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Longitudinal trajectories of region-level suicide mortality in Tokyo, Japan, 2011 to 2021

Asuka Suzuki[1], Kazue Yamaoka[1]*, Mariko Inoue[1], Toshiro Tango[2,1]

[1]Teikyo University Graduate School of Public Health, Tokyo, Japan
[2]Center for Medical Statistics, Tokyo, Japan

Article Info

Abstract

Background: Suicide mortality in Japan has declined over a period of more than 10 years, however, differences in longitudinal trajectories at a regional level are not well characterized. Objective was to clarify the longitudinal suicide mortality trajectories at the regional level in Tokyo from 2011 to 2021 by considering spatial smoothing, before and during the COVID-19 pandemic.

Methods: This longitudinal cross-sectional analysis used fifty-four regions in Tokyo, Japan. Suicide mortality trends used data from the Cabinet Office of the Japanese government from 2011 to 2021. Regional social and environmental characteristics were used as 10 covariates. Empirical Bayes estimates for the standardized mortality ratio were obtained. A conditional autoregressive (CAR) model was applied to capture the spatial correlation for a crude and adjusted with 10 covariates using OpenBUGS. Spatial clusters were also identified by FlexScan, SaTScan, and Tango's test.

Results: Longitudinal trajectories for both males and females were similar to a decreasing trend in all Japan until 2019. In 2020, the beginning of the COVID-19 pandemic, the age-specific suicide deaths were the highest among those in their 20s. However, those were the highest among males in their 50s in 2021.

The results of the CAR models adjusted for 10 covariates detected several regions as having higher suicide rates, but those regions were somewhat varied.

Conclusion: During the COVID-19 pandemic, both sexes in their 20s and males in their 50s showed a tendency toward an increase in suicides. The detected regions by spatial epidemiology varied with sex.

Introduction

According to Japan's National Police Agency, the monthly number of suicides in Japan rose to over 2000 in October 2020, and suicide claimed more lives than COVID-19 during 2020[1] and continued until 2021. Further, COVID-19 resulted in economic distress and is one of the direct or indirect factors such as mental stress, loneliness, stress and social separation resulting from lockdown for the increase in the number of suicides. The World Health Organization (WHO) has tackled the problem of suicide deaths in its Comprehensive Mental Health Action Plan[2,3] as a critical global public health issue. Suicide mortality in Japan is the second highest among Asian countries, and suicide prevention continues to be a significant health issue due to the magnitude of the impact of suicides[4].

In the former study, we examined the regional status of current suicide deaths in Kanagawa Prefecture as a useful tool for evaluating

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by the community[5]. A recent report analyzed whether suicide mortality changed during the COVID-19 pandemic based on month-level records of suicides covering the entire Japanese population[6]. In Tokyo, suicide prevention measures have been continuously implemented; however, regional variation and the impact of the COVID-19 pandemic since 2020 should be of concern.

So far, several studies have used spatial epidemiologic technics not only for infectious diseases but also for spatial-temporal suicide trends[7] and suicide risk around the world[5,8-11]. Factors related to community characteristics were analyzed and the young and the older adults were indicated to belong to highly vulnerable and marginalized groups. Suicide prevention is an important priority in policy making. Spatial statistics are widely used to detect geographical disease clusters for analyses of population status using regional data. The use of spatial correlations of suicide deaths can provide valuable information on the extent of spatial spreading[12,13].

In Japan, differences in longitudinal trajectories among residents at a regional level in Japan are not well characterized. The implications of COVID-19 pandemic, which has put the nation under attack since 2020, are of concern. We examined spatial clustering of suicide mortality in Tokyo using data from regional statistics on male and female suicide deaths from 2011 to 2021, before and after the onset of the COVID-19 pandemic. From the longitudinal trajectories, the impacts of COVID-19 was also examined.

Methods

This longitudinal cross-sectional analysis used regional statistics (54 regions in Tokyo) derived from the national vital statistics reported by the Cabinet Office of the Japanese government from 2011 to 2021 (e-Stat)[14]. Data on the number of suicide deaths according to region were based on information from the National Police Agency. In this study, we examined the regional variation in the status of suicide risk using the approach of "borrowing strength" in spatial epidemiology. We principally examined the following two questions: (i) are there any spatial clusters of suicide deaths in Tokyo according to the Conditional Autoregressive (CAR) model that assumed a spatial correlation and the 3 tests for detecting clusters as well, and ii) are the impacts of COVID-19 detected in the longitudinal trajectories by considering regional variation. Regional social and environmental characteristics were used as 10 covariates for the CAR model. The CAR model was applied to capture the spatial correlation for a crude and adjusted with 10 covariates using OpenBUGS.

Measures

Age-specific vital statistics for suicide were used and standardized mortality was calculated. We classified age into 8 groups (≤19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, 80+years). We obtained regional data for 2011 in 10 topics as covariates from the Japanese National Census[14] such as the proportion of single households (%), average family size, population density (persons/km^2), number of general clinics (per 1000 individuals), the proportion of foreigners (%), workforce [per 1000 workers (all workers and unemployed people over the age of 15)], unemployment (%), average income (10000 yen), number of criminals recognized, and the proportion of residents aged 65 years or older (%). Because population characteristics from these regional data did not largely vary during the above mentioned 10-year period, 2011 data were used as baseline covariates in the analyses. All unknown data were excluded from the analysis. We used regional vital statistics provided by the National government (the Cabinet Office). The summarized data by region in each prefecture were provided and we treated the unknown as missing.

