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Research article

Epidemiological impact of travel enhancement on the inter-prefectural importation dynamics of COVID-19 in Japan, 2020

Asami Anzai[1], Syudo Yamasaki[2], Amanda Bleichrodt[3], Gerardo Chowell[3], Atsushi Nishida[2,4] and Hiroshi Nishiura[1,*]

[1] Graduate School of Medicine, Kyoto University, Yoshidakonoecho, Sakyo-ku, Kyoto 606-8501, Japan
[2] Research Center for Social Science & Medicine, Tokyo Metropolitan Institute of Medical Science, Setagaya-ku, Tokyo, Japan
[3] School of Public Health, Georgia State University, 140 Decatur St., Atlanta, GA 30303, USA
[4] Tokyo Center for Infectious Disease Control and Prevention, Shinjuku-ku, Tokyo, Japan

* **Correspondence:** Email: nishiura.hiroshi.5r@kyoto-u.ac.jp; Tel: +81-75-753-4456; Fax: +81-75-753-4458.

Abstract: Mobility restrictions were widely practiced to reduce contact with others and prevent the spatial spread of COVID-19 infection. Using inter-prefectural mobility and epidemiological data, a statistical model was devised to predict the number of imported cases in each Japanese prefecture. The number of imported cases crossing prefectural borders in 2020 was predicted using inter-prefectural mobility rates based on mobile phone data and prevalence estimates in the origin prefectures. The simplistic model was quantified using surveillance data of cases with an inter-prefectural travel history. Subsequently, simulations were carried out to understand how imported cases vary with the mobility rate and prevalence at the origin. Overall, the predicted number of imported cases qualitatively captured the observed number of imported cases over time. Although Hokkaido and Okinawa are the northernmost and the southernmost prefectures, respectively, they were sensitive to differing prevalence rate in Tokyo and Osaka and the mobility rate. Additionally, other prefectures were sensitive to mobility change, assuming that an increment in the mobility rate was seen in all prefectures. Our findings indicate the need to account for the weight of an inter-prefectural mobility network when implementing countermeasures to restrict human movement. If the mobility rates were maintained lower than the observed rates, then the number of imported cases could have been maintained at substantially lower levels than the observed, thus potentially preventing the unnecessary spatial spread of COVID-19 in late 2020.

Keywords: spatial analysis; mobility; SARS-CoV-2; tourism; travel; importation

1. Introduction

Since the start of the coronavirus disease 2019 (COVID-19) pandemic, public health and social measures (PHSM) have acted as the main countermeasures before vaccination [1,2]. As part of the PHSM, travel restrictions and governmental requests for self-restraint behavior to minimize human mobility were widely practiced to reduce contact with others and prevent the spatial spread of infection [3–5]. In Japan, countermeasures associated with mobility control ranged from lockdown to voluntary requests for restricting movement; at an international scale, these have involved border control measures, including travel restriction, various screenings at the time of exit and entry, and the quarantine of immigrants [6–8]. Despite practical preventive efforts (e.g., travel bans on newly incoming passengers plus quarantine in previously zero-COVID countries), these countermeasures have had a substantial social and economic impact [9–11]. Numerous epidemiological studies have focused on international movement restrictions, the evaluation of the effectiveness of border control measures, and the relationship between the movement of people and the pandemic [5,8,12]. Some studies suggest that the optimal countermeasures to restrict human mobility may vary depending on the phase of the pandemic, the locally agreed goal of control, and the capacity of resources [13–16].

In Japan, the government declared the first state of emergency on April 7, 2020, following the rapid surge of cases in late March 2020. During this time, interventions included requesting a voluntary reduction in nonessential physical contact, self-restraint behaviors with respect to domestic movement (e.g., refraining from crossing prefectural borders), and reduced operating hours in high-risk settings (e.g., restaurants at night). By the end of 2022, Japan declared a state of emergency four times, starting in April 2020, January 2021, April 2021, and July 2021 [17]. During those periods, drastic reductions in human mobility were observed [18–22]. During the time between the second and third epidemic waves in 2020, economic countermeasures to enhance domestic travel activities were also implemented to support industry sectors associated with travel and food and beverage services that PHSM seriously impacted. The first nationwide economic booster campaign, referred to as the Go To Travel Campaign, started on July 22, 2020. The campaign involved a subsidy of accommodation fees and the distribution of coupons, excluding Tokyo, where epidemic activity was still observed [23]. Tokyo was added on October 1, 2020, when the second booster campaign started. The contents of these subsidy programs were frequently changed and adjusted according to the epidemic activity; however, the Go To travel campaign was suspended due to an excessive number of cases in late 2020, leading to the third COVID-19 wave in Japan from November 2020 to February, 2021 [24]. The economic campaign had not resumed by October 2022, which was the post-vaccination period during which a new nationwide support program was put in place [25].

With frequent revision of the length and types of travel to be restricted, mobility restrictions were implemented in Japan from 2020 to 2021 [26,27]. Despite their epidemiological usefulness, and due to their enormous social and economic impact, the effective timing, targets, and scale of mobility restriction at domestic levels clearly needed to be considered [28,29]. A scientific framework to support evidence-based policymaking is required to facilitate evidence-based decisions for reducing movement. For instance, policymakers would benefit from knowing when movement restrictions would become most effective and under what conditions economic booster programs can be put in place. Although it was discontinued during the pandemic, the Cabinet Secretariat of Japan publicly shared the COVID-19 importation risk index, which was estimated based on a simple product of the inter-prefectural mobility rate per capita and the incidence of SARS-CoV-2 infection in the prefectures of origin [30].

