Original Article

Tourist and business area recovery dynamics:
A spatial analysis of post-pandemic tourism in the Kansai region

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Abstract

This study analyzes tourist behavior during the recovery process of tourism demand following the COVID-19 pandemic. The survey was conducted from April 2020 to October 2023, encompassing tourist destinations and business areas in the Kansai region of Japan. The research sites included the following locations: Kyoto Station, Osaka Station, Shinkyogoku, Kiyomizu Temple, Kinkakuji Temple, Arashiyama, Byodoin, and Todaiji Temple. This study examined mobile phone network statistical population data to deduce the number of visitors at specific tourist destinations and examine their characteristics. Despite the pandemic, the declining tourist population quickly recovered in October 2020 in business and commerce areas. However, the recovery in dedicated tourist areas proceeded more gradually. Regarding visitors' place of residence, the population at Kyoto Station and Osaka Station in 2020 exhibited a notably reduced proportion of visitors from distant regions. In 2021, a higher proportion of visitors originated from closer geographical proximities, likely as a strategic measure to minimize potential COVID-19 transmission risks.

Keywords

statistical population data, Kansai region, Covid-19, tourism, recovery process

1. Introduction

Japan's tourism industry has been strategically navigating the challenging recovery from the COVID-19 pandemic. According to Japan Tourism Agency's Travel and Tourism Trends Survey, travel spending in 2023, including both domestic and international visitors to Japan, is expected to reach 28.1 trillion yen—a figure that marginally surpasses the pre-pandemic spending of 27.9 trillion yen in 2019. However, many regions continue to confront substantial challenges, including sudden drop in tourism demand due to natural disasters such as typhoons, heavy rains, and earthquakes. Consequently, tourism demand remains inherently volatile and unpredictable.

This study examines tourist behavior during the recovery process. Conventionally, regional governments have implemented diverse strategies to attract tourists to destinations that have overcome disasters and have resumed accepting tourists, including travel subsidies and local events. However, examining the recovery process is difficult, because the number and attributes of tourists cannot be identified at most tourist destinations. This study collected and analyzed demographic data across tourist destinations during the recovery process. The knowledge gained here can be used to efficiently recover tourist demand.

2. Previous studies

Studies based on mobile phone users' location data for tourism surveys can be traced back to 2008. Ahas et al. [2008] introduced the applicability of passive mobile positioning data for studying tourism. They used a database of roaming locations (foreign phones) and call activities in network cells: the location, time, random identification, and country of origin of each called phone. Using examples from Estonia, their study described the peculiarities of the data, data gathering, sampling, the handling of the spatial database, and some analytical methods to demonstrate that mobile positioning data have valuable applications for geographic studies. Japan Tourism Agency conducted a similar study using international roaming service in December 2014 [Japan Tourism Agency, 2014].

Since the work of Ahas et al. [2008], several studies employing location data have emerged. Liu et al. [2013] investigated the extent to which behavioral routines could reveal the activities being performed at mobile phone call locations captured when users initiate or receive voice calls or messages. Using data collected from the natural mobile phone communication patterns of 80 users over more than a year, they assessed the approach via a set of extensive experiments. Based on the ensemble of models, they achieved prediction accuracy of 69.7 %. The experiment results demonstrated the potential to annotate mobile phone locations based on the integration of data mining techniques with the characteristics of underlying activity-travel behavior.

Alternative related studies have also been conducted. Gao and Liu [2013] attempted to examine the methods used to estimate traffic measures using information from mobile phones, accounting for the fact that each vehicle likely contains more than one phone because of the popularity of mobile phones. Steenbruggen et al. [2015] used mobile phone data to provide new spatio-temporal tools for improving urban planning and reducing inefficiencies in current urban systems. They addressed the applicability of such digital data to develop innovative applications to improve urban management.

As described above, this study surveyed previous related research. Among those studies, the present study could be like Ahas et al. [2008]. However, the survey is based on results obtained by analyzing data roaming activity. The number of mobile phone users in the study is limited. This study analyzed data provided by the largest mobile phone service provider in

Japan. Therefore, the data should be more reliable in that the parameter is quite large.