Statistical analyses

Most likely clusters have been detected by cluster detection tests such as Tango-Takahashi's flexible spatial scan statistic using the software Flexible Scan (FlexScan)[17] and Kulldorff's circular spatial scan statistic (spatial, temporal, or space-time scan statistics; SaTScan.)[18,19] (FlexScan includes Kulldorff's circular spatial scan statistic.) Further, "hotspot" has been examined by Tango's test using "Disease Mapping System (DMS)" software provided by Tango[20]. The spatial scan statistics implemented by FleXScan and SaTScan offer several advantages over other techniques for detecting disease clusters. Spatial scan statistics may be changed by model assumptions. Consequently, we applied these models and checked whether similar results were obtained despite the various assumptions. The focus of this paper was on comparing various models with different assumptions to find similar results.

In this study, we focused on the detection of spatial clustering of suicide mortality and related community characteristics in Tokyo from 2011 to 2021. The CAR model was used to estimate of θ_i and the estimates of regression coefficients of covariates β_i by taking spatial correlations ϕ_i into account[15]. The estimates were shown with 95%CI (95% credible interval) (in tables) as well as the estimated region's suicide mortality using 5 levels (in maps). Ten covariable models were conducted. All analyses were performed according to sex. OpenBUGS was used for the analysis and is the open-source variant of WinBUGS (Bayesian inference Using Gibbs Sampling)[16]. For details of the indices for standardized mortality formula, see Appendix.

$$d_i \sim \text{Poisson}(e_i\theta_i)$$

$$\log\theta_i = \mu + \beta_1 x_{1i} + .. + \beta_2 x_{2i} + \beta_p x_{pi} + \epsilon_i + \phi_i, \quad \epsilon_i \sim N(0,\sigma^2)$$

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$\phi_i | \phi_{j \neq i} \sim N(\overline{\phi_i}, \frac{1}{m_i} \sigma_\phi^2)$: CAR model,

m_i = number of regions adjacent to region i,

$\overline{\phi_i}$ = average of ϕ_j among regions adjacent to region i,

where the following three hyperprior distributions are assumed:

$\mu \sim$ improper prior,

$\sigma_\varepsilon^2 \sim$ Gamma (0.5,0.0005),

$1/\sigma_\phi^2 \sim$ Gamma (0.5,0.0005).

For the expected number of deaths "e," we used 10 covariates only for the CAR model, not for the other models.

Results

Figure 1 shows the longitudinal trajectories for suicide by sex. Those in Tokyo showed similar decreasing trend all over Japan until 2019. Although the total suicide rates for each year examined in Tokyo were lower than the national rates for males, they were higher for females. As for age, suicide deaths for males and females in their 20s tended to increase in 2020 among age groups and both sexes in their 20s, and the rates were the highest. However, those were the highest among males in their 50s while those were the highest in females in their 20s in 2021.

As for the characteristics of suicides by sex, being in the 40s (18.8% and 18.0% for males and females, respectively), being unemployed (51.1% and 66.5% for males and females, respectively), and having health problems (34.3% and 48.6% for males and females, respectively) were comparatively frequent (Table 1). Characteristics of the variables are summarized in Supplementary File 1 with mean values, minimum and maximum values, and corresponding regional codes. The proportions of single households and foreigner residents were the highest in a downtown (Code 104).

The regions detected by the CAR models and several spatial tests by sex as regions with significantly higher relative risk are summarized in Table 2. A visual representation of the significantly detected regions is shown in Figure 2. In the maps, the region's relative risk of suicide (5 levels), estimated using the CAR model adjusted
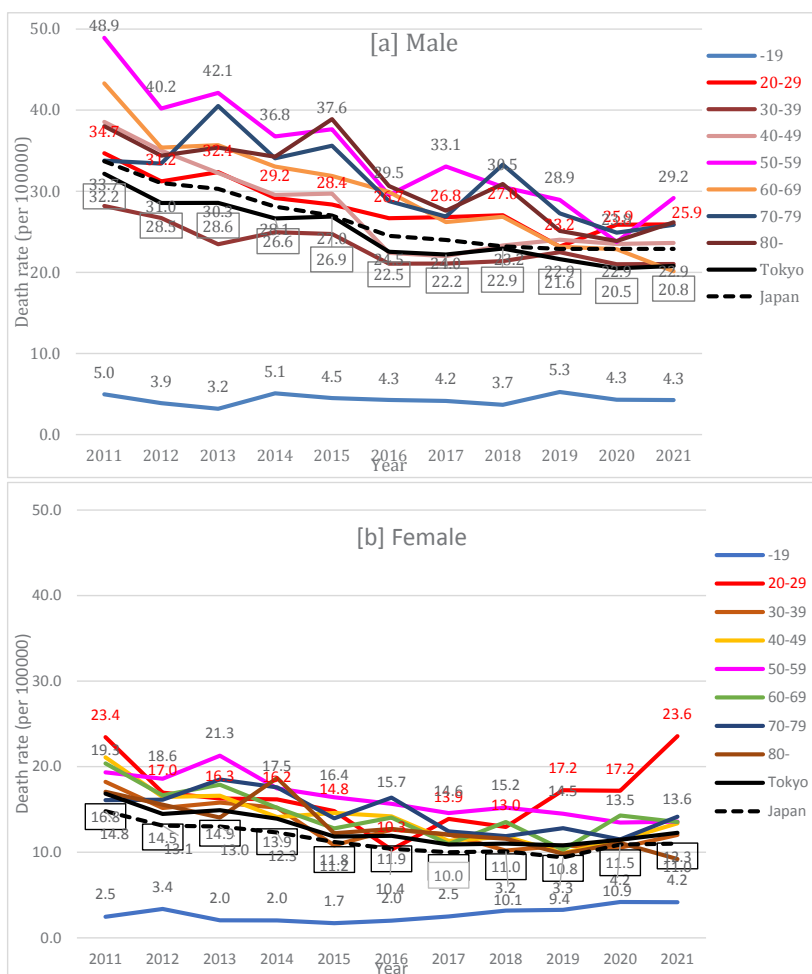

