Original Article

Estimation of accommodation performance by region using data from online travel agencies

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Abstract

This study identified the lack of data available to destination marketing organizations and other organizations in Japan. To enable strategic planning based on an immediate and detailed understanding of the situation, data beyond official statistics are required. Therefore, this study focused on plan data from online travel agencies. As online travel agency websites can be accessed free of charge, they can provide data, such as vacancies and plan types. This study proposed a methodology for estimating the number of vacancies at accommodations in Japan based on plan information. Accuracy was verified using graphical, autocorrelation, and regression analyses. The results indicated that the estimation was accurate. In addition, the estimated number of vacancies could predict accommodation performance in various regions. A comparison of the methods revealed that if the number of vacancies is unknown, using the number of rooms in a facility improves estimation accuracy. However, this method requires significant preliminary work compared to the method that assigns a constant. Therefore, analysts should select appropriate methods based on the aims.

Keywords

online travel agency, big data, tourism statistics, tourism marketing, periodicity

1. Introduction

Effective tourism marketing requires strategies based on evidence derived from data analysis. However, Japan, a country that aims to become a tourism nation, lacks quantitative data for analysis. In Japan, the types of data that can be used for tourism marketing are limited, and nationally common data are limited [Okamoto et al., 2020]. Moreover, even if the data are usable, data characteristics and methods of use remain unclear. In recent years, paid platforms have emerged, where information on the number of reservations and reservation holders is available [Matsuura and Saito, 2022]. However, many tourism-related organizations face a lack of financial resources [Suzuki, 2018]. Therefore, analysts often cannot use paid platforms to conduct large-scale surveys. Under these circumstances, free information collection from the Internet has attracted attention.

People worldwide use various services via the Internet. The Internet provides a variety of data on people's behaviors and sentiments free of charge, and new methods of data collection via the Internet are being explored worldwide. The analysis of user-generated content (UGC) on social networking sites (SNS), such as Twitter and Flicker, has been utilized in tourism research [Li et al., 2018]. Studies have examined sentiment toward tourism objects based on the content of posts [Jabreel et al., 2017] and extracted images of tourist destinations from posted photos [Miah et al., 2017]. However, concerns have been raised regarding difficulty in controlling data quantity and quality and issues related to personal privacy in SNS research [Suzuki, 2018; Yallop and Seraphin, 2020]. Therefore, decision-making for tourism promotion requires the analysis of data from diverse sources beyond SNS.

This study focused on online travel agencies (OTAs), such as Booking.com, as data sources. In recent years, tourists often use OTAs to reserve accommodations, and reserving accommodations via OTAs has not only increased convenience for tourists but has also provided new analytical opportunities for marketers. Data are available from OTAs free of charge and are directly linked to users' purchasing behavior. OTAs have a vast amount of data, such accommodation availability and plan types, that are updated daily. However, users cannot retroactively retrieve information on plans that have been offered in the past; therefore, a database that acquires and accumulates data in real time is required to use these data for analysis. Studies using OTAs as data sources are mainly concerned with the analysis of rating points and word-of-mouth for accommodations that do not require real-time data collection [Mariani and Borghi, 2018; Wong et al., 2020; Guo et al., 2022].

Mariani and Borghi [2018] noted that the use of OTAs as data sources must be discussed. Several studies have been conducted on the plans offered by OTAs; however, the discussion is insufficient, and there is still room for research. In particular, while it is clear that many tourists use OTAs to reserve accommodations, it is unknown to what extent data from OTAs can be used to understand accommodation performance, such as number of vacancies, occupancy rates. Therefore, this study examined the degree to which data collected from OTAs are linked to the number of vacancies in official statistics. In addition, this study considered estimation methods to obtain accurate accommodation performance.

