate offices, banks, and residential accommodations.

The selected facility data were applied for the process of extraction., which was divided into three steps (see Figure 2).

1) Kernel density estimation based on the point data
2) Aggregation of density to grid level
3) Calculation of relative accumulation degree and extraction of commercial area

First, the kernel density was constructed by using the ArcGIS 10.1 software tool. The bandwidth was set to 500 m as the walking distance, and the grid cell size was set to 100 m. Second, the calculated density values were aggregated to the grid level (500 m × 500 m) by using the mean density of each grid. The city-level means and the corresponding standard deviations were also calculated. Third, the Z-score of the commercial density of each grid was derived based on the district-level average estimate and standard deviation to consider the scale differences. The grids with Z-scores of > 1.0 were subsequently classified as commercial areas.

3.2 Human mobility change pattern

To identify the change in human mobility of the extracted commercial area, we used the population data from mobile spatial statistics (mobile population). The seven-day simple moving averages were subsequently calculated to diminish the outlier effects. At the next step, the change rate of the mobile population of grid i and day k (r_{ik}) was calculated by comparing the moving average of grid i and day k (p_{ik}) to the same day one year earlier as $p_{ik}/p_{i(k-364)}$. To further elucidate the difference in time, we applied three different time slots: 10:00, 15:00, and 20:00 (Japan Standard Time), related to work, daily shopping, and evening activities such as restaurants and pubs.

Time-series clustering is a technique for grouping a time-series set into multiple subsets (clusters) according to their similarity. Each time series with multiple data points can be considered a single object. Clustering of such complex objects can help in identifying the valuable patterns in time-series (Aghabozorgi et al., 2015). Thus, we applied the time-series clustering to identify the differences in human mobility changes in commercial areas. Further, we applied Euclidean distance to quantify the similarity among the time-series datasets. Note that the clustering was performed by using the k-means method in the Tslearn Python software package (Tavenard et al., 2020).

4. RESULTS

4.1 Commercial area distribution

The grid of the commercial area contained 2,416 cells, thereby accounting for 8.2% of the total grid. Figure 3 shows the number of commercial grid cells areas in each city. The proportions of commercial areas varied between 5.2% (Shizuoka) and 14.4% (Osaka).

