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日本在COVID-19疫情期間自殺率增加的空間群聚特徵

Characterizing Spatial Clusters of Increase in Suicide Rate during COVID-19 Pandemic in Japan

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口試委員會審定書

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本論文係楊宇翔君（學號：R09228001）在國立臺灣大學地理環境資源學系、所完成之碩（博）士學位論文，於民國 111 年 07 月 28 日承下列考試委員審查通過及口試及格，特此證明。

口試委員：

溫在弘

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謝辭

我的碩士論文題目為「日本在 COVID-19 疫情期間自殺率增加的空間群聚特徵」是一個很沉重，但需要面對的議題。

自殺的資料，在分析數據時，只是一個欄位、一個表格，讓我得以計算空間統計與顯著性分析，繪製出各式各樣的主題地圖與分析，但每一個「自殺」案件的發生，都代表一個家庭的破碎，更何況當自殺增加是一個具有「空間群聚」的鄰近社會集體傾向的時候，代表這樣的悲劇，其不容忽視，需要挖掘、釐清以及正視。

首先，最要感謝的是我的指導教授，溫在弘教授，對於我的議題發想、學術提問、證辯思考、統計方法、程式撰寫均給予我充分的教導，也讓我對於地理學術有更寬廣更深刻的視野與認識。

接著，要感謝我的碩士論文的口試委員，臺大公共衛生學院健康行為與社會科學研究所的 張書森教授 以及 臺大地理系的 林楨家教授，對於我的碩士論文反覆地提供意見與相關文獻，讓我能在統計模型方法上精益求精，並且追蹤論文截稿前的最新參考文獻，特別感謝。

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最後，我想跟挺過 COVID-19 疫情的讀者說，恭喜我們存活過來，在精神上、經濟上、健康上都挺過人類的百年大疫，希望我們帶著這個不屈不饒的精神，往我們更遠的將來前進，共勉之。

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摘要

背景：在 COVID-19 全球流行期間，世界多數國家地區自殺率降低或維持不變，而日本是少數自殺率增加的地區。現有文獻大多討論自殺率改變的時間序列特徵，而討論疫情對於自殺率影響的空間群聚位置與特徵較為缺乏。

研究目的：本研究欲偵測因為重大影響社會的事件（COVID-19），短期間「自殺率的變化」的空間群聚及環境特徵。並與疫情期間「自殺率」的空間群聚位置與特徵比較，闡述偵測「變化量」的空間群聚的在疫情期間的角色。

方法：本研究關注於 2020 年 4 月至 2021 年 6 月，日本疫情爆發至疫苗施打之前的四波疫情，以日本作為研究區，市區町村作為空間單元，針對「自殺率」與「自殺率的改變」兩者，偵測空間群聚。再利用多階層羅吉斯回歸模型捕捉熱區相對於冷區，分別找出可能的環境特徵，進行比較以及詮釋。

結果：自殺率增加的空間群聚與自殺率高的空間群聚，其位置與環境特徵均具差異。在位置上，自殺率增加傾向群聚於城市的邊緣，而高自殺率傾向群聚於鄉村與山區。在環境特徵上，前者群聚於 COVID-19 感染率高、人口密度高、獨居比例低的區域，而後者群聚於人口密度低的地方，且與 COVID-19 感染率無關。

詮釋：這項研究顯示了相較於偵測自殺率群聚，發生短期極端事件（疫情）時，偵測「自殺率改變」的空間群聚更能偵測到極端事件的影響。推測其能排除固有的地區環境因子，去偵測事件對於自殺率影響的空間群聚。

關鍵字：COVID-19、自殺、熱區偵測

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Abstract

Background: During the COVID-19 pandemic, Japan experienced an excess suicide rate compared to the pre-pandemic period, whereas most other countries experienced the opposite. Most studies have focused on the change in suicide rate in the timeline, but few have discussed the geographic variation in the impact of COVID-19 on the suicide rate.

Objectives: This study aimed to detect spatial clusters of increased suicide rates during an acute significant event (COVID-19 in Japan) and their environmental characteristics. Subsequently, the spatial clusters of high suicide rates were used as comparisons to interpret the role of detecting spatial clusters of increased suicide rates.

Methods: This study focused on four waves of virus outbreaks in Japan from April 2020 to June 2021, before the vaccine was implemented. This study considers non-isolated municipalities in Japan as the study area. After detecting the spatial clusters of increased suicide rates and high suicide rates, this study used multi-level logistic regression models to capture environmental characteristics.

Results: Spatial clusters of increased suicide rates differed from those of high suicide rates. In terms of location, increased suicide rates tend to be clustered on the fringes of urban areas, whereas high suicide rates tend to be clustered in rural areas. In terms of environmental characteristics, increased suicide rates tended to cluster in places with higher COVID-19 infection rates, higher population densities, and lower single-household ratios. However, spatial clusters with high suicide rates tend to occur in areas with lower population densities and are unrelated to COVID-19 infection rates.

Interpretation: This study shows that the detection of spatial clusters of "changes in suicide rates" during short-term extreme events (epidemics) might be more sensitive than the detection of clusters of suicide rates in detecting the impact of extreme events.

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This is because it can exclude inherent regional environmental factors and show geographic variation in the impact of events on suicide rates.

Keywords: COVID-19, suicide, hot spot detection

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Chapter 1 Exordium

1.1 Motivation

Significant geographic variations in the incidence of suicide within the nations all over the world have been reported (Chang et al., 2011). That is, suicide rates vary between regions and local features within the same country (Gunnell et al., 2012). Mapping the spatial pattern of suicide rate on a fine scale is useful because it helps detect the regions that need special care for suicide prevention intervention. Moreover, further investigation of the socioeconomic characteristics of the regions with serious suicide problems might help authorities to clarify the nature of the social environment in which people in high-risk suicide regions live and speculate the possible mechanisms of suicide in the social context. In summary, geographic patterning techniques are useful and crucial for suicide prevention interventions.

Spatial clustering is a common and useful tool for detecting geographic variation in suicide seriousness. It manifests where high suicide rates occur together, and where low suicide rates occur together geographically. After cluster detection, characterizing the local environment for suicide clusters is important to understand the suicide problem more comprehensively. Based on Durkheim's theories of social integration(Durkheim, 1951), suicide can be largely explained by the social environment. Among the many aspects of the social environment, social fragmentation and resource deprivation are the most discussed mechanisms for suicide in geographic clusters. Social fragmentation includes rurality, access to facilities and services, single household ratio, divorce rate and so on (Chang et al., 2011; Stark, Hopkins, Gibbs, Belbin, & Hay, 2007). Resource deprivation includes poverty level, education level, income, socioeconomic status, unemployment and so on (Agerbo, Sterne, & Gunnell, 2007; Ando & Furuichi, 2021; Santana, Costa, Cardoso, Loureiro, & Ferrão, 2015).

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Despite the well-developed results of suicide geography research, the impact of the COVID-19 pandemic on suicide rates remains obscure. COVID-19 is an acute infectious disease which has caused many casualties and also change people's lifestyle drastically in order to control the infection (P. J. Chen, Pusica, Sohaei, Prassas, & Diamandis, 2021).

At the beginning of the COVID-19 pandemic, several studies proposed that concerns of mental health, such as anxiety and fear of infection, loneliness during lockdown and quarantine, economic shock, and family problems during stay-at-home time might be potential risk factors for elevated suicide rate (Ando & Furuichi, 2021, 2022a, 2022b; P. J. Chen et al., 2021; Kumar & Nayar, 2021; Tanaka & Okamoto, 2021a). However, in evidence-based research (Pirkis et al., 2021), most studied regions or nations have reported unchanged or even decreased suicide rates during the COVID-19 pandemic. Among these, Japan stands out as a rare exclusion.

Japan has reported an increase in the suicide rate after an initial decline during the COVID-19 pandemic (Tanaka & Okamoto, 2021b), which differs from most other countries (Pirkis et al., 2021). Hence, there has been several research discussing the increased suicide rate during COVID-19 pandemic in Japan (Osaki et al., 2021; Sakamoto, Ishikane, Ghaznavi, & Ueda, 2021; Tanaka & Okamoto, 2021b; Watanabe & Tanaka, 2022). However, most studies have focused on the changes in time trends. There is little literature discussing the geography of COVID-19 impact on suicide rates.

Using data gathered from the Ministry of Health, Labour and Welfare, Japan, I first show the time series of suicide counts for the entire nation in Japan from 2016 to 2019 (see Figure 1). As we can see in the trend in Japan, suicide decreased in the long term but rose suddenly in 2020, which is the beginning of the COVID-19 pandemic in Japan. A heatmap of the time series is shown in Figure 2. We can see that the suicide count peaked in October 2020, which is in the 2nd wave of COVID-19 in Japan. This sudden change in

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time series during the COVID-19 pandemic makes me examine more about the places that might be most damaged during COVID-19 in terms of pandemic-induced mental risk from a geographical perspective.

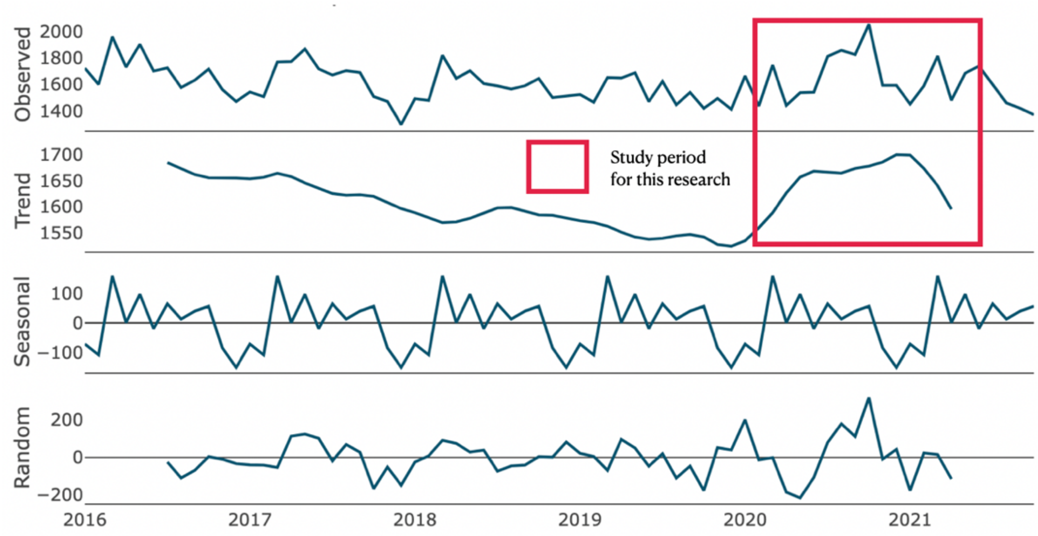

Figure 1 Time-series analysis of suicide count in Japan from Jan. 2016 to Oct. 2021.

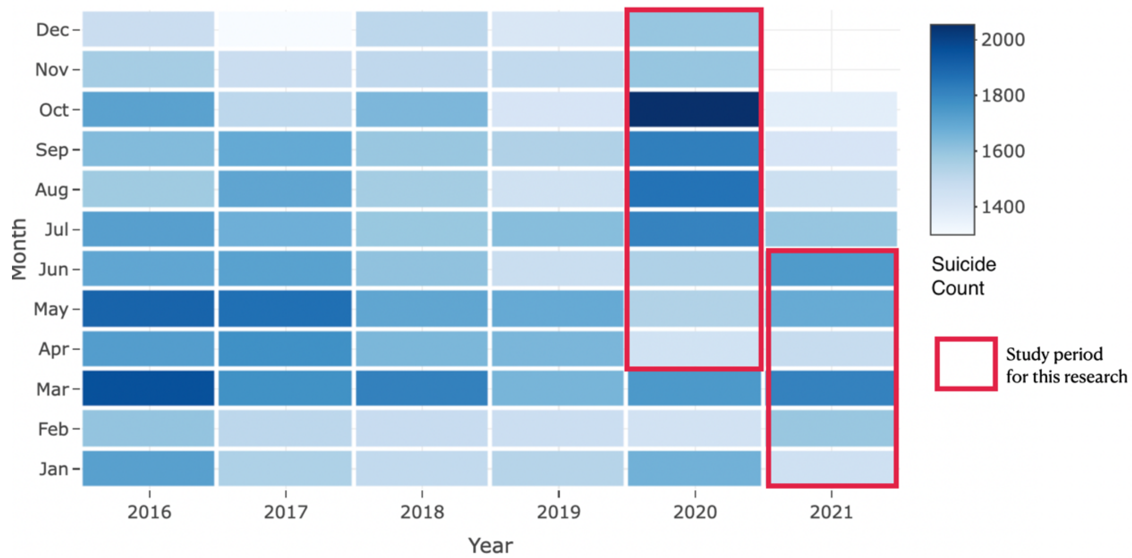

Figure 2 Time-series Heatmap of suicide count in Japan from Jan. 2016 to Oct. 2021.

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1.2 Research Objectives

Detecting the spatial cluster of suicide rates helps to identify where suicide problems are more serious geographically. This tool was used extensively before the COVID-19 pandemic. However, during an acute significant event (here, the COVID-19 pandemic), detecting the cluster of suicide rate might not reflect the impact of the event(COVID-19) on the suicide rate. In other words, the detected clusters may also be affected by inherent social environmental factors. However, by detecting the cluster of change in suicide rate, that is, the places where suicide rate increased together geographically during the event, we can extract the effect of the event (COVID-19) on suicide rate from the inherent social environment. Thus, detecting spatial clusters of suicide rates and ones of changes in suicide rates might have different results. However, this difference has not yet been discussed.

Based on this research gap, the main research objectives are to show whether it is more useful to detect the spatial cluster of change in suicide rates compared to detecting the spatial cluster of suicide rates when acute significant events, such as the COVID-19 pandemic, occur. For this, I propose three minor research objectives: First, we detect the spatial clusters of change in suicide rate ($\Delta Rate$) and suicide rate ($Rate$), respectively. Second, we characterize the spatial clusters of these two types. Third, we discuss the different discoveries and possible mechanisms between these two types of spatial clusters.

1.3 Research Hypotheses

Two hypotheses were formulated based on the proposed research objectives. To address the first research objective, Hypothesis 1 is proposed. Hypothesis 2 is proposed to address the second research objective.

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Hypothesis 1: The location of spatial clusters of change in the suicide rate differs from that of the suicide rate.

Before the COVID-19 pandemic, rurality (e.g., mountain Tohoku, south Kyusyu region) was reported as a long-term significant suicide risk factor in Japan (Yoshioka, Hanley, Sato, & Saijo, 2021). However, COVID-19 started spreading from urban areas in Japan, such as Tokyo, Yokohama, and Sapporo (Matsumoto, Motomura, Fukuyama, Shiroyama, & Okada, 2021), hence the effect on suicide rates might have been more serious in urban areas. Considering the inherent social environments, especially in rural areas, for suicide rate and COVID-19 effect, especially in urban areas for change in suicide rate, the locations of spatial clusters of change in suicide rate might differ from the spatial clusters of suicide rate.

Hypothesis 2: Environmental factors of change in suicide rate clusters differ from those of suicide rate clusters.

Before the COVID-19 pandemic in Japan, low education-level ratio, single-household ratio, low income, and rurality (low population density) were reported as long-term social environmental factors for suicide hotspots (Yoshioka et al., 2021). However, during the acute significant event (the COVID-19 pandemic), urban areas were the most infected. Moreover, there has been reported record-breaking increased domestic violence (indicate non-single household) during COVID-19 pandemic in Japan (Tanaka & Okamoto, 2021b; Watanabe & Tanaka, 2022). Considering the special situation during COVID-19, the environmental characteristics of changes in the suicide rate cluster might differ from the inherent environmental characteristics of the suicide rate. In my research, I selected population density, single household ratio, income, accessibility to the hospital,

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and COVID-19 infection rate with their interactions to characterize the spatial clusters. The reasons for selecting these variables is described in Chapter 3.

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Chapter 2 Literature Review

Chapter 2 presents three major sections. The first section describes the relationship between the epidemic and suicide ratein the history. The second section is the relation between COVID-19 and suicide in most regions and countries. The third section focus on the relationship between COVID-19 and suicide in Japan, where increased suicide rates have been reported as a relatively rare case study.

2.1 Epidemic and Suicide

When we retrospectively examined how epidemics in the history influenced suicide rates, several events were documented. From Russian flues in 1893 in the U.K. (Honigsbaum, 2010), Spanish flu in 1918 in the U.S.A. (I. M. Wasserman, 1992), SARS in 2003 in Hongkong(Chan, Chiu, Lam, Leung, & Conwell, 2006; Cheung, Chau, & Yip, 2008; Yip, Cheung, Chau, & Law, 2010) and Taiwan(Chang et al., 2022; Huang et al., 2005), and Ebola virus in Africa in 2016(Keita et al., 2017), it has been reported that the suicide rate increased during the epidemic (Zortea et al., 2020) (see Table 1). However, for COVID-19 from 2019 to 2021 and continuing, it caused infection or death, and also great social and lifestyle changes (John et al., 2021). Accordingly, the impact of COVID-19 on suicide is more complicated (John et al., 2021; Mres et al., 2021; Zortea et al., 2020).

Table 1 Epidemic and Suicide Rate Change

Time	Epidemics	Place	Change	Reference
1889-1893	Russian influenza	the U.K.	Increase	(Honigsbaum, 2010)
1918-1920	Spanish Flu	the U.S.A.	Increase	(I. M. Wasserman, 1992)
2003	SARS	Hongkong	Increase	(Chan et al., 2006; Cheung et al., 2008; Yip et al., 2010)

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2003	SARS	Taiwan	Unchanged	(Chang et al., 2022; Huang et al., 2005)
2016	Ebola	Conakry (Guinea)	Increase	(Keita et al., 2017)
2020-2022 (ongoing)	COVID-19	World Pandemic	Varied	(John et al., 2021; Mres et al., 2021; Zortea et al., 2020)

2.2 COVID-19 and Suicide

At the beginning of the virus outbreak, several studies proposed possible impacts of the COVID-19 outbreak on mental health. Firstly, some may feel anxious and fearful of getting infected by COVID-19 for themselves or their family and friends, even scared of being killed by the infectious disease, which may lead to excessive mental stress and increase suicide risk (Isumi, Doi, Yamaoka, Takahashi, & Fujiwara, 2020; Zortea et al., 2020). Moreover, during the community lockdown, loneliness caused by social distancing may lead to an elevated risk of suicide. Meanwhile, spending an unusually long time with the family may also lead to intense family relationships or domestic violence (Zortea et al., 2020). Third, poverty and financial insecurity might also be a factor in unhealthy mental conditions, especially during the COVID-19 pandemic, because people might have difficulty earning money to sustain their normal life during the lockdown periods (D. Wasserman, Iosue, Wuestefeld, & Carli, 2020).

In evidence-based research (Pirkis et al., 2021), changes in suicide rates have differed between nations during the COVID-19 pandemic. In the initial stage of COVID-19, from April 1 to July 1, 2020, the research suggests an unchanged or even dropped suicide rate in all investigated areas. However, when including suicide data until October 1, 2020, the study found a rise in suicide rate compared to the pre-pandemic normal situation in three regions: Japan, Puerto Rico, the U.S.A., and Vienna, Austria, while most

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of the other regions remained unchanged and dropped (see Table 2). Among the three studied exclusions, Japan was the only national-scale region, namely, the only country.

Despite the fact that Japan and South Korea are both relatively developed countries in Asia, research has only found an increase in the suicide rate in Japan but not in South Korea (Charlier, 2021). In addition, suicide decreased during the 1st year of the COVID-19 pandemic in Taiwan (Y.-Y. Chen, Yang, Pinkney, & Yip, 2022; Lin C-Y, Chang S-S, & L-J, 2021). Accordingly, Japan has provided a relatively rare case study in which the suicide rate increased during the COVID-19 pandemic.

Table 2 Cross-Country change in suicide rate meta analysis

Change	Initial pandemic stage	Extended to later stage pandemic
time	April 1 to July 31, 2020	April 1 to at least July 31, 2020 (with data included up to Oct 31, 2020, if available)
Decrease	New South Wales, Australia; Alberta, Canada; British Columbia, Canada; Chile; Leipzig, Germany; $\boxed{\text{Japan}}$; New Zealand; South Korea; California, USA; Illinois (Cook County), USA; Texas (four counties), USA; Ecuador	New South Wales, Australia; Victoria, Australia; Alberta, Canada; British Columbia, Canada; Chile; Thames Valley, the U.K.; Leipzig, Germany; New Zealand; South Korea; California, USA; Illinois (Cook County), USA; Texas (four counties), USA; Ecuador; Mexico City, Mexico;
Unchanged	Queensland, Australia; Victoria, Australia; Carinthia, Austria; Tyrol, Austria;	Queensland, Australia; Victoria, Australia; Carinthia, Austria; Manitoba, Canada;

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	Vienna, Austria; Manitoba, Canada; Croatia; Thames Valley, the U.K.; Estonia; Cologne and Leverkusen, Germany; Frankfurt, Germany; Udine and Pordenone, Italy; Netherlands; Poland; Las Palmas, Spain; Louisiana, the U.S.A; New Jersey, the U.S.A; Puerto Rico, the U.S.A; Botucatu, Brazil; Maceio, Brazil; Mexico City, Mexico; Peru; Saint Petersburg, Russia	Croatia; Estonia; Cologne and Leverkusen, Germany; Frankfurt, Germany; Udine and Pordenone, Italy; Netherlands; Las Palmas, Spain; Louisiana, the U.S.A; New Jersey, the U.S.A; Botucatu, Brazil; Maceio, Brazil; Peru; Saint Petersburg, Russia
Increased	-	Vienna, Austria; Japan; Puerto Rico, the U.S.A

Source: Country Names extracted by the statistic figures from (Pirkis et al., 2021)

2.3 Suicide in Japan during COVID-19

Suicide was a social problem in Japan before the COVID-19 pandemic, but even worse during the pandemic (Watanabe & Tanaka, 2022). Suicide mortality count during certain months in pandemic was even more than twice that of COVID-19 death count confirmed by PCR testing (Kurita, Sugawara, & Ohkusa, 2022).

During the COVID-19 pandemic, the suicide rate slightly dropped in the 1st wave of COVID-19 pandemic but rose largely in the 2nd wave of COVID-19 pandemic in Japan (Tanaka & Okamoto, 2021b). This phenomenon was especially significant in the younger

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and female groups. Most studies (Eguchi et al., 2021; Osaki et al., 2021; Sakamoto et al., 2021; Tanaka & Okamoto, 2021b; Watanabe & Tanaka, 2022) have provided rich results for changes in the suicide rate with respect to timeline change and more vulnerable groups. Nevertheless, the spatial patterns of the changes in suicide rates remain obscure.

Although some papers (Osaki et al., 2021; Tanaka & Okamoto, 2021b; Watanabe & Tanaka, 2022) mentioned the regional difference in the change in suicide rate during COVID-19, most of them view regional differences as non-spatial attributes. For example, the suicide rate has increased on the timeline from highly infected prefectures to zero infected prefectures (Osaki et al., 2021). In other words, most of the literature does not consider spatial contiguity or spatial neighboring properties, which are important elements when detecting geographic variation.