Figure 1. Longitudinal trajectory of suicide death rates according by age groups in Tokyo: 2011 to 2021. ([a] Male, [b] Female)
Note: Death rate per 100000 persons.

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Table 1: Characteristics of suicides by sex in Tokyo, Japan, 2011-2021.

		Male	%	Female	%
	Total	17582	100	12122	100
Age groups (years)	Under 20th	500	2.8%	368	3.0%
	20-29	2460	14.0%	1816	15.0%
	30-39	2615	14.9%	1833	15.1%
	40-49	3303	18.8%	2181	18.0%
	50-59	3139	17.9%	1922	15.9%
	60-69	2511	14.3%	1721	14.2%
	70-79	2000	11.4%	1391	11.5%
	Over 80th	1024	5.8%	866	7.1%
	Unknown	30	0.2%	11	0.1%
Living alone	Not alone	9520	54.1%	7551	62.3%
	Alone	7779	44.2%	4423	36.5%
	Unknown	283	1.6%	135	1.1%
Occupation	Self-employed	1407	8.0%	592	4.9%
	Employee	6044	34.4%	2944	24.3%
	Unemployed	8982	51.1%	8065	66.5%
	Unknown	619	3.5%	305	2.5%
Suicide method	Hanging	10560	60.1%	6774	55.9%
	Poison	215	1.2%	321	2.6%
	Firearm	912	5.2%	480	4.0%
	Jumping from a tall building	2660	15.1%	2287	18.9%
	Jumping in front of a train	706	4.0%	485	4.0%
	Other	1931	11.0%	1520	12.5%
	Unknown	68	0.4%	39	0.3%
Causes and motive[a]	Family problem	1626	9.2%	1527	12.6%
	Health problem	6033	34.3%	5890	48.6%
	Economic and life problem	3183	18.1%	1229	10.1%
	Job-related problem	1722	9.8%	685	5.7%
	Gender issues	489	2.8%	565	4.7%
	School problem	355	2.0%	192	1.7%
	Other	593	3.4%	357	3.2%
	Unknown	6796	38.7%	4140	34.2%

a: including multiple answers

by 10 covariates, are also shown. The parameter estimates of the covariates with a 95% credible interval [lower and upper] are shown in Supplementary File 4. Regions detected 5 times or more in 11 years in one of the spatial models was considered a "frequently detected region." Those were somewhat varied among the spatial models, year, and sex. In this way, however, certain regional characteristics may emerge. Two downtowns (Code 104 and Code 116), and one old town (Code 121) were denoted as "frequently detected regions." However, the old town was a "frequently detected region" only in the case of males. In females, the downtown (Code 104) was detected in most years, especially by the CAR model adjusted by 10 covariates. This trend was confirmed by the region's relative risk of suicide. Among the 10 covariates in the CAR model, significant hazardous effects on suicide were a large proportion of those under the age of 65 years old (for males) and in the workforce over 15 years old (for females). While the proportion of foreigner residents, the proportion of unemployment, and

the number of criminal offenses recognized were detected as significant, significant associations varied by year and sex.

Discussion

This longitudinal cross-sectional analysis of suicide mortality trends in Tokyo using vital statistics and census data from 2011 to 2021[14] showed that the longitudinal trajectories of suicides for both males and females had similar decreasing trends throughout Japan until for 2019. In 2020, the beginning of the COVID-19 pandemic, while age-specific suicide deaths were the highest among those in their 20s. However, those were the highest among males in their 50s in 2021.

Tokyo may seem like a single region, but it is diverse in its aspects and is divided into socioeconomically affluent and less affluent areas and has a different aging population. Recently, the division in lifestyles and living

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Table 2: Detected regions by spatial models.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Male											
Car model (10 covariates)	111, 112, 121, 123, 201	111, 112, 119, 121, 123	106, 116, 121	-	106, 121, 202, 213	104	104, 116, 118, 121, 202, 220	104, 106, 116, 118, 202	104, 121	111, 112, 119, 121, 123,	-[a]
Car model (no covariate)	-	106	-	-	106	-	-	121, 122	104, 121	-	-
Tango's global test (p<0.05)	-	119, 121, 123	-	-	-	-	-	121, 123	121, 122	-	-
Kulldorff's SatScan (p<0.05)	-	106, 107, 118, 121, 122, 123	106	-	202, 213, 220, 223	-	106, 107, 108, 118, 121, 122, 123	-	106, 107, 108, 118, 121, 122, 123	-	-
FlexScan (p<0.05)	-	103, 104, 105, 106, 116	-	-	-	-	-	-	-	-	-
Female											
Car model (10 covariates)	104, 116	104	104, 116, 117, 202	104, 116	104, 116	121	104, 106, 116, 118, 121, 202	104	104, 116	104, 114	104, 116, 218
Car model (no covariate)	-	-	-	-	-	-	-	-	-	104	-
Tango's global test (p<0.05)	-	-	-	104	-	121	-	-	-	104	104
Kulldorff's SatScan (p<0.05)	-	-	-	104	104	-	-	-	-	104	104
FlexScan (p<0.05)	101, 102, 103, 104, 109, 110, 112, 113, 116	-	-	104	-	-	-	102, 104, 106, 108, 116, 117, 118, 119, 123	101, 102, 104, 106, 113, 114, 116, 117, 118, 120	101, 102, 104, 106, 114, 115, 116, 117	102, 104, 106, 108, 116, 117, 118, 119, 123

