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Population shifts during the reconstruction period in areas marked as evacuation zones after the Fukushima Daiichi nuclear power plant accident: a mobile spatial statistics data-based time-series clustering analysis

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ABSTRACT

An accurate understanding of the population is essential for the development of medical care and social resources. However, the development of transportation networks has increased temporal and spatial fluctuations in the population, making it difficult to accurately forecast medical care demand, especially during disaster recovery. This study examined the population movement in areas affected by the Fukushima Daiichi nuclear power plant accident using demographic data. The target area includes two cities, seven towns, and three villages that are in the evacuation zone. Using a population estimation that reflects changes in population by time of day, which was obtained from a mobile phone company (NTT DOCOMO), we applied clustering analysis to examine the population dynamics over a 4-year period. From 2019 to 2022, the population increased in eight areas and decreased in four areas. The population was further classified into five groups, identifying the unique characteristics and fluctuations of each group. Different regions had different percentages of groups reflecting the characteristics of their populations. The differences among the regions and demographic transition showed the potential to understand the challenges of recovery and to use the data to inform healthcare planning and social policies. This method, which utilizes estimated population data, is also applicable to the study of medical resources and social policies in the event of future disasters and may be useful in analyzing regional characteristics in detail.

Keywords: population estimation; Fukushima Daiichi nuclear power plant accident; disaster; medical care; machine learning; community

INTRODUCTION

Accurate understanding of the population dynamics is crucial for the effective development of healthcare and social resources. Globally, the ascertainment of a regional population typically relies on tabulations based on registered dwellings or the population present in an area on a specific day. For example, in Japan, such data are collected through the Basic Resident Register, which is based on monthly registered residence data; and the national census, which is conducted every 5 years through household visits [1, 2]. These methods provide valuable snapshots of the population at specific points in time and facilitate an understanding of long-term trends within an area. However, with the advancement of transportation networks and increasing population mobility, temporal and spatial fluctuations in population have become more pronounced. Recent efforts to capture these dynamics include leveraging cell phone global positioning system (GPS) data to reflect actual population movements more accurately. For instance, during the coronavirus disease 2019 (COVID-19) pandemic in 2020, using nighttime population data derived from cell phone GPS proved to be effective in predicting COVID-19 outbreak trends, demonstrating the utility of real-time, spatially detailed population data in public health planning and responses [3]. Thus, accurate understanding of temporal and spatial populations is useful for accurately identifying and predicting demand for medical care in a target area.

During the post-disaster reconstruction process, accurately predicting the local healthcare demands becomes challenging because of population movement caused by evacuation and increased health risks among affected residents. Typically, after major disasters such as floods, tsunamis, and earthquakes, a region's healthcare supply may diminish, leading to a relative shortage of healthcare services [4]. This issue is especially acute in the aftermath of large-scale disasters, in which high-risk populations are often left in vulnerable states and the overall health risk escalates [5]. Consequently, there is a pressing need for preparedness to meet long-term healthcare demands [6, 7]. For instance, following major hurricanes, reports have indicated that individuals with disabilities who were left behind in the affected areas struggled to access adequate medical care [8, 9]. Similarly, during the Chernobyl nuclear disaster and the Great East Japan Earthquake, the mental health issues of residents in surrounding areas, particularly those related to evacuation, became prominent [10–14].

To effectively address and anticipate medical care needs in such scenarios, it is imperative to not only understand the health status of the population but also gain an accurate insight into the demographic composition of the target area [15, 16]. However, during the post-disaster recovery phase, populations tend to be more fluid, both temporally and spatially. As people return from evacuation, the workforce for recovery arrives and workers subsequently depart. Although the movement of residents after the Fukushima Daiichi nuclear power plant (FDNPP) accident has been analyzed [15, 17], few detailed reports have analyzed the long-term population movement and its impact on local healthcare demand.

The 2011 earthquake and subsequent tsunami in Japan, coupled with the FDNPP accident, caused extensive damage to the local population. This disaster was characterized by a prolonged evacuation, with the duration varying considerably across different regions. Following the disaster, areas near the FDNPP were designated as evacuation zones, forbidding residencies. Since then, numerous evacuation orders in designated areas have been lifted through 2017, signaling the beginning of reconstruction efforts. However, large areas across towns and villages, such as Futaba Town, Namie Town, Okuma Town, Katsurao Village, Tomioka Town, Minamisoma City and Iitate Village remained classified as difficult-to-return zones, corresponding to 337 km^2 in April 2019. Decontamination and challenges in rehousing and resettlement persisted. Post-2017, specific reconstruction and revitalization zones were established in each municipality within these areas, prioritizing decontamination and infrastructure development. Areas classified as difficult-to-return are anticipated to gradually welcome residents and undergo community rebuilding. The demographic dynamics in these areas are further complicated by the influx and outflow of decontamination workers, recovery effort employees, and evacuees, making accurate determination of the population challenging. Understanding the evolving distribution and demographic changes in the population during the recovery process is pivotal for informed medical planning and urban and infrastructure development in the region.