If it is shown that it is possible to ascertain accommodation performance can be ascertained using data from OTA, marketers lacking statistical data could obtain quantitative indicators to verify the effectiveness of their measures. Monitoring tourism indicators is crucial for public managers and private-sector tourism professionals who need evidence to assist decisionmakers in organizations [Oliveira and Baracho, 2018]. In the tourism field, it is common to use the number of tourists and overnight guests as indicators. In particular, as it is important to increase the number of overnight guests who have a higher economic impact on the region, the ability to conduct marketing based on accommodation performance provides marketers with many advantages. In the academic field, research on data from OTAs primarily involves word-of-mouth analysis. However, this study is expected to serve as a starting point for active analyses using actual accommodation performance based on OTAs. This could contribute to empirical research on various theories.

2. Related literature

Few studies have attempted to estimate accommodation performance using OTA data. Adhinugroho et al. [2020] tested the usefulness of statistical data generated by collecting data from OTAs. They collected accommodation data in Indonesia from Agoda and Pegipegi, calculated occupancy rates based on remaining rooms, and compared the results with official statistics. They concluded that data collected from OTAs could be used as a proxy or supplement to official statistics. However, as website specifications, utilization rates, and data characteristics differ by country, similar results might not be obtained for other countries. Therefore, the accuracy of these data must be verified for other countries.

Several studies have examined accommodation performance in Japan using OTA data. Tsuda et al. [2013] estimated the occupancy rates of 196 accommodations in Kyoto between 2011 and 2012. They noted that estimating the number of vacancies was complicated by multiple plans available for one room. They proposed a method in which all plans were divided based on rooms of the same size, and then the number of rooms available in each group was added together. Their analysis covered non-smoking and smoking single and twin rooms. If the number of vacancies was ≥ 5 in OTA specifications, the minimum value that satisfied the condition (in this case, 5) was substituted. The occupancy rates calculated using this method showed regular fluctuations depending on the season and day of the week. Moreover, the calculated occupancy rate was close to the statistical occupancy rate.

Yamamoto and Tsuda [2015] estimated the occupancy rates for 91 facilities in Kyoto City using the same method as Tsuda et al. [2013] for a three-year period (2011-2014). In addition, they proposed a new complementary method for handling an unknown number of vacancies. They used a weighted estimation based on the daily occupancy rates of eight hotels in Kyoto, where the occupancy rate decreases with the distance from Kyoto station. Estimation accuracy had improved with this method.

Ichifuji et al. [2017] used a similar method as the abovementioned studies but deleted plans with exactly the same pattern of changes in the number of vacancies in the 14 days leading up to the reservation date. In addition, the number of target facilities in Kyoto was expanded to 269, and the period was extended to four years (2011-2015). Furthermore, this study reported that combining data from multiple OTAs improved the estimation accuracy.

A limitation of these studies is that they covered only Kyoto. Kyoto is a famous tourist destination. Therefore, the estimation may not be feasible in other areas. For instance, Tsuda et al. [2013] assigned the minimum value that satisfies the $\geq x$ condition for the number of vacancies; however, this method underestimates the number of vacancies and assumes a high occupancy rate in the area. As most months in Kyoto City at that time had an occupancy rate of 80 % or higher, this would not have caused a major problem. However, in areas with low occupancy rates, the error is expected to be larger. Yamamoto and Tsuda [2015] used daily occupancy data provided by hotels in Kyoto; however, similar data may not be available in other regions. Furthermore, they base their estimates on distances from train stations, which is expected to be less accurate outside of urban tourist destinations where train stations are central to travel.

Other than above studies, Suzuki [2020] used the number of remaining plans, which does not necessarily correspond to the number of vacancies, as OTAs have multiple plans for each room. This method does not require complicated preprocessing, such as classification and deletion of plans, and has the advantage of being easy to handle even for data analysis beginners. Although the accuracy of the method is likely to be lower, it can estimate rough fluctuations in accommodation performance, suggesting the possibility of utilizing data for individual accommodations and in small cities. However, regional aggregates cannot be utilized for large cities, such as Tokyo and Osaka, due to the strong influence of facilities with many plans.