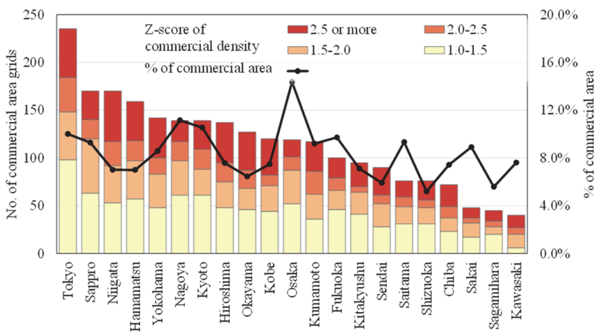


Figure 3. Number of commercial area grids

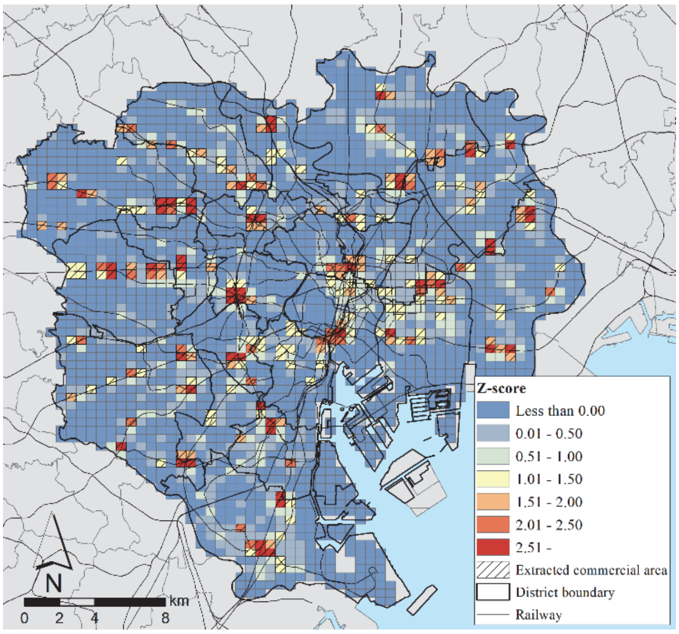


Figure 4. An example of the extracted commercial areas in Tokyo

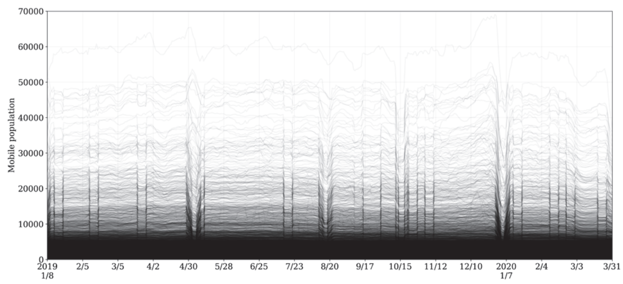
Figure 4 shows the results for Tokyo. As seen, the CBDs (central business districts) of Tokyo (such as Tokyo station, Shinjuku, and Shibuya) and the neighborhood-level commercial areas of each district were extracted. Note that the Z-score of each grid is a relative value within a district.

4.2 Human mobility change

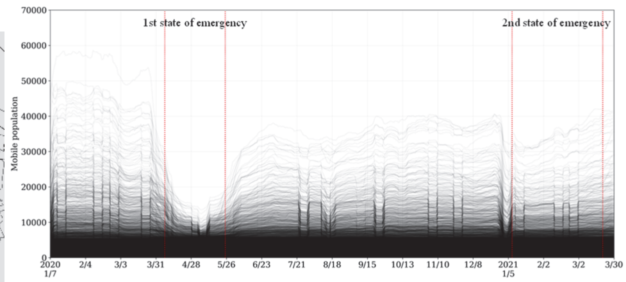
The Japanese national government had declared a state of emergency twice during the study period. Figure 5 shows the moving average and the change rate for each day, where the period of the emergency state was based on the Tokyo area. The analysis of the 1st state of emergency period (from April 7, 2020, to May 25, 2021) revealed a substantial weakening of human mobility in the grids with a large mobile population, which recovered after the release of the declaration. Furthermore, the impact of the 2nd state of emergency (from January 8, 2021, to March 21, 2021) was not noticeable. The human mobility change rate indicates that commercial areas experienced a decrease in mobile population during the state of emergency.

4.3 Classification of human mobility change pattern

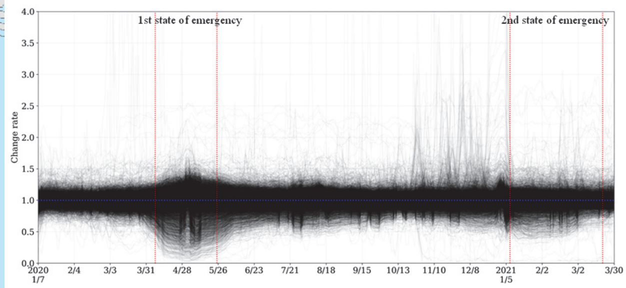
The difference in human mobility changes at the grid-scale is illustrated in Figure 6. The change rates of the three time slots (10:00, 15:00, and 20:00) were simultaneously classified to elucidate the differences according to the grid and time slot. As a result, five different patterns were identified: decreased cluster (C1), slightly decreased cluster (C2), no change cluster (C3),



(a) Trend of moving average (2019.1.7~2021.3.30)



(b) Trend of moving average (2020.1.8~2021.3.31)



(c) Change rate for time-series clustering

Figure 5. Mobile population change rate

slightly increased cluster (C4), and increased cluster (C5). We repeated the clustering with different numbers of clusters, whereas the number of clusters was determined based on the uniqueness of the features of each cluster.

C1 and C2 exhibited a decreased mobile population during the first state of emergency and recovery. Also, they exhibited a decrease during the second state of emergency but rebounded in early March before the release. Note that the emergency statement was released at the end of March in metropolitan areas such as Tokyo, Kanagawa, Saitama, and Chiba, but in early March in non-metropolitan areas.

It was also found that C4 and C5 exhibited an increased mobile population during the target period. Two potential drivers behind the increased mobile population at C4 and C5 can be suggested. Potentially, numerous companies expanded telecommuting, while the more previously mobile population remained at home. Alternatively, frequent visits of neighborhood commercial facilities instead of congested areas, where many people are concentrated, such as CBDs and large-scale shopping districts, can be the driver behind the increase in the mobile population in several areas. Note that to reduce the risk of COVID-19 infection, people tend to avoid long-distance travel by using public transportation and change their destination to neighborhood commercial facilities.