2.4 Potential mechanisms for increased suicide during COVID-19 in Japan

Japan was one of the few countries with increased suicide rate during COVID-19 pandemic (Pirkis et al., 2021), which means the mental health condition in Japan was specially adversely affected by COVID-19 pandemic than most of other countries.

There has been research (Rosyida, 2022) discussing why Japan experienced an increased suicide rate during COVID-19, while most other countries did not. In the context of modern Japanese culture, the value of similarity is overemphasized to maintain social harmony. That is, collective harmony sometimes surpasses individual interests, which might be a disadvantage characteristic of mental health. Moreover, in Japan, shame culture and social isolation from peers have been reported as control mechanisms for maintaining social cohesion. Hence, during the COVID-19 pandemic, Japanese people might have focused more on the collective prevention of infection rather than individual emotional needs. In addition to the unique Japanese cultural background, several potential mechanisms with operational environmental factors have been proposed in the literature.

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With regard to mental stress, elevated suicide mortality might be caused by the fact that people had fewer opportunities to meet their family members or neighbors due to the "stay home" announcement of the government, which might have induced prolonged social isolation, which is a risk factor for suicide. In addition, anxiety and fear of being infected by COVID-19 may also be risk factors for suicide.

Regarding family problems, the number of consultations for domestic violence reached a record high according to the police statistics database in Japan (Watanabe & Tanaka, 2022). This increase in domestic violence may be attributable to people refraining from leaving home to prevent the spread of COVID-19. The increased risk of domestic violence due to the stay-at-home public appeal (not compulsory in Japan due to the law) during the COVID-19 pandemic might also have contributed to excessive suicide mortality during the pandemic.

In terms of economics, the COVID-19 pandemic greatly shocked the labor markets and impacted mental health afterwards (Watanabe & Tanaka, 2022). Previous studies in Japan indicated that there were more lay-offs among contingent workers, young workers, women and workers engaged in non-flexible jobs (Kikuchi, Kitao, & Mikoshiba, 2021). In addition, long-term economic status might be a potential risk factor for elevated suicide rates during COVID-19 (Krumer-Nevo, 2021). Based on the literature review mentioned above, several social environmental factors were selected to characterize the spatial clusters of changes in suicide rates during the COVID-19 pandemic in Japan.

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Chapter 3 Methodology

3.1 Study Area

Japan is located in East–northern Asia and is mainly formed by four islands, HOKKAIDO, HONSHU, SHIKOKU, and KYUSHU (see Figure 3). On the four main islands, Japan is divided into eight regions, 47 prefectures, and 1,741 municipalities.

In this spatial-related analytic research, I investigated the change in suicide rate at the municipal level and discussed the spatial pattern of change in suicide rate across all regions without island municipalities, which have no neighbor sharing the same boundary. Accordingly, 48 municipalities were excluded (see Supplementary Table 1). That is, the study area comprises 1,693 municipalities with at least one neighbor sharing the same border.

As for the most densely populated regions in Japan, there are three major metropolises: Tokyo (including Tokyo, Saitama, Chiba, Kanagawa), Osaka (including Hyogo, Kyoto, and Nara), and Aichi (Nagoya city). In addition to these three major metropolises, there are large urban areas, for example, Fukuoka prefecture in northern Kyushu, Sendai City in Miyagi prefecture western Tohoku, Naha City in southern island prefecture, Okinawa, and Sapporo City in Hokkaido (see Figure 4). The middle of each of the four major islands is a sparsely populated mountainous area (see Figure 5).

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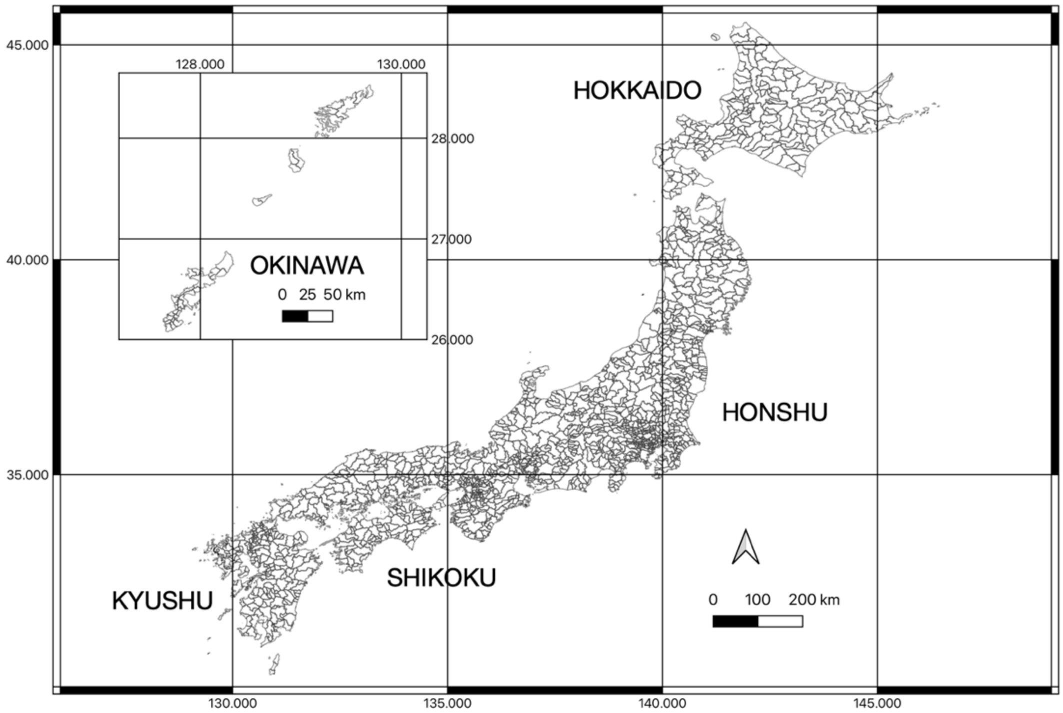

Figure 3 Study Area : Japan

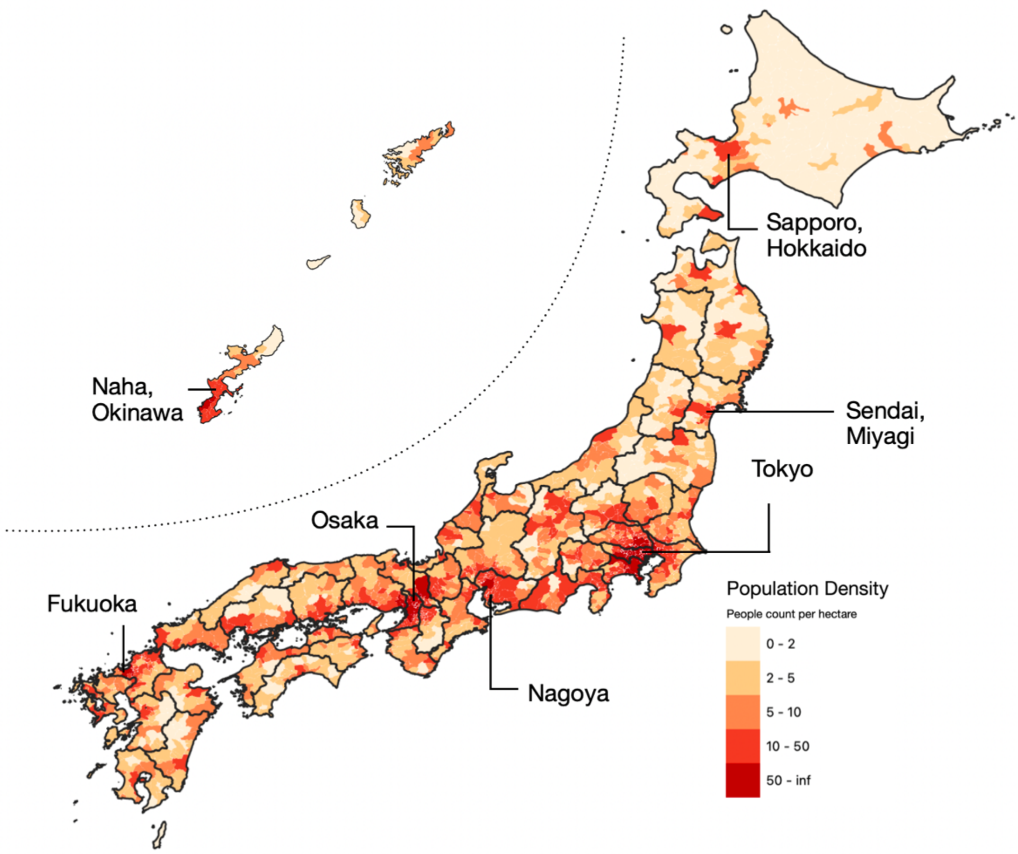

Figure 4 Population density choropleth of Japan in the municipality level.

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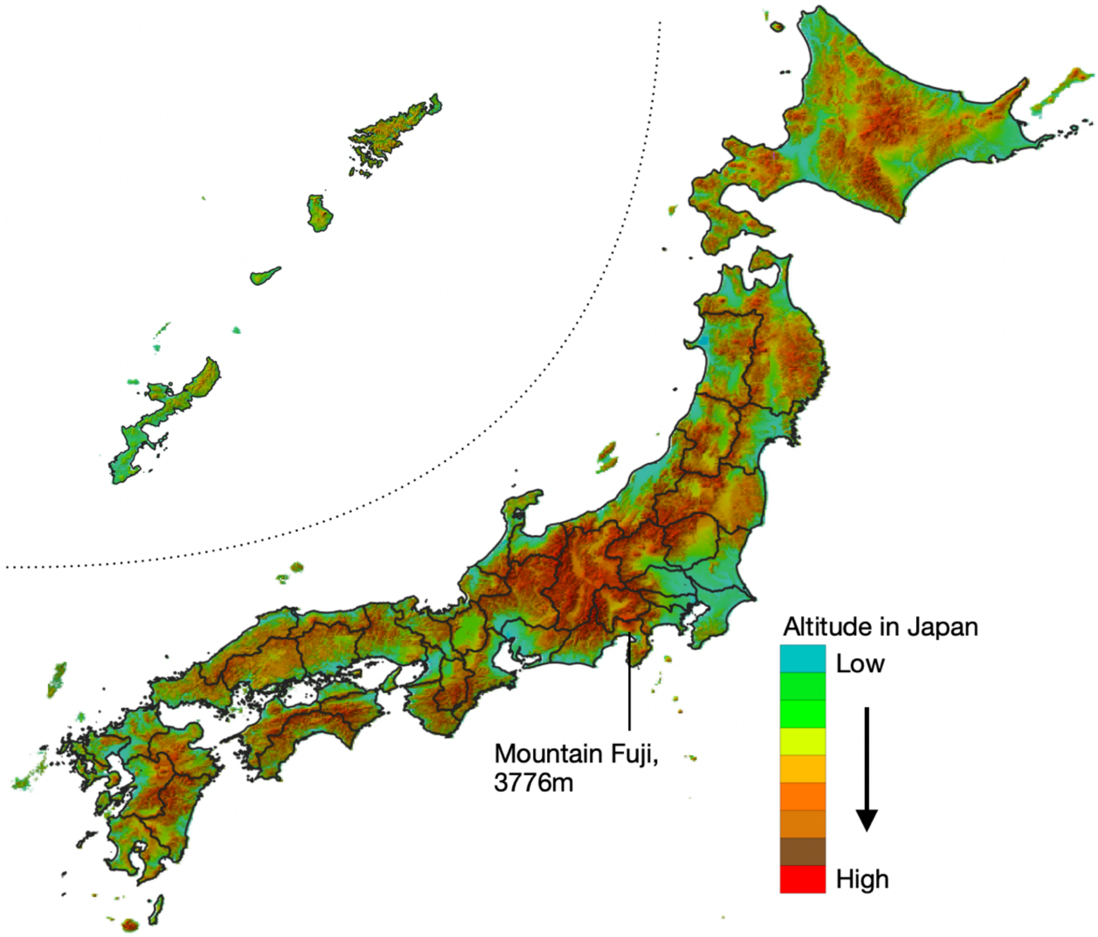

Figure 5 Topography Map of Japan.

3.3 Data

Suicide Data

Suicide data were obtained from official open data provided by the Ministry of Health, Labor and Welfare, Japan. Data were aggregated monthly and noted with sex, age group, family condition, occupation, suicide method, and suicide reason within administrative districts (municipality). This study extracts suicide data from April 2020 to July 2021 as COVID-19 pandemic time and uses suicide data from January 2016 to March 2020 as reference baseline to calculate the change in suicide rate.

Social Environment Data

All social-environment data were collected from the official database of the

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Japanese government. Population data for 2021 were obtained from the Statistics Bureau of Japan for all population adjustments. The COVID-19 infection rate (infection cases per ten thousand people) was calculated from the infection count data from the Ministry of Health, Labour and Welfare, Japan. Population density (people per hectare) was calculated using data from the Statistics Bureau of Japan. Hospital density (hospital count per ten thousand people) was calculated using 2019 data from the Statistics Bureau of Japan. Income based on tax records (thousand Japanese dollars) were calculated using the 2019 data from the Statistics Bureau of Japan. The single household ratio (single household/total household count) was calculated using 2019 data from the Statistics Bureau of Japan.

Suicide and COVID-19 infection data in Japan are provided on a monthly and daily basis, respectively. Whereas, population density, income, hospital density, and single household ratio are timely fixed for a certain year.

3.3 Research Design

To fulfill the research objectives and verify the research hypotheses, three major parts were set in the research design. The first part calculated the suicide rate and the change in suicide rate for each spatial unit (municipality) during COVID-19 in Japan. The second part calculated spatial clusters using Getis-Ord Gi star statistics for both the suicide rate and the change in suicide rate. The third part investigates the potential social environmental factors for both the suicide rate and the change in suicide rate.

The detailed workflow is as follows: For the first part, to investigate the spatial pattern of both suicide rate and change in suicide rate during the COVID-19 pandemic, I calculated both suicide rate and change in suicide count compared to the pre-pandemic time. Because it has been reported that each wave of the COVID-19 outbreak in Japan possesses different characteristics, this research investigated the spatial clusters and their local correlates in each wave of the virus outbreak in Japan.

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For the second part, I used Getis-Ord Gi* statistics to detect hotspots or cold spots for suicide rate and change in suicide in each wave of the virus outbreak.

For the third part, hot spots and cold spot areas were selected as dependent variables in multilevel logistic regression models to investigate local correlates. A flowchart of the research design is shown in Figure 6.

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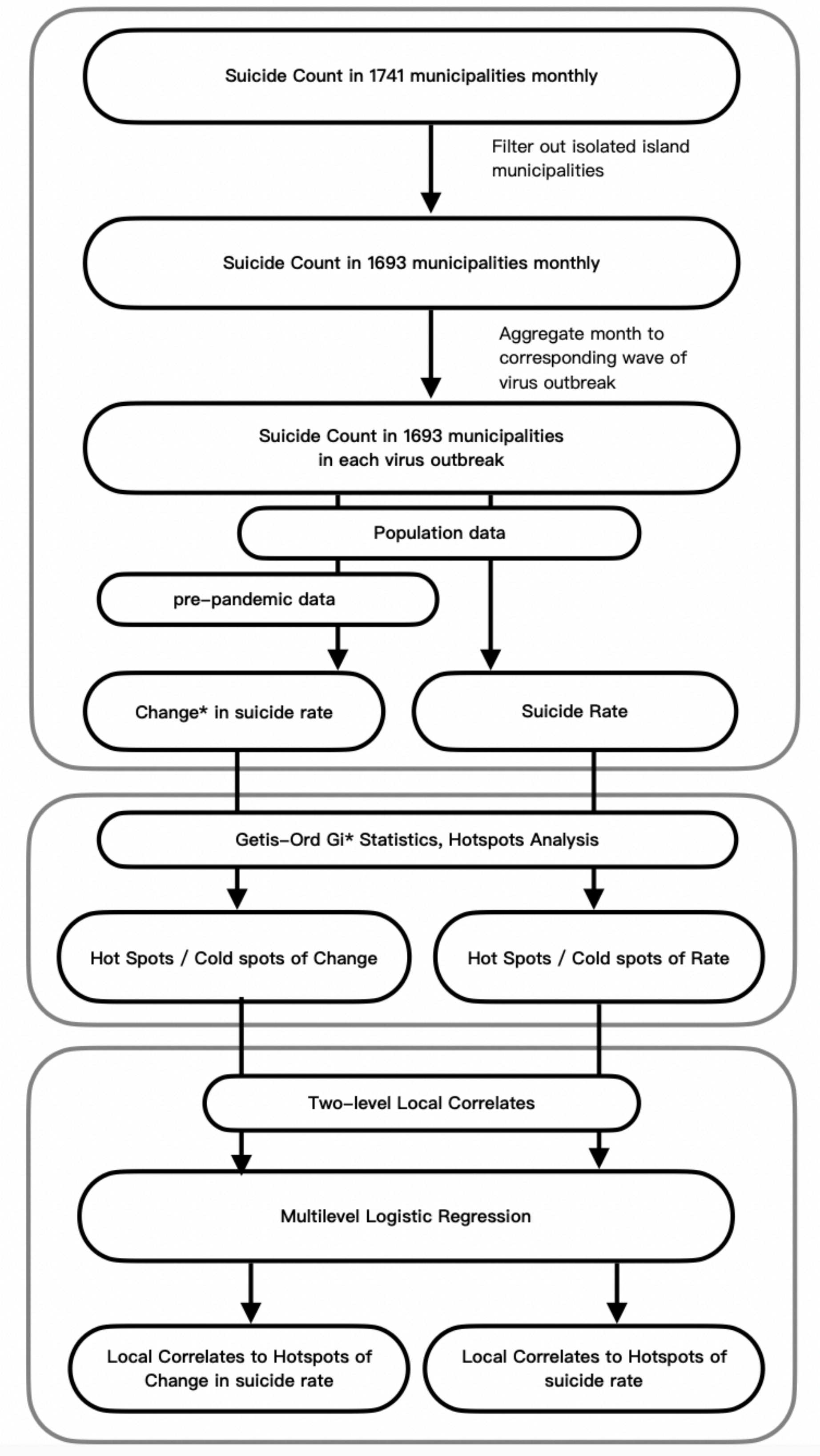

Figure 6 Research Flow. Change in suicide rate refers to the change in suicide rate in each wave of COVID-19 outbreak compared to the pre-pandemic times.

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3.3.1 Setting Study period

The study period was from April 2020 to June 2020; total of 14 months. The Japanese government formally began to implement vaccinations for normal citizens of all ages in late June 2021. Moreover, the Japanese government hosted the Olympics Games in Tokyo and Hokkaido, which started from late July to early August, with plenty of preparation and promotion work beforehand along with protests and demonstrations from citizens. Due to the implementation of vaccination and the host of international sporting events, the COVID-19 effect on suicide might not be easily captured. Hence, this research only included the pandemic time in the first four waves of the virus outbreak, before July 2021, to focus on the change in suicide rate during an acute significant event (COVID-19 pandemic).

This research divided the study periods into waves because different directions of change in suicide rates have been reported in different waves of the virus outbreak (Tanaka & Okamoto, 2021b). Hence, when investigating the spatial cluster of change in suicide rate and suicide rate, it seems more reasonable to investigate different waves of virus outbreak instead of viewing the whole pandemic as an entity.

Based on the literature (Sakamoto et al., 2021), this research used April 2020 as the beginning of the study period, with January, February and March, 2020 as the reference months for adjusting the change in suicide rate. Thus, the 1st wave is from April 2020 to May 2020, the 2nd wave is from June 2020 to September 2020, the 3rd wave is from October 2020 to February 2021, and the 4th wave is from March 2021 to June 2021 (see Figure 7).

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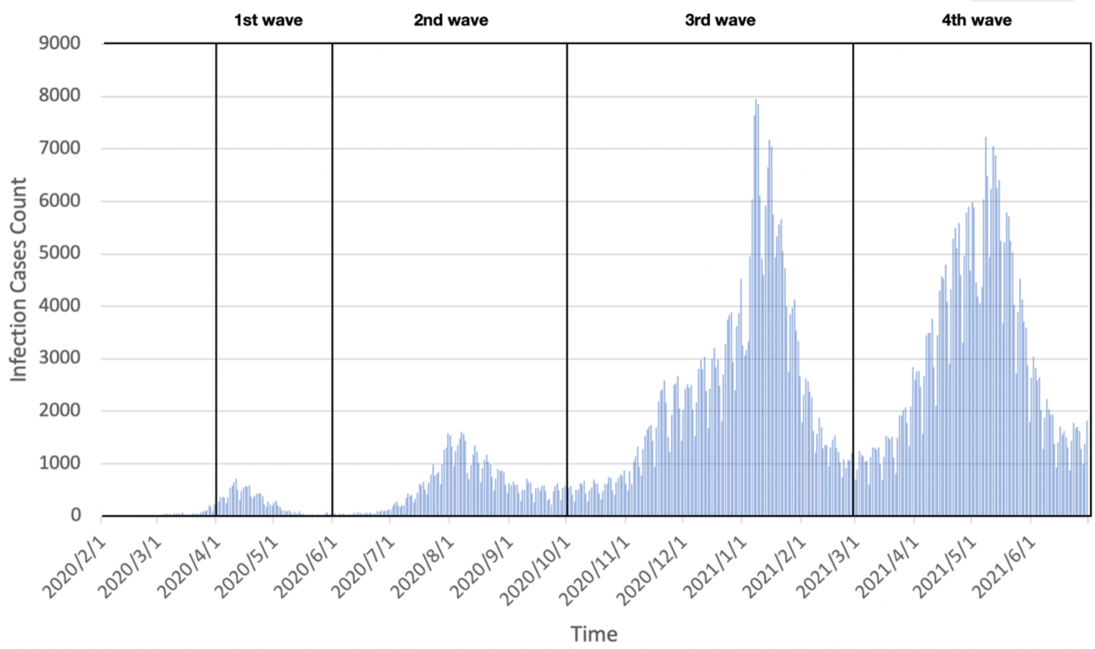

Figure 7 Research period: 4 waves of COVID-19 pandemic in Japan

3.3.2 Suicide mortality rate

The data available are the monthly mortality counts in each municipality. To consider the difference in population size, I calculated the suicide mortality rate (also called the suicide rate in this study). The calculation divides the number of suicides in each municipality by the population. The suicide rate has also been used as an index in the literatures (Tanaka & Okamoto, 2021a; Ueda, Nordström, & Matsubayashi, 2021).

3.3.3 Change in suicide mortality rate

When estimating the effect of COVID-19 on suicide rates, the challenge appears due to the long-term suicide trend and its seasonality (Tanaka & Okamoto, 2021b). These properties might affect the spatial patterning of the change in suicide rate. For example, on average, the suicide rate has declined by about six percent from 2017 to 2019 and even declined by about 25 percent from 2013 to 2019 (Tanaka & Okamoto, 2021a). In addition, before the pandemic, average suicide exits seasonal differences, such as school time and vacation time difference (Isumi et al., 2020). These trends suggest that study design based on the before–after comparison could be problematic;

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if we compare the suicide levels before and during the COVID-19 outbreak, the estimates might capture the seasonal trend. However, if we compare the suicide level relative to past years in the same season, the estimate might be confounded by a long-term ascending or descending trend.