a. Region Code 103 (Minato-ku) has detected as lower area.
Note: Region code (see Supplementary File 2)
CAR model by OpenBUGS (iterations=100000, Chain=2, Thining=10, Sample=20000) (regions 101 [Chiyoda] and 13400 [Islands] were excluded from the analysis.)
Estimates of related factors and statistics, see Supplementary File 3.

conditions between urban and suburban areas has also been reported[21]. Tokyo is the most populous region in Japan (with a population of around 14 million and more than 1/10 of Japan's population) and has the highest actual number of suicides in Japan. By examining the characteristics of areas in Tokyo with elevated suicide rates (especially during disaster periods such as COVID-19), we believe that the findings can be used for prevention in other areas of Japan, that have similar characteristics to those of the areas identified in this study. Clarifying the differences between regions and over time will have important implications for future suicide countermeasures. In this

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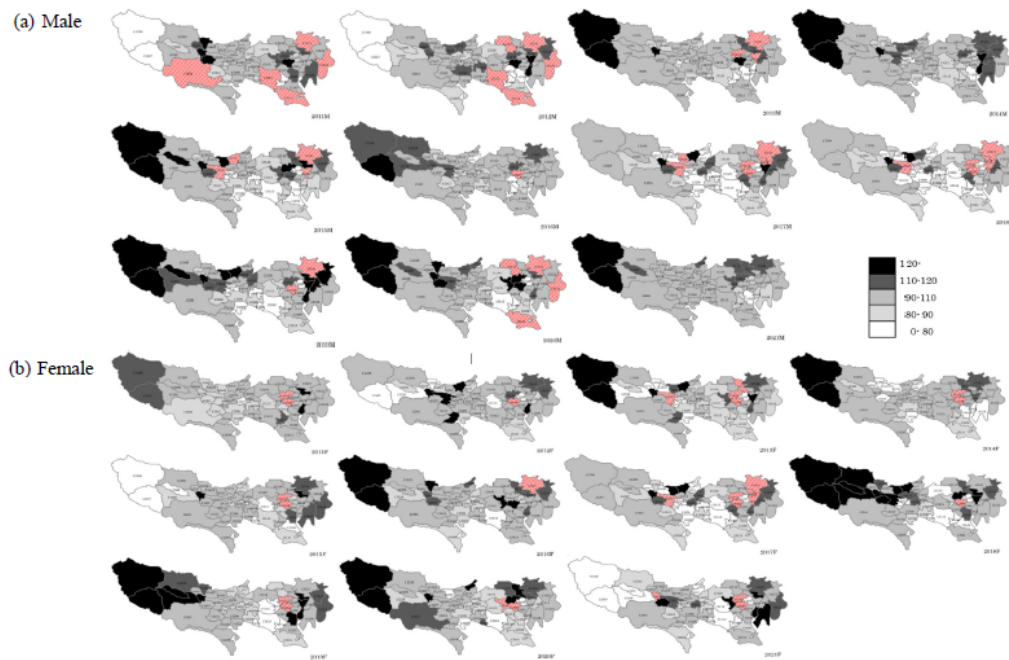
Figure 2. Region's relative risk of suicide (5 levels) estimated using the CAR model adjusted by 10 covariates for suicide deaths among those of all ages.

Shaded area with red colour was significantly detected regions by the CAR model.

study, the impact of COVID-19 is secondary and limited in that it considers changes over time, including the period. The CAR model detected a significant regional clustering for both sexes throughout the longitudinal trajectories. In particular, the downtown (Code 104) has frequently been frequently detected as a region with many suicides among both males and females. The old town (Code 121) for males and the downtown (Code 116) for females were also frequently found. The environmental factors symbolized by population concentration had an unstable relationship with suicide mortality. The results showed evidence of hotspots of suicide mortality across regions in Tokyo by several spatial clustering methods and we examined the spatial correlation with the incidence of suicide adjusted for related factors.

The WHO report[3] found that three times more males die by suicide than females in high-income countries. In Tokyo, this ratio suggests that roughly twice as many males as females committed suicide in all age groups (Figure 1 [a], [b]). Suicide deaths among males and females were more frequent in the 50s and in most years, until 2019. In 2020, the 20s were the age group with the highest rate of suicide deaths, both for males (25.9) and females (17.2), and in 2021, it was the highest in their 50s in males (29.2) while in females it was the highest in their 20s (23.6). Amazingly, the rates in their 20s became almost similar between males and females in 2021.

Previous studies on yearly or monthly trends in Japan's suicide rate have used the overall suicide rate in Japan[22-27]. In these studies, the impact of COVID-19 under a pandemic was tracked and evaluated for 2020. For instance, Sakamoto and colleagues[23] reported that monthly suicide rates in Japan during the COVID-19 pandemic in 2020 increased in October and November for males and in July through November for females compared with 2016 to 2019. They reported that the relative increases were particularly pronounced for males and females under the age of 30 and between ages 30 to 49 years. While a study[24] that examined monthly excess suicide rates during the COVID-19 pandemic showed the gender differences in reasons for suicide in Japan from January 2019 to May 2021, and they summarized age group by 20 years.