As the mobile population in this study includes both people staying at home and visitors, it is necessary to exclude the people at home. This is required to identify the commercial areas, which are more intensively visited by people, compared to the pre-COVID-19 period. To this end, we quantified the gap with the mobile population at three time slots and 4:00 am during the COVID-19 period because most of the population in this time slot can be considered residents. We, therefore, assumed that grids with the positive mean values have more visitors than

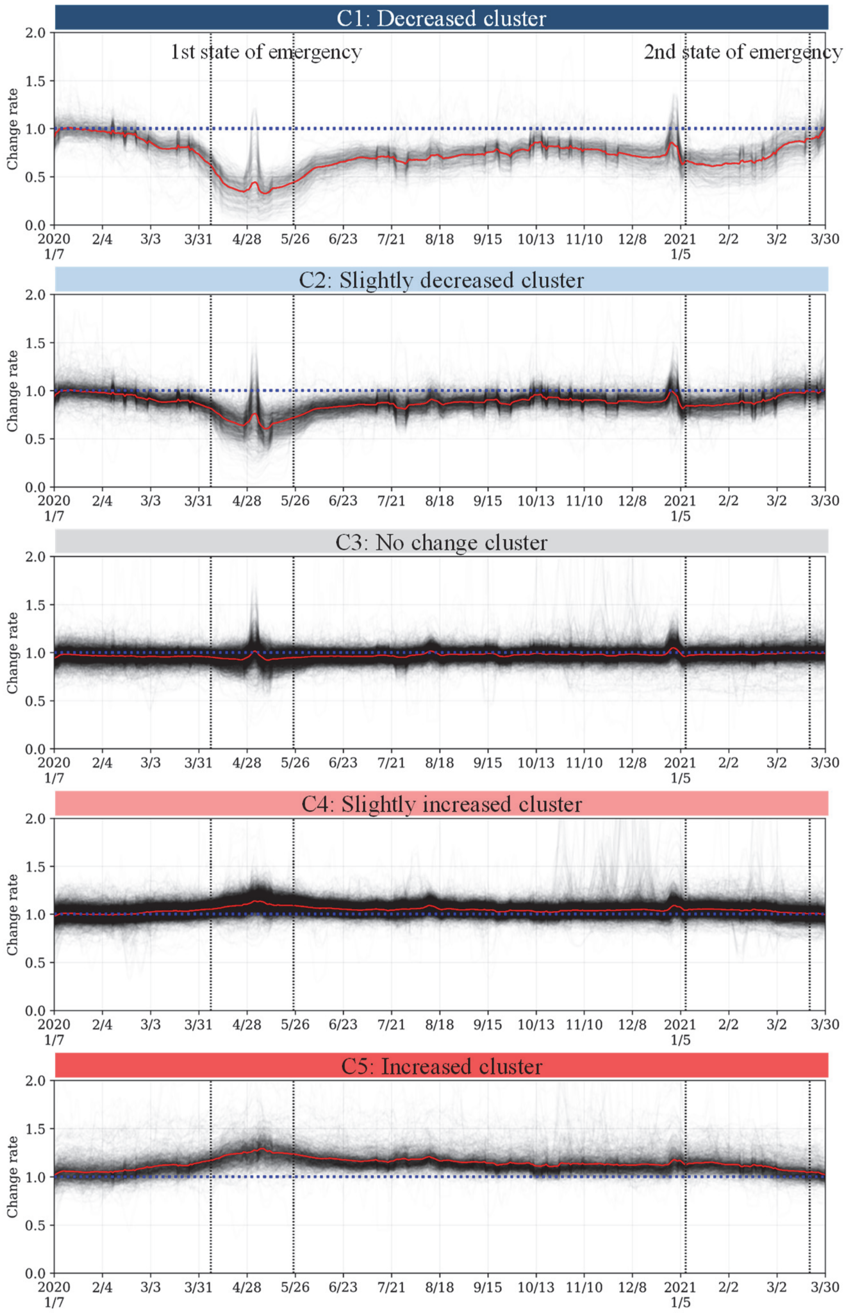


Figure 6. Human mobility change patterns in commercial areas

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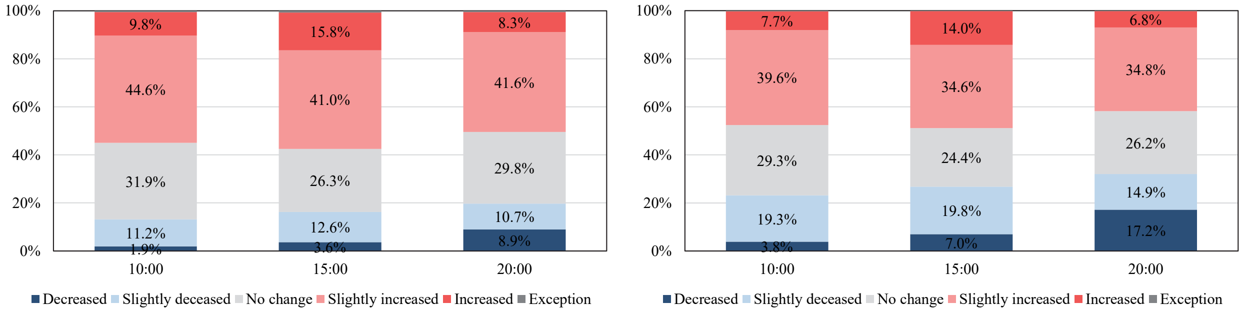


(a) All commercial area grids (b) Commercial area grids with more visitors in daytime

Figure 7. Proportion of clusters by time slots

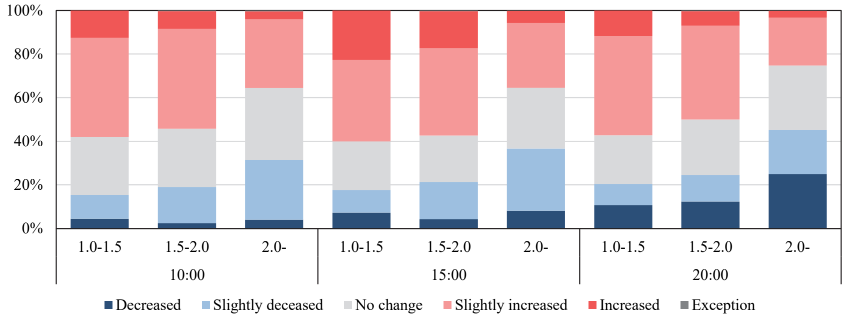


Figure 8. Proportion of clusters by time slots and commercial density level