Studies on the impact of the spread of COVID-19 on tourism have already emerged since 2020. Most of those studies attempted to analyze the economic impact of the infectious disease or its prevention measures on the tourism industry. Yang et al. [2021] used statistical change-point analysis to investigate the impact of COVID-19 on people's mobility in nine tourism cities such as Bali, Dubai, Hong Kong, London, Mecca, New York, Osaka, Tokyo, and Singapore. They pointed out that there was a lag between the decrease in people's mobility and the introduction of lockdown measures, suggesting that the latter is not the reason for the movement reduction. Skare et al. [2021] measured the potential effects of the pandemic on the tourism industry using panel structural vector autoregression (PSVAR) on data from 1995 to 2019 of 185 countries and system dynamic modeling (real-time data parameters connected to the COVID-19).

Much of the research in this category considers the impact on a particular country or industry. Japutra and Situmorang [2021] explored the impact of the pandemic on hotels in Indonesia. It examined the deployed strategies and discussed their effectiveness. Chen et al. [2020] analyzed the impact of government restrictions during the COVID-19 pandemic on stock returns of U.S. travel and leisure companies. They demonstrated that the stringency of government restrictions has a negative impact on stock returns even after controlling the pandemic. Moreover, stock prices of travel and leisure firms with a smaller size, less tangibility, and higher cash reserves are more resilient to the COVID-19 related government restrictions. The airline industry has been hit the hardest due to these restrictions, followed by the travel and tourism and the casinos and gambling sectors. This study used demographic data to shed light on how COVID-19 affects tourists' behavioral patterns.

3. Methods

This study used mobile phone network statistical population data to determine the number of visitors to specific tourist destinations and to examine their characteristics. It helps estimate the population structure of a region by gender, age, and residence. The survey was conducted between April 2020 and October 2023. The study sites included tourist destinations and business areas in the Kansai region, and are presented in Table 1.

This study examined the transition and attributes of the population in these regions, with a particular focus on the pre- and post-COVID-19 pandemic landscape.

The survey specifications are as follows:

- Survey areas: The meshes are listed in Table 1.
- Duration: April-October 2020, 2021, 2022, and 2023
- Period: Strategic time intervals: 8:00-9:00, 12:00-13:00, 16:00-17:00
- Investigated Attributes: Gender, age (every 10 years), residence (prefecture or municipality)

By systematically organizing, visualizing, and comparatively analyzing these data, it is possible to examine the recovery processes in tourist and business areas.

4. Results

The following paragraphs discuss the transitions and residences of the population in each area, based on statistical population data. These data were derived from mobile phone network demographics Japan's largest telecommunications providers. Therefore, they are considered sufficiently reliable.

4.1 Transition in population in each period

Regarding the transition of the regional population, recoveries in the population of each area were observed after the 2020 pandemic.

The population decline was particularly pronounced in April 2020, coinciding with the Japanese government's declaration of a state of emergency. This initial emergency declaration, issued

Table 1: Survey areas and regional mesh codes

Survey areas	Regional mesh code	Type of codes
(1) Kyoto Station	5235-3680	Tertiary
(2) Osaka Station	5235-0349	Tertiary
(3) Shinkyogoku	5235-4601	Tertiary
(4) Kiyomizu Temple	5235-3692-2	1/2
(5) Kinkakuji Temple	5235-4548-3	1/2
(6) Arashiyama	5235-4514-3	1/2
(7) Byodoin Temple	5235-2664-4	1/2
(8) Todaiji Temple/Nara Park	5235-0627	Tertiary

Notes: A regional mesh code is a code for identifying the regional mesh, which is substantially divided into the same size of a square (mesh) based on the latitude and longitude to use it for statistics. The length of one side of a primary mesh is about 80 km, and those of secondary and tertiary meshes are about 10 km and 1 km, respectively.