To overcome the two problems mentioned above, I calculated the change in the suicide rate as follows: Consider the calculation of the 1st wave outbreak as an example. First, I compared the difference in suicide rates before (January 2020 to March 2020) and during the COVID-19 outbreak (April 2020 to June 2021) with the difference in the corresponding period in the previous three years (January 2016 to June 2019). Since the model focuses on the relative difference before and during the sudden pandemic within a year, the overall suicide level across years, which is the long-term suicide trend and seasonality, was eliminated. After calculating the change in suicide rate in each municipality for each month during the COVID-19 pandemic, I calculated the mean change in each wave. The process of calculating the change in the suicide rate in each municipal-level spatial unit is illustrated in Figure 8.

With this method, there should be a parallel hypothesis for a change in the suicide rate in the scenario of no COVID-19. The assumption that the change quantity estimator is valid is that the pandemic period (April to June) in 2020 and the same period in 2016–2019 would have parallel trends in suicide rates in the absence of the pandemic. If this assumption is not satisfied, the estimated parameter would be biased because the results could be driven by systematic differences between the treatment and control groups rather than the event of interest.

According to the literature, the parallel assumption has been verified (Tanaka & Okamoto, 2021b) in the national timeline trend in Japan. Hence, when calculating the change in suicide rate in each spatial unit (municipality), I used a verified parallel assumption of national trends to calculate the change in suicide rate.

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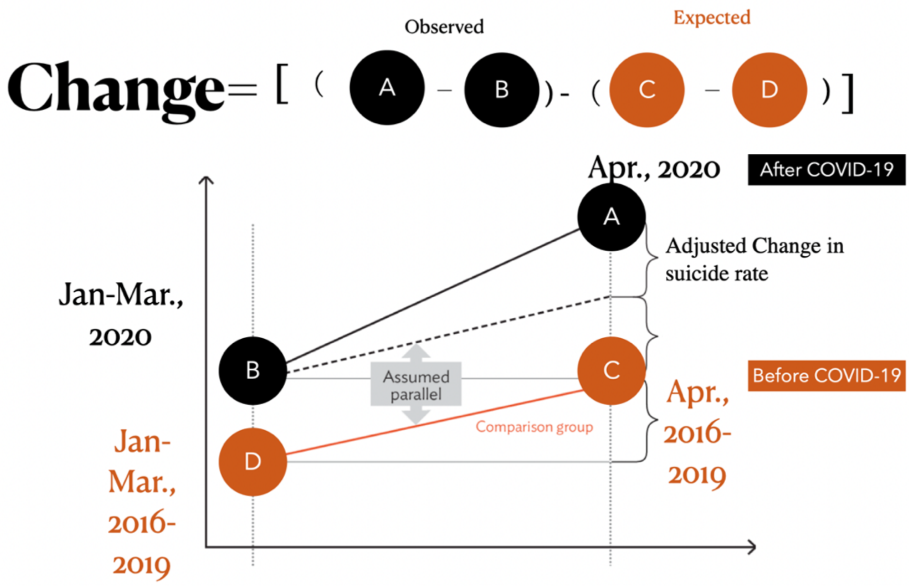

Figure 8 Illustration of the process of calculating the adjusted change in suicide rate in each municipal-level spatial unit

3.3.4 Difference Between Spatial Cluster of Rate and $\Delta Rate$

Most studies discussing the impact of COVID-19 on suicide rates have mainly focused on timeline changes. That is, little research has discussed the spatial pattern or spatial clusters of change in suicide rates during COVID-19. Accordingly, the spatial distribution or spatial cluster of changes in suicide rates after the COVID-19 outbreak is obscure. Detecting hotspots of change in suicide rates may provide insight into suicide prevention planning. By evaluating the positions of hotspots, we can understand which regions are the most vulnerable under the threat of COVID-19 and need special care regarding COVID-19 induced mental crises.

Although the spatial cluster of change in suicide rates during COVID-19 has been little discussed, there have been long-developed analysis methods discussing suicide clusters, especially for those in the long term (Gunnell et al., 2012; Santana et al., 2015; Yeom, 2021). Most of them focused on the relatively long-term (years and above) rather than short-term and acute effects, such as COVID-19. Accordingly, there might be a

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reason why we do not just look at the suicide rate cluster before and after the outbreak of COVID-19.

There might be a significant difference between the spatial clusters of "change in suicide rate" instead of "suicide rate" (see Figure 9). For the suicide rate cluster, there was no baseline for comparison (the hotspots may only explain the excessive area in the ONE period). Unable to capture the increase and decrease compared to pre-COVID-19 in each wave. Hence, the cluster might capture the region that was originally high with inherently structured reasoning, instead of COVID-19 reasoning.

However, for the cluster of change in suicide rate, the results were based on the values with a baseline for comparison (the hotspots may explain the excessive area in each period compared to pre-COVID-19). In other words, the cluster of change in suicide rate is more capable of reflecting the geographic pattern of how the suicide rate changes compared to the pre-pandemic period during the COVID-19 pandemic.

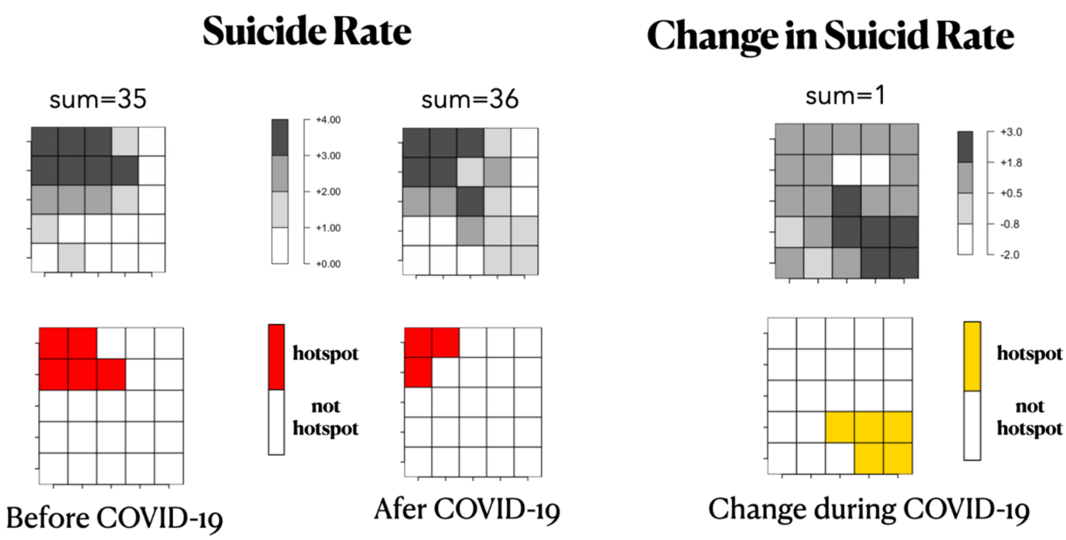

Figure 9 Illustrations of different meanings in the cluster of suicide rate and change in suicide rate.

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3.3.5 Getis-Ord Gi* Statistics for Hotspots Detection

Cluster detection is an important tool to explore a spatial distribution or geographical phenomenon. This research use Getis-Ord Gi* statistics as cluster detecting tools because it focused on the hotspots and colds pots, which correspond the questions this study proposed, the cluster of change (increase or decrease) in suicide rate.

Getis-Ord Gi* Statistics indicates whether features with high values or features with low values cluster in a specific area, by looking at each feature within the context of neighboring features. If a feature's value is high, and the values for all its neighboring features are also high, it is a statistically significant 'hot spot'. The local sum for a feature and its neighbors is compared proportionally to the sum of all features. When the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, a statistically significant z-score (p-value < 0.10 for this research in order to obtain sufficient data for modeling, making the z-score threshold equals ± 1.645) is the result. The equation for calculating the Gi* statistic is as follows:

$$Gi *= \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2]}{n-1}}}$$

Where x_j is the attribute value (value of suicide rate and change in suicide rate respectively for this research) for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n equals the total number of features, and :

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \overline{(X)}^2}$$

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The weights in this study is defined as Queen method, which is a kind of contiguity weights. Queen defines neighbors as spatial units sharing a common edge or a common vertex. The spatial weight is also used in the previous Japan geographical research for suicide-related research(Jiang, Stickley, & Ueda, 2021)

3.3.6 Multilevel Logistic Regression Model

To find the possible local correlates of hotspots of change in suicide rate with two-level (prefecture-level and municipal-level) variables, I use a multilevel logistic model as a statistical approach. Multilevel logistic regression aims to model the two levels and above nominal outcome variables, in which the log odds of the outcomes are modeled as a linear combination of the predictor variables.

In multilevel logistic models, for the dependent variable, cold spot areas were used as a reference to check the possible correlates of the hotspots. That is, the responsive variable is binary. The hotspots are equal to 1 and the cold spots are equal to 0. Non-spatially clustered or isolated areas (neighbourless isolated islands) were excluded from the models. Accordingly, the sample size of the data for each model varies based on the results of Getis-Ord Gi* spatial cluster detection.

For the dependent variable, I pick two-level variables of interest. The 1st level is a variable at the municipality level, including population density, income, living-alone ratio, and hospital density. In the 2nd level variables, I selected the COVID-19 infection rate at the prefecture scale as variables. With two-level variables, local characteristics may be found with a direct or indirect (interaction) effect (see Figure 10).

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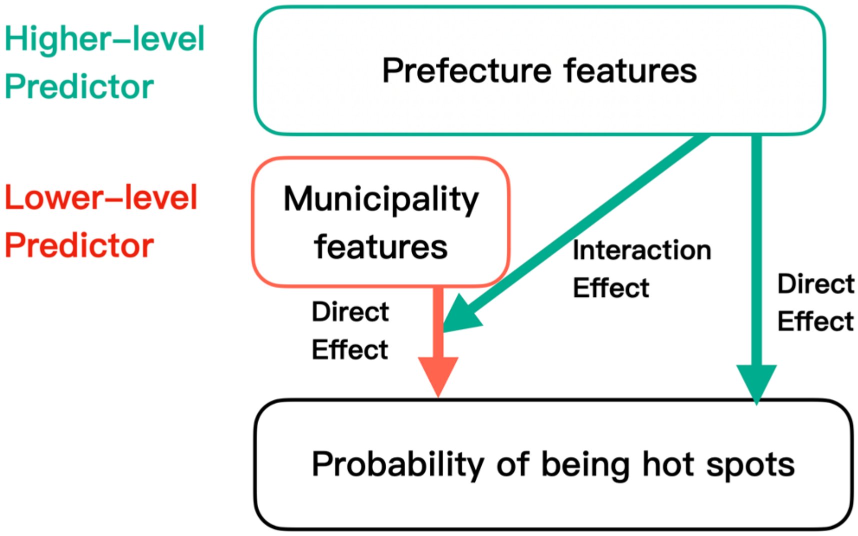

Figure 10 Illustration of multilevel logistic regression in this study

Models for clusters of suicide rates and clusters of change in suicide rates were conducted independently. Each model contains four waves. Hence, eight models were used. The effects of environmental factors on the position of hotspots were studied using a multilevel logistic regression model through the following steps:

Null model

I built an empty multilevel logistic regression model (null model) and calculated the intraclass correlation coefficient (ICC). The empty model can be described by the following equation:

Null model:

$$logit(p) = \ln\left(\frac{P(cluster = High - High)}{1 - P(cluster = High - High)}\right) = \ln\left(\frac{P(cluster = High - High)}{P(cluster = Low - Low)}\right)$$
$$= \gamma_{00} + u_{0\,j} + e_{ij}$$

where p is the probability of being a hot spot. Because the models only consider the spatially clustered areas, 1-p is the probability of not-being hot spots but also means the probability of being cold spots. In other words, $\frac{p}{1-p}$ is the odds of being hot spots, in

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contrast to being cold spots in this study. By comparing hot and cold spots, the difference in potential local correlates may be more detectable.

Compared to cold spots, γ_{00} is the fixed intercept, u_{0j} is the random intercept, which is the residual error of the highest-level variables, and e_{ij} is the lowest-level residual error. For the subscript, the symbol i is the municipal level (lowest level), and j is the prefecture level (highest level).

In this model, γ_{00} represents the overall average probability that the clusters are hotspots, while u_{0j} represents the variety in the average probability that the cluster is a hotspot among different prefectures. e_{ij} represents the variety in the average probability that the cluster is a hotspot among different municipalities, which is the residual.

Intra-class correlation coefficient, ICC

ICC, which is an abbreviation of intra-class correlation coefficient, is an index evaluating the heterogeneity of the dependent variables among groups, which can be calculated as follows:

$$ICC = \rho = \frac{\sigma_{uo}^2}{\sigma_{uo}^2 + \sigma_e^2}$$

where σ_{uo}^2 is the variance of the highest level of residual errors and σ_e^2 is the lowest level of residual errors. The value of ICC ranges from 0 to 1, where 0 means that the outcome probability does not vary among groups, while 1 means that the outcome probability only differentiates between groups.

Full multilevel logistic regression models

Building a full multilevel logistic regression model for each of the higher-level prefecture features. This model accounts for the direct effect of the lower-lever predictor variable, the direct effect of the higher-level predictor variable, the effect of

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the interaction terms and the random intercept effect. The full model can be described as follows:

- Level 1:

$$logit(p) = \ln\left(\frac{P(cluster = High - High)}{1 - P(cluster = High - High)}\right) =$$

$$\beta_{o\,j} + \beta_{1\,j}(population\ density_{ij}) + \beta_{2\,j}(income_{ij}) + \beta_{3\,j}(livingalone\ ratio_{ij}) +$$

$$\beta_{4\,j}(hospital\ density_{ij}) + e_{ij} \qquad \text{(Equation 2.1)}$$

- Level 2:
  - Intercept:

$$\beta_{0\,j} = \gamma_{00} + \gamma_{01}(COVID19\ infection\ rate_j) + u_{0j}$$

  - Slopes:

$$\beta_{1\,j} = \gamma_{10} + \gamma_{11}(COVID19\ infection\ rate_j) + u_{1j}$$

$$\beta_{2\,j} = \gamma_{20} + \gamma_{21}(COVID19\ infection\ rate_j) + u_{2j}$$

$$\beta_{3\,j} = \gamma_{30} + \gamma_{31}(COVID19\ infection\ rate_j) + u_{3j}$$

$$\beta_{4\,j} = \gamma_{40} + \gamma_{41}(COVID19\ infection\ rate_j) + u_{4j} \qquad \text{(Equation 2.2)}$$

In this regression equation, the subscript j is for the prefectures (j = 1 ... nj) and the subscript i is for municipalities (i = 1 ... nj). Hence, the dependent variable Y_{ij} is the probability of each municipality nested in prefectures being a hotspot compared to cold spots.

β_{0j} is the intercept; β_{1j} is the regression coefficient (regression slope) for the continuous explanatory variable population density; β_{2j} is the regression coefficient (slope) for the continuous explanatory variable income; β_{3j} is the regression coefficient (slope) for the continuous explanatory variable living-alone household ratio; and β_{4j} is the regression coefficient (slope) for the continuous explanatory variable hospital density. e_{ij} is the typical residual error term.

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In contrast to the usual regression model, we assume that each prefecture has a different intercept coefficient β_{oj}, and each prefectures has different slope coefficients β_{1j}, β_{2j}, β_{3j} and β_{4j}. This is indicated in equations 2.1 by attaching subscript j to the regression coefficients. The residual errors e_{ij} are assumed to have a mean of zero and the variance to be estimated. Most multilevel software programs assume that the variance of the residual errors is the same in all classes.

To combine the equations in level 2 into level equations, the equations were converged into Equation 2.4.

$$logit(p) = \ln\left(\frac{P(cluster = High - High)}{1 - P(cluster = High - High)}\right) =$$

$$\gamma_{00} + \gamma_{01}\left(COVID19\ infection\ rate_j\right) + u_{0j}$$

$$+(\gamma_{10} + \gamma_{11}\left(COVID19\ infection\ rate_j\right) + u_{1j})\ *\left(population\ density_{ij}\right)$$

$$+(\gamma_{20} + \gamma_{21}\left(COVID19\ infection\ rate_j\right) + u_{2j})\ *\ \left(income_{ij}\right)$$

$$+(\gamma_{30} + \gamma_{31}\left(COVID19\ infection\ rate_j\right) + u_{3j})\ *\ \left(livingalone\ ratio_{ij}\right)$$

$$+(\gamma_{40} + \gamma_{41}\left(COVID19\ infection\ rate_j\right) + u_{4j}) \times\ \left(hospital\ density_{ij}\right) + e_{ij}$$

(Equation 2.3)

where p refers to the probability of hotspots in the spatially-clustered dataset, that is, the probability of being hotspots compared to being cold spots. The u-terms u0j, u1j, u2j, u3j and u4j in equations 2.3 are random residual error terms at the higher(prefecture) level. These residual errors, uj, are assumed to have a mean of zero and are independent of the residual errors eij at the lower (municipal) level. On the other hand, note that in equation 2.3, the regression coefficients γ are not assumed to vary across groups (higher levels, namely prefectures). Therefore, they have no subscript j to indicate the prefecture to which they belong. As they apply to all groups, they are referred to as fixed coefficients. All between-group variation left in the β coefficients, after processing these with the prefectures variable $COVID19\ infection\ rate_j$, is assumed

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to be residual error variation. This is captured by the residual error terms uj, which have subscript j to indicate the groups to which they belong.

As for the significance threshold, in this study, the regression tables show p-values of 0.1, 0.05, and 0.001 simultaneously as significant thresholds. P-value <0.1 is considered slightly significant (also called borderline statistically significant (Campbell et al., 2010)), p-value <0.05 is considered typically significant, and p-value <0.001 is considered strongly significant.

Based on literature reviews of mental health concerns during COVID-19 with academic reasoning for selecting potential variables, I used maximal modeling, which is the most complex random structure that can be applied to the data. It assumes sufficient variance in the subjects and items (and for random slopes for both subjects and items) to sustain the models (Barr, Levy, Scheepers, & Tily, 2013).

3.3.7 Model Variables

Based on literature reviews about the influence of the COVID-19 pandemic on suicide in Japan, several social environmental factors were selected as model variables, including COVID-19 infection rate, population density, single household ratio, income, and accessibility to the hospital. For the changes in suicide rate and the suicide rate, this study used the same set of variables to investigate the different local characteristics between these two types of spatial clusters. In the setting of this research, spatial clusters of high suicide rates might be affected by both the COVID-19 pandemic and the inherent social structure effect. However, the spatial cluster of increased suicide rates might reflect where the COVID-19 pandemic effect is the most serious, excluding the inherent social structural effect (see Figure 11).

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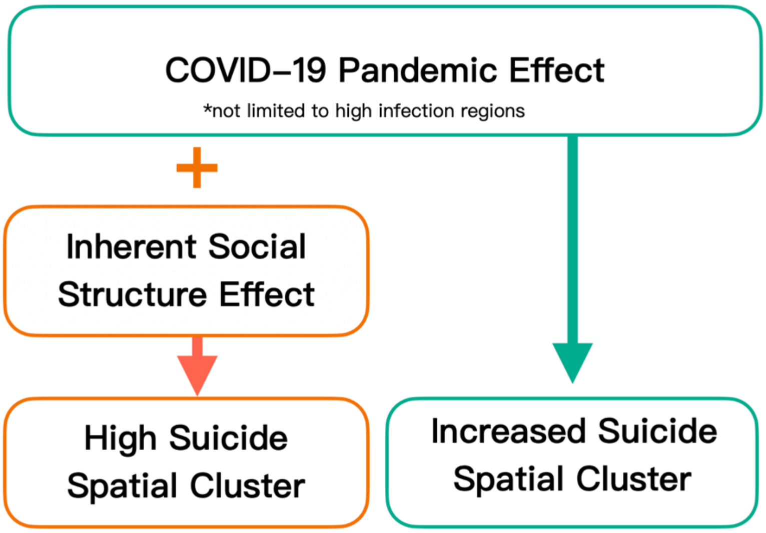

Figure 11 Different Mechanism in local correlates for spatial cluster of high suicide rate and ones of increased suicide rate.

There are two types of variables: One type changes along with different waves of the virus outbreak, for example, COVID-19 infection rate and its interaction with other local correlates; the other type is fixed all the time, for example, population density, single household ratio, income, and accessibility to the hospital. For the former, the spatial cluster of change in suicide rate might be affected by changes in local correlations, for example, the occurrence of COVID-19 infection, which is straightforward. For the latter, the spatial cluster of change in suicide rate might also be affected by fixed local correlates, because some fixed environments might be significant local correlates throughout the study period or at certain stages of the COVID-19 pandemic. For example, urban and rural properties do not change with time but can still serve as a variable for characterizing the spatial cluster.

1. COVID-19 infection rate:

According to previous research, COVID-19 seriousness may increase the level of anxiety of people and cause a negative impact on their mental condition due to being afraid of infection. Accordingly, the COVID-19 infection rate as an index of COVID-

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19 will be used as an index of anxiety or worry about being infected during the COVID-19 pandemic(Tanaka & Okamoto, 2021a).

COVID-19 mortality and infection rates have high multicollinearity, and the infection rate might reflect more anxiety and fear information throughout the COVID-19 pandemic because mortality mainly occurs in certain demographic groups. Therefore, this study used COVID-19 infection rate as an index of COVID-19 severity.

However, the COVID-19 infection rate cannot fully represent the COVID-19 pandemic effect because economic recess, anxiety, and other pandemic-induced risk factors may not be limited to highly infected regions. Accordingly, this study also considered other potential risk factors in the model.

2. Urbanity/ Rurality (population density):

Before the COVID-19 pandemic, rurality, a less densely populated region, was linked to a high risk of suicide mortality rate compared to urban areas, not only in Japan (Yoshioka et al., 2021). Dwellers of rural communities, where the places are less densely populated, might be more likely to experience social isolation, loneliness, lack of belonging, and perceived burdensomeness, which are all risk factors for suicide, relative to those living in urban communities (Monteith, Holliday, Brown, Brenner, & Mohatt, 2021).

During the COVID-19 pandemic in Japan, some (Monteith et al., 2021) worried that rural areas might experience more mental risk because suicide prevention intervention-related resources might be more limited or inaccessible in rural areas during the lockdown period of the pandemic. Some worried (Menculini et al., 2021) that the suicide rate might increase in urban areas during the COVID-19 pandemic. Urban areas, namely densely populated areas, are particularly affected by the COVID-19 virus spread. This influence might be more significant for certain vulnerable groups that are

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common in urban areas, such as people living in non-bathroom-attached rental rooms, part-time job workers, and foreign workers. Hence, urbanity/rurality was selected as one of the variables to characterize spatial clusters.