The purpose of the present study was to devise a statistical model to predict the number of imported cases in each prefecture using inter-prefectural mobility data and epidemiological data. Considering that the metapopulation epidemic model can quantitatively capture the patterns of geographic spread, and that domestic mobility patterns have been recorded, the inter-prefectural spreading patterns of COVID-19 in Japan during the pre-vaccination period could feasibly be reconstructed. The quantified model allowed us to examine the epidemiological impact of mobility restrictions and local epidemic dynamics of the origin on the importation epidemiology of the destination. Using the model, we explicitly and quantitatively assessed the impact of mobility on the local risk of COVID-19 across Japan.

2. Materials and methods

2.1. Data

In Japan, COVID-19 has been designated as a notifiable infectious disease according to the Infectious Disease Control Law, and all confirmed cases must be reported [31]. A confirmatory diagnosis is made mostly using reverse transcriptase polymerase chain reaction (RT-PCR), and sometimes with rapid antigen testing. Upon notification, a dataset is compiled at a local health center using an online surveillance system, the Health Center Real-time Information-sharing System on COVID-19 [32]. In the present study, we investigated the number of newly confirmed COVID-19 cases from March 1, 2020 to December 31, 2020. The dataset was extracted from open data published by the Ministry of Health, Labour and Welfare [33]. Additionally, we collected the number of infected individuals with a history of movement across the prefecture from each prefectural announcement of the epidemic situation. The reporting of mobility history was only available for some prefectures, and we ensured a systematic collection of the corresponding travel information whenever publicly available.

In addition to the epidemiological data of cases and their travel history, we collected mobility data, which is comprised of “LocationMind xPop” data on the daily number of travelers from one prefecture to another, provided by LocationMind Inc. "LocationMind xPop" data is data that NTT DOCOMO has processed statistically and comprehensively from cell phone location data sent with permission from users of the Zenrin Map Navi service provided by ZENRIN DataCom CO., LTD. The location information is GPS data (latitude and longitude information), which is located at a minimum of every five minutes and does not contain information that identifies the individuals. NTT Docomo, Inc. accounts for approximately 44% of total mobile phone subscribers in Japan [34,35]. For each prefecture, the mobile phone trajectories were used to selectively collect the population volume that moved from one prefecture to another on each date. Accordingly, the anonymized number of domestic travelers from one prefecture to another was continuously recorded for all 47 prefectures. In addition to mobility data, we used population estimates as of October 1, 2019 from the Statistics Bureau of the Ministry of Internal Affairs and Communications [36].

2.2. Estimation of the number of imported cases

In this study, we first estimated the COVID-19 prevalence in each prefecture. Letting $p_{i,t}$ represent the prevalence of prefecture *i* on a calendar time day *t*, this was modeled as follows:

$$p_{i,t} = \sum_{s=0}^{t-1} c_{i,t-s}\Gamma_s, \tag{1}$$

where $c_{i,t}$ is the number of newly confirmed COVID-19 cases (i.e., incidence) in the corresponding prefecture i, and Γ_s is the survival probability of PCR positivity on day *s* since infection, extracted from the literature [37].

Using the prevalence $p_{i,t}$ and the observed mobility from mobile phone data $m_{i,j,t}$, which describes the absolute number of movements (persons) on day *t* from prefecture *i* to *j*, the importation risk $r_{j,t}$ in prefecture *j* is modeled as follows:

$$r_{j,t} = \sum_{i \neq j} \frac{m_{i,j,t}p_{i,t}}{N_i} \tag{2}$$

where N_i is the population size of prefecture i, and $m_{i,j,t}$ is the volume of movement from prefecture *i* to prefecture *j* on day *t*. The estimated $r_{j,t}$ was fitted to the observed number of imported COVID-19 cases (i.e., incidence) with a documented history of inter-prefectural movement. A total of 24 prefectures allowed us to analyze the imported case data. Let E(.) represent the expected value. The expected value of the incidence of imported cases in prefecture *j* on day *t*, $x_{j,t}$ is modeled as follows:

$$E(x_{j,t}) = kr_{j,t}. \tag{3}$$

where *k* is a constant parameter for scaling. Both under-ascertainment and asymptomatic infections are encompassed by incorporating the parameter *k*. We estimated the scaling parameter *k* by the prefecture via statistical fitting of $E(x_{j,t})$ to the observed empirical data. Using a maximum likelihood method and assuming that the number of imported cases does not often deviate from the mean, and thus, are sufficiently captured by a Poisson distribution every day, the parameter *k* was estimated from the observed incidence in 24 prefectures.