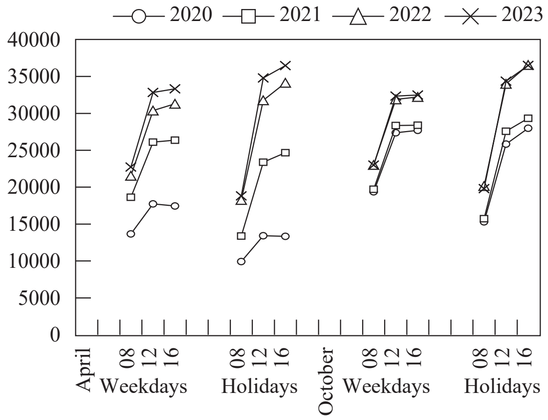

Figure 1: Population transition at Kyoto Station

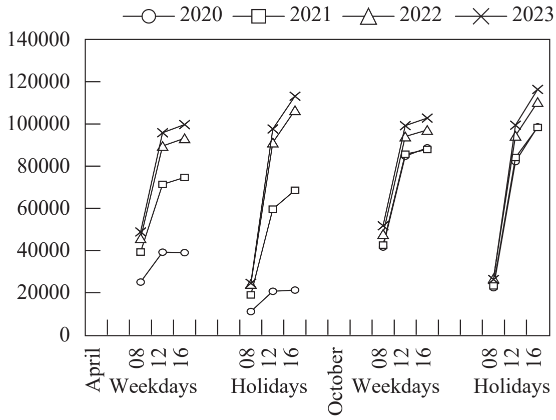

Figure 2: Population transition at Osaka Station

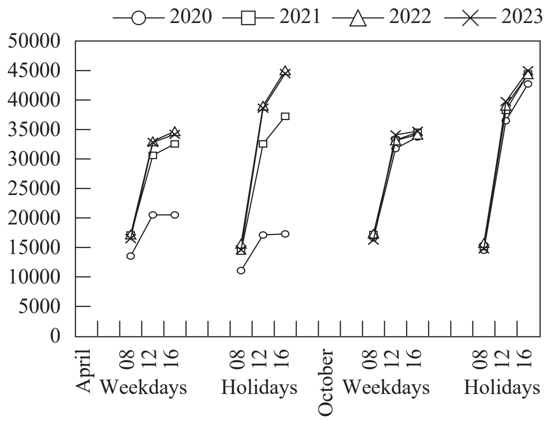

Figure 3: Population transition at Shinkyogoku

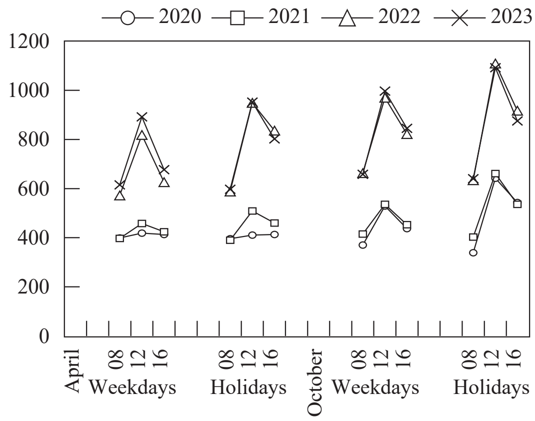

Figure 4: Population transition at Kiyomizu Temple

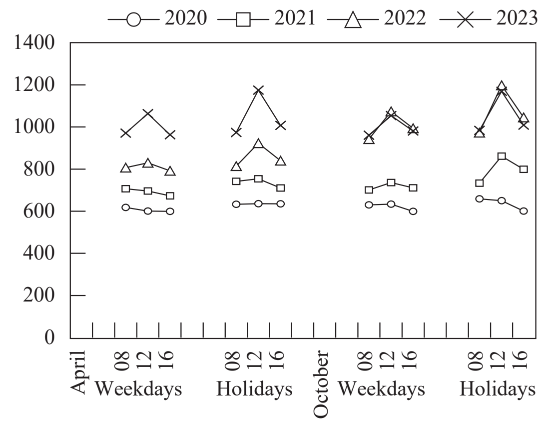

Figure 5: Population transition at Kinkakuji Temple

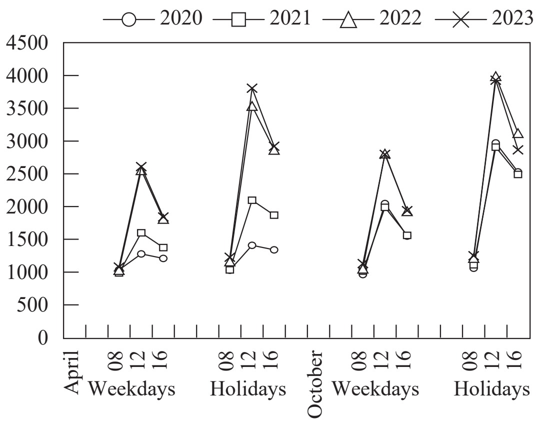

Figure 6: Population transition at Arashiyama

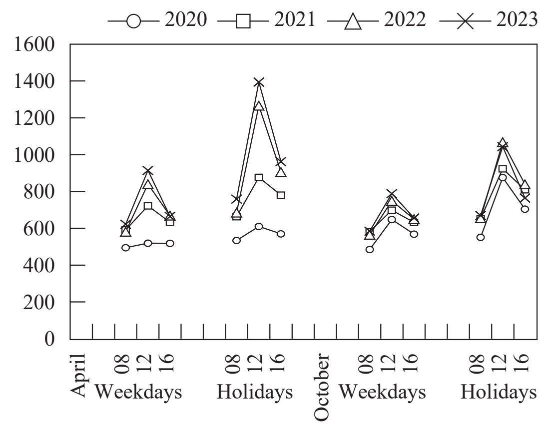

Figure 7: Population transition at Byodoin Temple

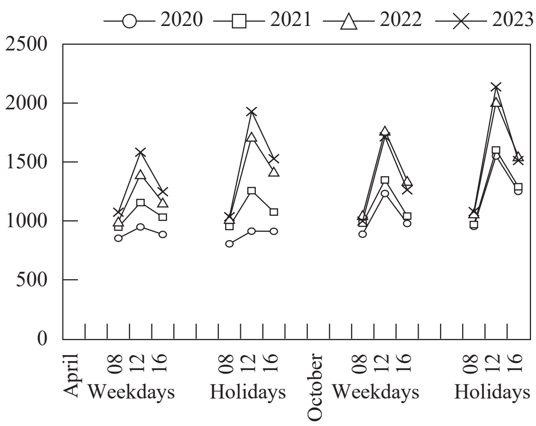

Figure 8: Population transition at Todaiji Temple and Nara Park

Table 2: Rate of recovery for each area

		2021/2020	2022/2020	2023/2020
Kyoto Station	Weekdays	147.1 %	116.4 %	108.1 %
	Holidays	174.0 %	135.9 %	109.5 %
Osaka Station	Weekdays	182.0 %	125.5 %	107.1 %
	Holidays	288.4 %	153.0 %	107.1 %
Shinkyogoku	Weekdays	149.2 %	107.8 %	99.5 %
	Holidays	190.4 %	119.8 %	98.9 %
Kiyomizu Temple	Weekdays	109.3 %	178.6 %	109.0 %
	Holidays	123.8 %	186.4 %	100.3 %