As noted above, discussions on the methods and characteristics of accommodation performance based on the analysis of OTA data are gradually progressing. In recent years, empirical studies have examined issues such as the impact of measures based on changes in the number of vacancies during events and changes in the number of remaining plans when lodging subsidies support are provided [Shibuki, 2021; Suzuki et al., 2022]. However, the accuracy of the estimation has only been verified in a limited number of regions, and further verification is needed before more regions can use these data for analysis. Moreover, the COVID-19 pandemic had a significant impact on the tourism industry. As most studies were conducted before the pandemic, post-pandemic data should be analyzed for future data utilization.

3. Methods

3.1 Data and analysis target

This study examined accommodation performance using data collected from OTAs using the application programming interface. Following Adhinugroho et al. [2020], data were collected from major OTAs in Japan. This study collected data from Jalan [Recruit Lifestyle, n.d.], which is one of the most commonly used OTAs in Japan. The number of vacancies was estimated based on available reservation plans on Jalan as of the day before the stay, under the condition of one night for one adult. Data from January 1, 2021, to December 31, 2022, were collected. This study collected hotel codes, room names (including standard names such as "single room" and facility-specific names), and number of vacancies.

Two issues arose in this process due to the platform specifications. First, multiple plans were associated with a single room. This can lead to an overestimation of the number of vacancies, as several available plans may be displayed while there is one vacancy. Second, Jalan does not display the number of vacancies if it is more than 10. This is common for several OTAs. Solving these problems is important for marketers and researchers who use OTAs as data sources.

Therefore, this study derived the number of vacancies using five steps (Figure 1). First, this study collected information on reservable plans (hotel code, room name, and number of vacancies) for accommodations throughout Japan. Second, if the hotel code, room name, and number of vacancies matched, the other plans were deleted, leaving only one plan. Third, if the hotel code and room name matched while the number of vacancies did not match, the plan with the largest number of vacancies was retained, and the other plans were deleted. This was done because plans with a low number of vacancies may be special plans with user limits and may not represent the true number of vacancies. Fourth, if the room type is the same (e.g., single room) while the room name differs, and the number of vacancies is the same for one year, the other plans were deleted, retaining one plan. This was done because one room may be sold as different rooms, such as a non-smoking and smoking single room. Fifth, plans for which room names were not specified (e.g., "unspecified" or "single or double") were deleted. This was done to eliminate plans not associated with the number of vacancies.

If the number of vacancies was unknown (i.e., more than 10) after performing these steps, this study assigned the minimum value (10; Method 1), assigned the maximum value (number of rooms for the corresponding room type in the accommodation; Method 2), or assigned an intermediate value between the minimum and maximum (Method 3). Method 1 is similar to that followed by Tsuda et al. [2013], using the minimum value that satisfies the $\geq x$ condition. However, as noted above, this method underestimates the number of vacancies. For instance, if the maximum number of vacancies is 100, and 10 is set as the number of vacancies, it is assumed that 90 % of the rooms are reserved. It is not realistic for many regions to expect that accommodations with a large number of rooms are more than 90 % occupied on days when the number of guests is low, such as weekdays. Conversely, if the number of rooms is 15, setting 10 as the value is unlikely to have a major impact on the analysis. Therefore, the assigned value should vary depending on accommodation size.

Therefore, Method 2 uses the maximum number for each room type, reflecting accommodation size. However, this method may overestimate vacancies, as it assumes that none of the rooms are reserved. However, the overestimation was expected to be smaller than with the first method because the difference between the true value is likely to be smaller when occupancy is low (large number of vacancies). Method 3, which assigns an intermediate value, is expected to reduce the error margin when the number of vacancies is large or small.