2.3. Simulations

By quantifying a system that can conveniently predict imported cases, while enabling us to hypothetically vary the mobility rate and the epidemiological dynamics of origin, we examined how importation dynamics are characterized. Using quantified systems with equations (2) and (3), simulations were carried out with different scenarios of mobility and prevalence at the origin prefecture. First, we examined the impact of mobility itself during the period under the second Go To travel campaign from October 1, 2020. Inter-prefectural mobility was varied from 0.5 (low scenario) and 2.0 (high scenario) times the observed empirical count. The value 0.5 corresponds to the observed lowest value in 2020 (i.e., shortly after declaration of the first state of emergency), and 2.0 was the observed highest value during consecutive public holidays in 2020 (i.e., consecutive autumn holidays in early November). When varying the mobility $m_{i,j,t}$ in equation (2), instead of using the observed mobility, we used values that were 0.5 and 2.0 times the empirically observed value. Second, the prevalence at origin was also varied. To create prevalence scenarios, we fitted an exponential growth model to the incidence and examined the daily growth rate of −0.016 and 0.012 to 0.020 per day. The rate −0.016 was the empirical estimate in November only in Tokyo, and 0.012 per day was the estimate from fitting the single exponential growth to the entire 3 months from October to December in Tokyo. The largest value (i.e., 0.020 per day) was obtained as the upper bound of the estimate in Osaka by fitting the model to data from October to December (Supplementary Figure S1). After computing the incidence, it was then converted to prevalence using equation (1).

Considering the fact that Tokyo was selectively excluded during the first Go To travel campaign, we examined potential scenarios in which only the mobility (or prevalence) from/in two mega-prefectures (Tokyo and Osaka) was varied. Alternatively, we explored the impact when either the mobility or the prevalence in all prefectures other than the destination was varied.

2.4. Data-sharing statement

The original epidemiological data analyzed in the present study are available in the Additional Data file. The mobility data are partly publicly shared by the Cabinet Office of Japan [38].

3. Results

Figure 1 compares the observed data against the estimated number of imported cases over time. Of the 47 prefectures, 24 publicly reported the number of infected cases with a history of movement crossing prefectural borders (referred to as imported cases) from May 1, 2020 to October 31, 2020. The estimates showed a large peak around August 2020, followed by a gradual increase through the end of October, which roughly captures the trend of the observed data. During this period, the cumulative number of imported cases ranged from 7 to 158 individuals, with a median of 33 and a mean of 47. Figure 1 shows comparisons in five prefectures (Tochigi, Gunma, Shizuoka, Mie, and Shiga), which are the five documented prefectures with the largest number of imported cases, with a cumulative count in these prefectures of 70 cases or more. The parameter k was independently estimated for each of the 24 prefectures, with a range from 0.037 to 0.362 and a mean value of 0.126.

Figure 2 shows the estimated number of imported cases in each prefecture, stratified according to four categories based on the characteristics of the place of origin (i.e., whether the origin of imported cases was Tokyo, Osaka, neighboring prefecture(s), or others). Figure 2 shows nine prefectures (Hokkaido, Miyagi, Kanagawa, Nagano, Shizuoka, Mie, Shiga, Fukuoka, and Okinawa) based on geographical characteristics, covering substantially different qualitative patterns. The results for all 47 prefectures are presented in Supplementary Figures S2–S7. According to the origin breakdown, Hokkaido (Japan's northernmost prefecture) and Okinawa (Japan's southernmost prefecture) had a large share of importations from Tokyo. Kanagawa and Hyogo prefectures neighbor the mega-prefectures of Tokyo and Osaka, respectively; thus, a substantial fraction of importations were from the neighboring mega-prefectures. Moreover, unlike Hokkaido and Okinawa, other prefectures were found to be influenced by neighboring prefectures.