Time slot		10:00			15:00			20:00	
Z-score	1.0-1.5	1.5-2.0	Over 2.0	1.0-1.5	1.5-2.0	Over 2.0	1.0-1.5	1.5-2.0	Over 2.0
C1: Decreased	1.18	0.61	1.08	1.05	0.61	1.18	0.62	0.72	1.45
C2: Slightly decreased	0.57	0.86	1.41	0.53	0.86	1.44	0.66	0.81	1.37
C3: No change	0.90	0.91	1.13	0.91	0.87	1.14	0.85	0.98	1.13
C4: Slightly increased	1.15	1.16	0.80	1.08	1.15	0.85	1.31	1.24	0.63
C5: Increased	1.64	1.06	0.48	1.62	1.22	0.40	1.74	0.97	0.45

Note: Values over than 1.0 are highlighted.

Table 1. Relative concentration of clusters considering commercial density level

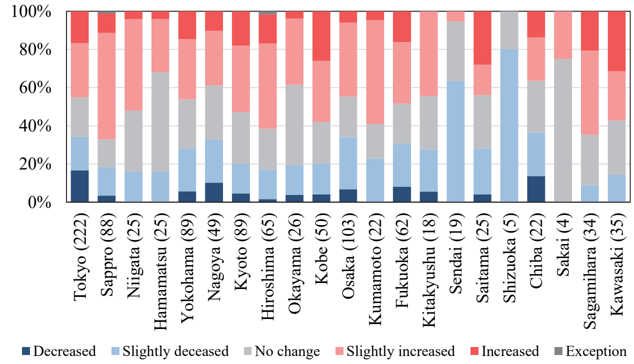
residents. About 45% of grids (1,077 grids) had more visitors than residents during the daytime (10:00 and 15:00). It should be noted that some grids with more residents than visitors may have more visitors compared with the pre-COVID-19 period. However, these areas were excluded from the further analysis because, given the data limitations, it was impossible to elucidate the drivers behind the mobile population increase.