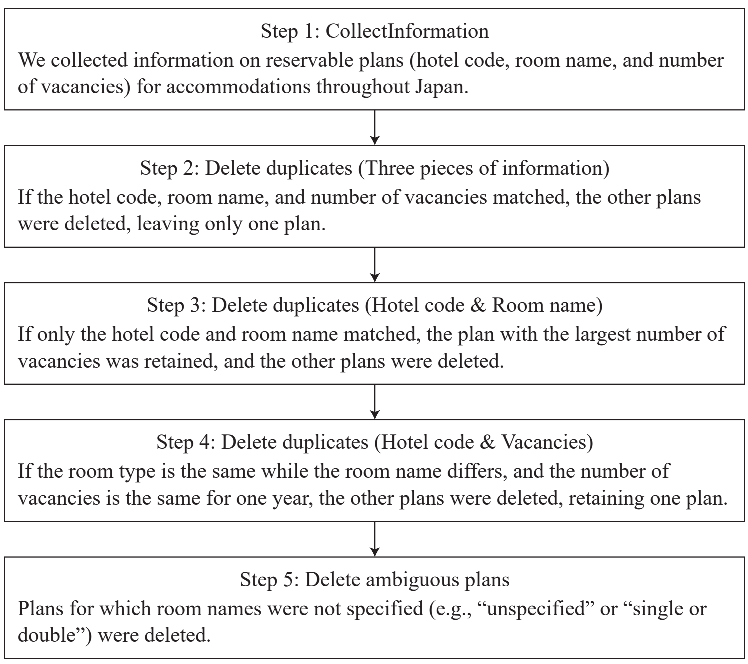


Figure 1: Five steps to derive the number of vacancies

3.2 Verification of estimation

The estimated number of vacancies was calculated using data collected from OTAs. The association between the estimated and actual number of vacancies was evaluated.

The periodicity of the number of vacancies was examined, as the number of guests generally increases during holidays. A graphical analysis was performed to verify the results. This simple method intuitively captures peaks, valleys, and patterns in a line graph of time-series data [Ogasawara 2022]. The estimated number of vacancies was used to confirm the pattern of fluctuation and consistency with the number of vacancies in official statistics (hereafter, official number of vacancies). The reasons for sharp decreases in vacancies were investigated by comparing to holidays and major events. An autocorrelation analysis was used to check for cycles for specific days of the week. As the number of guests generally increases on certain days of the week, such as Saturdays, if the estimated number is accurate, the correlation is expected to be high in a seven-day cycle.

In addition, a regression analysis was used to verify whether the estimated number of vacancies reproduced time-series changes in the official number of vacancies by prefecture. The official number of vacancies was obtained from a statistical survey on overnight travel published by the Japan Tourism Agency [2023]. As the survey did not publish the number of vacancies but reported the number of rooms in use and occupancy rates, these figures were used to calculate the number of vacancies. OTA data can be analyzed by prefecture or day, whereas official statistics are limited to prefectural and monthly data. Therefore, this study compiled data on the estimated number of vacancies by prefecture and month and used 24-monthly panel data for 47 regions in the analysis. This analysis was used to verify the usability of the data, which has only been verified for Kyoto in previous studies, in other regions.

Analyzing panel data by region requires different analyses that focus on regional and seasonal variations. Specifically, to analyze seasonal variations, it is necessary to remove the differences region size. Therefore, this study conducted analyses in two stages.

First, the mean value for each prefecture was used for the estimated and official number of vacancies. This method, known as between estimation, verified the reproducibility of size differences between prefectures. Next, seasonal variations in the estimated and official number of vacancies by prefecture were analyzed using within estimation, which is a fixed-effect model [Hsiao, 2014]. Within estimation is equivalent to ordinary least squares with deviation. Deviations between mean values by prefecture and month were used for the estimated and official number of vacancies. This method eliminates the effects of differences between prefectures. Although least squares dummy variables can also be considered for eliminating the effects of differences between prefectures, this was not used in this study due to the large number of variables.

4. Results

Figure 2 shows the daily changes in the estimated number of vacancies and official monthly vacancies. The estimated number of vacancies increased and decreased regularly, with a decrease on Saturdays, when demand is high, which was consistent with the general theory. In addition, estimated and actual number of monthly vacancies were correlated. The estimated number of vacancies on July 22 and November 20, 2021, and May 3, 2022, were lower than that of the surrounding days.