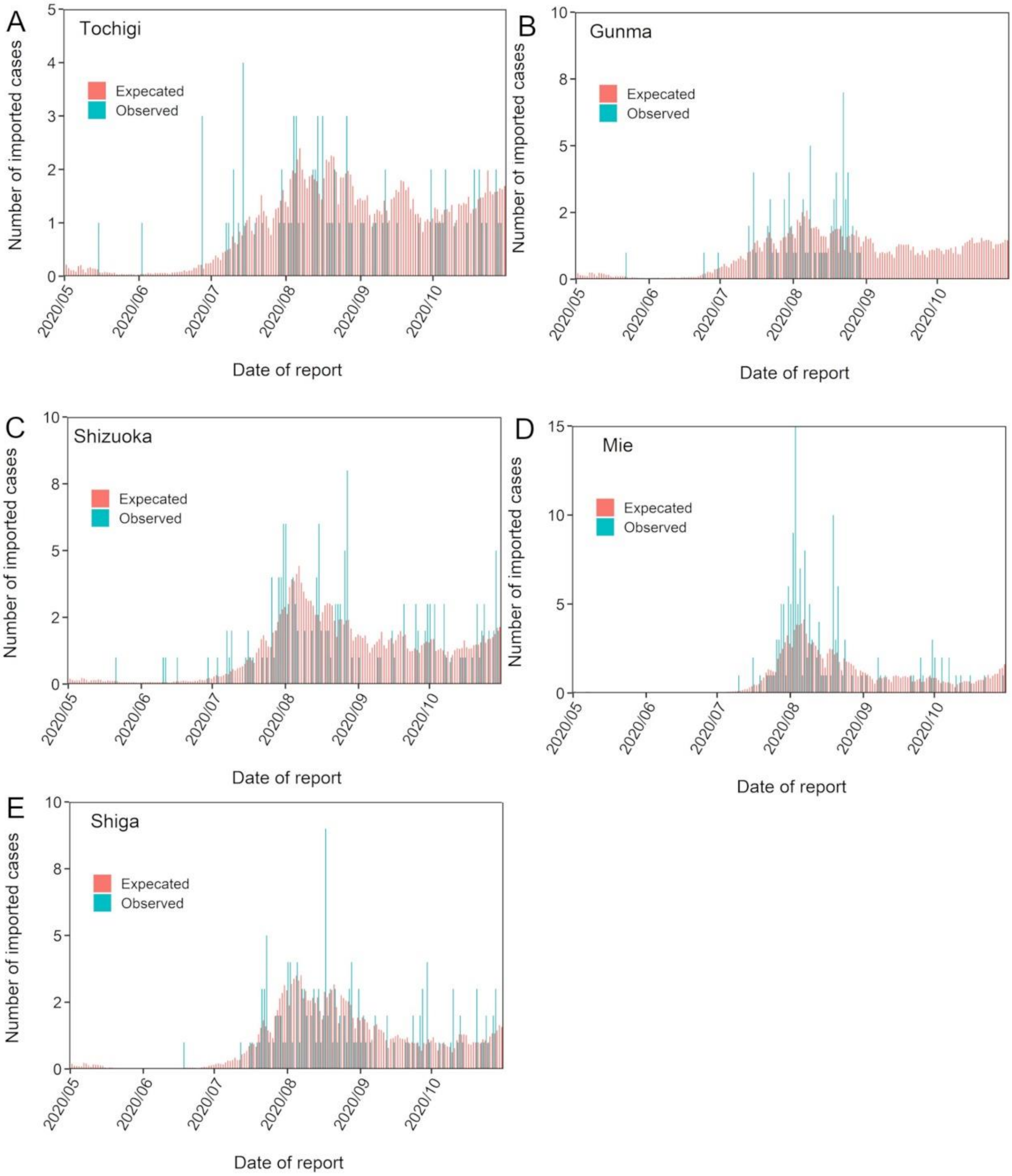

Figure 1. Observed and estimated number of imported cases. Observed (blue bar) and estimated numbers of imported (red bar) cases from May 1 to October 31, 2020 are shown. Five prefectures (Tochigi, Gunma, Shizuoka, Mie, and Shiga) with 70 or more infected cases are shown.