Figure 7 illustrates the proportion of clusters according to the time slots. The analysis of the grids with more visitors than residents revealed 39.6%, 34.6% and 34.8% of grids with the increased patterns (C4 and C5) in 10:00, 15:00, and 20:00, respectively. Figure 8 shows that the proportion of the increased clusters decreased as the commercial density increased. To elucidate the relative concentration of each cluster, Table 1 shows the calculated relative concentration index based on the location quotient. In brief, it represents a ratio that compares the given range of Z-scores to the entire grid, according to each cluster. This calculated value of > 1.0 indicates that the grids with a given range of Z-scores have a higher concentration of a given cluster. According to Table 1, the increased patterns (C4 and C5) were clustered in the grids with low Z-scores, while the decreased patterns (C1 and C2) were clustered in the grids with a Z-score of > 2.0. These results suggest that more people visited commercial areas with relatively low commercial density compared to the pre-COVID-19 period. However, these changes in human mobility were somewhat temporary. All the clusters exhibited similar levels of human mobility at the end of March 2021. Potentially, the enaction of the 2nd state of emergency may have affected this change.

Time slots			No. of grids	%
10:00	15:00	20:00		
▲	▲	▲	395	36.7%
▼	▼	▼	239	22.2%
-	-	-	141	13.1%
▲	▲	-	84	7.8%
-	-	▼	64	5.9%
-	▼	▼	35	3.2%
-	-	▲	26	2.4%
-	▲	-	23	2.1%
-	▲	▲	22	2.0%
▲	-	-	20	1.9%
▼	▼	-	7	0.6%
-	▼	-	7	0.6%
▲	-	▲	4	0.4%
	Others		10	0.9%

Note: ▲: increase, -: no change, ▼: decrease

Table 2. Change patterns for three time slots



Note: Values in parentheses indicate the number of grids.

Figure 9. Proportion of change pattern by cities

Table 2 summarizes the human mobility change patterns according to the time slots. The five clusters were classified into three patterns: decreased (C1, C2), no change(C3), and increased type (C4, C5). Also, ~40% of grids were classified as the increased type, and 23% of grids were classified as the decreased type for all the time slots. Although the change patterns fluctuated according to the time slot, we identified few contrasting patterns between time slots, such as the increased type in the morning and decreased pattern in the afternoon.

Figure 9 illustrates the proportion of clusters according to cities with the focus on grids with more visitors than residents during the daytime. The proportion varied from city to city, but most cities experienced both increased and decreased patterns. Several cities with small populations within, such as Niigata, Hamamatsu, and Sakai, did not reveal C1, thereby indicating a significant