Against this backdrop of complex demographic shifts, we utilized population estimation data based on the cell phone information of NTT DOCOMO—a major Japanese telecommunications company. We analyzed the population residing in the evacuation zone and its temporal changes. These population estimate data have been used in previous studies and have been compared and verified with census data, highlighting their validity [18, 19]. By leveraging these data, we aim to reveal more precise population flows over time and clarify the actual status of the local population. Our analysis focused on identifying the characteristics of the population in the area and elucidating the differences in demographic composition. A detailed examination of the population dynamics in these reconstructed areas over time, capturing changes and trends, will contribute considerably to our understanding of the current state of these regions and future challenges. This knowledge is vital for effective medical planning, urban planning, and infrastructure development, ultimately aiding the recovery and revitalization of the region.

MATERIALS AND METHODS

Study areas and populations

Our study focused on 12 municipalities—two cities, seven towns, and three villages—within the evacuation-ordered zone resulting from the FDNPP accident (Fig. 1). On 11 March 2011, following the Great East Japan Earthquake and the ensuing nuclear power plant accident, evacuation orders were issued within a 3 km radius of the FDNPP and an indoor evacuation order within a 10 km radius [20]. The evacuation order was expanded to a 10 km radius on 12 March, and an evacuation advisory was issued within a 20 km radius on the same day.

Subsequently, on 22 April 2011, the government established three evacuation zones in accordance with international standards [21]: emergency evacuation preparation, planned evacuation, and evacuation-ordered zones. The planned and ordered evacuation zones were mandated for evacuation. Specifically, the planned evacuation zone included areas outside the 20 km radius of the FDNPP where the annual radiation dose could reach 20 mSv, and the evacuation-ordered zone covered areas within a 20 km radius of the plant—restricted except for critical cases. Tomioka, Okuma, and Futaba towns were classified among the municipalities designated as restricted areas.

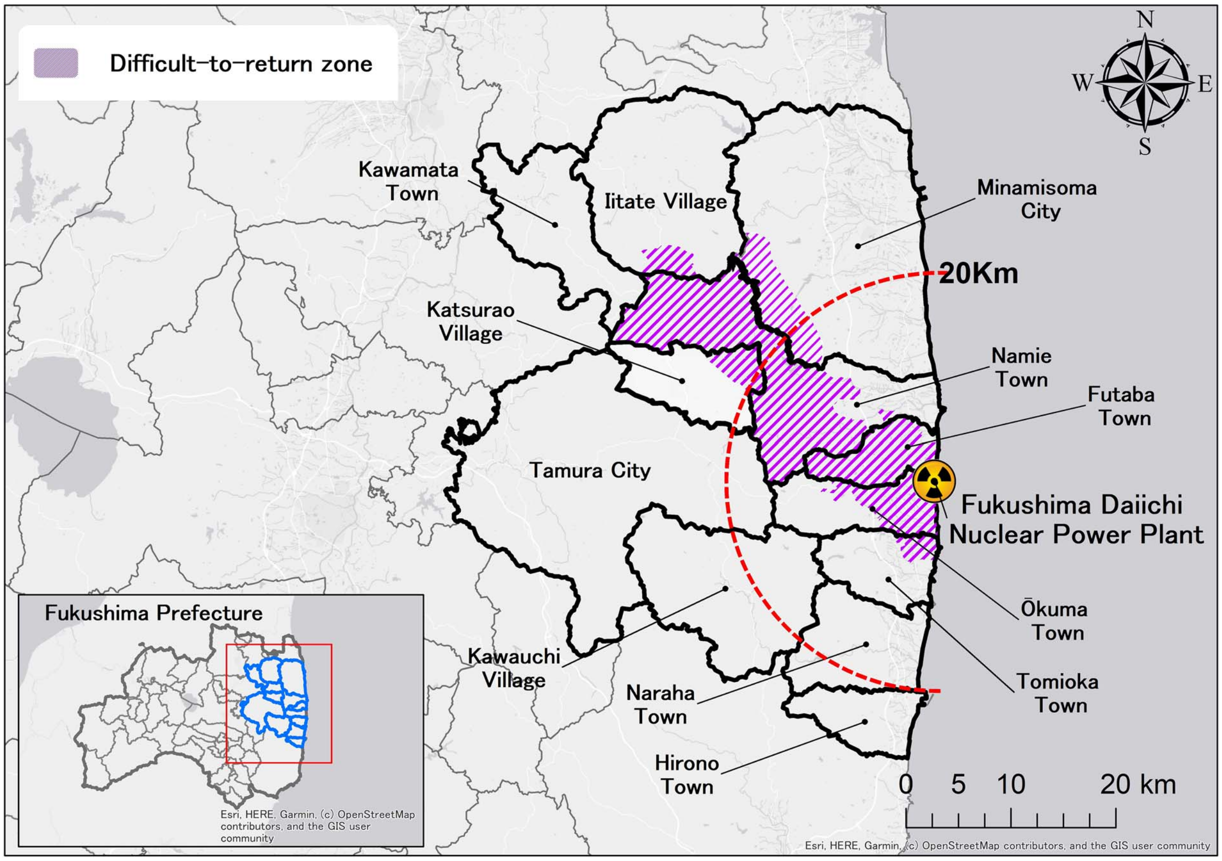

Fig. 1. The target area map. Figure 1 shows a map of the targeted area with difficult-to-return zones (as of 2022). The dotted circle indicates the location of the area within 20 km of the Fukushima Daiichi Nuclear Power Plant.