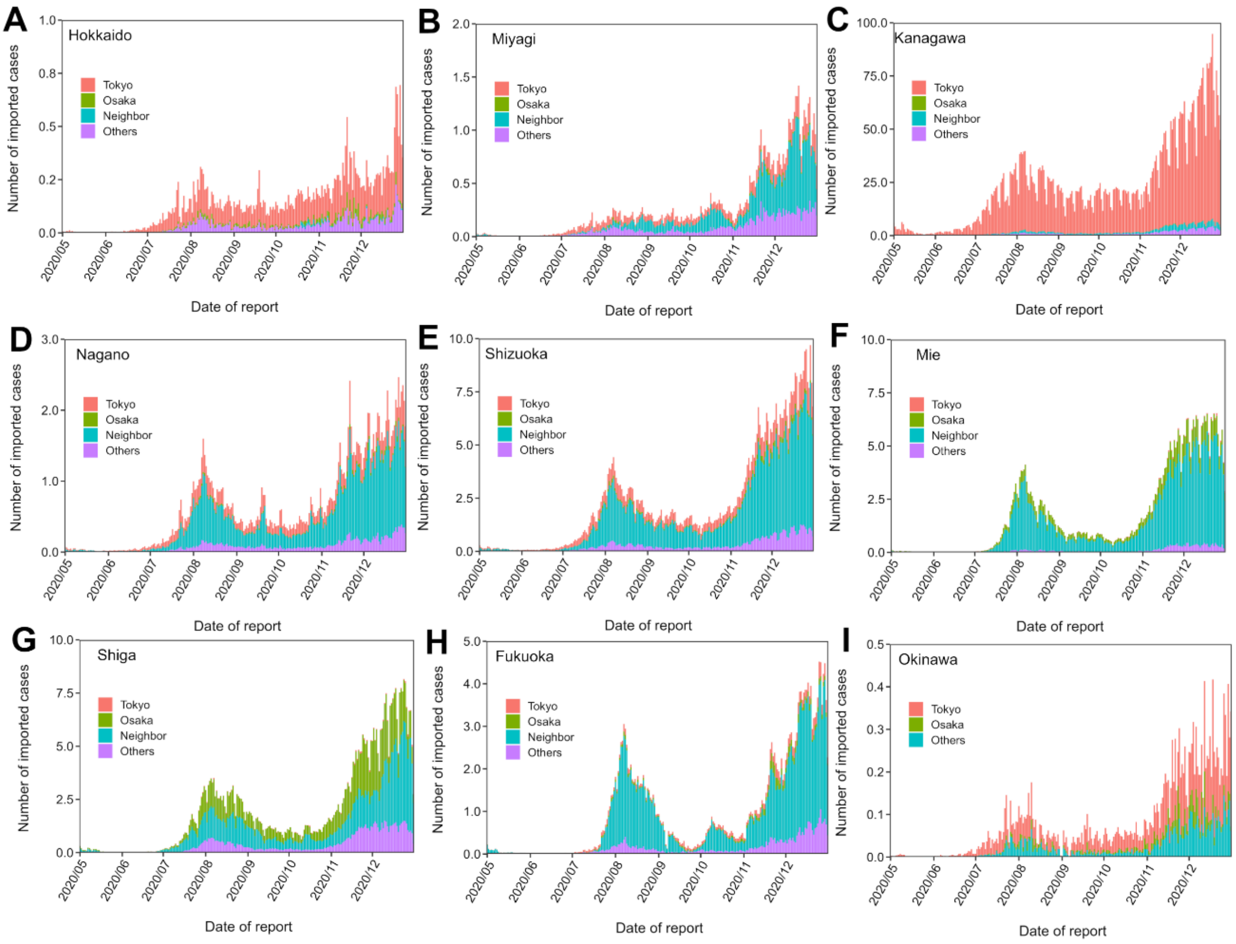

Figure 2. Estimated number of imported cases in nine selected prefectures. Estimates of the number of imported cases each day from May 1 to October 31, 2020 are shown. The daily estimates are divided into four groups according to characteristics of the originating prefecture: Tokyo (red), Osaka (green), neighboring prefectures (blue), and others (purple). Nine prefectures (Hokkaido, Miyagi, Kanagawa, Nagano, Shizuoka, Mie, Shiga, Fukuoka, and Okinawa) were specifically selected due to their different roles (e.g., urban/rural, next to mega-prefecture and distant touristic prefecture).

Figure 3 shows the estimated number of imported cases by varying the prevalence in Tokyo and Osaka. In Hokkaido, Kanagawa, and Okinawa prefectures, the number of imported cases sensitively varied according to the prevalence in the origin. In comparison, the impact of varying prevalence in mega-prefectures was minimal in Miyagi, Mie, and Fukuoka prefectures. In Hokkaido, Kanagawa, and Okinawa prefectures, the estimated number of imported cases was either flat or declined slowly over time, with a growth rate of −0.016. However, in the other prefectures, an upward trend was maintained even when the prevalence was declining in Tokyo and Osaka.