Figure 3 presents a graph of the daily autocorrelation of the estimated number of vacancies. The correlations were strong on days 7, 14, 21, and 28. Overall, the correlation decreased as the number of days increased.

Figure 4 shows the relationship between the mean estimated

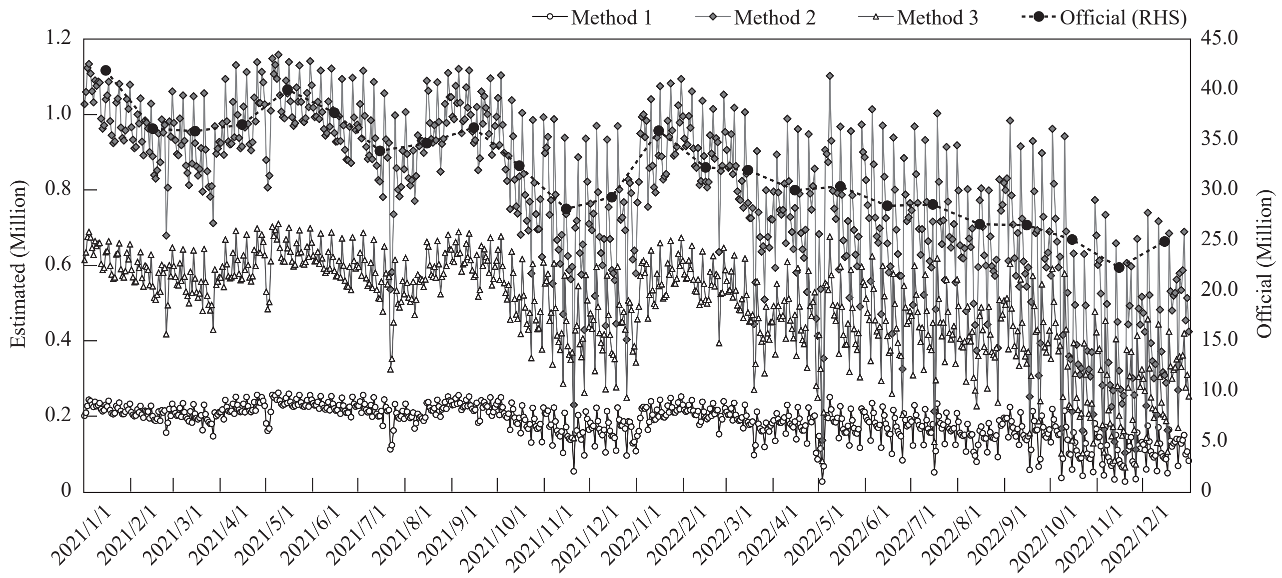


Figure 2: Daily changes in the number of vacancies

Note: Estimated/estimated number of vacancies; Official/ official number of vacancies.