Some areas have been designated as evacuation zones in Tamura City, Minamisoma City, Naraha Town, Kawauchi Village, Namie Town and Katsurao Village. Iitate Village and parts of Namie Town and Katsurao Village were designated as planned evacuation zones. Parts of Kawamata Town and Minamisoma City were designated as planned evacuation zones [20]. Kawauchi Village and Hirono Town were evacuated at the sole discretion of the local government; however, the evacuation orders were lifted on 31 January 2012 and 31 March 2012, respectively [22]. On 1 April 2012, the planned and restricted evacuation zones were redefined to facilitate the return of residents, subdividing them into preparation zones for lifting evacuation directives, restricted zones, and difficult-to-return zones. In the preparation zone for lifting evacuation directives, residents were allowed to return home temporarily, and essential facilities, such as medical and welfare centers and stores, were permitted to partially reopen. Temporary home return and road restoration access were granted in restricted residential areas. The difficult-to-return zone was delineated as an area where continued evacuation was necessary.

The essential requirements for the lifting of the evacuation order were the following: it is certain that the annual dose of radiation will be < 20 mSv after the lifting date; infrastructure and daily life-related services have generally been restored; decontamination work has made sufficient progress, mainly in the living environment for children; and sufficient consultations have been held with local governments and residents [23]. In addition, the period for residents was set according to the progress of decontamination work in the affected areas [24].

Following these reclassifications, the evacuation orders in Tamura City and Kawauchi Village were lifted in April 2014, and the evacuation preparation zone in Naraha Town was lifted in September 2015. By 2019, evacuation orders were completely lifted in all of Kawauchi Village and Minamisoma City, as well as parts of Namie Town, Iitate Village, Tomioka Town and Okuma Town; in April 2019, the evacuation order lifting preparation zone and restricted residential area in Okuma Town were also lifted. By 2020, parts of the difficult-to-return zones in Tomioka and Okuma Town were lifted, and in 2020, parts of the evacuation order preparation and difficult-to-return zones in Futaba Town were lifted. Further, by 2022, parts of the difficult-to-return zones in Katsurao Village, Okuma Town, and Futaba Town were partially lifted. However, Katsurao Village and certain parts of Namie Town, Futaba Town, Okuma Town, Minamisoma City, Iitate Village and Tomioka Town were designated as difficult-to-return zones.

Population estimation based on mobile spatial statistics

The population estimate utilized the 'Mobile Spatial Statistics' developed by NTT DOCOMO and provided by NTT DOCOMO Insight

Marketing. Mobile Spatial Statistics estimates population data by statistically processing operational data from cell phone networks, such as the number of cell phones within each base station area. These data can be independently estimated by including cell phone holders of other companies owing to a combination of domestic market share rates and other factors. Moreover, it provides an estimation of the number of people present in specific areas across Japan on a 500-m mesh grid, updated hourly [25]. In making population estimates, we used data from the 2020 census. Any information regarding this estimation method is a trade secret of DOCOMO Insight Marketing, Inc. and is not publicly available. The estimates of cell phone operation data are based on information known to DOCOMO Insight Marketing. The method of estimating the population using cell phones has been used previously [26, 27]. The results do not necessarily mean that non-NTT DOCOMO cell phones are included in the population estimates; however, the estimates were made using the DOCOMO user share ratio, which accounts for about 44% of total subscribers [28]; thus, the population estimates include both those who use cell phones from other cell phone companies and those who do not own a cell phone.

We utilized population estimates from November of each year over a 4-year period spanning 2019 to 2022 across 12 municipalities in Fukushima. November was selected because of the absence of major holiday seasons and the historically stable demographics in the region. Data were collected for two consecutive weeks each year and divided into Monday–Sunday cycles. The population data were stratified by various demographics, including age groups (15–19, 20s, 30s, 40s, 50s, 60s, 70s and $\geq$ 80 years), sex, reasons for stay (resident, worker, resident and worker, visitor), and city or ward where the cell phone was registered. Additionally, to provide a reference for Mobile Spatial Statistics, population data reported by municipalities and the 2020 census data for the area were also used.

Grouping of the population by dynamics using cluster analysis

We employed cluster analysis to classify the population dynamics based on the estimated population data. A total of 3072 observation points were set up in the estimated population data according to age (eight categories), sex (two categories), reason for stay (four categories), municipality (12 categories) and year (four categories). Hierarchical clustering analysis using the Ward method was performed on the 2-week population data obtained from these observation points. The distances between observation points were calculated using Euclidean distances. A z-scored version of the population data was used to perform calculations. This allowed the clustering of relative increases or decreases in the population rather than simple absolute population numbers. Finally, the mean of each group obtained by clustering was visualized for each year. Based on these groupings, we classified and examined the population composition of each municipality and observed the changes over a four-year period. Statistical analyses were performed with Python version 3.10.