The point that the suicide deaths in males were twice that in females was like our findings until 2019. However, our results suggested that suicides among younger females tended to increase in several recent years, not in 2020 as that report indicated. Especially in 2021, the rate of females in their 20s becomes almost like that of male. One probable reason for these different tendencies was because our data were from Tokyo. Tokyo is the biggest urban city in Japan and the circumstances during the time examined were different from the average in Japan. According to the White paper[4], many young females work in the service and food service sectors and may have been financially affected by unemployment and closures due to COVID-19. Although the rates were low in the youngest age group (under 19 years), the trend increased from 2016 in females, but not in males. This was because women, such as those in

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informal employment work, lost their jobs, mainly in the service sector, affected by absence and unemployment, and were economically vulnerable and isolated. However, during this pandemic period, the situation in Japan was diverse. It was necessary to separate the impact on non-metropolitan areas from that on metropolitan areas, rather than the Japanese average. This is because Tokyo was the area that received the most emergency declarations and other restrictions on behavior and needed to be discussed separately from other general Japanese averages. In fact, we showed the different female suicide rates in different parts of Tokyo.

The identified regions by spatial models showed interesting results. In the longitudinal trajectory, in the two downtowns (Code 104 and Code 116) suicides were frequently detected in most years for both males and females. However, a characteristic point was the difference between sex and age groups. Namely, regions with significant rates of suicide include the old town (Code 121); however, in the two downtowns (Code 104 and Code 116) such significant suicide rates were identified in females (See Supplementary File 4). Our study data could not explain the reason for this result. Especially for 2020 and 2021, the COVID-19 pandemic had complex effects on people's lives. The old town (Code 121) is an area where small businesses account for about 80% of the businesses in the ward, and the proportion of the residents aged 65 years or older is high at 24.7% in 2017 (second highest in the 23 wards). Further, according to the ratio of government welfare-payment recipients to the total population in 23 Wards of Tokyo, the rates in the old town (Code 121) and the two downtowns (Code 104 and Code 116) were higher than the average in Tokyo[27]. One probable interpretation was that the two downtowns (Code 104 and Code 116) are among the most famous nightlife destinations in Tokyo and were characterized by business and commercial facilities around the railroad station, a relatively large proportion of young and single households with lower income and foreigners[28,29], a large difference between the daytime and the nighttime population, and the number of criminal offenses recognized was relatively high among Tokyo regions, with improving security being an issue. The old town (Code 121) is a mixed commercial, industrial and residential zone with a shrinking and aging population. Therefore, not only younger, but also older men were probably affected by the pandemic. A large social disparity[28] including income inequality[30] were also issues. Further, for males, the number of detection areas decreased in 2020 and 2021, but for females, Shinjuku (Code 104) was detected by both methods. However, in our analysis, only temporality was considered in terms of years only. Due their regional specificity, further study is warranted. World-wide, several social factors have been addressed in suicide prevention, but those are varied according

to sociocultural conditions and effective interventions within a certain population. To obtain useful information, spatial epidemiology in one's own country is useful. In this study, we concentrated on detecting high-risk districts within Tokyo for suicide deaths. Only sociocultural factors were included in the analyses. However, the attributed factors were relatively stable during this period by factor analysis (results not shown). Therefore, the results of the CAR models using covariates provided certain pertinent information. There were studies in Japan[5,31] as well as in other countries[8-11] that socioeconomic deprivation was associated with high-risk suicide clusters detected. In our study, notwithstanding these differences, findings that detected high-risk suicide clusters were associated with socioeconomic deprivation during pre-pandemic, not after the pandemic. After the pandemic, as Spittal[32] mentioned, increased suicides in Japan among employed people, adult women have been identified. To address these issues, a detailed social epidemiological analysis is warranted.

Strengths, limitations, and future research

To use novel spatial clustering techniques to provide ecological information on suicide risk. We applied several clustering methods that consider spatial correlation and spatial smoothing methods because, these methods stand on special assumptions. Thus far, the studies that consider geographical correlations in suicide research have been conducted in Japan[25] and in other countries[8-10]. The results provide insights into the potential for direct interventions in high-risk areas. Regarding the limitations of our study, first, our data on socio-economic and environmental factors were limited to a single point in the census year (2011). However, these factors identified a similar association between 2011 and 2015 in the regions by factor analyses using the available census data. Therefore, the effects of the covariates potentially do not largely affect the spatial correlation in the regions of Tokyo, and thus the probable bias is not large. Second, our analysis used the data from national agency sources, the most reliable sources at present. They provided the summarized data by region in each prefecture, and we treated unknown as missing. In our data, those who die by suicide cannot report on the actual reasoning behind their act and we excluded the data with age and/or sex unknown. However, the number was few. Effective suicide prevention should be an important public health consideration, particularly among vulnerable populations. This study also highlighted the characteristics of the trajectory changes in suicide mortality before and after COVID-19 not only yearly trend, but also regional variation and trend, which were examined by considering spatial smoothing. Namely, the primary objective of this study was spatial clustering of suicide mortality in Tokyo using data from regional statistics on male and female suicide deaths from 2011 to 2021, before and after the

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onset of the COVID-19 pandemic and the second objective was to examine the impacts of COVID-19. The first objective was met, but not the second. As COVID-19 was excluded from the analyses, in the sense that only temporality is considered in terms of years only. The impact of COVID-19 was mainly the interpretation of the socio-economic regional characteristics. Other factors that might contribute to an increased suicide rate were not adequately addressed. For example, mental stress, loneliness, stress and social separation resulting from lockdown increased mental health problems and suicide risk during COVID-19. These factors that might vary according to jurisdictions with a level of lockdown will also rationalize why the analysis of regional trends of suicide rate is important.