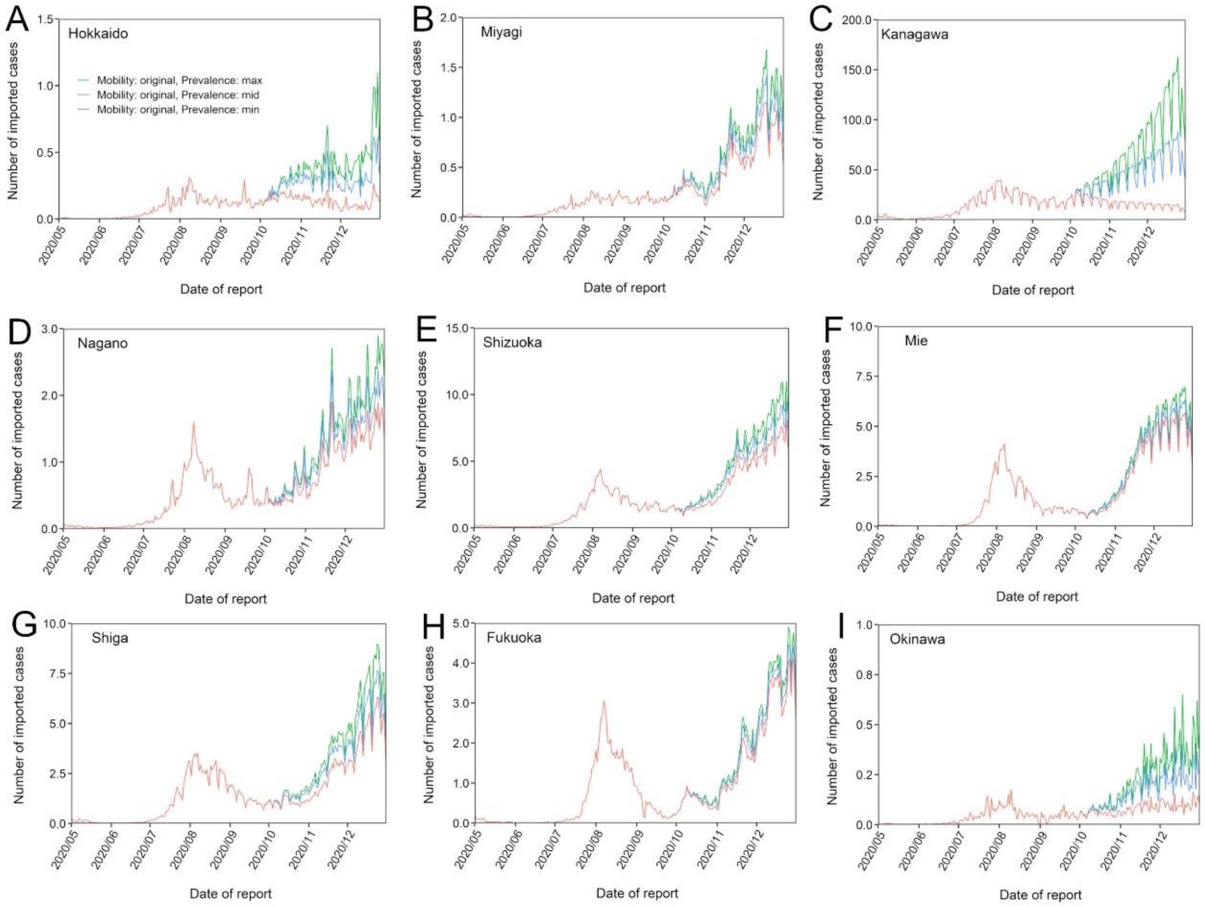

Figure 3. Estimated number of imported cases using different prevalence scenarios. Estimates of the number of imported cases each day using different prevalence scenarios in Tokyo and Osaka are shown. The three prevalence scenarios from October 1, 2020 are calculated from growth rates set to −0.016 (red line), 0.012 (blue line), and 0.02 (green line), respectively. Nine prefectures (Hokkaido, Miyagi, Kanagawa, Nagano, Shizuoka, Mie, Shiga, Fukuoka, and Okinawa) were specifically selected due to their different roles (e.g., urban/rural, next to mega-prefecture and distant touristic prefecture).

Figure 4 shows the estimated number of imported cases by varying the mobility rate from Tokyo and Osaka prefectures to others. As previously seen, the temporal patterns of imported cases appeared to be sensitive to the mobility rate in Hokkaido, Kanagawa, and Okinawa. Even when the smallest mobility rate was used, the estimated values of imported cases showed an upward trend in all nine prefectures, as shown in the figure.