Ethical considerations

These data were processed to ensure privacy and confidentiality, and individual identification information was irreversibly encrypted and further anonymized to prevent individual identification through data matching. Therefore, it was determined that this study did not require ethics committee review since the data were used in a non-personal information format, ensuring that this research fell outside the scope of the Ethical Guidelines for Life Science and Medical Research Involving Human Subjects.

RESULTS

Study area characteristics

The estimated population data for the 12 municipalities are summarized in Table 1. The data represent the average population for each municipality over a 4-year period and, as a representative point, the average population of the municipality by age, sex, and attributes as of 2022. From 2019 to 2022, eight of the 12 municipalities (Minamisoma City, Hirono Town, Naraha Town, Tomioka Town, Kawauchi Village, Okuma Town, Namie Town and Iitate Village) increased their population. The most populated area in 2022 was Minamisoma City. The area with the highest percentage increase from 2019 to 2022 was Naraha Town, followed by Tomioka Town and Iitate Village with increase rates of 65.6%, 60.9% and 41.0%, respectively. Contrastingly, four municipalities (Tamura City, Kawamata Town, Futaba Town and Katsurao Village) observed an average population decrease between 2019 and 2022. The area with the lowest average population was Katsurao Village, followed by Futaba Town and Tamura City: decreasing by 36.4%, 29.3% and 4.1%, respectively.

Time series of municipal population and grouping by cluster analysis

Population dynamics were grouped based on the estimated population of all targeted areas, and the 14-day population trends are summarized in Fig. 2. The population dynamics were divided into five groups: Class 1 is a group that appears during all days, but especially during holidays; Class 2 is active on weekdays, but absent during nights and holidays; Class 3 is a group that changes little between days and holidays and between days and nights; Class 4 is a group that decreases during days and increases during nights; and Class 5 exhibits an increase during daytime and a decrease during nighttime hours. The gray shaded areas shown in Fig. 2 indicate weekends.

The four-year time series of population movements in all regions and the clustering results are shown in Fig. 3, which are expressed based on the average total population per municipality. Figure 3 shows the actual estimated population by group per municipality, and Fig. 4 shows the percentages. Municipalities with specific classes increasing by more than 5% over the four-year period were Naraha Town (12.7%), Katsurao Village (11.5%) and Namie Town (10.9%) for Class 1; and Iitate Village (26.8%), Tomioka Town (17.8%) and Okuma Town (16.4%) for Class 4 (Fig. 4). In Katsurao Village, Class 1 increased by 11.5% and Class 2 decreased by 11.8% from 2019 to 2022. Kawauchi Village and Okuma Town were the two municipalities with the largest changes in multiple classes. In Kawauchi Village, Classes 1 and 4 increased by 7.4% and 9.3%, respectively. In Okuma Town, Class 2 decreased by 7.2%, Class 4 increased by 16.4%,and Class 5 increased by 8.2%.

Table 1. Average population by municipality

		Tamura	Minamisoma	Kawamata	Hirono	Naraha	Tomioka	Kawauchi	Okuma	Futaba	Namie	Katsurao	Iitate
Year	2019	30552.9	51657.0	9621.1	5144.3	4020.2	3165.8	1301.4	3037.7	1184.2	2987.2	182.1	1034.7
	2020	30463.3	52100.3	9634.8	4866.1	4039.0	3341.8	1379.8	3179.7	879.0	2956.1	240.9	1287.0
	2021	30883.8	53035.5	10277.3	5948.9	6815.6	4566.4	1343.7	3762.6	815.7	3104.6	162.0	1529.9
	2022	29290.1	51664.9	9585.8	5713.6	6658.4	5094.1	1335.5	4237.0	837.4	3031.2	115.9	1458.5
Age (2022)[a]	15–19	1095.24	1581.3	0	0	0	0	0	0	0	0	0	0
	20	2166.8	3243.1	648.4	1012.9	492.5	411.7	0	499.0	41.0	143.3	0	31.7
	30	3159.8	5202.4	886.5	782.9	689.0	615.4	63.9	713.1	126.9	356.5	0.4	63.7
	40	3498.4	7395.9	1282.7	1067.7	1063.0	1032.0	182.6	1064.0	210.3	595.6	27.5	183.1
	50	4134.3	8248.2	1319.8	998.0	1242.3	1682.7	233.8	1305.1	261.3	748.9	32.5	206.4
	60	5608.7	9527.9	1763.8	1033.9	1339.7	1092.9	402.9	564.3	164.1	742.1	42.2	574.6
	70	4825.8	9432.9	2017.5	817.5	1193.0	255.3	341.1	91.5	33.8	341.6	13.3	399.1
	≧80	4800.9	7033.3	1667.2	0.7	638.9	4.1	111.1	0	0	103.2	0	0
Sex (2022)	Male	14167.9	27384.6	4616.8	2798.9	4729.6	4450.7	861.4	3834.2	792.1	2349.4	115.2	1079.7
	Female	15122.2	24280.4	4969.1	2914.7	1928.8	643.3	474.1	402.8	45.4	681.7	0.6	378.8
Attribute (2022)	Resident	19372.3	32908.3	7124.4	3400.7	3346.1	2535.8	920.6	350.3	49.9	1203.6	29.2	611.5
	Worker	1220.3	1901.8	643.9	788.6	942.9	934.6	84.8	2350.7	422.3	513.6	44.2	362.7
	Residents & Workers	7000.9	14321.5	1246.8	641.4	1109.6	552.7	212.2	588.3	5.7	616.7	1.5	148.0
	Visitors	1696.6	2533.3	570.7	882.9	1259.9	1070.9	117.9	947.6	359.5	697.3	42.0	336.4