This study clarified the longitudinal suicide mortality trajectories at the regional level in Tokyo. The strategy for this purpose, we used several analyses for estimating suicide risk by CAR models (with / without covariates), and testing for spatial clustering. Spatial accumulation is tested under the assumptions of each model and the results change according to the assumption. Consider such properties, it is worthwhile to consider in several ways and notwithstanding several assumptions, a few regions were detected.

Our study provides some important information for a better understanding of where to target resources and expend preventive efforts to reduce the burden of suicide in high-risk regions not only in Japan but also in global health. Because of their regional specificity, further study is warranted. Further, this study on region-level suicide mortality in Tokyo and its potential to inspire future studies for greater suicide risk prevention.

Conclusions

During the COVID-19 pandemic in 2020 and 2021, males and females in their 20s as well as males in their 50s showed a tendency toward an increase in suicides. The result of the spatial scan statistics showed evidence of hotspots of suicide mortality across regions of Tokyo. To proceed with regional health policy making, spatial epidemiology is one of the useful tools.

Appendix

Indices for standardized mortality

Standardization was conducted by the year based on each year's sum from 2011 to 2020. The detail formula was shown in the below.

Let d_i indicates the observed number of deaths of disease under study in the region i (=1,..., M) and e_i indicates the expected number of deaths calculated based on the number of suicides per age group in the reference population (Tokyo) in each year and the age distribution

of the population of region i. Further, let θ_i denotes the relative risk of the disease under study in the region i. Then, under the assumption that the observed number of deaths d_i follows a Poisson distribution with the expected number of deaths $e_i\theta_i$, the maximum likelihood estimator of θ_i is so-called standardized mortality ratio (SMR):

$$SMR_i = d_i / e_i$$

SMRs are frequently used as disease maps. However, SMRs have an undesirable property that they can be largely affected by the difference in population size. Therefore, the empirical Bayes estimator (EBSMR) are used for the relative risk θ_i as follows. Let us assume that θ_i (i =1,..., M) is independently distributed with a prior gamma distribution with parameter $\eta = (\alpha, \beta)$,

$$\theta_i \sim Gamma\ (\alpha, \beta), \text{ with mean } \alpha/\beta, \text{ variance } \alpha/\beta^2$$

Then, EBSMR $\hat{\theta}_{i,EB}$ is estimated as follows.

$$EBSMR_i = \hat{\theta}_{i,EB} = \frac{\hat{\alpha} + d_i}{\hat{\beta} + e_i} = \frac{e_i}{\hat{\beta} + e_i}\frac{d_i}{e_i} + \frac{\hat{\beta}}{\hat{\beta} + e_i}\frac{\hat{\alpha}}{\hat{\beta}}$$

where (α, β) denote the marginal maximum likelihood estimator[17].

Conflicts of interest

The authors declare that they have no competing interests.

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Supplementary Files

Supplementary File 1. Characteristics of variables in 54 regions in Tokyo.

variables[a]	mean (SD) or medican [Q1,Q3]		minimum	region code	maximum	region code
single household (%)	41.6	11.0	16.5	305(hinode-cho)	62.6	104 (Shinjuku)
average family size	2.1	0.3	1.6	1 (Shibuya)	2.8	305 (Hinode-cho)
poplation density (persons/km^2)	10438	[5931,14928]	78	118 (Arakawa)	82	116 (Toshima)
general clinics (per 1000)	77.8	[65.1,117.6]	37.1	223 (Musashimurayama)	986.9	101 (Chiyoda)
foreighnere residens (%)	1.5	[1.1, 2.9]	0.3	308 (Okutama-cho)	7.9	104 (Shinjuku)
work force (over 15 years old)	52.6	3.1	45.5	308 (Okutama-cho)	61.5	102 (Chuo)
unemployment (%)	3.3	0.6	1.9	101 (Chiyoda), 400 (Islands)	4.7	303 (Mizuho-cho)
average income (10000 yen)	372	[335, 417]	261	307 (Hinohara-mura)	877	103 (Minato)
# of criminal offenses recognized[a]	14.4	[1.8, 2.3]	0.0	12 regions [b]	102.4	101 (Chiyoda)
>65 yeas old (%)	21.4	4.9	15.9	102 (Chuo)	43.4	307 (Hinoharamura)

a. Variables were from census data in 2011.
b. 214, 215, 219, 221, 222, 223, 225, 227, 303, 305, 307, 308.

Supplementary File 2. Map with region code

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Supplementary File 3. Related factors analysed by multivariable model using the CAR model (analysed using OpenBUGS).