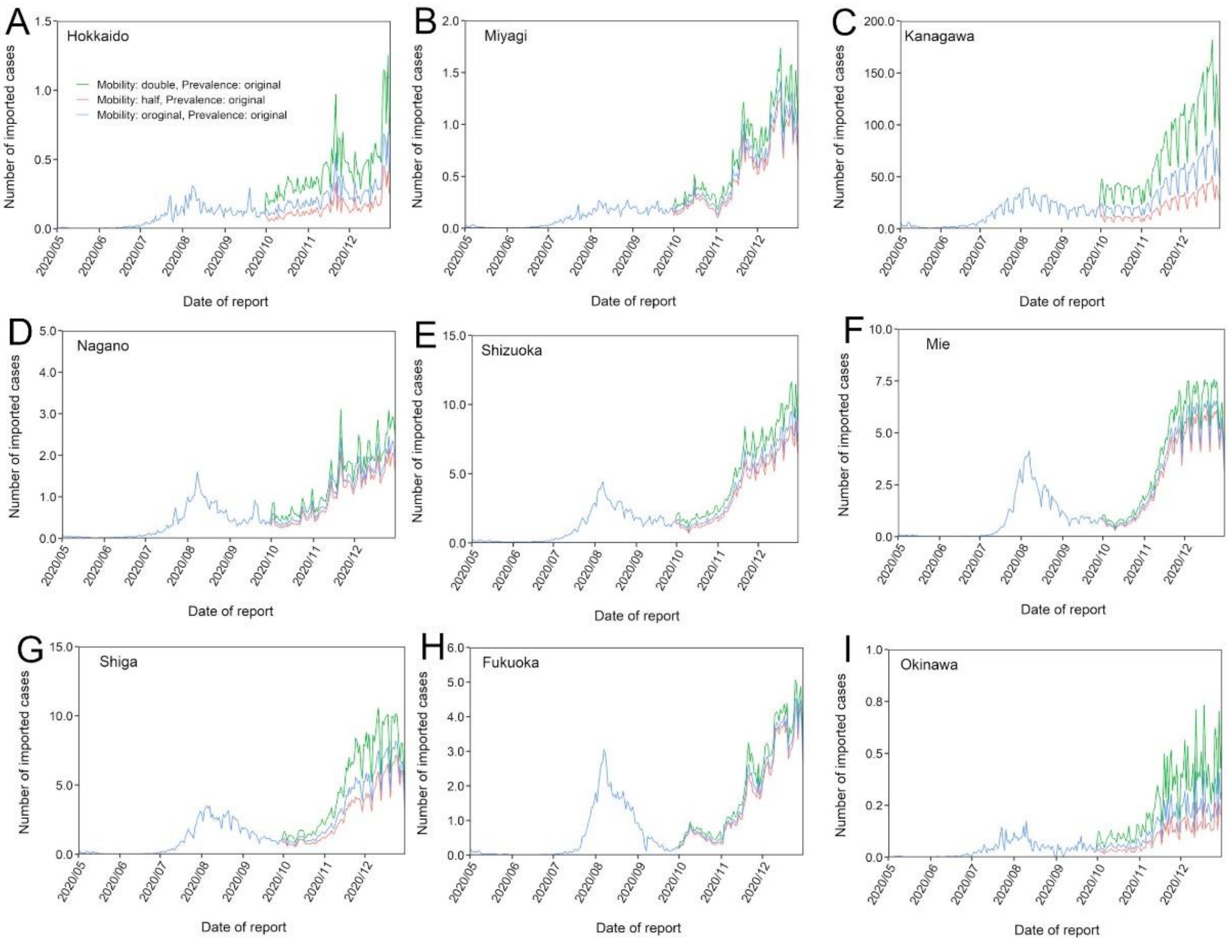

Figure 4. Estimated number of imported cases using different mobility from Tokyo and Osaka. Estimates of the number of imported cases each day using different mobility from Tokyo and Osaka are shown. The three mobility values used were the baseline (blue line), 0.5 times the baseline (red line), and 2.0 times the baseline (green line). Nine prefectures (Hokkaido, Miyagi, Kanagawa, Nagano, Shizuoka, Mie, Shiga, Fukuoka, and Okinawa) were specifically selected due to their different roles (e.g., urban/rural, next to mega-prefecture and distant touristic prefecture).

Figure 5 shows the estimated number of imported cases when the mobility rate from all prefectures was varied. Differences are evident in all prefectures, with either a flat or increasing trend, even in the low mobility scenario. The results when both the prevalence and the mobility were varied for all prefectures are shown in Supplementary Figure S8. In all prefectures (i.e., not limited to Hokkaido, Okinawa, and Kanagawa), the results were sensitive to either an increase or decrease in the mobility rate. Given that the mobility rate was half the actually observed mobility rate, the incidence did not exceed the peak of an earlier wave, even at the end of 2020 (i.e., the spatial spread and subsequent declaration of the state of emergency in January 2021 could possibly have been avoided or at least delayed).

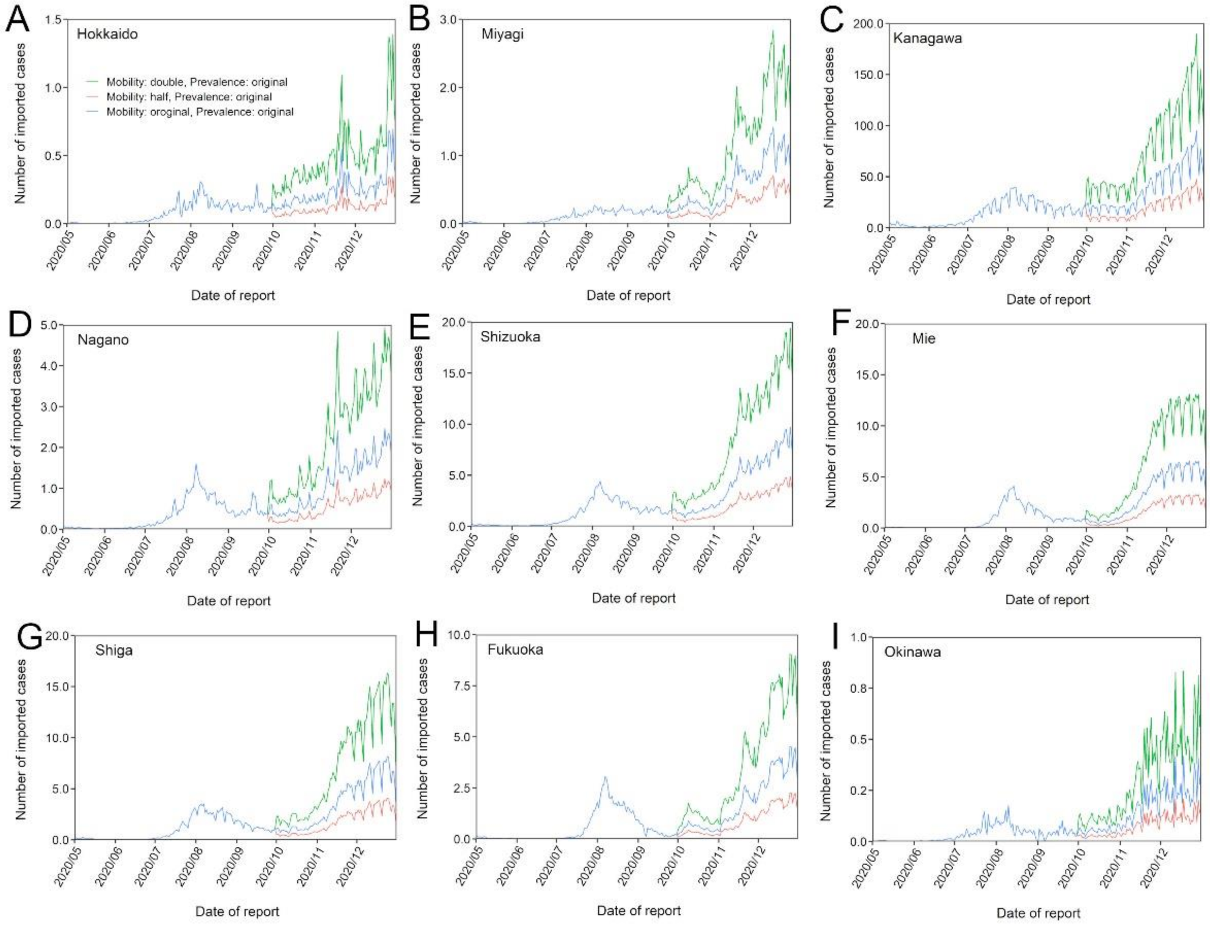

Figure 5. Estimated number of imported cases using different mobility assumptions from all prefectures. Estimates of the number of imported cases each day using different mobility from all prefectures are shown. The three mobility values used were the baseline (blue line), 0.5 times the baseline (red line), and 2.0 times the baseline (green line). Nine prefectures (Hokkaido, Miyagi, Kanagawa, Nagano, Shizuoka, Mie, Shiga, Fukuoka, and Okinawa) were specifically selected due to their different roles (e.g., urban/rural, next to mega-prefecture and distant touristic prefecture).