[a] Age, sex, and attribute figures break down for 2022

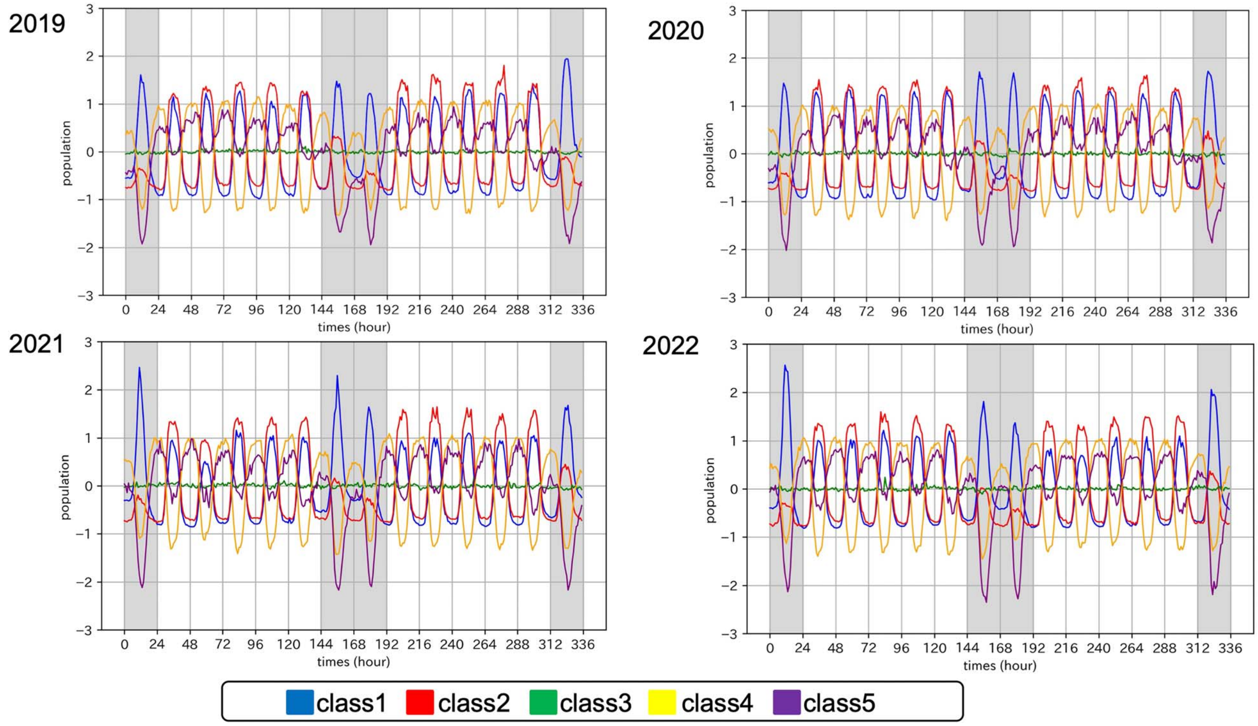

Fig. 2. Four-year demographics of the target area with clustering group. Figure 2 shows the demographics of the target area divided into five classes. The vertical axis illustrates the z-scored population change. The mean of each group, obtained by clustering, is visualized annually. The horizontal axis represents a two-week period, spanning 24 hours times 14 days. Darker-colored areas indicate weekends.

DISCUSSION

Using the estimated population data, we conducted clustering to illustrate the breakdown and fluctuations in the population dynamics in disaster-affected regions after the FDNPP. These areas exhibited distinctive population compositions owing to variations in the impact of the earthquake, allowing for observations of post-reconstruction changes in several regions. Additionally, the four-year changes across the target areas revealed the challenges of reconstruction. Capturing population movements using estimated population data after prolonged evacuation and reconstruction following a major disaster, such as the FDNPP, is crucial for evaluating medical resources and social policies. These findings indicate the potential applicability of this approach to future disasters.