3. Income:

Regions in poverty might be affected more by COVID-19; accordingly, there might be a relevant factors (D. Wasserman et al., 2020). A previous study indicated that poverty might be a potential risk factor for elevated suicide rates during COVID-19 (Krumer-Nevo, 2021) because of more financial stress and unstable income resources. Hence, I used the income in each municipality as an index of regional economic status. This might reflect the financial status of different regions when facing COVID-19 challenges.

4. Hospital Density:

Regions with high accessibility to hospital might have less death result (Tondo, Albert, & Baldessarini, 2006). That is, in cases where suicide events increase during COVID-19, areas with higher hospital density might rescue more suicided people back but not in areas with low or little hospital density. In other words, hospital density might be a local factor in changing the suicide rate, and this phenomenon might be more serious in rural areas if they face excessive increased suicide rates during COVID-19 but have insufficient medical resources to rescue the tragedy in time. According to the World Health Organization (WHO), the density of hospitals in this study was defined as the number of hospitals per 100,000 population.

5. Living-alone household ratio:

Living alone is a risk factor for excessive suicide before the COVID-19 pandemic (Yoshioka et al., 2021). However, during COVID-19, the effects was obscure. There is also another point of view that living with family might have more mental burden because of sudden extra time spent with family, causing more domestic fights, parenting

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issues, and even domestic violence during the stay-at-home period of the pandemic time (Banerjee, Kosagisharaf, & Sathyanarayana Rao, 2021). In short, the effect of living-alone households is obscure for municipality-level spatial clusters of changes in suicide rates. Thus, the living-alone household ratio was considered as a model variable.

3.4 Processing Software

Statistical analysis was conducted using the statistical software R with R studio (R Studio Version 1.4.1717, "Juliet Rose" for macOS). The time series analysis, including trend and seasonality, was conducted with the package, “TSstudio”. The Getis-Ord Gi* statistics were generated using the package rgeoda (version 0.0.9), which is an R package for spatial data analysis based on libgeoda and GeoDa. Mapping figures were generated using Quantum GIS software (version 3.16, long-term release). The regression of the multilevel logistic regression model was conducted using the package “lme4” (version 1.1-29) with “glmer” command function. Using these functions, I fitted a generalized linear mixed model, which incorporates both fixed-effects parameters and random effects in a linear predictor via maximum likelihood estimation.

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Chapter 4 Results

4.1 Explore the suicide data in Japan

Based on the summary of the suicide rate before COVID-19, suicide rate during COVID-19, and change in suicide rate during the COVID-19 pandemic in 1,693 municipalities (see Table 3, Table 4 and Table 5), we found that the mean suicide rates during COVID-19 were lower than those before COVID-19 in the 1st wave but higher in the 2nd, 3rd, 4th wave of the virus outbreak. Moreover, the mean of change in suicide rate is negative in the 1st wave but remains positive in the 2nd, 3rd and 4th wave with spikes in the 2nd and 3rd waves.

4.3 Cluster Location Difference between $\Delta Rate\ and\ Rate$

With contingency tables for the spatial clusters of change in suicide rate($\Delta Rate$) and suicide rate($Rate$), we can roughly understand whether places with increased suicide rates during the COVID-19 pandemic also had high suicide rates. According to the contingency table (see Table 6, Table Table 7, Table Table 8, Table Table 9) we can obtain the proportion of places with increased suicide rate clusters (High-High) over places that are high suicide clusters. From the 1st wave to the 4th wave, the proportions are 0.55 (which is 99/180), 0.44, 0.50, 0.51 respectively. Based on these results, we can see that places with high suicide rate clusters are not necessarily places with increased suicide rate clusters. In other words, detecting high suicide rates might yield different results from detecting increased suicide rates when an acute significant event occurs.

4.2 Cluster Mapping

This section showed the cluster Maps of change in suicide rates and suicide rates respectively from the 1st wave to the 4th wave of COVID-19 pandemic in Japan. Red areas are hotspots, blue areas are cold spots and white areas are non-clustered areas.

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The raw data choropleths are also shown in advance of cluster maps. For change in suicide rate($\vartriangle Rate$), hotspots mean where increased suicide rates clusters while cold spots means where decreased suicide rates cluster. On the other hand, for suicide rate($Rate$), hotspots mean where high suicide rates clusters while cold spots means where low or zero suicide rates cluster.

In the 1st wave of COVID-19(see Figure 12), for $\vartriangle Rate$, hotspots, which means where increased value cluster during pandemic time, clustered in urban area of Hokkaido and east north Hokkaido, west north Tohoku, west Chubu, west Chugoku, west north Shikoku and east south Shikoku, west Kyusyu and urban Okinawa. The cold spots, which means where declined value cluster during pandemic time, clustered in west north Hokkaido, inland Tohoku, inland Kanto, inland Chubu, south Kinki, south east Shikoku and south Kyusyu. As for $Rate$, hotspots, which mean where high value cluster during pandemic time, clustered in west north inland Hokkaido, south peninsula of Hokkaido, west north and east south Tohoku, west Chubu, north Chugoku, inland and south Kinki, west north Shikoku and east south Shikoku and south Kyusyu. The cold spots, which mean where low value cluster during pandemic time, clustered in west north Hokkaido, west Kanto, inland Chubu, east Chugoku, south Shikoku, urban Kyusyu and Okinawa.

In the 2nd wave of COVID-19(see Figure 13), for $\vartriangle Rate$, hotspots clustered in east north Hokkaido, north and south Tohoku, west Chubu, east Kinki, north Chugoku, east side and west side of Shikoku, east north and inland Kyusyu and urban Okinawa. Cold spots clustered in west north Hokkaido and southern Hokkaido, middle Tohoku, Kanto, east south Chubu, south Kinki, east Shikoku and east north Kyusyu. As for $Rate$, hotspots clustered in urban Hokkaido, east inland Hokkaido, Tohoku, west Chubu, south Kinki, south Shikoku, south Kyusyu and urban Okinawa. Cold spots

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clustered in inland urban Hokkaido(Asahikawa), west coastal Hokkaido, west urban Tohoku, inland urban Chubu, urban Kyushu, west Kyushu and south town in Okinawa.

In the 3rd wave of COVID-19(see Figure 14), for $\triangle Rate$, hotspots clustered in east north Hokkaido including Asahikawa city, north and south Tohoku, west north Kanto, inland Chubu, east Kinki, west Shikoku, west Chugoku, north and south Kyusyu. Cold spots of change in suicide rates clustered at west north Hokkaido, west Tohoku, south Chubu, south Kinki, south Shikoku and west Kyusyu. As for $Rate$, hotspots clustered in inland Hokkaido, south peninsula Hokkaido, north Tohoku, west Kanto, west and inland Chubu, east Kinki, west Shikoku, west Chugoku, north and south Kyusyu. Cold spots clustered at urban Hokkaido(Sapporo), west north Hokkaido, west Tohoku, east Chubu, south Shikoku, middle Kyusyu and Okinawa.

In the 4th wave of COVID-19(see Figure 15), for $\triangle Rate$, hotspots clustered at east north and south Hokkaido, north and middle Tohoku, west and south Chubu, east Kinki, south Chugoku, east and west part of Shikoku, north and middle Kyusyu and town in Okinawa. Cold spots clustered west north Hokkaido, north Tohoku, west Kanto, south Chubu, south Kinki, east Shikoku and west Kyusyu. As for $Rate$, hotspots clustered at west north and east south Hokkaido, south peninsula Hokkaido, north and west Tohoku, west and south Chubu, east Kinki, east Chugoku, east and west part of Shikoku, north and south Kyusyu and north Okinawa. Cold spots clustered in urban Kanto, south urban Chubu, urban Kinki, urban Chugoku and west Kyusyu.

To conclude, the spatial cluster patterns were different between change in suicide rates and suicide rates during COVID-19 pandemic in Japan. In all 4 waves of COVID-19 pandemic in Japan, the hotspots of change in suicide rates mostly occurred in east north Hokkaido, north Tohoku, peripheral Kanto, west Chubu, north Chugoku, east Kinki, north and east Kyusyu and urban Okinawa. On the other hand, the hotspots of

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suicide rates clustered at east inland Hokkaido, all part of Tohoku, west Chubu, south Kinki, south Kyusyu.

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Table 3 Suicide Rate before COVID-19

period	Wave1	Wave2	Wave3	Wave4
Min.	0	0	0	0
1st Qu.	0.73	0.892	0.655	0.979
Median.	1.34	1.318	1.173	1.418
Mean.	1.69	1.496	1.383	1.636
3rd Qu.	2.13	1.86	1.754	2.024
Max.	35.21	11.973	16.79	17.606
Sd	2.084	1.171	1.368	1.325

Table 4 Suicide Rate After COVID-19

Period	Wave1	Wave2	Wave3	Wave4
Min.	0	0	0	0
1st Qu.	0	0	0	0
Median.	0	1.14	1.16	1.09
Mean.	1.32	1.53	1.42	1.53
3rd Qu.	1.6	1.98	1.88	2.05
Max.	32.72	28.47	32.84	25.87
Sd	2.723	2.2	1.88	2.021

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Table 5 Change of suicide rate during COVID-19

Period	Wave1	Wave2	Wave3	Wave4
Min.	-51.68	-51.68	-51.68	-51.68
1st Qu.	-1.41	-0.98	-0.76	-1.08
Median.	-0.09	0.06	0.09	0
Mean.	-0.24	0.16	0.14	0.02
3rd Qu.	1.1	1.28	1.17	1.2
Max.	38.18	33.22	39.68	24.95
Sd	4.494	3.615	3.288	3.519

Table 6　Contingency table of clusters of $\Delta Rate\ and\ Rate$ for 1st wave COVID-19

1st wave of COVID-19		$Rate$			
		High-High	Low-Low	Not significant	Sum
ΔR	High-High	99	4	48	151
a	Low-Low	11	46	78	135
t	Not significant	70	92	1245	1407
e	Sum	180	142	1371	1693

Table 7 Contingency table of clusters of $\Delta Rate\ and\ Rate$ for 2nd wave COVID-19

2nd wave of COVID-19		$Rate$			
		High-High	Low-Low	Not significant	Sum
ΔR	High-High	69	1	55	125
a	Low-Low	15	33	89	137
t	Not significant	74	88	1269	1431
e	Sum	158	122	1413	1693

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Table 8 Contingency table of clusters of $\Delta Rate\ and\ Rate$ for 3rd wave COVID-19

3rd wave of COVID-19		$Rate$			
		High-High	Low-Low	Not significant	Sum
ΔR	High-High	78	1	52	131
a	Low-Low	7	38	78	123
t	Not significant	70	99	1270	1439
e	Sum	155	138	1400	1693

Table 9 Contingency table of clusters of $\Delta Rate\ and\ Rate$ for 4th wave COVID-19

4th wave of COVID-19		$Rate$			
		High-High	Low-Low	Not significant	Sum
ΔR	High-High	77	2	51	130
a	Low-Low	9	38	72	119
t	Not significant	65	107	1272	1444
e	Sum	151	147	1395	1693

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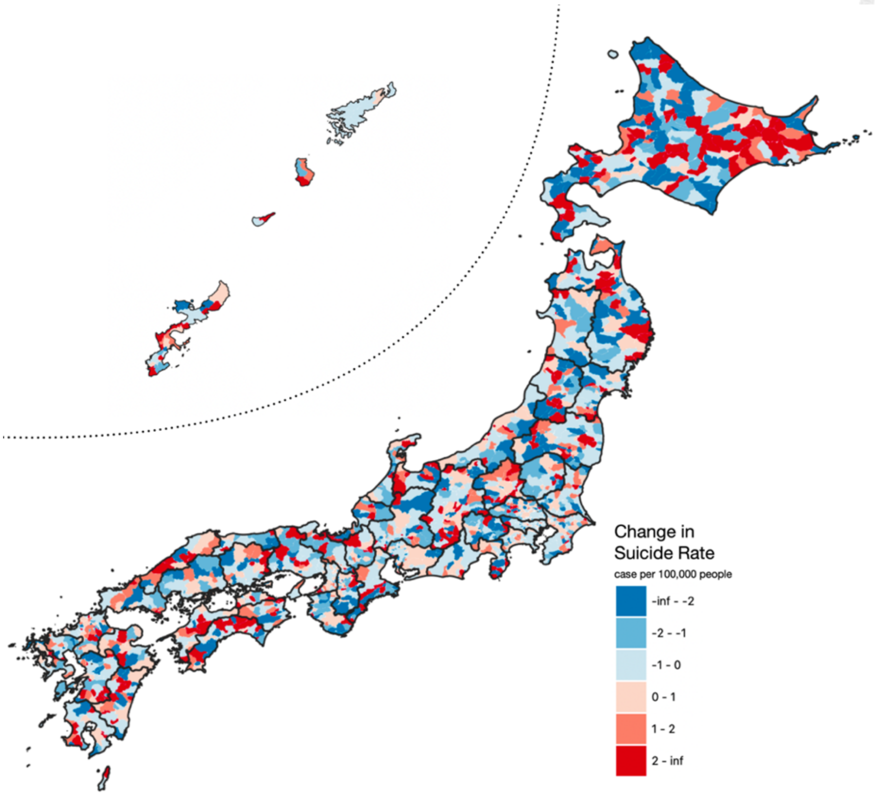
Wave 1



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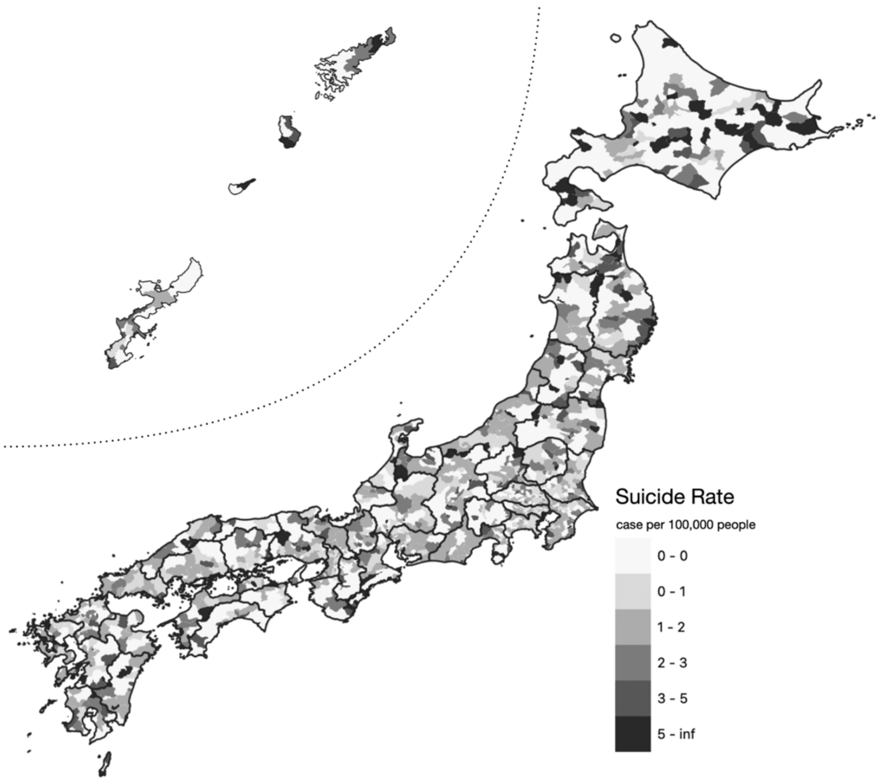

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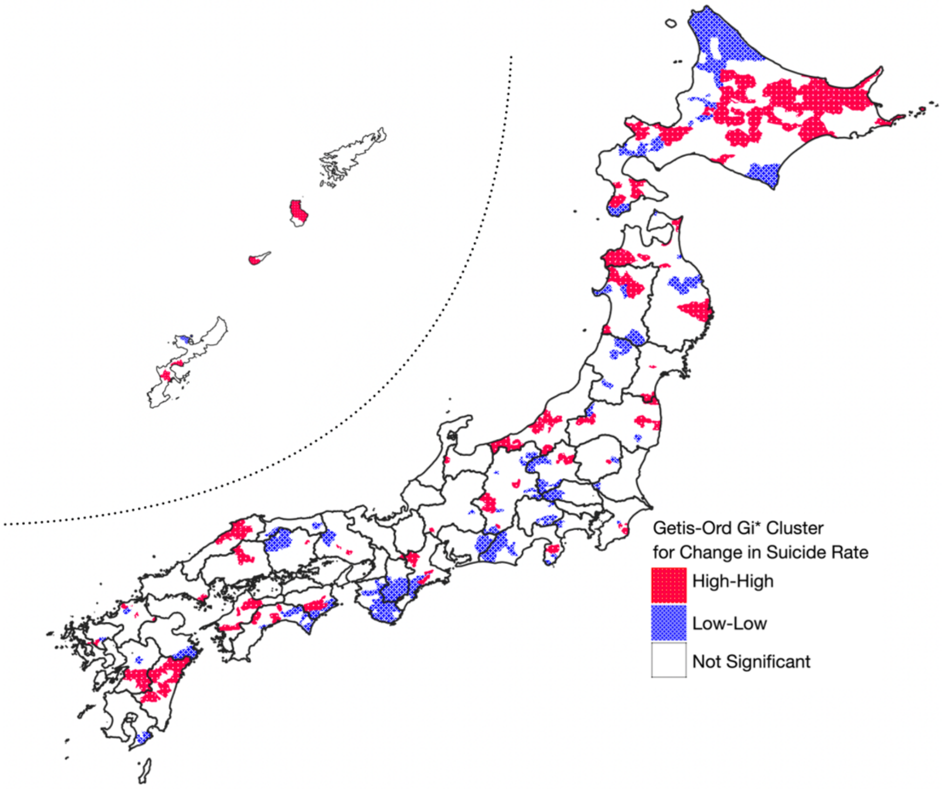

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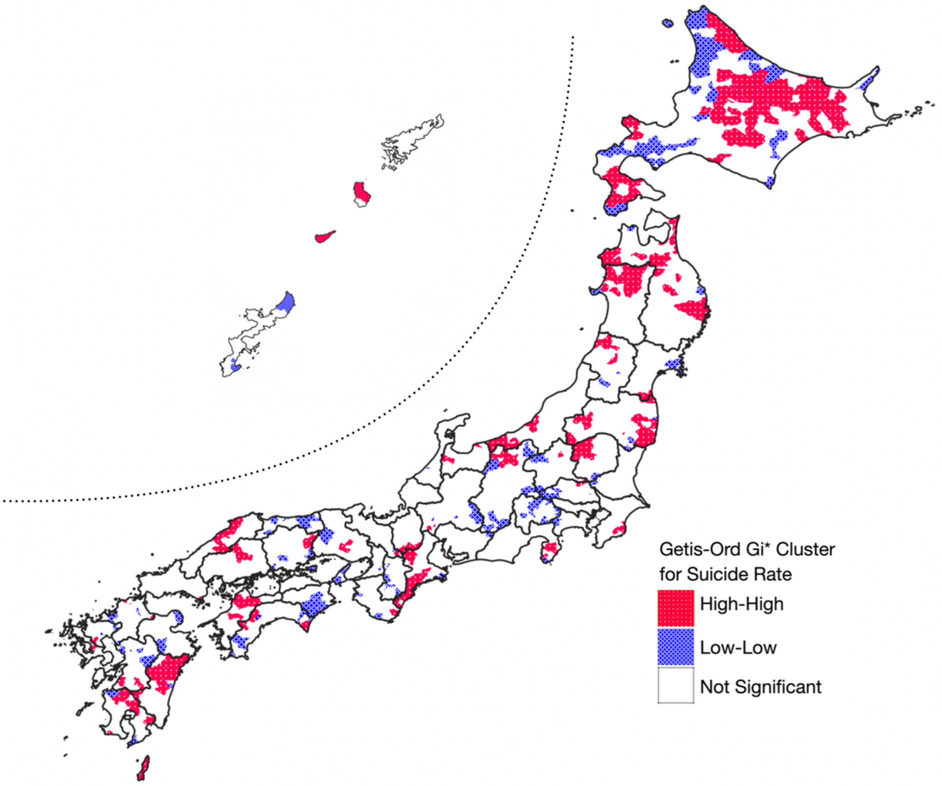

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Figure 12　Maps of Raw data and spatial clusters for the 1st wave of COVID-19 in Japan: (A) Raw data of change in suicide rate($\Delta\ Rate$); (B) Raw data of suicide rate($Rate$); (C) Spatial Cluster of Change in suicide rate; and (D) Spatial Cluster of Suicide rate

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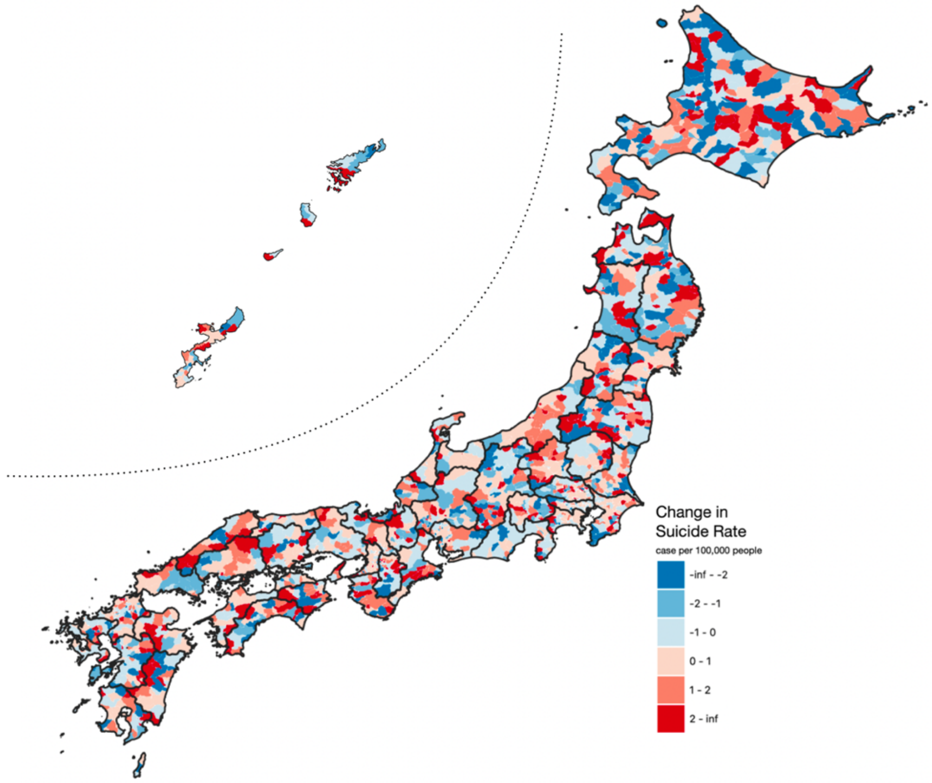
Wave 2