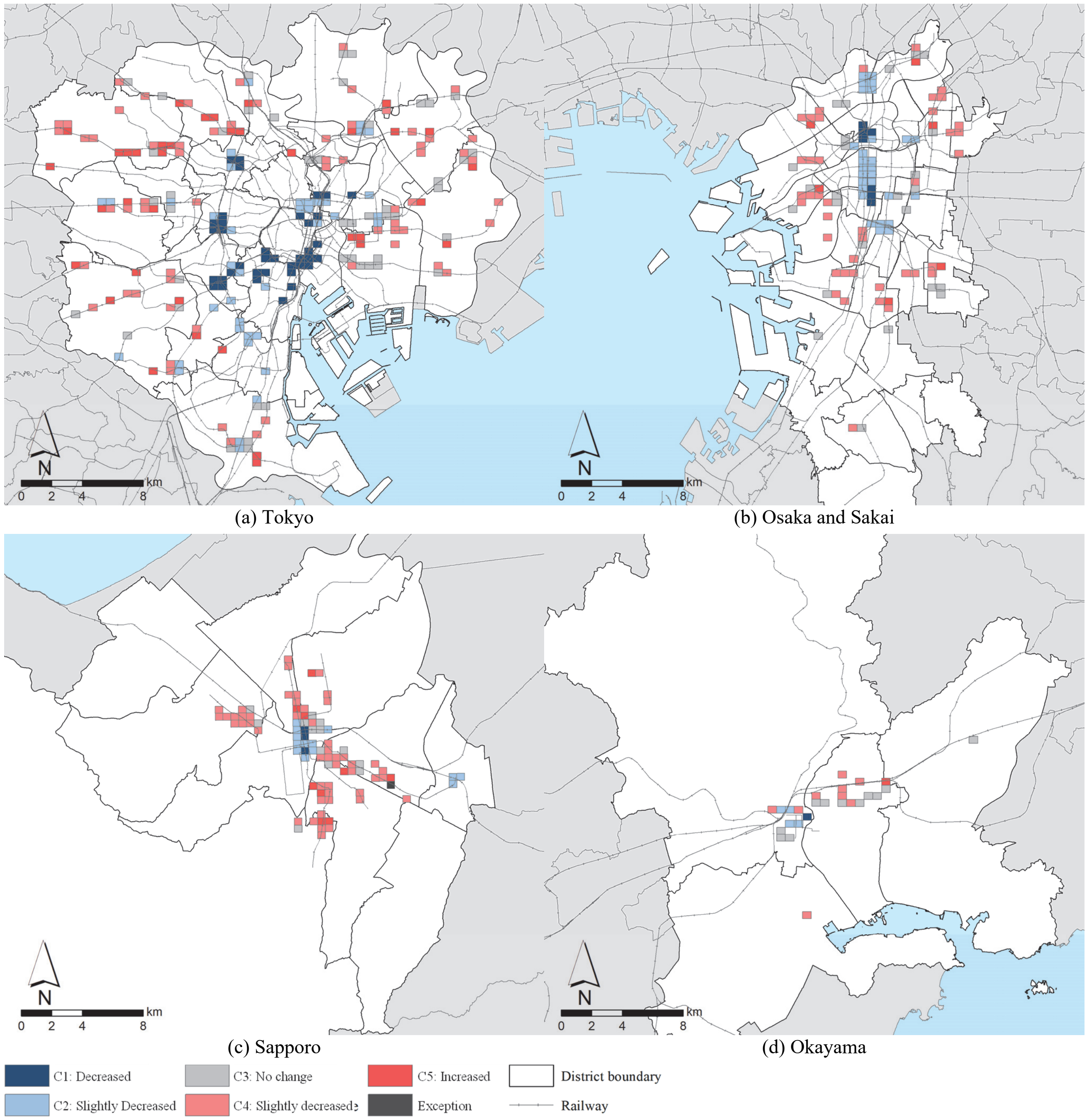


Figure 10. Spatial distribution of clusters in four cities

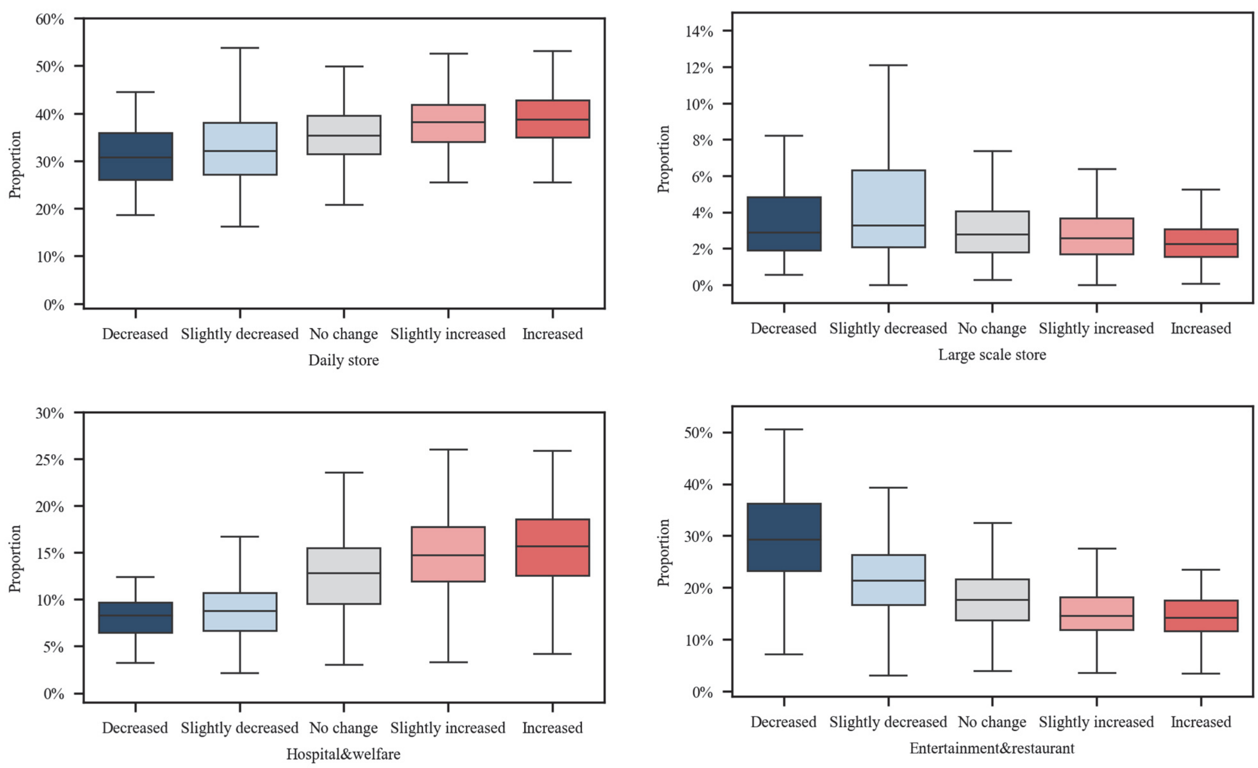


Figure 11. The proportion of commercial facility categories according to change patterns

decrease. This is because the number of COVID-19 patients was relatively small, and the human mobility change was not very noticeable.

4.4 Features of clusters regarding commercial facility type

To examine the features of the clusters, we investigated the geographical distribution and proportion of commercial density according to facility type. Figure 10 shows the distribution of clusters in the four cities of Tokyo, Osaka, Sapporo, and Okayama. The decreased patterns (C1 and C2) were mainly identified in the CBD areas, while the increased patterns (C4 and C5) were found in peripheral areas. The drivers behind the increasing patterns in peripheral areas may be related to the increasing number of visitors, who changed their destination for essential activities such as shopping and hospitals from large-scale commercial areas to neighborhood commercial areas.

Figure 11 illustrates the proportion of commercial density according to the commercial facility categories. The proportion of daily stores, hospitals, and welfare facilities exhibited a significantly high level in the increased clusters and a low level in the decreased clusters. This finding indicates that the increased clusters were mainly composed of facilities that provide products or services essential for everyday life, despite the total commercial density being low. However, large-scale stores, entertainment, and restaurants exhibited somewhat low levels in the increased clusters, being possibly driven by the congestion of these facilities and their use for non-essential activities. Moreover, National governments requested that these facilities shorten business hours or close a store temporarily during the state of emergency. These results indicate that people visited more neighborhood-level commercial areas that provide essential services, compared to those before COVID-19.

5. CONCLUSION

During the COVID-19 pandemic, the patterns of visiting commercial areas were altered due to numerous reasons, such as the risk of infection and the government’s state of emergency. This study investigated human mobility changes in commercial areas by applying time-series clustering with mobile big data from 21 cities in Japan to understand how the patterns of visiting commercial areas changed during the COVID-19 pandemic. The main findings are summarized below.