Kinkakuji Temple	Weekdays	115.8 %	119.3 %	128.1 %
	Holidays	118.6 %	122.4 %	127.3 %
Arashiyama	Weekdays	125.0 %	159.7 %	102.2 %
	Holidays	148.8 %	168.6 %	107.7 %
Byodoin Temple	Weekdays	139.1 %	116.3 %	108.8 %
	Holidays	143.8 %	144.4 %	110.2 %
Todaiji Temple and Nara Park	Weekdays	121.9 %	120.7 %	113.3 %
	Holidays	137.7 %	136.4 %	112.4 %

Note: Numbers show the ratio of the population from 12:00 a.m. to 1:00 p.m. on holidays in April.

on April 7, 2020, targeted seven prefectures: Saitama, Chiba, Tokyo, Kanagawa, Osaka, Hyogo, and Fukuoka. By April 16, 2020, the state of emergency was expanded to all prefectures.

Despite the pandemic, the declining tourist population quickly recovered in October 2020 in business and commercial areas such as Kyoto Station, Osaka Station, and Shinkyogoku (see Figures 1, 2, and 3). Table 2 shows the ratio of the population between years in each area.

However, the recovery was gradual in tourist areas that housed famous temples. For Kiyomizu Temple, the population in 2021 remained almost the same as that in 2020 (Figure 4). Figure 5 shows that population at Kinkakuji Temple indicates a prompter recovery than that at Kiyomizu Temple by 2021.