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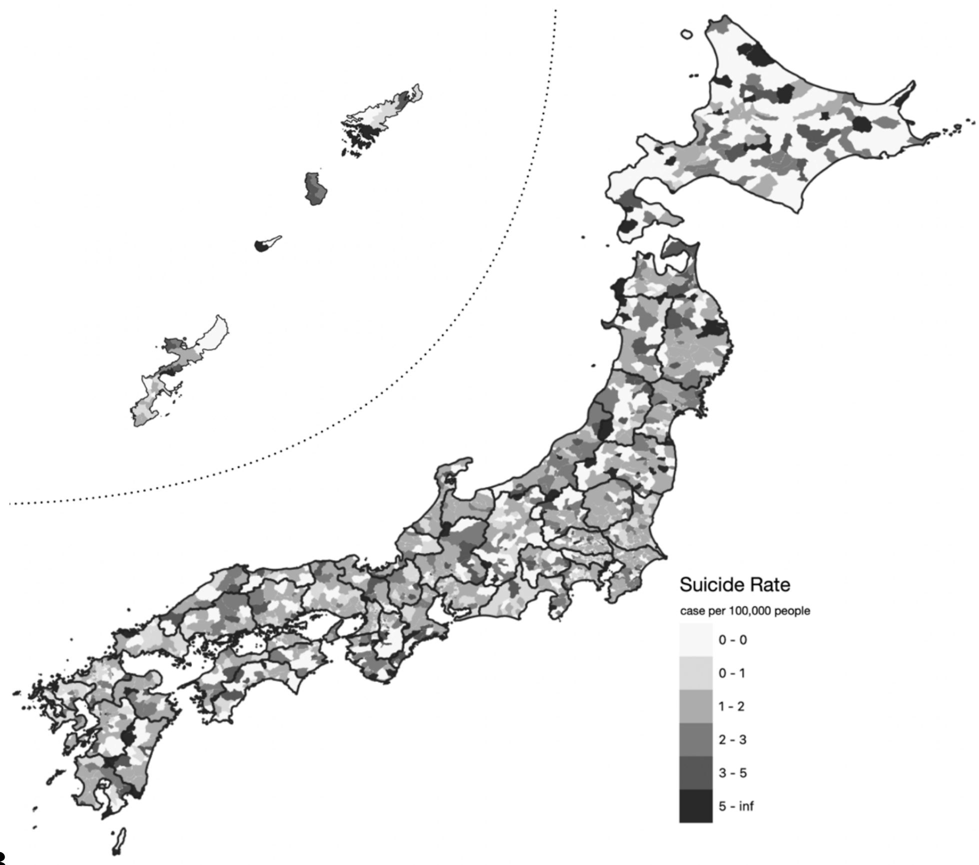

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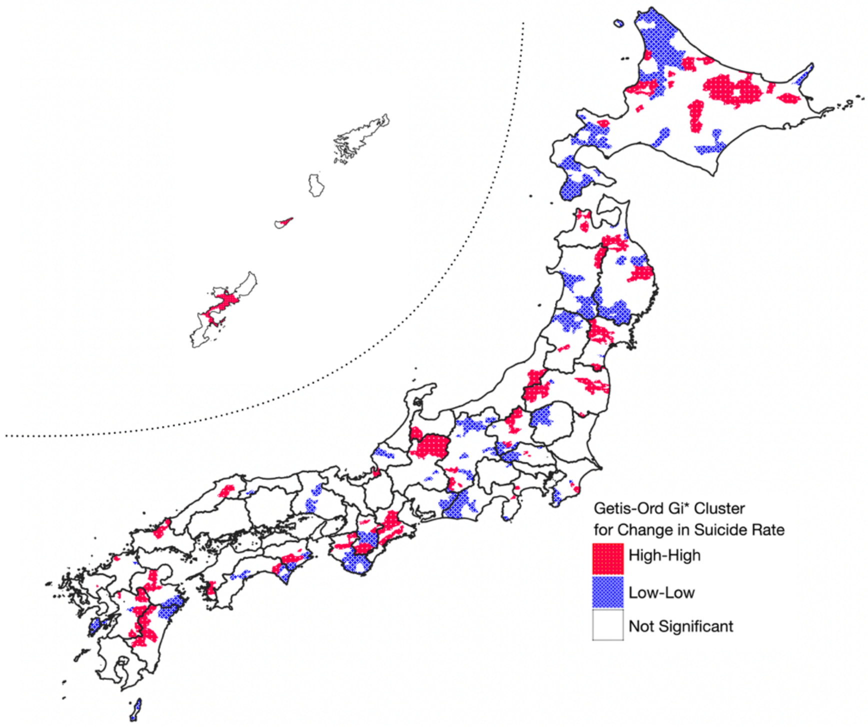

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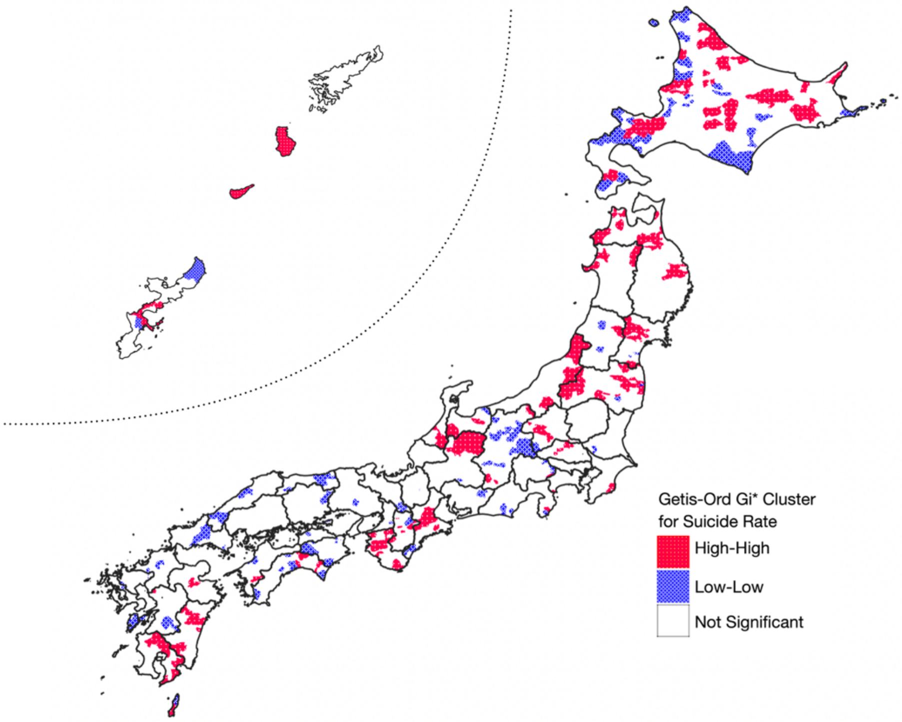

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Figure 13 Maps of Raw data and spatial clusters for the 2nd wave of COVID-19 in Japan: (A) Raw data of change in suicide rate(Δ $Rate$); (B) Raw data of suicide rate($Rate$); (C) Spatial Cluster of Change in suicide rate; and (D) Spatial Cluster of Suicide rate

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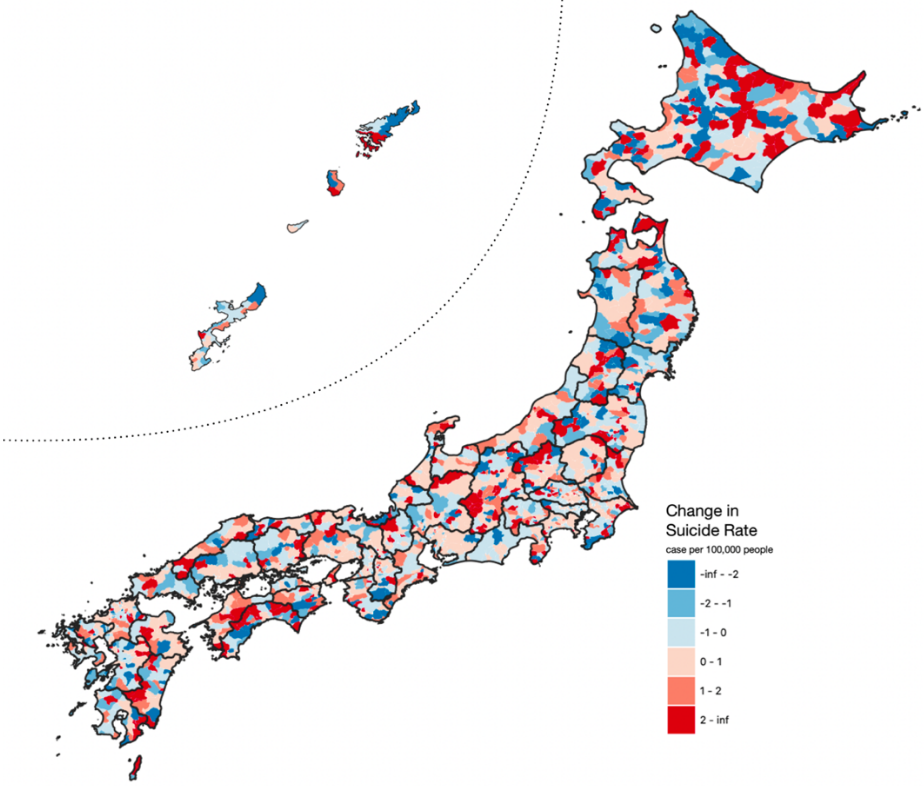
Wave 3



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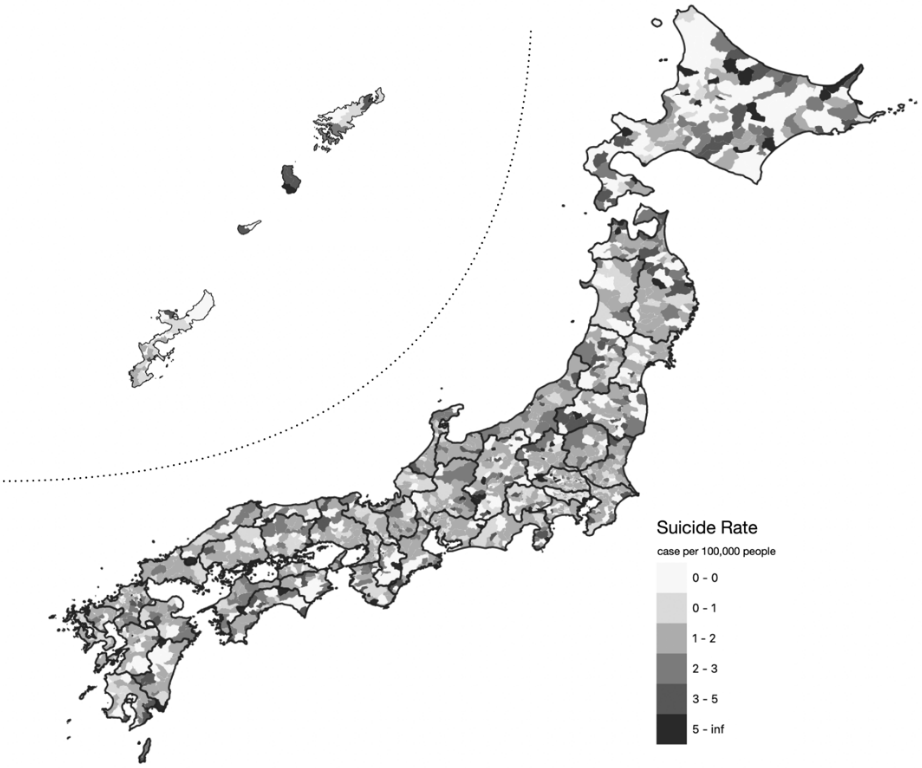

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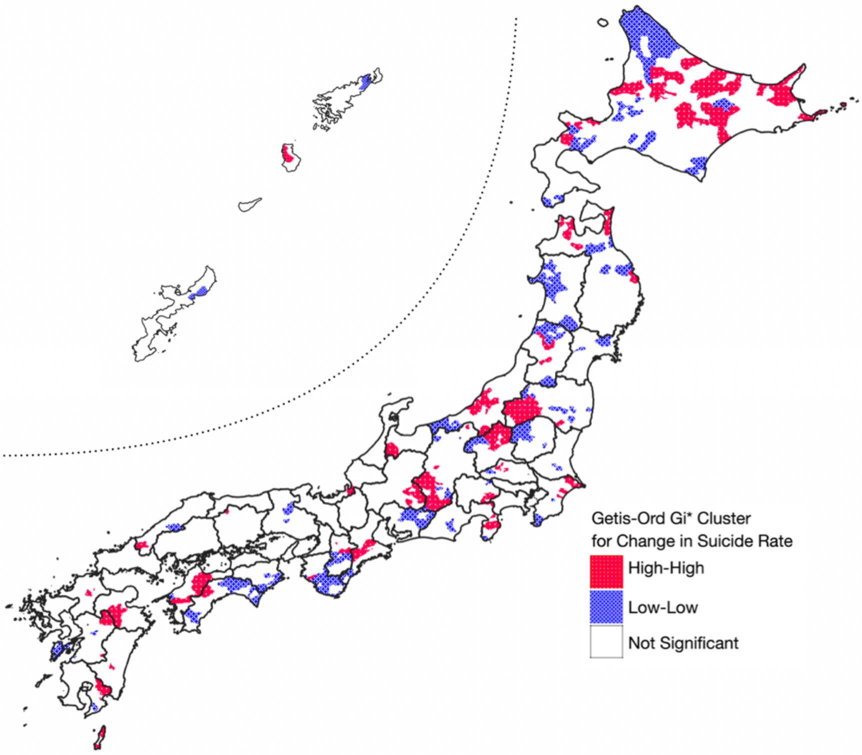

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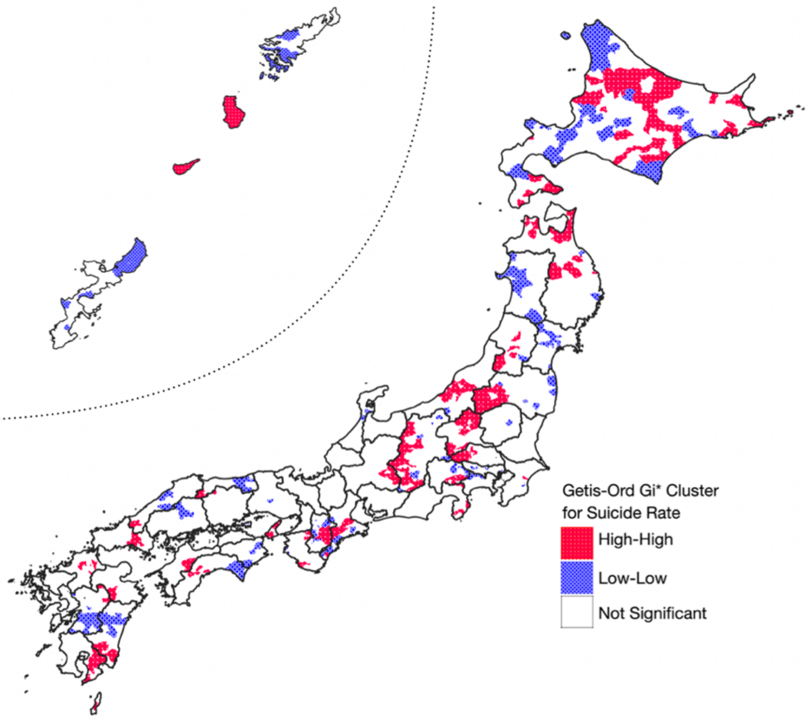

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Figure 14 Maps of Raw data and spatial clusters for the 3rd wave of COVID-19 in Japan: (A) Raw data of change in suicide rate($\Delta\ Rate$); (B) Raw data of suicide rate($Rate$); (C) Spatial Cluster of Change in suicide rate; and (D) Spatial Cluster of Suicide rate

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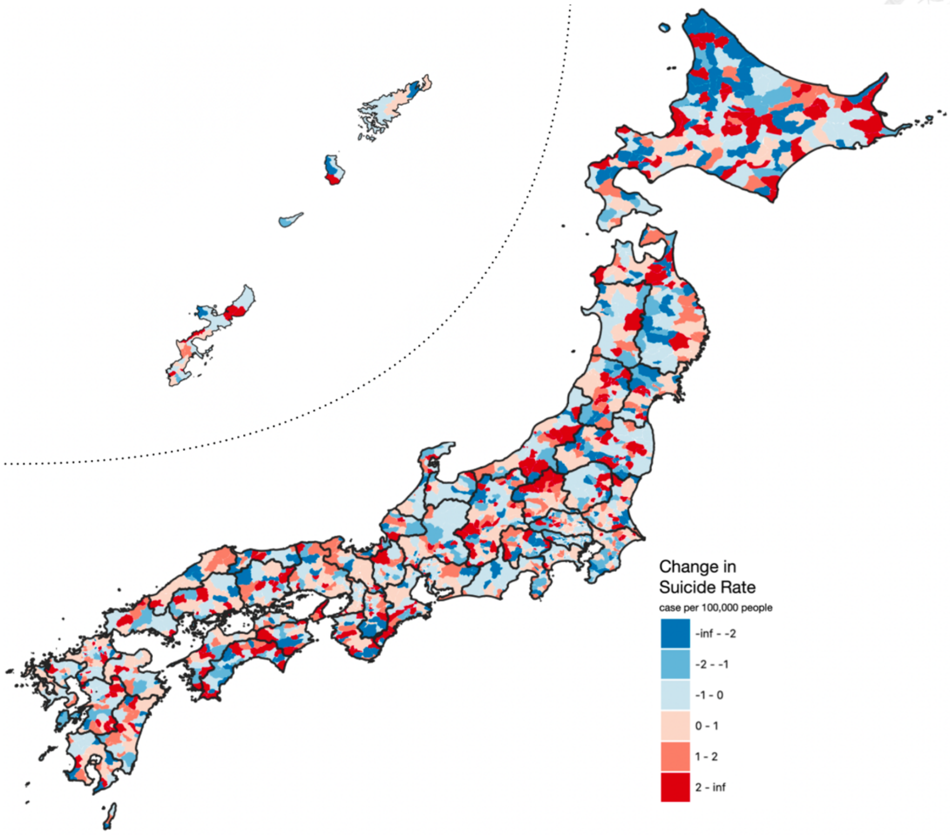
Wave 4



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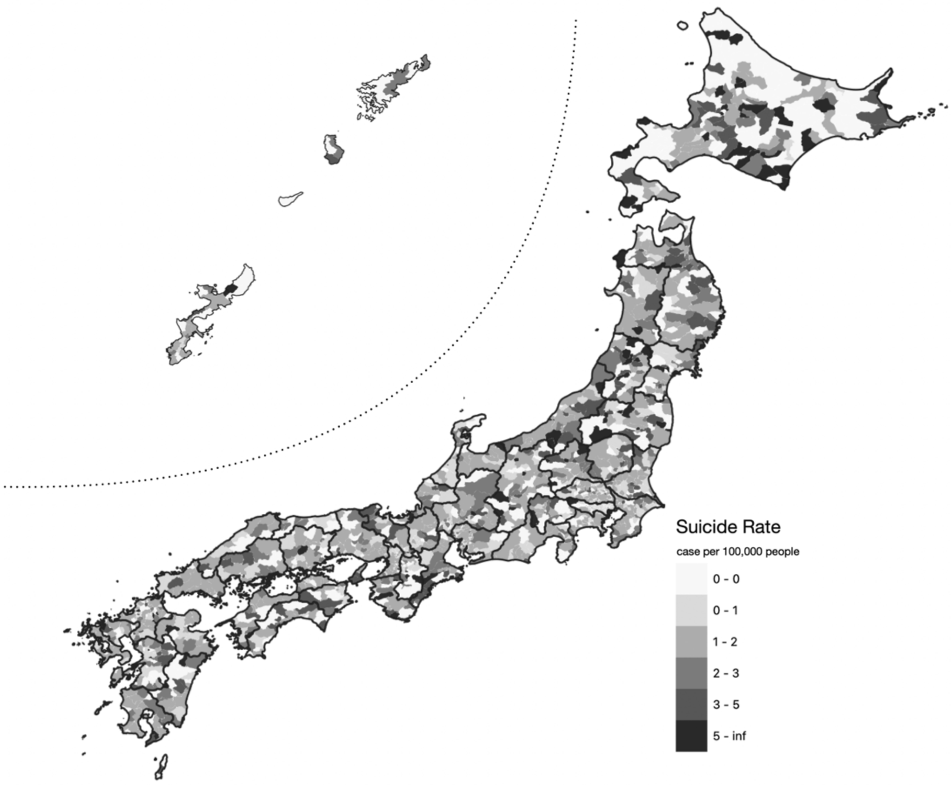

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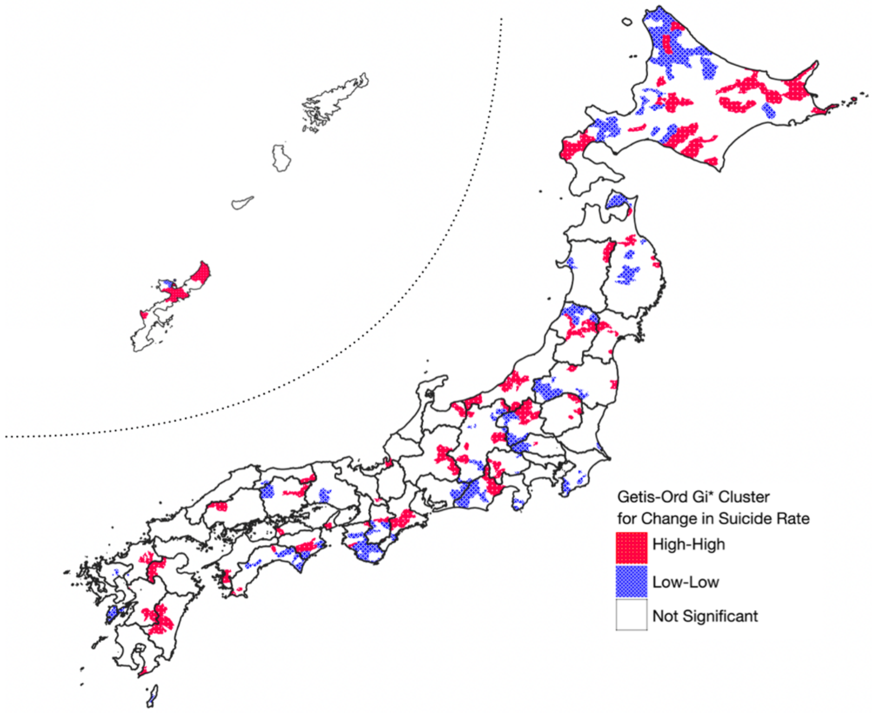

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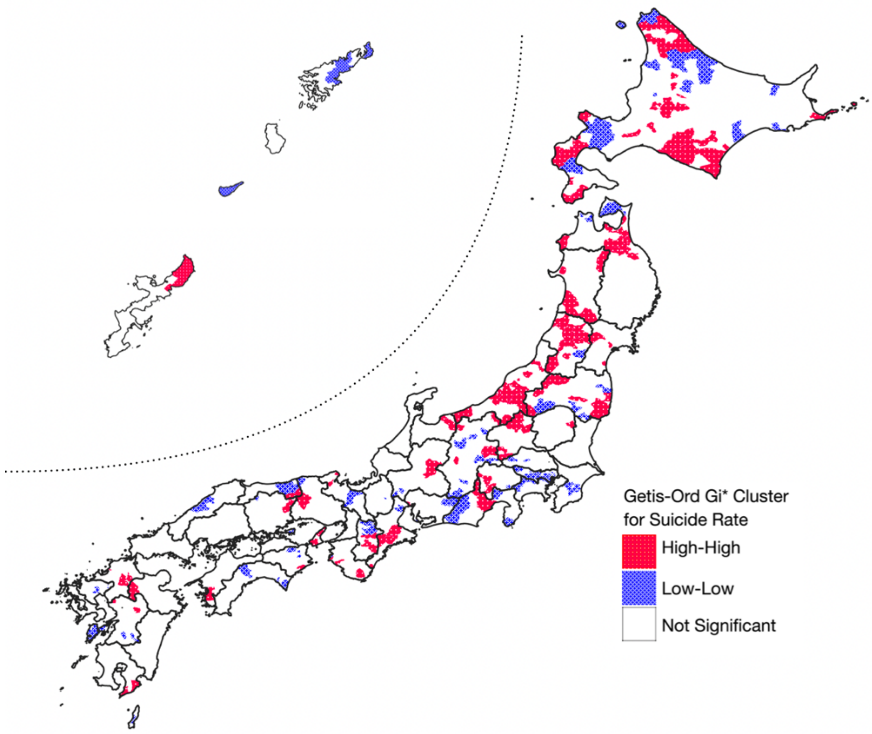

D

Figure 15 Maps of Raw data and spatial clusters for the 4th wave of COVID-19 in Japan: (A) Raw data of change in suicide rate(Δ $Rate$); (B) Raw data of suicide rate($Rate$); (C) Spatial Cluster of Change in suicide rate; and (D) Spatial Cluster of Suicide rate

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4.4 Multi-Level Logistic Regression Results

A summary of the variables in the models is presented in Table 10. The COVID-19 infection rate increased from the 1st wave to the 4th wave of the virus outbreak. The temporal fixed variables were at different scales because of the unit differences. Different scales of variables might result in biased regression results. Therefore, before using these variables in the models, all dependent variables were standardized to a similar scale. Accordingly, all variables in the models have means equal to 0 and a standard deviation equal to 1.