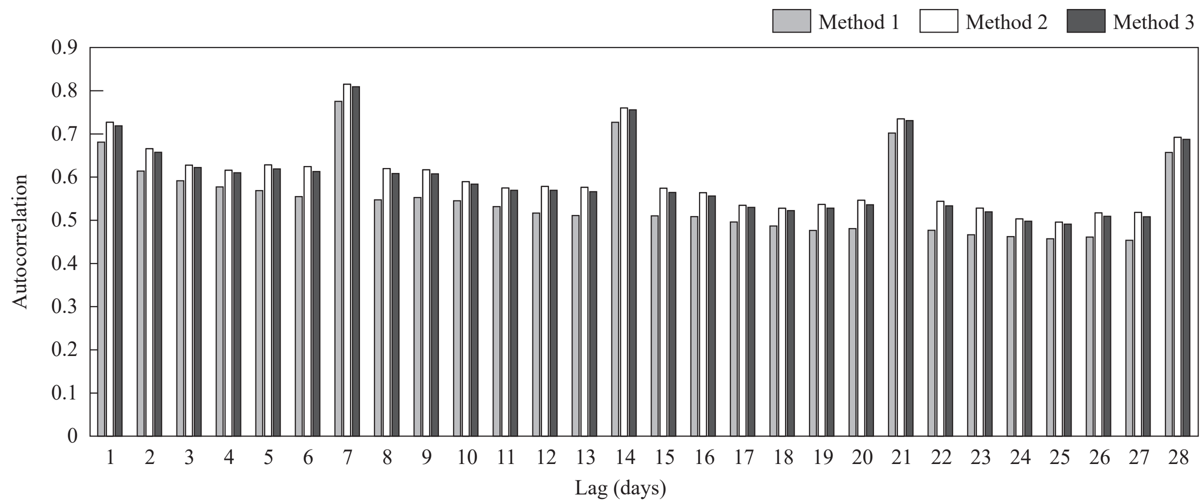
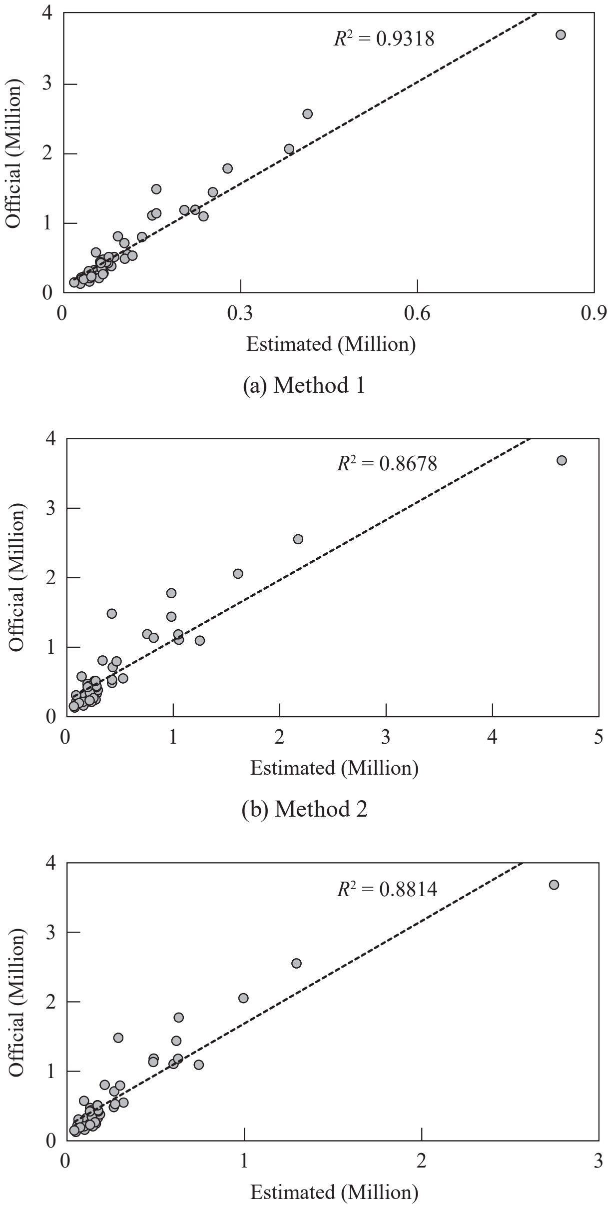


Figure 3: Daily autocorrelation of the estimated number of vacancies



(a) Method 1

(b) Method 2

(c) Method 3

Figure 4: Correlation between the estimated and official number of vacancies by prefecture (Mean)

and official number of vacancies by prefecture. There was a positive correlation between the two estimated and official values, with Method 1 having the highest coefficient of determination (0.9318). The coefficients of determination for Methods 2 and 3 were 0.8678 and 0.8814.