First, human mobility change patterns exhibited spatial variability, based on which five patterns were identified: decreased, slightly decreased, no change, slightly increased, and increased patterns. Despite the fact that total mobile population in commercial areas decreased due to the risk of infection and the state of emergency, there were commercial areas with more visitors, compared with the pre-COVID-19 period, and these patterns were prominent in low-level commercial areas.

Second, the increased patterns were identified in peripheral areas and included a high proportion of commercial facilities that provide essential services, such as daily stores and hospitals. These results indicate that local-level commercial areas were essential for supporting daily life. Although the data limitations critically hampered the determination of starting points, where people came from, visitors from the neighborhood are suggested to be the main driver of the increase in the mobile population.

Third, human mobility in commercial areas temporarily changed, but rebounded to the pre-COVID-19 level. Although human mobility rebounded to the pre-COVID-19 level, this pattern is unlikely desirable. In particular, a walkable neighborhood with sufficient facilities for daily life was suggested as a resilient urban structure for risk management. Moreover, a walking-oriented city such as “15 minutes city” was discussed before

COVID-19. Also, the pandemic continued, and the Japanese government declared two more states of emergency in 2021. Notably, monitoring human mobility and investigating its relationship with urban structures can shed light on the blueprint of our future city.

Despite promising findings of this study, further studies need to consider the origins (e.g., starting points) of people as well as destinations to understand how the spatial range of commercial areas has changed. Furthermore, investigating the relationship between human mobility change patterns and features of commercial areas, including land use and the built environment, can unravel useful insights for spatial planning and related decision-makers.

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