The population of Arashiyama, which has many restaurants and souvenir shops, rebounded in October 2020 like Kyoto Station and Shinkyogoku (Figure 6). Byodoin Temple in Uji City (Figure 7) and Todaiji Temple in Nara Prefecture (Figure 8) show similar transitions to Kiyomizu Temple.

4.2 Residence of the population

Regarding the place of residence, the population at Kyoto Station in April 2020 (Figure 9) had fewer visitors from distant regions than those in April 2021, 2022, and 2023 (Figures 10, 11, and 12). A similar tendency was observed at the Osaka Station (Figures 13, 14, 15, and 16). Overall, travelers avoided long-distance travel in 2020 to reduce the risk of infection. In other words, tourists from nearby areas began visiting earlier than those from distant areas.

As stated above, famous tourist areas take more time to fully recover. The more popular an area, the more visitors there are from distant regions. Thus, recovery should be more gradual.

5. Conclusion and future challenges

The tourism industry has been promoted to stimulate the regional economies in Japan. Generally, the industry is labor-intensive and is expected to play an important role in revitalizing local economies and creating jobs. However, in recent years, the impact of external factors, such as natural disasters and pandemics, on the tourism industry has become increasingly devastating, making tourism recovery an urgent issue in each region.

This study examined statistical population data from eight areas in the Kansai region of Japan. Compared to the recovery process after the pandemic, the impact was particularly significant in many areas in April 2020. Business areas, such as Kyoto Station and Osaka Station, showed relatively more prompt recovery than tourist areas. Based on this research, it can be inferred that more visitors will return from nearby regions in 2021 than from distant ones due to people attempting to minimize the risk of infection.

Japan has hosted numerous events to attract visitors. Combining statistical population data with ICT services such as Google Trends could improve predictions of visitors at new events. Specifically, by analyzing trends in search data for specific tourist destinations, predict the number of tourists more accurately. Better forecasting of demand would enable the optimization of resources and staffing. Moreover, understanding consumer characteristics in advance could enable us to optimize services and improve customer satisfaction.

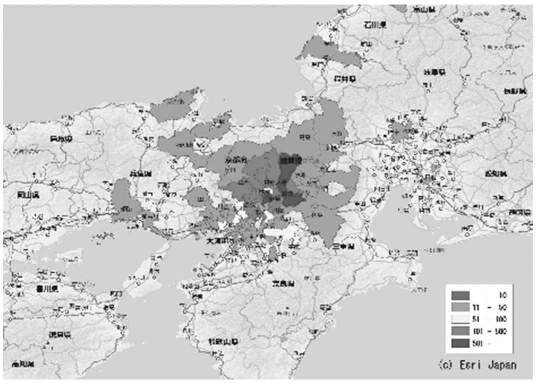

Figure 9: Residence of the population at Kyoto Station (12:00 am-1:00 pm on holidays in April 2020)

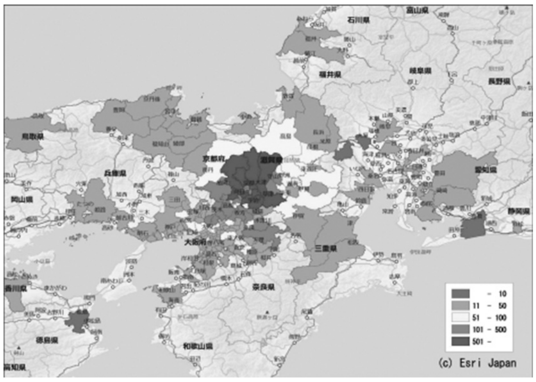

Figure 10: Residence of the population at Kyoto Station (12:00 am-1:00 pm on holidays in April 2021)

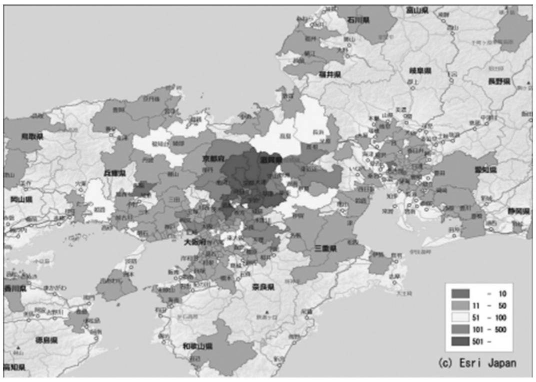

Figure 11: Residence of the population at Kyoto Station (12:00 am-1:00 pm on holidays in April 2022)