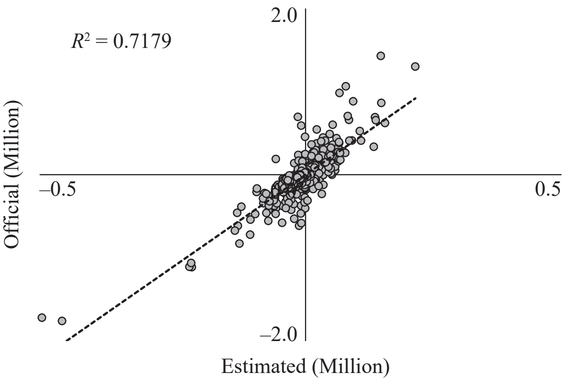
Figure 5 shows the monthly deviation of the estimated and official number of vacancies by prefecture. A positive correlation was observed. Table 1 compares the estimation accuracy. The estimation accuracy exceeded 0.7 for all three methods, with Method 2 being the most accurate (0.7625). The regression coefficient was 4.2781 for Method 1, which minimized the number of vacancies, suggesting that the absolute value of the number of vacancies was small compared to the statistical value. The regression coefficient for Method 2 was 0.7833, which suggests that the number of vacancies was overestimated compared to the actual value. These results were consistent with the assumptions.

5. Discussion

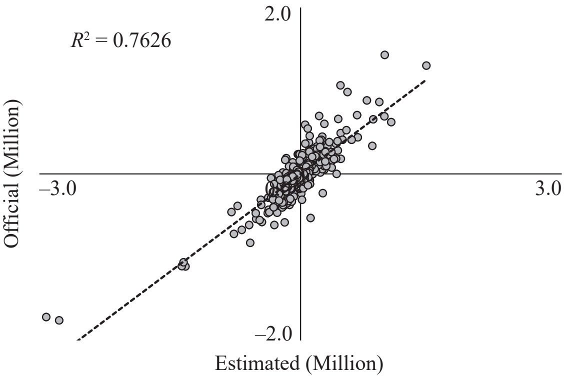
A comparison of the estimated and official number of vacancies in the graphical analysis suggested that monthly trends could be determined used the estimated number. Although the number of vacancies in Japan is usually the lowest in August [Japan Tourism Agency, 2023], the number of vacancies in August 2021 was high, which could be due to the COVID-19 pandemic.

In addition, July 22, 2021, was the first day of a four-day holiday in connection with the Tokyo Olympics. Although November had the highest number of vacancies in 2021, November 20, 2021, was Saturday, and November 23 was a national holiday; therefore, many people likely travelled on the four-day holiday. May 3, 2022, was the middle of a long holiday, called Golden Week, in Japan, the impact of the COVID-19 pandemic decreased in 2022, and many people likely travelled during this period.

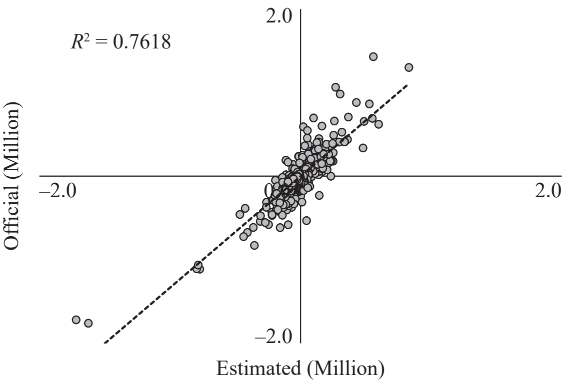
Moreover, a strong autocorrelation was found in the seven-day cycle, indicating periodicity by day of the week. This was



(a) Method 1



(b) Method 2



(c) Method 3

Figure 5: Correlation between the estimated and official number of vacancies by prefecture (Monthly deviations)

Table 1: Estimation accuracy of the three methods

	Method 1	Method 2	Method 3
Regression coefficient	4.2781	0.7833	1.3350
Observations	1,128	1,128	1,128
Within R^2	0.7178	0.7626	0.7618

consistent with the hypothesis and suggested that the estimated number of vacancies reproduced accommodation performance. The gradual decrease in autocorrelation, except for the seven-day period, indicated travel seasonality. Method 1 had a lower correlation than the other methods. This was likely because difference between the busy and off-peak periods was smaller, as the unknown value was set to minimum. However, the overall trend was consistent across all methods, indicating that the periodicity was reproduced by all methods.