The categorized 'classes' reflect the demographic characteristics and exhibit distinct variations in the population composition ratios across the target areas. These differences might signify variations in the timing of the evacuation lifted in different regions and the varying impacts of the FDNPP. The lifting of the evacuation order impacts the return of evacuees, yet it is not the sole determinant. Their return is influenced by multiple factors, not just the timing of the evacuation order. In fact, there are many areas where return has not progressed even after the evacuation order has been lifted, and the progress of return depends on the availability of social services, personal property, and work in each area [29]. Particularly, this demographic analysis suggests that considerable disparities in the proportion of permanent residents within the regional population are evident. Based on this analysis, Classes 3 and 4 represent populations of permanent residents staying in the area at night, and are notably higher in Tamura City, Minamisoma City and Kawamata Town. Lower proportions were observed in Okuma Town, Futaba Town, Namie Town, Katsurao Village and Iitate Village. In former areas, evacuations were lifted shortly after the earthquake [20], suggesting a relatively minor impact on evacuations. However, the latter still encompasses areas designated for evacuation, leading to a presumed low number of permanent residents owing to the recent commencement of resident returns. Specifically, Class 4 constitutes a group that diminishes during the day and increases at night, likely representing demographic commuting beyond the target area, particularly among settled residents. During the observed four-year period, key increases in Class 4 were noted in Kawamata Town, Naraha Town, Tomioka Town and Okuma Town. The Okuma Town evacuation order was lifted in June 2022. [30]. In contrast to other regions, this area experienced a prolonged evacuation period and remains a difficult-to-return zone [31]. Consequently, it is anticipated that many relocated to Okuma Town after evacuation while maintaining their work and living ties with their previously evacuated residences. These regions are forecasted to witness a progressive increase in permanent residents over a four-year period. During the recovery process, returning to one's original residence serves as a crucial indicator [32]. Assessing the proportion of permanent residents in the local population remains an essential method for forecasting recovery progress.

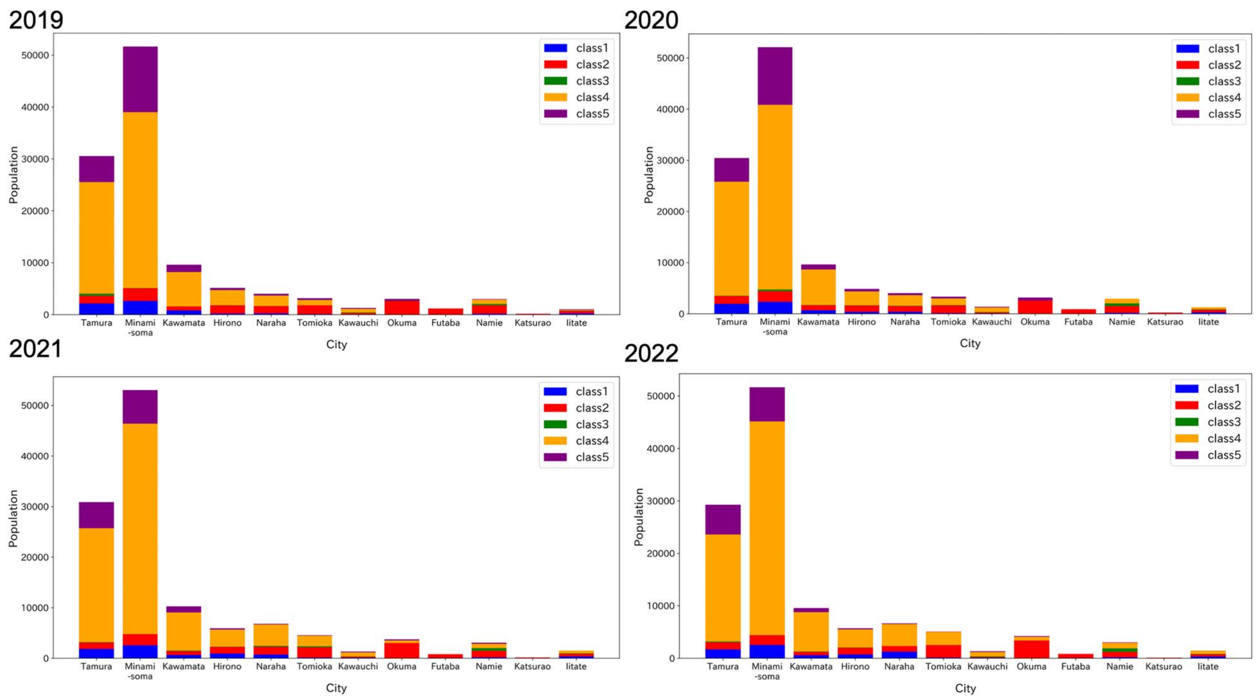

Fig. 3. The estimated population of the target area. Figure 3 shows the population percentages for each class in the target area. The color coding of the classes is the same as that shown in Fig. 2.