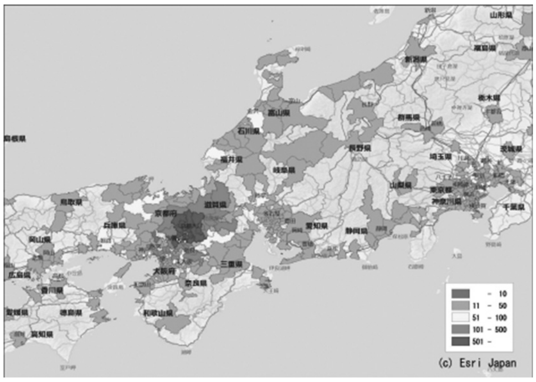

Figure 12: Residence of the population at Kyoto Station (12:00 am-1:00 pm on holidays in April 2023)

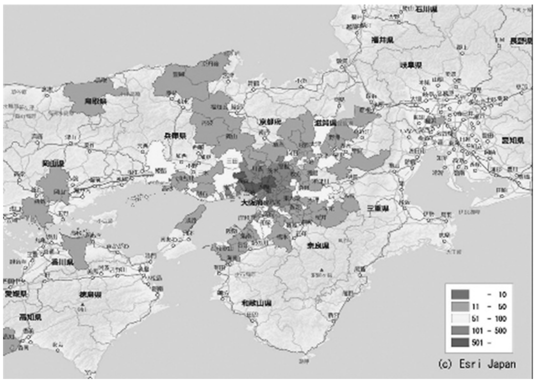

Figure 13: Residence of the population at Osaka Station (12:00 am-1:00 pm on holidays in April 2020)

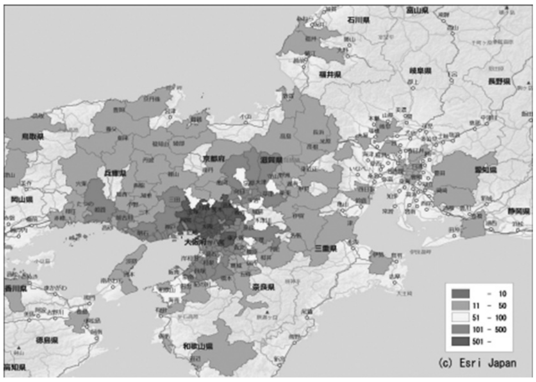

Figure 14: Residence of the population at Osaka Station (12:00 am-1:00 pm on holidays in April 2021)

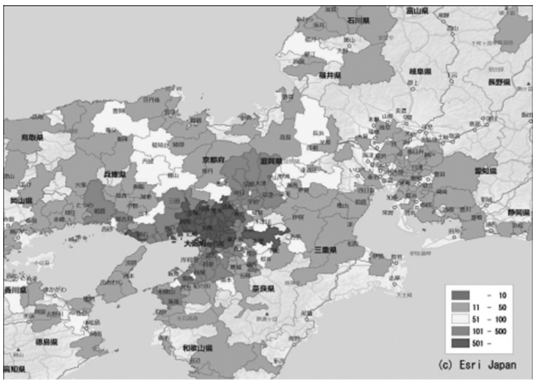

Figure 15: Residence of the population at Osaka Station (12:00 am-1:00 pm on holidays in April 2022)

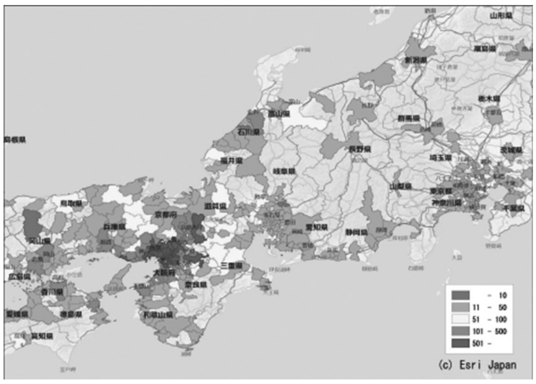

Figure 16: Residence of the population at Osaka Station (12:00 am-1:00 pm on holidays in April 2023)

Acknowledgements

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