Car model	2011 β	2.5%tile	97.5%tile	2012 β	2.5%tile	97.5%tile	2013 β	2.5%tile	97.5%tile	2014 β	2.5%tile	97.5%tile	2015 β	2.5%tile	97.5%tile	2016 β	2.5%tile	97.5%tile	2017 β	2.5%tile	97.5%tile	2018 β	2.5%tile	97.5%tile	2019 β	2.5%tile	97.5%tile	2020 β	2.5%tile	97.5%tile
Male																														
10 covariates model																														
single household (%)	0.365	-0.127	0.858	0.034	-0.724	0.724	0.254	-0.276	0.774	-0.262	-0.788	0.269	0.231	-0.321	0.778	0.124	-0.558	0.790	0.005	-0.578	0.591	0.017	-0.563	0.593	0.013	-0.603	0.628	0.115	-0.472	1.470
average family size	0.305	-0.259	0.869	-0.005	-0.875	0.787	0.184	-0.432	0.781	-0.241	-0.852	0.370	0.326	-0.316	0.954	0.088	-0.693	0.852	0.119	-0.558	0.795	0.130	-0.542	0.790	0.223	-0.488	0.932	0.099	-0.578	1.376
population density	-0.103	-0.240	0.029	-0.018	-0.225	0.183	-0.031	-0.172	0.105	0.025	-0.115	0.164	0.067	-0.085	0.215	-0.059	-0.240	0.122	0.055	-0.104	0.208	0.056	-0.102	0.209	0.123	-0.060	0.296	-0.055	-0.208	0.308
general clinics (per 1000)	-0.059	-0.206	0.083	0.052	-0.135	0.237	-0.103	-0.270	0.056	0.030	-0.119	0.173	0.007	-0.161	0.167	-0.032	-0.227	0.154	-0.022	-0.184	0.133	-0.028	-0.189	0.127	0.109	-0.052	0.263	0.099	-0.060	0.296
foreigner residens (%)	**0.081**	**0.000**	**0.160**	0.043	-0.076	0.161	0.056	-0.029	0.142	0.011	-0.075	0.097	-0.012	-0.102	0.078	0.079	-0.028	0.192	0.029	-0.062	0.119	0.029	-0.062	0.118	-0.010	-0.111	0.091	0.034	-0.057	0.091
work force (over 15 years)	0.019	-0.058	0.092	-0.001	-0.110	0.106	0.017	-0.018	0.092	0.013	-0.064	0.091	-0.052	-0.136	0.028	-0.036	-0.136	0.063	-0.003	-0.089	0.082	-0.004	-0.091	0.080	0.040	-0.052	0.135	-0.050	-0.135	0.050
unemployment (%)	**0.102**	**0.017**	**0.187**	0.011	-0.112	0.131	-0.018	-0.111	0.073	-0.022	-0.119	0.072	0.076	-0.020	0.169	-0.049	-0.178	0.066	0.050	-0.053	0.151	0.052	-0.052	0.153	0.020	-0.091	0.128	0.090	-0.010	0.200
average income (10000 yen)	0.056	-0.083	0.196	-0.183	-0.379	0.008	-0.057	-0.218	0.105	-0.127	-0.280	0.025	-0.015	-0.177	0.147	-0.100	-0.292	0.086	-0.033	-0.192	0.128	-0.028	-0.187	0.133	-0.053	-0.218	0.110	-0.114	-0.274	0.126
# criminal offenses recognize	0.044	-0.060	0.147	0.009	-0.127	0.140	0.097	-0.014	0.207	0.098	-0.015	0.210	**0.158**	**0.043**	**0.269**	0.032	-0.102	0.168	**0.297**	**0.179**	**0.415**	**0.299**	**0.180**	**0.417**	**0.162**	**0.035**	**0.290**	0.030	-0.093	0.288
>65 yeas old (%)	-0.020	-0.208	0.162	-0.115	-0.374	0.125	0.138	-0.049	0.320	0.039	-0.154	0.226	0.136	-0.058	0.324	-0.003	-0.239	0.229	0.078	-0.134	0.286	0.074	-0.139	0.281	0.200	-0.009	0.403	**-0.027**	**-0.244**	**-0.452**
mu	-0.032		0.035	-0.037	-0.133	0.035	-0.02	-0.09	0.0529	-0.009	-0.083	0.062	-0.078	-0.078	0.067	-0.035	-0.129	0.051	-0.053	-0.136	0.028	-0.095	-0.178	-0.015	0.031	-0.055	0.109	0.006	-0.075	0.085
tau.b	1032	21	4952	994	9	3511	1213	44	4968	1276	54	5481	1109	27	5177	1203	28	5358	1083	31	5115	1080	30	5113	1027	17	5057	1300	47	5547
tau.h	1581	83	6022	189	15	5439	1502	109	5865	1538	118	5939	1099	48	5110	581	18	3838	1372	87	5616	1385	87	5654	897	27	4689	1331	77	5553
no covariate model																														
mu	-0.016	-0.070	0.035	-0.013	-0.087	0.057	-0.016	0.000	0.057	-0.015	-0.072	0.0395	-0.008	-0.080	0.0595	-0.016	-0.086	0.046	-0.030	-0.101	0.038	-0.070	-0.141	-0.001	-0.021	-0.093	0.049	0.000	-0.061	0.062
tau.b	537	21	3511	902	10	4786	723	8	4786	735	31	4097	738	10	4411	1206	35	5345	127	6	1211	128	6	1241	236	6	2342	1144	30	5283
tau.h	1287	83	5439	153	16	1401	1144	8	1401	1398	99	5637	307	18	2689	678	25	4092	892	22	4721	888	22	4707	811	18	4585	802	41	4347
Female																														
10 covariates model																														