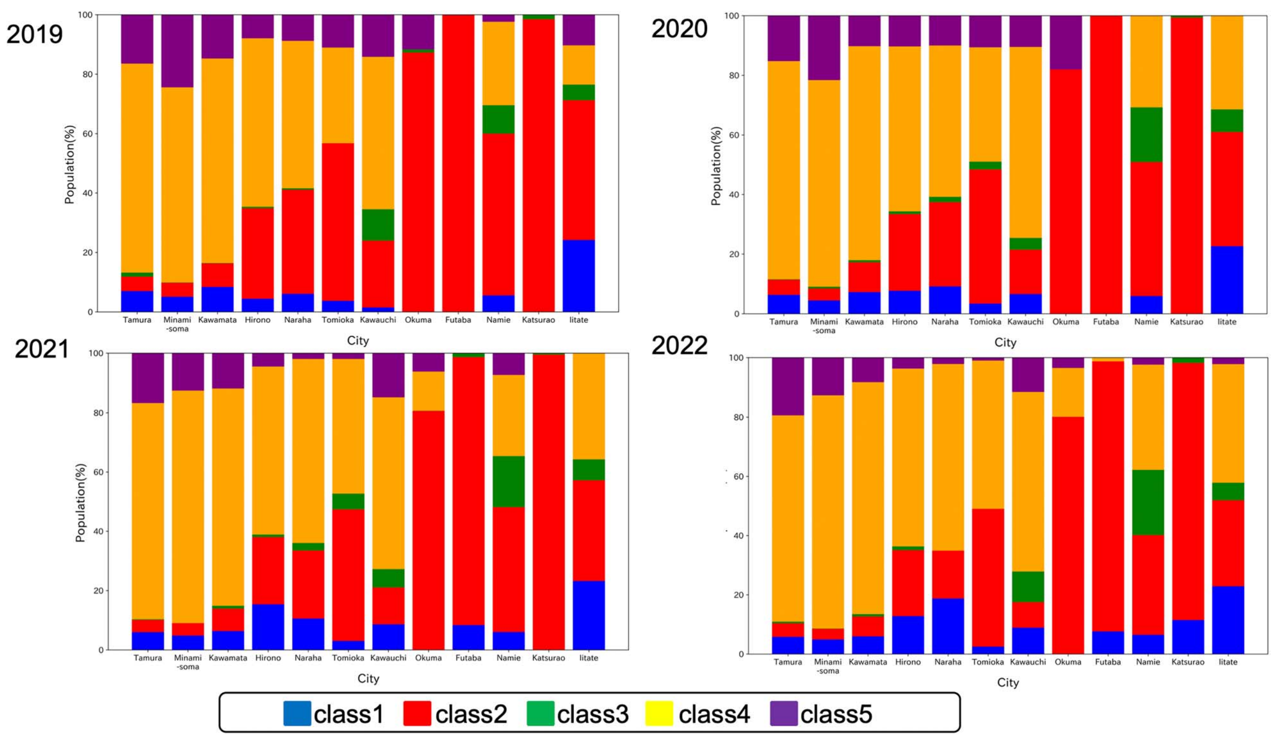

Fig. 4. The percentage of the estimated population by clustering classes. Figure 4 shows the population percentages for each class in the target area. The color coding of the classes is the same as that shown in Fig. 2.

Contrary to the resident populations of Classes 3 and 4, Katsurao Village, Okuma Town and Futaba Town were predominantly Class 2 residents. Class 2 represents a group present on weekdays during daytime hours, but absent during nights and holidays, possibly indicating residents from outside the target area. These are largely the working population commuting from outside to contribute to the reconstruction of the area. These regions have experienced an influx of working-age people engaged in local decontamination activities and industries associated with post-nuclear disaster recovery efforts. Moreover, in some instances, time-limited projects have been implemented in affected regions for reconstruction purposes. In Katsurao Village, a solar power development project called the Katsurao Village Smart Community was implemented from December 2018 to December 2020 [33], and an increase in Class 2 was observed in Katsurao Village from 2019 to 2020. Additionally, former residents who settled outside the region and returned to the area may also be included in Class 2. In areas such as Katsurao Village, where the evacuation order was given for a long period and the period when it became possible to return was recent, there are cases of people living in multiple locations, with new homes in evacuation areas and former homes in evacuation-ordered areas [34, 35]. By capturing demographic data, we could estimate the number of workers who commute to work from outside the area and the number of people who have bases outside the area, which is difficult to do using ordinary statistics, such as the national census and the Basic Resident Resister. Understanding these populations will be useful for understanding the status of the recovery process and estimating the additional healthcare demands that may arise in the region. In fact, in the affected areas, an increase in hospital visits by decontamination workers who came to work after the disaster was reported [36–39]. Such a fluid population is characteristic of the reconstruction period after a major disaster, and it is important to continue monitoring population dynamics.