4.4.1 Models for Change in Suicide Rate

The regression results of the multilevel logistic regression models for changes in suicide rate and the suicide rates are shown in comparison (see Table 11). For the 1st wave of the virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots were significantly positively correlated with COVID-19 infection rate, significantly positively correlated with the interaction between COVID-19 infection rate and population density, and significantly negatively correlated with the interaction between COVID-19 infection rate and living-alone household ratio.

For the 2nd wave of the virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots were found to be significantly positively correlated with the COVID-19 infection rate, significantly negatively correlated with the living-alone household ratio, and significantly positively correlated with the interaction between COVID-19 infection rate and population density.

For the 3rd wave of the virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots were found to be significantly positively correlated with higher population density, significantly negatively correlated with the living-alone household ratio, and significantly negatively correlated with the interaction between COVID-19 infection rate and living-alone household ratio.

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For the 4th wave of the virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots were found to be significantly positively correlated with a higher living-alone household ratio.

4.4.2 Models for suicide rate

For the 1st and the 3rd waves of the virus outbreak in Japan, hotspots of suicide rate compared to cold spots were found to have no significant correlations with the studied environmental factors. For the 2nd and the 4th waves of the virus outbreak in Japan, hotspots of change in suicide rates compared to cold spots were found to be significantly negatively correlated with population density. This means that hotspots of suicide rate, namely spatial clusters of high suicide rate areas during the COVID-19 pandemic compared to the cold spots, occurred in places with less densely populated areas, namely more rural areas.

4.4.3 Comparison between Change in suicide rate and Suicide rate

For changes in suicide rate, the hotspots clustered more in areas with higher COVID-19 infection rates in the 1st and the 2nd waves of the virus outbreak. Moreover, based on the interaction term, I found that COVID-19 seriousness might adjust to other environmental factors became more significant, including population density(positively) and living-alone household ratio(negatively).

On the other hand, for suicide rate, hotspots were found to be negatively correlated with population density in the 2nd and the 4th virus outbreaks in rural areas. In other words, spatial clusters of high suicide rates are not sensitive to the COVID-19 infection rate or its interaction terms.

The details of regression models for two types of spatial clusters, including the univariate regression models, random effect of models, goodness of fit for the multilevel logistic model, and multicollinearity check were conducted and are attached to the supplement(see content from Supplementary Table 2 to Supplementary Table 14).

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Descriptive Analysis

Table 10 Descriptive analysis of Local Correlates (Before standardized scaling)

item	time	Min.	Max.	Mean	Median	Std. dev.
COVID-19	Wave1	0.00	16.90	4.16	2.90	3.74
Seriousness	Wave2	0.18	40.30	8.25	4.84	8.68
(Infection rate per 10k people)	Wave3	4.27	123.47	39.81	32.82	27.32
	Wave4	9.98	1.098	61.32	45.95	37.92
Urbanity (Population Density, people per ha)		0.099	220.83	14.239	5.589	26.571
Income (k JPD)		2055	12170	2799	2911	593.15
Hospital Density (hospital per 10k people)		0	823.38	60.76	76.07	80.22
Living-Alone Ratio (living-alone-ratio household / total household)		0.10	0.88	0.28	0.28	0.076

Multilevel Logistic Regression Result

Table 11 Multilevel Logistic Regression Results for hotspots of change in suicide rate and ones of suicide rate

Waves	variables	Hotspots of Change in suicide rate		Hotspots of Suicide rate	
		Coefficient	S.E.	Coefficient	S.E.
1st	Intercept, γ_{00}	0.78	0.74	-0.28	0.55
	COVID-19 infection rate, γ_{01}	2.67**	1.16	-0.19	0.82
	Population density, γ_{10}	1.23	1.59	-1.2	1.31
	Income, γ_{20}	0.46	0.5	0.23	0.41

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	Living alone ratio, γ_{30}	0.16	0.22	-0.29	0.22
	Hospital Density, γ_{40}	-0.01	0.17	0.12	0.13
	COVID-19 infection rate*Population density, γ_{11}	6.8**	2.7	0.84	1.76
	COVID-19 infection rate*Income, γ_{21}	0.24	0.61	-0.4	0.42
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.61*	0.33	-0.16	0.24
	COVID-19 infection rate*Hospital Density, γ_{41}	0.23	0.22	-0.1	0.16
2nd	Intercept, γ_{00}	-2.3	1.17	-1.74	1.33
	COVID-19 infection rate, γ_{01}	4.07***	1.58	0.58	1.14
	Population density, γ_{10}	-5.7	3.52	-6.01*	3.14
	Income, γ_{20}	-0.08	0.95	0.8	0.6
	Living alone ratio, γ_{30}	-0.9***	0.34	-0.39	0.39
	Hospital Density, γ_{40}	-0.36	0.27	0.35	0.32
	COVID-19 infection rate*Population density, γ_{11}	11.86**	5.11	0.18	1.99
	COVID-19 infection rate*Income, γ_{21}	-1.63	1.61	0.5	0.81
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.38	0.55	-0.34	0.54
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.67	0.56	0.24	0.46
3rd	Intercept, γ_{00}	1.51	0.87	-0.26	0.72
	COVID-19 infection rate, γ_{01}	1.59	1.13	-0.13	0.52
	Population density, γ_{10}	4.28*	2.36	-1.8	1.67
	Income, γ_{20}	-0.49	0.56	0.21	0.4
	Living alone ratio, γ_{30}	-0.54**	0.23	0.22	0.28
	Hospital Density, γ_{40}	-0.03	0.12	0.01	0.12
	COVID-19 infection rate*Population density, γ_{11}	4.45	2.86	-0.13	1.08

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	COVID-19 infection rate*Income, γ_{21}	-0.27	0.54	-0.47	0.41
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.51*	0.27	-0.27	0.33
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.08	0.2	-0.07	0.13
4th	Intercept, γ_{00}	0.06	0.49	-0.88	0.66
	COVID-19 infection rate, γ_{01}	0.45	0.46	0.36	0.69
	Population density, γ_{10}	-0.6	1.16	-3.28*	1.83
	Income, γ_{20}	-0.19	0.22	-0.64	0.55
	Living alone ratio, γ_{30}	-0.44**	0.22	-0.06	0.34
	Hospital Density, γ_{40}	-0.19	0.12	-0.09	0.23
	COVID-19 infection rate*Population density, γ_{11}	1.41	1.3	0.5	1.42
	COVID-19 infection rate*Income, γ_{21}	-0.14	0.38	-0.12	0.39
	COVID-19 infection rate*Living alone ratio, γ_{31}	0.17	0.26	0.2	0.47
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.04	0.16	-0.06	0.22

Note: Complete regression table see supplementary. Significant sign : *p<0.1; **p<0.05; ***p<0.01

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Chapter 5 Discussion

Corresponding to the three proposed research objectives, there are three major sections in the Discussion chapter. The 1st section is to discuss the locations of the spatial clusters of suicide rates and changes in suicide rates. The 2nd section is to discuss the local correlates of the spatial cluster of change in the suicide rate and suicide rate. The 3rd section is to discuss the differences in discoveries and meanings between the spatial cluster of change in suicide rates and those of suicide rates.

5.1 Locations of spatial cluster

This study found that the locations of spatial clusters (hotspots and cold spots) differ in suicide rates and changes in suicide rates. Although there are differences in each wave of the virus outbreak, compared to the hotspots of suicide rate, the hotspots of change in suicide rate appear to occur in more densely populated areas or regions that are less mountainous.

Moreover, when comparing the two kinds of cluster maps in this research to previous literature (Yoshioka et al., 2021), I found that spatial clusters of suicide rate during COVID-19 bear more resemblance to the pre-pandemic compared to the spatial cluster of change in suicide rate. That is, suicide rate hotspots occur more in Tohoku regions with few cold spots. However, when I focused on the hotspots of change in suicide rate, I detected several places that are the hotspots of change in suicide rate but not the hotspots of suicide rate, including Okinawa and Oita in Kyusyu.

That is, in a conventional way to merely detect the spatial cluster of suicide rates, it is difficult to verify the regions where increased suicide rates cluster during an acute significant event (COVID-19). Accordingly, the detection of spatial clusters of change in suicide rates might become more useful for detecting regions where mental health has been largely compromised by an acute significant event. Merely from cluster maps,

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we can identify differences in the distribution of changes in suicide rates and suicide rates. To understand the possible rationales behind the maps, regression tools were used to investigate potential local correlates.

5.2 Local Correlates to clusters

This study found different local correlates to the spatial clusters of change in suicide rate and suicide rate in each wave. Throughout the four waves, there was no direction changes for the local correlates to the spatial clusters.

This study had four major findings. First, the COVID-19 infection rate was positively correlated with the hotspots of change in suicide rate. Second, population density was found to be positively correlated with hotspots of change in suicide rates. Third, the single household ratio was found to be negatively correlated with hotspots of change in suicide rate. Fourth, the spatial clusters of suicide rates were found to be negatively correlated with population density in this study. The details are as follows:

5.2.1 COVID-19 infection rate and cluster of change in suicide rate

According to the multilevel logistic regression results, this study found that the hotspots of change in suicide rate during COVID-19 in Japan were more sensitive to the COVID-19 infection rate in the initial periods (directly in the 1^{st} wave and the 2^{nd} wave and indirectly in the 3^{rd} wave) of the virus outbreak. This result shows that regions with higher infection rates may experience a spatial cluster of increased suicide rates. This finding aligns with the concern for mental health proposed in the literature (Osaki et al., 2021). Positive correlations were only found in the early stages of the pandemic (1^{st}, 2^{nd} and 3^{rd} virus outbreak). During the early stages, people were unfamiliar with the virus outbreak and might have felt more anxious and afraid of contracting the disease and accordingly implemented stricter social distancing practices in certain more infected areas (Tanaka & Okamoto, 2021b).

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Afterwards, in the 4th wave of virus outbreaks, the virus spread to the whole nation. People all over Japan might be in a state of uneasiness, not knowing when they will be infected by an invisible virus, and when they can return to normal life (Osaki et al., 2021). Hence, the mental influence was not only limited to the high infection rate region. That is, the hotspots of change in suicide rate might have occurred in regions with high COVID-19 infection rates and also in regions with low infection rates in the later stages of the virus outbreak.

5.2.2 Population density and cluster of change in suicide rate

Population density, which was used as an index of urbanity, showed significant positive correlations in the interaction terms with the COVID-19 infection rate in the initial stages of the pandemic (directly in the 3rd wave and indirectly in the 1st and 2nd wave of virus outbreaks). In the 4th wave, there was no correlation between population density and hotspots of change in suicide rate.

The possible mechanism for the reason why hotspots of change in suicide occurred in more densely populated and more infected areas than cold spots only in the initial stage might be that urban residents might face higher financial stress due to part-time job suspension or lay-off (Watanabe & Tanaka, 2022), higher rent prices. Moreover, the housing conditions for the lower-socioeconomic groups might be inconvenient (including no-shower-space rooms, small living spaces, and so on) during the stay-at-home periods, which made people stay at home for a long time (which is extremely abnormal for most Japanese students and workers in the pre-pandemic period) during the initial periods of COVID-19 pandemic. The situations mentioned above were all risk factors for elevated suicide rates, which has come along with the COVID-19 pandemic. In the 3rd waves of the pandemic, hotspots of change in suicide rates occurred directly in more densely populated areas compared to cold spots.

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However, in the 4th wave of the pandemic, there were no significant urban-rural differences for hotspots in the change in suicide rate. In other words, there might be hotspots for both urban and rural areas. Thus, we found that the urban-rural difference was more significant in the early stages of an acute significant event (the COVID-19 pandemic).

In addition, from the random slope maps and charts, we can see that metropolis groups have a stronger population density effect on other prefectures. These visualized results can fortify the interpretation of the regression table that population density was positively correlated with the hotspots of change in suicide rate because the population effect was especially strong in metropolitan prefectures, including three main metropolises in Japan (Tokyo, Osaka, and Nagoya) (see Supplementary Figure 1 to Supplementary Figure 4).

5.2.3 Single household ratio and cluster of change in suicide rate

Living-alone was a well-known factor for suicide hotspots in Japan before the COVID-19 pandemic. However, when discussing changes in suicide rate (compared to the pre-pandemic time) instead of suicide rate during the COVID-19 pandemic, I found that the living-alone household ratio was significantly negatively correlated with hotspots of change in suicide rate (directly in the 2nd, 3rd, and 4th waves and directly in the 1st and 3rd waves of the virus outbreak). That is, in areas where a lower proportion of single-living households might be correlated to the hotspots of change in the suicide rate. In other words, regions where a higher proportion of people live with family members might be hotspots of change in the suicide rate during COVID-19.

This finding can be explained by observations from previous research. First, it may have been caused by domestic violence. During the COVID-19 pandemic, family members had an abnormally long time hanging out from each other at home. Sometimes, it might cause fraction among family members, especially when facing financial stress,

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pandemic anxiety, and excessive house chores. In the worst situation, even domestic violence happened. During the COVID-19 pandemic, it might have been difficult for victims of domestic violence to attain physical help or find new places during the outbreak. Hence, help-seeking for victims of domestic violence has become increasingly challenging. As a result, the increased risk of domestic violence due to the spread of COVID-19 may also have contributed to excess suicide mortality.

5.2.4 Cluster of suicide rate and population density

For the hotspots in suicide rate, I did not find significant correlations to the COVID-19 infection rate or interaction terms involving the COVID-19 infection rate. This might mean that hotspots of suicide rates were not sensitive to the COVID-19 serious regions at all times during the COVID-19 pandemic.

As for urbanity, unlike the change in suicide rate clustered more in densely populated areas, the suicide rate clustered more in sparsely populated areas, namely, more rural areas. These results align with those of the pre-pandemic study (Yoshioka et al., 2021) in Japan, where hotspots of suicide rates were correlated with rurality. To some extent, we can speculate that, unlike the change in suicide rate, the fact that the location of hotspots of suicide rate still clustered in more rural areas might be affected by inherent factors despite COVID-19 virus outbreaks.

5.3 Difference discovery between two kinds of spatial clusters

From the cluster maps, the locations of spatial clusters of change in suicide rates differ from those of suicide rates. The former shows where suicide problems became significantly worse, whereas the latter shows where suicide problems are serious. These two types of spatial clusters have different meanings. With conventional suicide rate detection, the places where it increased significantly might be neglected, such as Oita and Okinawa. Hence, detecting the change in suicide rate might be important to capture

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the impact of an acute significant event (the COVID-19 pandemic) on suicide rate geographically.

As for cluster characterization, the most significant difference between the spatial cluster of change in suicide rate and suicide rate is that the former is sensitive to the COVID-19 infection rate, but the latter is not. Additionally, the hotspots of change in suicide rate, namely the spatial clusters of increased suicide rate, were correlated with several different social environments, but the hotspots of suicide rate, namely the spatial cluster of high suicide rate, were still correlated with rurality, similar to the pre-pandemic time.

With this finding, we can speculate that detecting the spatial cluster of change in suicide rate might identify the geographic variation in the impact of acute significant events (COVID-19 pandemic) on the suicide rate. However, if we merely detect the spatial cluster of suicide rates, we might detect the COVID-19 effect together with inherent environmental effects, which might not necessarily reflect the impact of the acute significant event.

5.4 Verifying Research Hypothesis

For the 1st research hypothesis, this study found a difference between detecting high suicide rates and detecting increased suicide rates. **By detecting high suicide rate, we only can detect around 50% of increased suicide rate, which is nearly random** (see Table 6, Table 7, Table 8 and Table 9). For the 2nd research hypothesis, this research found **that hotspots of increased suicide rate are** correlated with COVID-19 infection rate and urban areas, **but** those with high suicide rates **are insensitive to infection rate but cluster** more in rural areas. In short, the social environment for each type of spatial cluster was different.

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5.5 Research Suggestion

As for suicide prevention intervention suggestions, we can understand that the change in suicide rate during COVID-19 occurred more in both urban and rural areas and was especially serious in urban areas at the beginning of the COVID-19 pandemic. Meanwhile, overall suicide still clustered in rural areas.

To address this phenomenon, the regular prevention of rural suicide needs to be maintained through websites, phones, or other non-contact interactions for mental health during COVID-19. However, COVID-19-related suicide prevention should be addressed more in urban areas and areas with higher COVID-19 situations. Hopefully, the outcome may be used to understand the spatial pattern of suicide rate change, which is affected by the virus outbreak, and used as a reference to make suicide gatekeeper policies for regional needs.

5.6 Research Limitation

This research focuses on the spatial clusters of change in suicide rates and detected several places with excessive change in suicide rates during the COVID-19 pandemic compared to the pre-pandemic period. However, this study has some limitations. First, there are no national municipality-level COVID-19 infection data available, and this study uses prefecture-level data in multilevel regression to analyze the local correlates. If municipal-level data are provided, the results may change. Second, because I focused on the spatial cluster of change in suicide rate, there might have been spatial autocorrelation in the dependent variables in my multilevel logistic regression models. Despite the use of a random intercept (u0j) and random slopes (ukj, k=1–8) to control for the group effect in the same prefectures, cross-prefecture spatial autocorrelations might remain. That is, with a multilevel logistic spatial error model to consider cross-group spatial autocorrelation, there might be a better-fitted model to address these geographical questions. Nevertheless, the results from this research still provide

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information about how the change in suicide rates spatially clustered during the COVID-19 pandemic in Japan, and there were distinct differences in spatial patterns for changes in suicide rates and suicide rates. The former is more sensitive to the COVID-19 infection rate, which should be considered when implementing COVID-19-related suicide prevention interventions.

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Chapter 6 Conclusion

Spatial clusters of increased suicide rates differ from those of the suicide rates. Although it has been a convention to detect the spatial clusters of suicide rates for a long time before the COVID-19 pandemic, we found it useful to detect the spatial clusters of increased suicide rates, which are the hotspots of change in suicide rate during an acute significant event (COVID-19). With detected spatial clusters of increased suicide rate during the virus outbreak, we can understand which places were most affected by the events that occurred outside the context of the inherent social environment, for example, Oita and Okinawa in Kyusyu in Japan during the COVID-19 pandemic.

By characterizing the spatial clusters, this research found that the spatial cluster of increased suicide rates tends to occur in places with higher COVID-19 infection rates, higher population densities, and lower single-household ratios. On the other hand, the spatial cluster of high suicide rate tends to occur in places with lower population density and is not sensitive to the COVID-19 infection rate.

To sum up, this research shows that in the case of discussing the impact of acute significant events, such as the COVID-19 pandemic, on suicide geographically, it might be more suitable to detect the spatial cluster of increased suicide rates instead of high suicide rates.

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Supplementary

Supplementary Table 1 48 Isolated island (without contiguity or neighboring administrative spatial units) municipalities excluded from this research

北海道	奥尻町	Hokkaido	Okushiri-cho
北海道	礼文町	Hokkaido	Rebun-cho
大分県	姫島村	Oita-ken	Himeshima-mura
山口県	周防大島町	Yamaguchi-ken	Suooshima-cho
島根県	知夫村	Shimane-ken	Chibu-mura
島根県	隠岐の島町	Shimane-ken	Okinoshima-cho
島根県	海士町	Shimane-ken	Ama-cho
島根県	西ノ島町	Shimane-ken	Nishinoshima-cho
広島県	江田島市	Hiroshima-ken	Etajima-shi
広島県	大崎上島町	Hiroshima-ken	Osakikamijima-cho
愛媛県	上島町	Ehime-ken	Kamijima-cho
新潟県	佐渡市	Niigata-ken	Sado-shi
新潟県	粟島浦村	Niigata-ken	Awashimaura-mura
東京都	青ヶ島村	Tokyo-to	Aogashima-mura
東京都	大島町	Tokyo-to	Oshima-machi
東京都	小笠原村	Tokyo-to	Ogasawara-mura
東京都	御蔵島村	Tokyo-to	Mikurajima-mura

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東京都	八丈町	Tokyo-to	Hachijo-machi
東京都	新島村	Tokyo-to	Niijima-mura
東京都	神津島村	Tokyo-to	Kouzushima-mura
東京都	三宅村	Tokyo-to	Miyake-mura
東京都	利島村	Tokyo-to	Toshima-mura
沖縄県	石垣市	Okinawa-ken	Ishigaki-shi
沖縄県	宮古島市	Okinawa-ken	Miyakojima-shi
沖縄県	伊江村	Okinawa-ken	Ie-son
沖縄県	渡嘉敷村	Okinawa-ken	Tokashiki-son
沖縄県	座間味村	Okinawa-ken	Zamami-son
沖縄県	粟国村	Okinawa-ken	Aguni-son
沖縄県	渡名喜村	Okinawa-ken	Tonaki-son
沖縄県	南大東村	Okinawa-ken	Minamidaito-son
沖縄県	北大東村	Okinawa-ken	Kitadaito-son
沖縄県	伊平屋村	Okinawa-ken	Iheya-son
沖縄県	伊是名村	Okinawa-ken	Izena-son
沖縄県	久米島町	Okinawa-ken	Kumejima-cho
沖縄県	多良間村	Okinawa-ken	Tarama-son
沖縄県	竹富町	Okinawa-ken	Taketomi-cho
沖縄県	与那国町	Okinawa-ken	Yonaguni-cho

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長崎県	対馬市	Nagasaki-ken	Tsushima-shi
長崎県	小値賀町	Nagasaki-ken	Ojika-cho
長崎県	新上五島町	Nagasaki-ken	Shinkamigoto-cho
長崎県	壱岐市	Nagasaki-ken	Iki-shi
長崎県	五島市	Nagasaki-ken	Goto-shi
鹿児島県	三島村	Kagoshima-ken	Mishima-mura
鹿児島県	十島村	Kagoshima-ken	Toshima-mura
鹿児島県	長島町	Kagoshima-ken	Nagashima-cho
鹿児島県	屋久島町	Kagoshima-ken	Yakushima-cho
鹿児島県	喜界町	Kagoshima-ken	Kikai-cho
鹿児島県	与論町	Kagoshima-ken	Yoron-cho

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S1 Multi-Level Logistic Regression Results

In the results of multilevel logistic regression, there are major three parts. The first one is null model, the second one is ICC, the third one is the full model including fixed effect and random effect. After that, the goodness of model and the multicollinearity check are also shown.