4. Discussion

In the present study, we predicted the number of imported cases crossing prefectural borders using the inter-prefectural mobility rate based on mobile phone data and prevalence estimates in the origin prefectures. By quantifying the simplistic model using surveillance data of cases with and without an inter-prefectural travel history, we carried out simulations to understand how imported cases vary with the mobility rate and prevalence in the origin. Although the empirical data were somewhat sparse, the predicted number of imported cases largely qualitatively captured the observed number of imported cases over time, and simulations successfully identified the differing strength of inter-prefectural dependence. Although Hokkaido and Okinawa are the northernmost and the southernmost prefectures, respectively, they were sensitive to the differing prevalence in Tokyo and Osaka as well as the mobility rate. Moreover, other prefectures were sensitive to mobility change, assuming that the increment in the mobility rate was seen in all prefectures.

To the best of our knowledge, the present study was the first to capture the inter-prefectural spread of COVID-19 in Japan and to simulate various impacts of hypothetical changes in mobility and prevalence on the expected number of imported cases in Japan, using the empirically observed daily mobility rate and cases with a travel history. Verification of this was straightforward. The time period during the epidemic that we explored was late 2020, during which the Go To travel campaign took place. As expected, if the mobility rate increased with the subsidy program, and if the prevalence in the origin was in an upward trend, then the number of imported cases increased. The positive association between human mobility and inter-prefectural spread is consistent with the findings of a graphical modeling study [39]. If the mobility rates were maintained lower than the observed rate, then the number of imported cases could have been maintained at substantially lower levels than the observed number, thus potentially preventing unnecessary spatial spread of COVID-19.

Another key finding was that the sensitivity of imported cases to different mobilities and prevalences varied by prefecture. Hokkaido and Okinawa are known tourist spots in Japan and have greater weights for their connection with Tokyo and Osaka [40]. A large number of travelers from Tokyo and Osaka made Hokkaido and Okinawa vulnerable to importations of COVID-19, especially during the time period when epidemic activities were selectively high in only urban prefectures. The remaining prefectures were mainly influenced by neighboring prefectures. For instance, Kanagawa is next to Tokyo, and Hyogo is next to Osaka, and they share common temporal risks. In addition to mega-prefectures, prefectures with a high population density characterized the observed dependence (e.g., among prefectures in Figure 2, Mie is next to Aichi, which was the most influential). Unlike the Euclidian distance, the volume of travelers was shown to characterize the observed spatial spreading pattern.

The results obtained from our simulation indicate the need to account for the weight of an inter-prefectural mobility network when implementing countermeasures to restrict human movement. That is, given an ongoing epidemic in Tokyo, possible countermeasures in Hokkaido or Okinawa and elsewhere (e.g., Mie) would be different. Restricting the mobility rate from Tokyo is more influential to Hokkaido and Okinawa than to other prefectures. Thus, nationwide uniform restrictions unnecessarily interfere with the freedom of movement in other locations. Moreover, when importation of a single infected individual is anticipated, it is vital to consider how the impactful importation of the single case would be to each prefecture; for example, one importation during the containment phase versus in the midst of an epidemic wave can be completely different [15]. Such factors in the origin–destination pairs should be taken into account when deciding the type and strictness of movement restrictions [29].

This study had several limitations. First, data on the number of infected cases with a history of movement across the prefecture were only available for a limited period of time and in a limited number of prefectures. The parameter k was estimated using that data; the ascertainment bias could be considerably different across prefectures, which may be partly reflected in a variation in the estimate of k. We found that the predicted number of imported cases was well aligned with the observed number. Second, the parameter k was assumed to be time-invariant; however, the size of the epidemic in each prefecture could have affected testing capacity. Third, the statistical model used to estimate the number of imported cases included prevalence, mobility, and the parameter k, which do not take other key epidemiological factors into account. For instance, we were unable to use age in the model, and if a certain type of mobility is dominated by younger (or older) people, our model could yield biased estimates. Moreover, social heterogeneity was not taken into account. For instance, a certain fraction of businessmen constitutes the majority of long-distance travelers, and thus, their risk of infection may be higher than others who do not travel frequently. For that reason, we could have potentially underestimated the risk of importation, and to address that point, epidemiological characteristics of both travelers and mobile cases need to be investigated.

5. Conclusions

We calibrated a statistical model to describe the number of inter-prefectrually imported cases using the prevalence at the origin and the mobility between prefectures. When an epidemic is in an upward trend, the cross prefectural movement tended to result in inter-prefectural spread of COVID-19. Major tourist destinations were shown to be more sensitive to epidemic situations in Tokyo and Osaka compared to other prefectures.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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