The changes observed in population composition also highlight reconstruction challenges in specific areas. Over the four observed years, Naraha Town and Okuma Town exhibited a decline in Class 3 population. Class 3 comprises individuals displaying minimal variation between daytime, holidays, and nighttime activities, indicating non-working-age residents, such as students and the older people, who tend to remain in the same location for extended periods. The decrease in Class 3 within these towns and villages across the 4 years implies a decline in such populations. These three towns and villages have kindergartens, elementary schools, and middle schools, but lack high schools [40, 41]. Consequently, students above high school age must commute outside the district. This may have contributed to a decrease in the number of educated generations. Generally, the female population and frail older people tend to move out of affected areas after an earthquake. In the case of Bangladesh and the Great Hanshin-Awaji Earthquake of 1995, the displacement of frail women was related to the impact of natural disasters [42, 43]. Indeed, in the recent FDNPP, health effects owing to the evacuation of frail older people and the outflow of the female population from affected areas have been reported [44–46]. In these areas, even after the evacuation order is lifted, it may be difficult for the elderly and children, as well as families with small children, to return. Conversely, in area such as Futaba Town, Namie Town and Katsurao Village, where the resident population (representing Class 1) is small, there has been an increase in certain demographics, potentially representing tourists or outside visitors, in 2022. These areas are witnessing an influx of returnees, ongoing local reconstruction initiatives, and a gradual increase in interactions with external communities. A more comprehensive analysis of population dynamics could be crucial for accurately monitoring the recovery progress.

Variations in population composition were observed among municipalities. In post-disaster recovery planning, it is important to understand the diversity of the post-disaster population changes across regions. Population recovery after a meaningful post-hurricane population decline is prompted by social policies, such as housing reconstruction, but the degree of recovery and fluctuation is uneven over time and space [47, 48]. Previous studies of Minamisoma City have produced similar results [49–51], which may emphasize the heterogeneity of post-disaster population changes in this study, as well. The FDNPP accident is a complex disaster that comprised earthquakes, tsunami, and radiation. It is difficult to compare the impact of this disaster on the local population and population changes during the recovery process with those of previously reported disasters. However, this study could be crucial for examining how population characteristics change after a complex disaster, and the changes that occur during the recovery phase. Further, tracking population changes over time and during the recovery process could provide important insights for planning the allocation of healthcare resources in the area and for modeling and forecasting population changes and recovery after other major disasters in the future.

This study highlights the utility of Mobile Spatial Statistics in capturing dynamic populations. The aggregation of Class 3 and 4 closely approximated the population figures obtained from the census for the relevant area. The census is a statistical survey of all people living in Japan, and is conducted to determine the resident population in an area. Class 3 and 4 denote a settled population, mirroring the census data. Conversely, Classes 1, 2 and 5 represent transient populations that move across regions and can be effectively analyzed using Mobile Spatial Statistics. This demographic approach holds promise, especially in post-disaster recovery scenarios, warranting further investigation into its applicability.

Limitation

Despite its strengths, this study also has several limitations. One limitation is the restricted timeframe of the analysis. This study only analyzed a span of 4 years because of the available data, thereby missing the population changes from the immediate aftermath of the FDNPP to the recovery period. Second, this study used two weeks within each year as representative samples. However, this selection, although based on periods with fewer events, may provide limited insight into area-specific characteristics. The analysis failed to identify the origin districts of the relocating demographic groups, thus limiting the insights into their movement patterns. Third, the analysis is limited to individuals aged 15 years or older. In age groups where few people remain, certain factors in this estimation can hinder the production of accurate data. Additionally, during data collection, if there are <10 individuals in a specific area under observation, their count is recorded as 0 to protect privacy. Consequently, populations with a small number of individuals may end up with underestimated figures. Particular attention should be paid to the fact that the impact may be greater in areas with small populations, such as Katsurao Village. Fourth, tourists and visitors from abroad were excluded from these measurements. However, because the number of tourists in the evacuation zone was small, the error was small. In addition, note that the period analyzed in this study was a time when COVID-19 infections were prevalent. Although the number of the COVID-19 cases in the region were not large from 2019 to 2022, the COVID-19 pandemic could have affected the population of exchange in the region. Therefore, population movement in the affected area should be analyzed continuously even after the COVID-19 outbreak has subsided. Please note that this population is not confined to a specific group but encompasses both newcomers and departures. Consequently, while changes in age over time are unlikely to have a key impact on the outcomes, they should be factored into future comprehensive analyses.

By clustering the population characteristics based on the demographic data obtained from the mobile population estimates, this study revealed differences in the characteristics of the population composition of the affected areas. This type of analysis can reveal variations in the population composition over time during the recovery process. This demonstrates the potential to comprehensively understand the regional conditions influenced by differences in evacuation timing and the impact of disaster-related evacuations. This method of analyzing local population characteristics may contribute to resolving issues in healthcare planning and reconstruction, potentially aiding the strategic allocation of personnel and medical resources. These results could be an important resource in the affected areas. For example, in municipalities with several visitor demographics, this could lead to consideration of business and commercial facility construction targeting visitors. Further, in municipalities with several permanent and elderly residents, it may be possible to consider the timing of the introduction of medical resources and long-term care services.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest related to this research.

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No registration details to present.

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