S1.1 Null multilevel models for change in suicide rate

For the hotspots of change in suicide rate, the calculated intra-class correlation coefficient(ICC) of the total dataset was 0.423, 0.258, 0.215 and 0.216 from the 1st virus outbreak to the 4th outbreak respectively(see Supplementary Table 2). Take the ICC of 1st outbreak for example, the ICC value is 0.423 which means 42.3% of the difference in the probability of being hotspots was attributable to the difference in prefectures. Therefore, it is not appropriate to harness single-level logistic regression describing the relationship between the probability of hotspots and environmental factors without considering the prefecture-level variety.

S1.2 Full multilevel logistic regression models for change in suicide rate

The regressed results of the full multilevel logistic regression models including the higher-level prefecture features were shown in Supplementary Table 7. The Deviance of all the full multilevel logistic regression models are smaller than those of the null models. This means that adding the cross-level interaction term from two-level variables improves the quality of the regression. For each of the full multilevel logistic regression model, it means different waves of COVID-19 outbreaks.

For the 1st wave of virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots are significantly positively correlated to COVID-19 infection rate, significantly positively correlated to the interaction between COVID-19 infection rate and population density and significantly negatively correlated to the interaction between COVID-19 infection rate and living-alone household ratio.

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For the 2nd wave of virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots are found still significantly positively correlated to COVID-19 infection rate, significantly negatively correlated to the living-alone household ratio, and significantly positively correlated to the interaction between COVID-19 infection rate and population density.

For the 3rd wave of virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots are found significantly positively correlated to higher population density, significantly negatively correlated to the living-alone household ratio, and significantly negatively correlated to the interaction between COVID-19 infection rate and living-alone household ratio.

For the 4th wave of virus outbreak in Japan, hotspots of change in suicide rate compared to the cold spots are found significantly positively correlated to higher living-alone household ratio.

S1.3 Null multilevel models for suicide rate

For the hotspots of suicide rate after the outbreak of COVID-19, the calculated intra-class correlation coefficient(ICC) of the total dataset was 0.419, 0.593, 0.465 and 0.555 from the 1st virus outbreak to the 4th outbreak respectively(see Supplementary Table 2). Take the ICC of 1st outbreak for example, the ICC value is 0.419 which means 41.9% of the difference in the probability of being hotspots was attributable to the difference in prefectures. Therefore, it is not appropriate to harness single-level logistic regression describing the relationship between the probability of hotspots and environmental factors without considering the prefecture-level variety.

S1.4 Full multilevel logistic regression models for suicide rate

For the 1st and the 3rd waves of virus outbreak in Japan, hotspots of suicide rate compared to the cold spots are found no significant correlations to the studied environmental factors. For the 2nd and the 4th waves of virus outbreak in Japan, hotspots

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of change in suicide rate compared to the cold spots are found significantly negatively correlated to population density. This means hotspots of suicide rate, namely spatial cluster of relatively high suicide rate area during COVID-19 pandemic compared to the cold spots, occurred in places with less densely populated, namely more rural areas(see Supplementary Table 9 and Supplementary Table 10).

S1.5 Goodness of fit of regression models

For the goodness of fit for the multilevel logistic model, I used Deviance as the goodness of fit for the models. The smaller the deviance is, the better the model fits. According to the result, for the change in suicide rate, the models are all well-fitting, and for suicide rate, most models are well-fitting because the deviances of full models are all smaller than the null models' deviance(see Supplementary Table 6 and Supplementary Table 12).

S1.6 Multicollinearity check

For the multicollinearity check, which is a statistical concept where several independent variables in a model are correlated and might worsen the performance of model, I use VIF (variance inflation factors) to check. As a results, there is no multicollinearity found (all variables in each model, VIF is smaller than 10) (see Supplementary Table 7 and Supplementary Table 13).

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Change in Suicide Rate

Supplementary Table 2 Null models of multi-level logistic regression for spatial hotspots of change in suicide rate during COVID-19 in Japan

Virus outbreak	Number of observations	groups	Intercept, r00	Var(u0j), variance of residual error of highest-level	Var(eij), variance of residual error of lowest-level*	IntraClass Correlation Coefficient, ICC	Correlations interpret
1st wave	286	42	0.138	2.41	3.29	0.423	High
2nd wave	262	37	0.0897	1.14	3.29	0.258	High
3rd wave	254	35	0.092	0.908	3.29	0.216	High
4th wave	249	40	0.339	0.873	3.29	0.210	High

* variance of residual error of lowest-level is fixed to (pi^2)/3, which is almost 3.29 (Wu, Crespi, & Wong, 2012)

Supplementary Table 3 Univariate Models for Hotspots of Change in suicide rate

Waves	variables	Coefficient	Standard Error	Odds ratio	90%Confidence Interval	p-value
1st	COVID-19 infection rate, γ_{01}	0.11	0.48	1.12	(0.51,2.46)	0.823
	Population density, γ_{10}	1.88	2.44	6.55	(0.12,362.78)	0.441
	Income, γ_{20}	0.13	0.43	1.14	(0.56,2.31)	0.76
	Living alone ratio, γ_{30}	0.2	0.26	1.22	(0.8,1.87)	0.438
	Hospital Density, γ_{40}	-0.13	0.11	0.88	(0.73,1.05)	0.263
2nd	COVID-19 infection rate, γ_{01}	0.44	0.35	1.55	(0.87,2.76)	0.202
	Population density, γ_{10}	-3.29	2.24	0.04	(0,1.48)	0.143
	Income, γ_{20}	-0.2	0.49	0.82	(0.37,1.83)	0.683

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	Living alone ratio, γ_{30}	-0.53**	0.23	0.59	(0.4,0.86)	0.02
	Hospital Density, γ_{40}	-0.1	0.1	0.9	(0.77,1.07)	0.347
3rd	COVID-19 infection rate, γ_{01}	0.06	0.33	0.94	(0.55,1.62)	0.855
	Population density, γ_{10}	2.86	1.51	17.46	(1.46,209.34)	0.058
	Income, γ_{20}	-0.21	0.28	0.81	(0.51,1.28)	0.442
	Living alone ratio, γ_{30}	-0.32**	0.16	0.73	(0.56,0.94)	0.05
	Hospital Density, γ_{40}	-0.14	0.12	0.87	(0.71,1.06)	0.246
4th	COVID-19 infection rate, γ_{01}	0.02	0.24	1.02	(0.69,1.51)	0.918
	Population density, γ_{10}	0.08	1.3	1.08	(0.13,9.19)	0.954
	Income, γ_{20}	-0.39	0.28	0.68	(0.43,1.07)	0.16
	Living alone ratio, γ_{30}	-0.46**	0.19	0.63	(0.46,0.86)	0.012
	Hospital Density, γ_{40}	-0.17	0.11	0.84	(0.7,1.01)	0.134

Significant sign : *p<0.1; **p<0.05; ***p<0.01

Supplementary Table 4 Fixed Effect of multi-level logistic regression model for spatial hotspots of change in suicide rate during COVID-19 in Japan

Waves	variables	Coefficient	Standard Error	Odds ratio	90%Confidence Interval	p-value
1st	Intercept, γ_{00}	0.78	0.74	2.18	(0.65,7.37)	0.296
	COVID-19 infection rate, γ_{01}	2.67**	1.16	14.44	(2.14,97.34)	0.022
	Population density, γ_{10}	1.23	1.59	3.42	(0.25,46.78)	0.439
	Income, γ_{20}	0.46	0.5	1.58	(0.7,3.61)	0.352
	Living alone ratio, γ_{30}	0.16	0.22	1.17	(0.82,1.69)	0.472

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	Hospital Density, γ_{40}	-0.01	0.17	0.99	(0.75,1.31)	0.962
	COVID-19 infection rate*Population density, γ_{11}	6.8**	2.7	897.85	(10.58,76229.21)	0.012
	COVID-19 infection rate*Income, γ_{21}	0.24	0.61	1.27	(0.47,3.47)	0.699
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.61*	0.33	0.54	(0.32,0.94)	0.062
	COVID-19 infection rate*Hospital Density, γ_{41}	0.23	0.22	1.26	(0.88,1.81)	0.305
2nd	Intercept, γ_{00}	-2.3	1.17	0.1	(0.01,0.69)	0.048
	COVID-19 infection rate, γ_{01}	4.07***	1.58	58.56	(4.35,787.69)	0.01
	Population density, γ_{10}	-5.7	3.52	0	(0,1.09)	0.106
	Income, γ_{20}	-0.08	0.95	0.92	(0.19,4.41)	0.937
	Living alone ratio, γ_{30}	-0.9***	0.34	0.41	(0.23,0.71)	0.009
	Hospital Density, γ_{40}	-0.36	0.27	0.7	(0.45,1.09)	0.187
	COVID-19 infection rate*Population density, γ_{11}	11.86**	5.11	141492.22	(31.63,632980389.9)	0.02
	COVID-19 infection rate*Income, γ_{21}	-1.63	1.61	0.2	(0.01,2.77)	0.312
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.38	0.55	0.68	(0.28,1.69)	0.486
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.67	0.56	0.51	(0.2,1.29)	0.231
3rd	Intercept, γ_{00}	1.51	0.87	4.53	(1.08,18.94)	0.084

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	COVID-19 infection rate, γ_{01}	1.59	1.13	4.9	(0.76,31.46)	0.159
	Population density, γ_{10}	4.28*	2.36	72.24	(1.49,3505.89)	0.07
	Income, γ_{20}	-0.49	0.56	0.61	(0.24,1.54)	0.375
	Living alone ratio, γ_{30}	-0.54**	0.23	0.58	(0.4,0.85)	0.02
	Hospital Density, γ_{40}	-0.03	0.12	0.97	(0.8,1.18)	0.775
	COVID-19 infection rate*Population density, γ_{11}	4.45	2.86	85.63	(0.78,9458.79)	0.119
	COVID-19 infection rate*Income, γ_{21}	-0.27	0.54	0.76	(0.31,1.86)	0.62
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.51*	0.27	0.6	(0.39,0.94)	0.056
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.08	0.2	0.92	(0.66,1.28)	0.7
4th	Intercept, γ_{00}	0.06	0.49	1.06	(0.47,2.38)	0.907
	COVID-19 infection rate, γ_{01}	0.45	0.46	1.57	(0.74,3.34)	0.321
	Population density, γ_{10}	-0.6	1.16	0.55	(0.08,3.7)	0.604
	Income, γ_{20}	-0.19	0.22	0.83	(0.58,1.19)	0.371
	Living alone ratio, γ_{30}	-0.44**	0.22	0.64	(0.45,0.92)	0.04
	Hospital Density, γ_{40}	-0.19	0.12	0.83	(0.68,1.01)	0.102
	COVID-19 infection rate*Population density, γ_{11}	1.41	1.3	4.1	(0.48,34.76)	0.279
	COVID-19 infection rate*Income, γ_{21}	-0.14	0.38	0.87	(0.47,1.62)	0.724

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COVID-19 infection rate*Living alone ratio, γ_{31}	0.17	0.26	1.19	(0.77,1.82)	0.506
COVID-19 infection rate*Hospital Density, γ_{41}	-0.04	0.16	0.96	(0.74,1.25)	0.813

Significant sign : *p<0.1; **p<0.05; ***p<0.01

Supplementary Table 5 Random Effect of multi-level logistic regression model for spatial hotspots of change in suicide rate during COVID-19 in Japan

Waves	Residual Error Terms	Variance	Standard Deviation
The 1st wave of virus outbreak	Intercept, u_{0j}	3.2358	1.799
	Population density, u_{1j}	0.5499	0.742
	Income, u_{2j}	1.0992	1.048
	Living alone ratio, u_{3j}	0.0583	0.241
	Hospital Density, u_{4j}	0.2152	0.464
The 2nd wave of virus outbreak	Intercept, u_{0j}	5.0962	2.257
	Population density, u_{1j}	73.6293	8.581
	Income, u_{2j}	5.2477	2.291
	Living alone ratio, u_{3j}	0.7258	0.852
	Hospital Density, u_{4j}	0.0189	0.138
The 3rd wave of virus outbreak	Intercept, u_{0j}	2.4651	1.57
	Population density, u_{1j}	0.0399	0.2
	Income, u_{2j}	0.3396	0.583
	Living alone ratio, u_{3j}	0.0326	0.18

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	Hospital Density, u_{4j}	0.014	0.12
The 4th wave of virus outbreak	Intercept, u_{0j}	0.854	0.924
	Population density, u_{1j}	0.190	0.435
	Income, u_{2j}	0.013	0.114
	Living alone ratio, u_{3j}	0.420	0.648
	Hospital Density, u_{4j}	0.00008	0.009

Supplementary Table 6 Deviance for Change in suicide Rate Models

Waves	Null model	Full Model
1st	363.3	338.1
2nd	340.5	302.8
3rd	341.2	322.1
4th	334.3	317.4

Note : generalized linear model (GLM) to model the relationship, deviance* is a measure of goodness of fit: the smaller the deviance, the better the fit.

Supplementary Table 7 Variance of inflation, VIF for multicollinearity detection of multi-level logistic regression model (exclude interaction term) for spatial hotspots of change in suicide rate during COVID-19 in Japan

Wave	COVID-19 infection rate	Population density	Income	Living alone ratio	Hospital Density
1st	1.18	1.12	1.27	1.41	1.48
2nd	1.13	1.61	1.42	1.28	1.08
3rd	1.30	1.07	1.38	1.05	1.02

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4th	1.23	1.08	1.07	1.21	1.07

Models for Suicide Rate

Supplementary Table 8 Null models of multi-level logistic regression for spatial hotspots suicide rate during COVID-19 in Japan

wave	Number of observations	groups	Intercept, r00	Var(uij), variance of residual error of highest-level	Var(eij), variance of residual error of lowest-level*	IntraClass Correlation Coefficient, ICC	Correlations interpret
1st	322	45	0.148	2.37	3.29	0.419	High
2nd	280	43	0.0176	4.8	3.29	0.593	High
3rd	293	38	0.102	2.86	3.29	0.465	High
4th	298	40	0.238	4.1	3.29	0.555	High

* variance of residual error of lowest-level is fixed to (pi^2)/3, which is almost 3.29 (Wu et al., 2012)

Supplementary Table 9 Univariate Model for Hotspots of Suicide Rate

Waves	variables	Coefficient	Standard Error	Odds ratio	90%Confidence Interval	p-value
1st	COVID-19 infection rate, γ_{01}	-0.28	0.41	0.76	(0.39,1.48)	0.492
	Population density, γ_{10}	-0.80***	0.001	0.45	(0.45,0.45)	<0.001
	Income, γ_{20}	-0.02	0.25	0.98	(0.65,1.48)	0.948
	Living alone ratio, γ_{30}	-0.2	0.19	0.82	(0.6,1.12)	0.274
	Hospital Density, γ_{40}	0.09	0.11	1.09	(0.91,1.31)	0.948
2nd	COVID-19 infection rate, γ_{01}	-0.31	0.46	0.73	(0.34,1.56)	0.509
	Population density, γ_{10}	-4.2	2.76	0.01	(0,1.41)	0.128

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	Income, γ_{20}	0.38	0.29	1.46	(0.91,2.36)	0.193
	Living alone ratio, γ_{30}	-0.18	0.21	0.84	(0.59,1.18)	0.394
	Hospital Density, γ_{40}	0.11	0.12	1.12	(0.92,1.36)	0.335
3rd	COVID-19 infection rate, γ_{01}	-0.38	0.38	0.68	(0.37,1.28)	0.322
	Population density, γ_{10}	-1.88	2.01	0.15	(0.01,4.16)	0.348
	Income, γ_{20}	-0.31	0.47	0.73	(0.34,1.59)	0.519
	Living alone ratio, γ_{30}	0.31	0.27	1.36	(0.87,2.13)	0.252
	Hospital Density, γ_{40}	-0.003	0.094	1	(0.86,1.16)	0.979
4th	COVID-19 infection rate, γ_{01}	-0.05	0.42	0.95	(0.48,1.9)	0.906
	Population density, γ_{10}	-5.25***	1.91	0.01	(0,0.12)	0.006
	Income, γ_{20}	-1.08**	0.56	0.34	(0.14,0.85)	0.053
	Living alone ratio, γ_{30}	-0.3	0.3	0.74	(0.45,1.21)	0.315
	Hospital Density, γ_{40}	-0.03	0.13	0.97	(0.78,1.2)	0.821

Significant sign : *p<0.1; **p<0.05; ***p<0.01

Supplementary Table 10 Fixed Effect of multi-level logistic regression model for spatial hotspots of suicide rate during COVID-19 in Japan

Waves	Item	Coefficient	Standard Error	Odds ratio	90% Confidence Interval	p-value
The 1st wave of virus outbreak	Intercept, γ_{00}	-0.28	0.55	0.76	(0.31,1.87)	0.613
	COVID-19 infection rate, γ_{01}	-0.19	0.82	0.83	(0.21,3.19)	0.82
	Population density, γ_{10}	-1.2	1.31	0.3	(0.03,2.6)	0.358
	Income, γ_{20}	0.23	0.41	1.26	(0.64,2.47)	0.577

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	Living alone ratio, γ_{30}	-0.29	0.22	0.75	(0.52,1.07)	0.197
	Hospital Density, γ_{40}	0.12	0.13	1.13	(0.91,1.4)	0.385
	COVID-19 infection rate*Population density, γ_{11}	0.84	1.76	2.32	(0.13,41.9)	0.632
	COVID-19 infection rate*Income, γ_{21}	-0.4	0.42	0.67	(0.34,1.34)	0.336
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.16	0.24	0.85	(0.57,1.26)	0.506
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.1	0.16	0.9	(0.7,1.18)	0.529
The 2nd wave of virus outbreak	Intercept, γ_{00}	-1.74	1.33	0.18	(0.02,1.56)	0.192
	COVID-19 infection rate, γ_{01}	0.58	1.14	1.79	(0.27,11.65)	0.607
	Population density, γ_{10}	-6.01*	3.14	0.002	(0,0.43)	0.056
	Income, γ_{20}	0.8	0.6	2.23	(0.83,5.97)	0.183
	Living alone ratio, γ_{30}	-0.39	0.39	0.68	(0.36,1.29)	0.311
	Hospital Density, γ_{40}	0.35	0.32	1.42	(0.84,2.4)	0.282
	COVID-19 infection rate*Population density, γ_{11}	0.18	1.99	1.2	(0.05,31.61)	0.93
	COVID-19 infection rate*Income, γ_{21}	0.5	0.81	1.65	(0.43,6.25)	0.538
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.34	0.54	0.71	(0.29,1.73)	0.528
	COVID-19 infection rate*Hospital Density, γ_{41}	0.24	0.46	1.27	(0.6,2.71)	0.606
The 3rd wave of virus outbreak	Intercept, γ_{00}	-0.26	0.72	0.77	(0.24,2.52)	0.723
	COVID-19 infection rate, γ_{01}	-0.13	0.52	0.88	(0.37,2.07)	0.794
	Population density, γ_{10}	-1.8	1.67	0.17	(0.01,2.58)	0.282
	Income, γ_{20}	0.21	0.4	1.23	(0.64,2.38)	0.606

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	Living alone ratio, γ_{30}	0.22	0.28	1.25	(0.79,1.98)	0.419
	Hospital Density, γ_{40}	0.01	0.12	1.01	(0.83,1.23)	0.953
	COVID-19 infection rate*Population density, γ_{11}	-0.13	1.08	0.88	(0.15,5.19)	0.906
	COVID-19 infection rate*Income, γ_{21}	-0.47	0.41	0.63	(0.32,1.23)	0.249
	COVID-19 infection rate*Living alone ratio, γ_{31}	-0.27	0.33	0.76	(0.44,1.31)	0.406
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.07	0.13	0.93	(0.75,1.15)	0.569
The 4th wave of virus outbreak	Intercept, γ_{00}	-0.88	0.66	0.41	(0.14,1.23)	0.183
	COVID-19 infection rate, γ_{01}	0.36	0.69	1.43	(0.46,4.46)	0.597
	Population density, γ_{10}	-3.28*	1.83	0.04	(0,0.76)	0.073
	Income, γ_{20}	-0.64	0.55	0.53	(0.21,1.3)	0.242
	Living alone ratio, γ_{30}	-0.06	0.34	0.94	(0.54,1.65)	0.865
	Hospital Density, γ_{40}	-0.09	0.23	0.91	(0.63,1.33)	0.713
	COVID-19 infection rate*Population density, γ_{11}	0.5	1.42	1.65	(0.16,17.05)	0.725
	COVID-19 infection rate*Income, γ_{21}	-0.12	0.39	0.89	(0.47,1.68)	0.76
	COVID-19 infection rate*Living alone ratio, γ_{31}	0.2	0.47	1.22	(0.56,2.65)	0.667
	COVID-19 infection rate*Hospital Density, γ_{41}	-0.06	0.22	0.94	(0.66,1.35)	0.799

Significant sign : *p<0.1; **p<0.05; ***p<0.01

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Supplementary Table 11 Random Effect of multi-level logistic regression model for spatial hotspots of suicide rate during COVID-19 in Japan

Waves	Residual Error Terms	Variance	Standard Deviation
The 1st wave of virus outbreak	Intercept, u_{0j}	3.4133	1.848
	Population density, u_{1j}	0.0617	0.248
	Income, u_{2j}	0.1445	0.38
	Living alone ratio, u_{3j}	0.116	0.341
	Hospital Density, u_{4j}	0.0292	0.171
The 2nd wave of virus outbreak	Intercept, u_{0j}	19.0356	4.363
	Population density, u_{1j}	44.1264	6.643
	Income, u_{2j}	0.1187	0.345
	Living alone ratio, u_{3j}	0.0948	0.308
	Hospital Density, u_{4j}	0.0276	0.166
The 3rd wave of virus outbreak	Intercept, u_{0j}	2.3878	1.545
	Population density, u_{1j}	1.9294	1.389
	Income, u_{2j}	0.3034	0.551
	Living alone ratio, u_{3j}	0.3291	0.574
	Hospital Density, u_{4j}	0.0136	0.116
The 4th wave of virus outbreak	Intercept, u_{0j}	1.4058	1.186
	Population density, u_{1j}	1.2023	1.097
	Income, u_{2j}	1.9762	1.406
	Living alone ratio, u_{3j}	0.7556	0.869
	Hospital Density, u_{4j}	0.0201	0.142

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Supplementary Table 12 Deviance for Suicide Rate Models

Waves	Null model	Full Model
1st	395.3	386.1
2nd	313.2	298.3
3rd	364.9	346.7
4th	330.0	298.8

Note : generalized linear model (GLM) to model the relationship, deviance* is a measure of goodness of fit: the smaller the deviance, the better the fit.