single household (%)	-0.201	-0.862	0.458	-0.738	-1.444	**-0.033**	-0.578	-1.289	0.130	0.205	-0.542	0.949	-0.334	-1.092	0.433	-0.075	-0.907	0.735	0.005	-0.578	0.591	0.060	-0.832	0.927	0.274	-0.521	1.068	-0.274	-1.100	0.536
average family size	-0.102	-0.874	0.668	-0.776	-1.607	0.042	-0.740	-1.575	0.080	0.117	-0.750	0.974	-0.315	-1.189	0.566	-0.146	-1.112	0.797	-0.146	-0.558	0.795	0.099	-0.929	1.102	0.415	-0.501	1.321	-0.502	-1.466	0.430
population density	0.112	-0.064	0.294	-0.089	-0.286	0.100	-0.101	-0.289	0.083	-0.018	-0.215	0.175	-0.086	-0.285	0.113	-0.068	-0.308	0.161	0.055	-0.104	0.208	-0.103	-0.344	0.134	-0.008	-0.226	0.202	-0.162	-0.381	0.051
general clinics (per 1000)	0.150	-0.035	0.328	0.096	-0.100	0.285	0.022	-0.176	0.211	0.050	-0.177	0.266	-0.040	-0.270	0.177	0.043	-0.186	0.261	-0.022	-0.184	0.133	-0.035	-0.278	0.196	0.165	-0.039	0.361	0.099	-0.126	0.314
work force (over 15 years)	0.072	-0.034	0.179	0.034	-0.080	0.146	0.046	-0.074	0.156	0.082	-0.035	0.198	**0.172**	**0.052**	**0.293**	0.057	-0.076	0.189	0.029	-0.062	0.119	0.122	-0.018	0.268	**0.127**	**0.001**	**0.253**	0.119	-0.004	0.244
unemployment (%)	-0.053	-0.152	0.046	-0.128	-0.237	-0.021	-0.074	-0.177	0.028	**-0.133**	**-0.244**	**-0.026**	-0.071	-0.185	0.044	-0.013	-0.139	0.109	-0.003	-0.089	0.082	0.016	-0.119	0.149	0.012	-0.108	0.131	**-0.119**	**-0.238**	**-0.001**
average income (10000 yen)	-0.026	-0.146	0.093	-0.007	-0.138	0.122	0.032	-0.093	0.154	-0.086	-0.221	0.045	0.004	-0.140	0.143	0.112	-0.032	0.252	0.050	-0.053	0.151	0.015	-0.143	0.168	-0.059	-0.210	0.087	0.083	-0.057	0.217
# criminal offenses recognize	-0.113	-0.291	0.065	-0.162	-0.352	0.029	-0.145	-0.341	0.050	-0.190	-0.404	0.025	-0.067	-0.278	0.143	-0.014	-0.233	0.206	-0.033	-0.192	0.128	-0.024	-0.257	0.208	-0.134	-0.332	0.065	-0.192	-0.409	0.026
>65 yeas old (%)	-0.067	-0.216	0.080	0.047	-0.105	0.198	0.121	-0.025	0.266	-0.002	-0.164	0.158	0.050	-0.119	0.216	-0.036	-0.210	0.136	0.155	-0.019	0.328	0.155	-0.019	0.328	0.042	-0.135	0.216	-0.087	-0.258	0.081
mu	-0.036	-0.130	0.054	-0.042	-0.148	0.054	-0.011	-0.109	0.084	-0.064	-0.168	0.035	-0.062	-0.178	0.048	-0.011	-0.135	0.100	-0.053	-0.136	0.028	0.046	-0.070	0.156	0.005	-0.107	0.112	-0.013	-0.124	0.094
tau.b	1063	21	5061	1004	22	4977	1199	30	4977	1138	23	5216	1164	26	5324	990	13	4924	1083	31	5115	972	11	4889	1118	22	5203	977	11	4915
tau.h	1346	68	5616	1295	63	5498	1171	45	5286	1162	42	5286	1316	60	5566	719	17	4285	1372	87	5627	531	14	3703	1144	39	5277	834	25	4582
no covariate model																														
mu	-0.019	-0.088	0.045	-0.011	-0.083	0.060	-0.002	-0.076	0.069	-0.022	-0.111	0.060	-0.006	-0.088	0.073	-0.020	-0.108	0.062	-0.030	-0.101	0.038	0.021	-0.075	0.118	-0.019	-0.108	0.067	-0.016	-0.112	0.073
tau.b	1159	38	5294	1097	29	5122	1049	22	5122	828	9	4597	829	13	4559	965	20	4869	1083	6	1211	834	8	4681	444	8	3377	915	8	4816
tau.h	1367	75	5653	1060	48	5006	852	27	4593	468	16	3462	972	31	4845	570	20	3789	892	22	4721	254	11	2353	872	23	4674	239	13	2230

Supplementary File 2. Map

CAR model by OpenBUGS (iterations=100000, Chain=2, Thining=10, Sample=20000) (regions 13101[Chiyoda] and 13400 [Islands] were excluded from the analysis.)

β: parameter estimates,

SE: standard error,

β: parameter estimates; SE: standard error; all covariates were used after centroided (mean 0, variance 1).

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Supplementary File 4. Longitudinal trajectory of suicide death (EBSMR) according by 22 Wards[a] in Tokyo: 2011 to 2021.

([a] Male, [b] Female)

a. Chiyoda-ward (Code 101) was an area that includes the Imperial Palace and has been excluded due to its peculiarity.

[a] Male

[b] Female

Longitudinal trajectories of 22 Wards: Males

Longitudinal trajectories of 22 Wards: Females