The estimation results showed that the coefficients of determination for all three methods were approximately 0.9. This indicated that the estimated number of vacancies reproduced differences in scale among regions. Method 2 had a low coefficient of determination, as the number of vacancies was overestimated in regions with large maximum vacancies, the number of vacancies was reversed between some regions.

The results of within estimation showed that the accuracy of all methods was greater than 0.7. Therefore, accommodation performance by region could be determine using OTA data. The relative estimation accuracy was significantly better than that report by Suzuki [2020], who used the number of remaining plans. However, it was not as accurate as previous studies on Kyoto [Tsuda et al., 2013; Yamamoto and Tsuda, 2015: Ichifuji et al., 2017]. This could be due to the increase in the number of target areas and uncertainties in each area that cannot all be observed with OTA data, resulting in a decrease in accuracy. In addition, as mentioned above, the occupancy rate in Kyoto was high during periods examined in previous studies; thus, the variance was small, making it easy to increase estimate accuracy.

Further improvement of accuracy would require also information on plans not provided by Jalan (plans provided by other travel agencies and direct sales of accommodation). Previous studies have shown that using multiple OTA datasets improves accuracy [Ichifuji et al., 2017]. However, increasing the number of data sources significantly increases the workload; therefore, it is important to achieve a balance to obtain the required accuracy.

Method 2 was the most accurate, followed by Method 3, indicating that incorporating a scale factor could improve accuracy. However, the overall occupancy rate was low (less than 50 % in many areas). This may have contributed to the higher accuracy of Method 2, which overestimates the number of vacancies. Although Method 3 was slightly less accurate than Method 2, Method 3 is likely to be more accurate than Method 2 in areas with high occupancy rates (low number of vacancies). These two methods include accommodation size, which may be particularly useful when the analysis includes large accommodations.

Although Method 1 was the least accurate, it has the advantage of not requiring a survey on the number of rooms. Therefore, if most of the analyzed accommodations are small, Method 1 could be used. In addition, Method 1 could be useful for areas with occupancy rates exceeding 80 % or 90 %, such as Kyoto. Occupancy rates are expected to increase, and number of international visitors is expected to increase as the impact of the COVID-19 pandemic decreases [Japan Tourism Agency, 2023]. Analysts should choose appropriate methods for the local situation.

6. Conclusion

To address the problem of insufficient information sources for tourism marketing, this study focused on data collected from OTAs. OTAs are used by many tourists and provide a vast amount of information daily; however, the data are not fully utilized in marketing. Therefore, this study collected information on the available reservation plans in accommodations from OTAs and examined the feasibility of using these data to estimate accommodation performance by region. Based on previous studies, this study proposed solutions to the problems of multiple plans tied to one room and unknown number of vacancies and compared the estimation accuracy between methods.

The results demonstrated that the characteristics of days of the week were reproduced using all methods, and days with sharp increases in the number of guests were observed. Therefore, unlike existing official statistics, estimating the number of vacancies based on OTA data could provide daily statistics. The analysis of all prefectures in Japan revealed that the estimated number of vacancies reproduced differences by region with high accuracy. In addition, the estimated number of vacancies reproduced time-series changes by region with high accuracy.

Although there is no absolute standard for evaluating accuracy, our methods could be particularly useful in cases that require quick reporting and areas with no available statistical data. Assigning the maximum value instead of an unknown value resulted in the highest accuracy. However, as accuracy varies depending on the occupancy rate, analysts should use appropriate methods for the situation. Method 1 was the easiest to use, as it required less work than Methods 2 and 3.

There is a trade-off between estimation accuracy and workload. Methods of improving accuracy with less effort should be investigated in future studies. However, this study provided useful results for marketers who require quantitative data. Finally, future empirical studies should examine the use of estimated number of vacancies and occupancy rates based on OTA data.

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