Supplementary Table 13 Variance of inflation, VIF for multicollinearity detection of multi-level logistic regression model (exclude interaction term) for spatial hotspots of suicide rate during COVID-19 in Japan

Wave	COVID-19 infection rate	Population density	Income	Living alone ratio	Hospital Density
1^{st}	1.26	1.19	1.05	1.22	1.22
2^{nd}	1.00	1.14	1.30	1.04	1.11
3^{rd}	1.19	1.07	1.09	1.13	1.14
4^{th}	1.17	1.23	1.31	1.08	1.02

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S1.5 Random Slopes of population density for odds being hotspots of change in suicide rate

The multilevel logistic regression tables have already provided abundant information to confirm that the hotspots change in suicide rate tends to occurred in more densely populated regions in the indirection effect along with COVID-19 effect, that is , interaction term in the 1st and 2nd wave of virus outbreak and direction effect in the 3rd wave of virus outbreak.

From Supplementary Figure 1 to Supplementary Figure 4, there show the varying random slopes along each groups in multilevel logistic regression. Each group means each prefecture, which is the largest administrative district in Japan. I extracted the local variable concerned, population density to investigate the random slopes for population density and log odds of being hotspots of change in suicide rate compared to the cold spots. The value (see Supplementary Table 14) on the map and chart are coefficients of multilevel logistic regression, β_{1j} in equation 2.2 in section 3.6.4.

According to the maps and the slopes figures of random slopes, I found in addition to the interpretation of regression table, in the visualize illustration, we can also found the effect of population density was more positively strong in the urban areas including Tokyo Metropolis(including Tokyo, Saitama, Kanagawa, Chiba), Osaka Metropolis(including Osaka, Kyoto, Nara and Hyogo) and Nagoya Metropolis(which is located in Aichi). On top of that, based on the map and the slopes chart, I also found the population density effect for odds being hotspots of change in suicide rate was strong in Okinawa since the 2nd wave to the 4th wave of outbreak.

The coefficient β_{1j} was the slopes for population density, which means one unit in scaled population density will lead to how much change in log odds of being hotspots compared to the cold spots. The positive coefficient means that the higher the population is, the higher the odds being hotspots of change in suicide rate compared to

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the cold spots in the group(prefecture). On the contrary, the negative coefficient means that the higher the population is, the lower the odds of being hotspots of change in suicide rate compared to the cold spots in the group(prefecture).

Seeing that we found most large slopes occurred in the prefecture of metropolis in Japan, it works in concert with the regression tables that the population density was positively correlated to hotspots of change in suicide rate indirectly(interaction term) or directly(sole term)(see Table 11).

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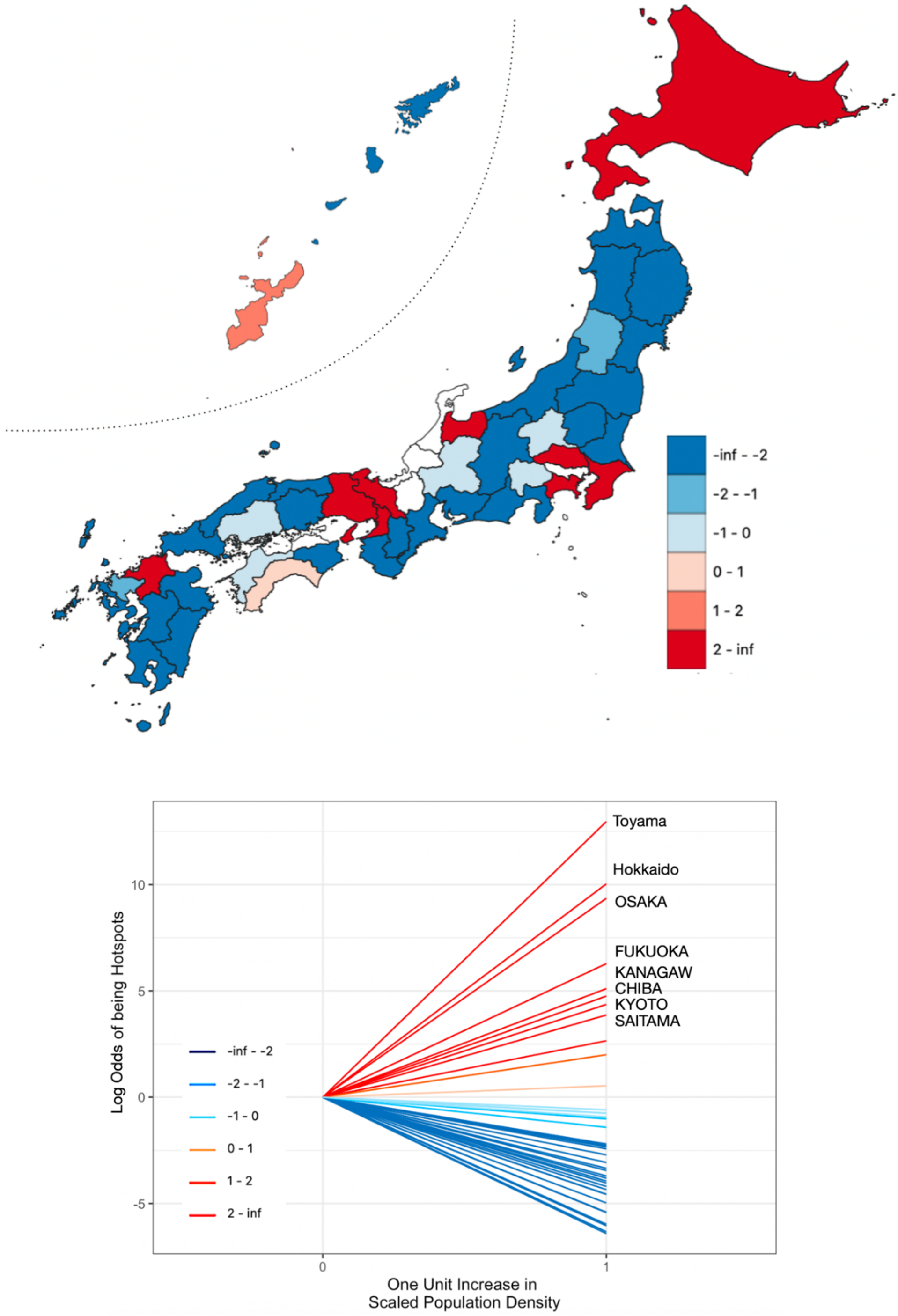
Wave 1



Supplementary Figure 1 Random slopes(coefficient) for population density in the 1st wave of virus outbreak . The map(left) and the slope chart(right).

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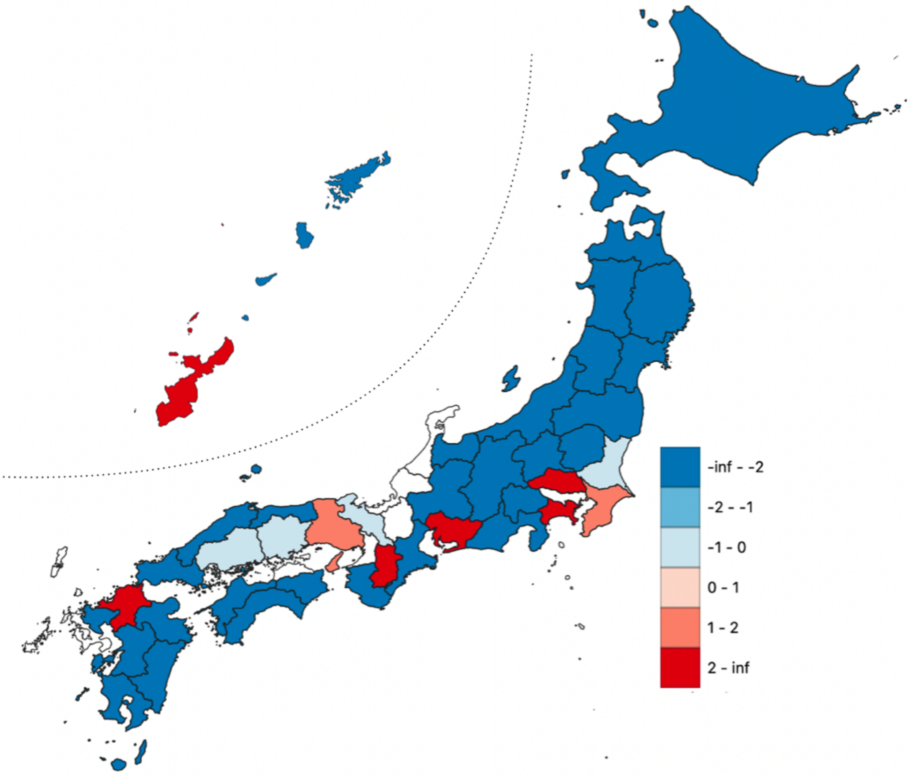
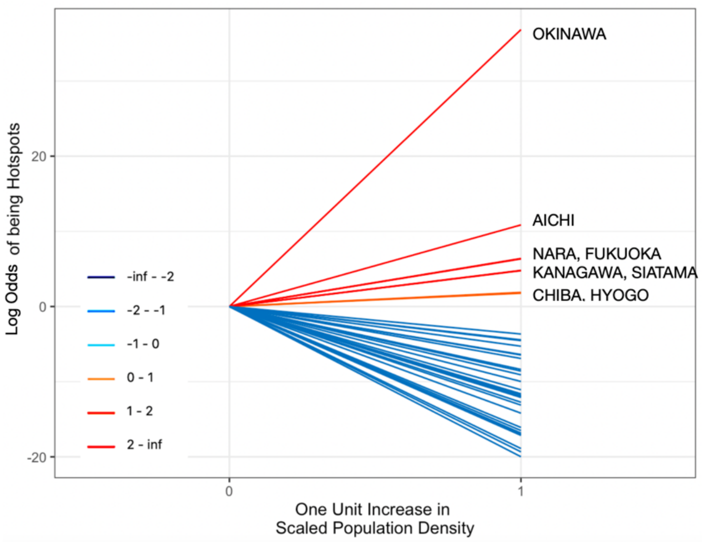
Wave 2





Supplementary Figure 2 Random slopes(coefficient) for population density in the 2nd wave of virus outbreak . The map(left) and the slope chart(right).

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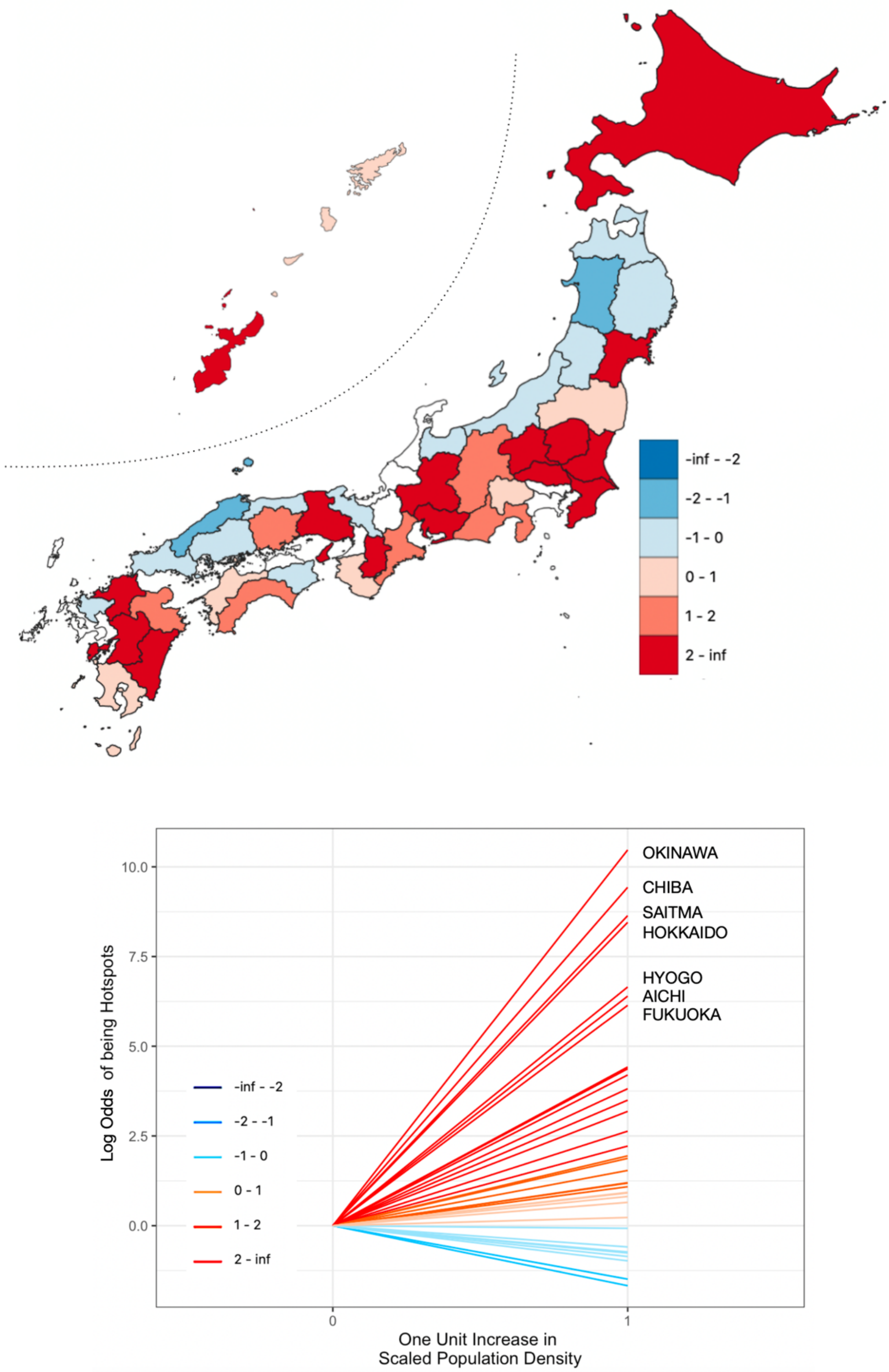
Wave 3



Supplementary Figure 3 Random slopes(coefficient) for population density in the 3rd wave of virus outbreak. The map(left) and the slope chart(right).

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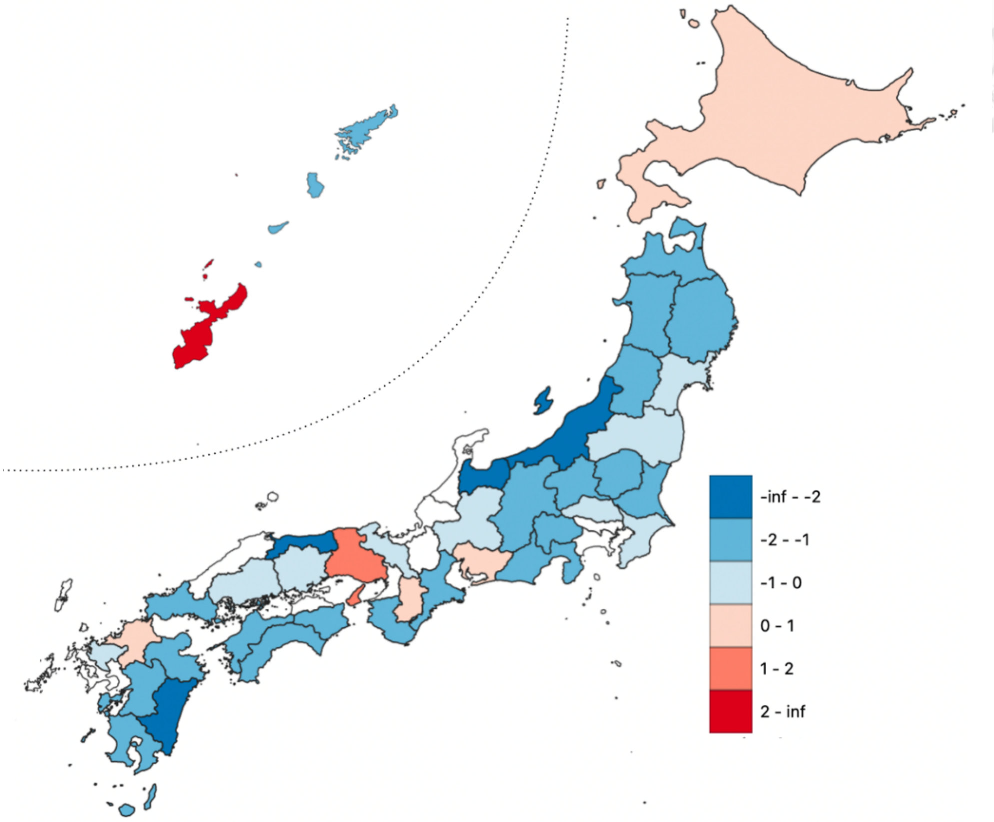
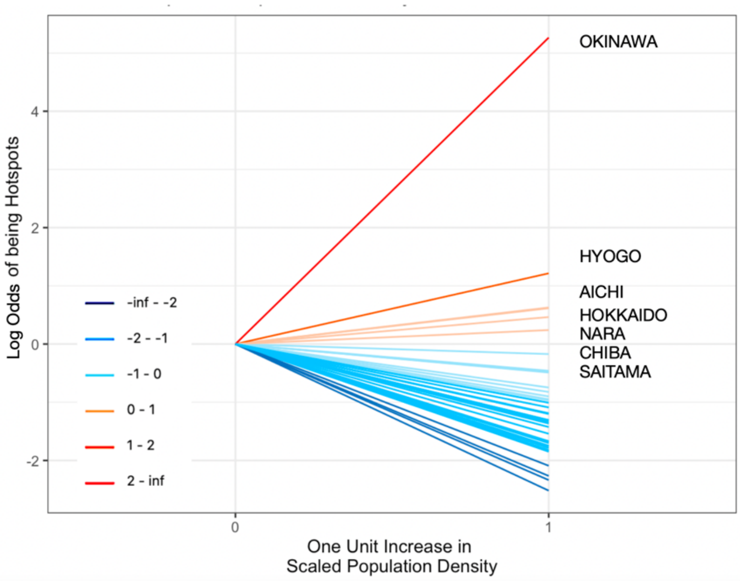
Wave 4





Supplementary Figure 4 Random slopes(coefficient) for population density in the 4th wave of virus outbreak . The map(left) and the slope chart(right)

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Supplementary Table 14 Random Slopes (Coefficient) for population density to log odd ratio of begin hotspots of change in suicide rate compared to the cold spots

EN	**place**	**random slope 1**	**random slope 2**	**random slope 3**	**random slope 4**
Aichi	愛知県	-3.069298665	10.86168997	6.399184549	0.628064858
Akita	秋田県	-5.422760964	-8.36957289	-1.671898455	-1.821447174
Aomori	青森県	-4.342597269	-19.9847292	-0.073797797	-1.747879577
Chiba	千葉県	4.752939531	1.884822293	9.429831654	-0.172455068
Ehime	愛媛県	-0.594396213	-17.00329736	0.229256929	-1.84877298
Fukui	福井県				
Fukuoka	福岡県	6.28353277	6.334214017	6.141981751	0.240606093
Fukushima	福島県	-2.426232669	-16.49900396	0.814495565	-0.823126186
Gifu	岐阜県	-0.741702286	-4.538513054	4.422315952	-0.969977133
Gunma	群馬県	-0.980909829	-11.07996849	4.200034424	-1.089159573
Hiroshima	広島県	-0.758550005			-0.899603825

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Hokkaido	北海道	10.03388427	-9.974828655	8.453758045	0.615781115
Hyogo	兵庫県	2.653104149	1.776903348	6.653847936	1.216235475
Ibaraki	茨城県	-2.302873688		3.499330038	-1.189035819
Ishikawa	石川県				
Iwate	岩手県	-6.325159254	-6.912426122	-0.732505527	-1.786195745
Kagawa	香川県				
Kagoshima	鹿児島県	-5.970985593	-5.281440702	0.64976729	-1.701271259
Kanagawa	神奈川県	5.106177285	4.815261608		
Kōchi	高知県	0.536973655	-9.085643148	1.087343154	-1.201316394
Kumamoto	熊本県	-3.93929003	-12.0951363	3.185558768	-1.541035583
Kyoto	京都府	4.359277993			-0.488843353
Mie	三重県	-4.567950326	-11.61254584	1.540997778	-1.842086979
Miyagi	宮城県	-2.335367729	-18.89470077	2.220383928	-0.948795984
Miyazaki	宮崎県	-3.807146957	-17.14612457	2.633893283	-2.337234698

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Nagano	長野県	-3.705983701	-3.66113313	1.188266174	-1.311166497
Nagasaki	長崎県	-4.559376816			
Nara	奈良県	-2.197269487	6.393013411	4.372841399	0.464993132
Niigata	新潟県	-3.34290556	-16.83801413	-0.761074237	-2.266369256
Oita	大分県	-4.195622809	-19.33469856	1.198737628	-1.365381808
Okayama	岡山県	-5.405005428		1.877691118	-0.459462693
Okinawa	沖縄県	1.997844546	36.84678182	10.47186785	5.26575248
Osaka	大阪府	9.35349946			
Saga	佐賀県	-1.021302958	-11.93121939		-0.747216897
Saitama	埼玉県	3.865918538	4.769547143	8.639883177	-0.480141736
Shiga	滋賀県				
Shimane	島根県	-2.256847769	-13.11578516	-1.488490395	
Shizuoka	静岡県	-4.968557939	-4.434092715	1.946795664	-1.337815569
Tochigi	栃木県	-4.036265953	-6.385692424	3.817888481	-1.757675291

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Tokushima	徳島県	-6.043307974	-11.79411395	-0.978835052	-1.305770339
Tokyo	東京都				
Tottori	鳥取県	-6.41217325	-8.594672593		-2.51866537
Toyama	富山県	12.96465994	-12.7353869	-0.591803549	-2.09128353
Wakayama	和歌山県	-2.714799508	-16.09457031	0.912434869	-1.008637362
Yamagata	山形県	-1.416611649	-6.45456683	-0.857532511	-1.425744735
Yamaguchi	山口県	-3.443367461	-14.19000441		-1.677164346
Yamanashi	山梨県	-0.925437336	-12.01862774	0.928690497	-1.668863411

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