Detecting Urban Spatial Porosity and Fragmentation from Local Population Patterns

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Abstract

In Japan, the combined effects of declining birth and marriage rates have accelerated population decline, leading to spatial porosity and fragmentation in urbanised areas: a phenomenon known as "Urban spongification". This study analyses local population distributions in order to identify localised low-population areas embedded within densely populated urban environments, with the aim of understanding spatial porosity and fragmentation in Osaka Prefecture. A multi-scale spatial autocorrelation approach was applied to detect the spatial extent of localised low-population areas, and results were compared between 1995 and 2020. The analysis further examined how the formation and change of localised low-population areas differ across use districts (i.e., zoning categories) and according to long-term land-use transition histories. The findings reveal pronounced spatial variability within districts that cannot be captured by conventional population density metrics alone. The study demonstrates that the emergence, persistence, and transformation of localised low-population areas are closely related to use district regulations and historical land-use processes. These results provide insights into the spatial processes contributing to urban porosity and fragmentation and offer a basis for future evaluations of residential inducement areas designated under Location Optimisation Plans.

1. Introduction

Japan is experiencing a globally unusual pace of population decline. The principal causes include falling birth and marriage rates that have persisted across multiple generations, and because these have continued, it has been pointed out that a rapid recovery is difficult under current conditions (National Institute of Population and Social Security Research, 2019). From the perspective of spatial characteristics, even as cities continue to grow outward from their centres, population decline gives rise to increases in vacant houses and vacant lots within already built-up districts, accelerating the porosity and fragmentation of urban space. This phenomenon in existing urbanised areas is referred to as "Urban spongification" (Aoki, 2022); integrated redevelopment becomes difficult because underutilised and unused spaces emerge in a random pattern. The spongification therefore has become one of the major urban challenges (Ministry of Land, Infrastructure, Transport and Tourism, 2019). In response to this phenomenon, policies have been introduced that designate multiple core areas within the urban region and seek to maintain sufficient population densities there so as to support efficient day-to-day activity. Consequently, Japan currently faces outward urban expansion, increasing porosity and fragmentation of built-up districts, and policy-driven consolidation all at once. Thus, technologies for spatially monitoring urban change that is both spatial and complex have become indispensable today.

As population decreases, increases in vacant houses and vacant lots expand idle urban space, which in principle should make relocation and rebuilding easier. At the same time, under the current tax system, established during the housing shortage of the 1960s, property taxes and related levies can be reduced when a building exists on a parcel. As a result, even when buildings are functionally vacant, the number of cases in which owners avoid removing buildings also continues to increase. In other words, due to the responses of residents and businesses, urban conditions fluctuate. The occurrence and progression of "Urban spongification" are therefore closely related to human behaviour by residents and business operators.

In this study, we take local population distributions as a basic indicator representing urban porosity and fragmentation. We compare the generally used indicator of population density with the outcomes obtained from this spatial analysis and clarify the features of each. Focusing on district characteristics and on land-use histories that directly reflect human behaviour, we discuss the potential occurrence of "Urban spongification" from the perspective of spatial interactions by comparing these with the spatial characteristics of local population distributions.

2. Data and Methodology

2.1 Study Area

The study area is Osaka Prefecture, which corresponds to the Kansai region, shown in Figure 1. Osaka Prefecture includes Osaka City, known as Japan's second-largest urban core, together with many surrounding satellite cities. The patterns of urban development around Osaka City differ between the southern, northern, and eastern sectors.

2.2 Geographical Data

We adopt the basic unit block population data of the Population Census of Japan for 1995 and 2020, as local population data. These data are the smallest spatial units of the census. The 1995 data are provided as points, while the 2020 data are polygons. Although the 1995 dataset does not contain polygon area information for the basic unit blocks, each record is stored as the centroid point of the corresponding block. To ensure methodological consistency, the 2020 polygon dataset was also converted to centroid point representations of each basic unit block. Because the survey unit changes each census year, the spatial positions of each dataset differ. Moreover, due to differences based on parcel structures, street networks, and land-use patterns, the shapes and areas of the survey units are

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irregular. In addition, for this local population dataset, enumeration at the building level occurs for high-rise apartment buildings, while in some cases multiple blocks are aggregated for survey efficiency. To address these properties, we generate a 60 m × 60 m grid and aggregate each basic unit block data to the corresponding grid cell to create local population data. The area of basic unit blocks ranges from a minimum of 40 m² to a maximum of 15,304,216 m², with the lower quartile at 2,294 m², the median at 3,942 m², and the upper quartile at 6,718 m². In suburban areas, block areas tend to be larger due to the presence of agricultural land and low-density residential development. In contrast, because this study focuses primarily on urban areas, most block areas are smaller and clustered around the median value. Based on these statistical characteristics, a grid size of 60 m × 60 m was selected as a value approximating the square root of the median area of the basic unit blocks. As land-use regulation information that constrains and guides resident and business activities, we adopt Use District data (2021) from the National Land Numerical Information download service. As land-use status data, we use the Detailed Digital Information (10 m Grid Land Use) datasets in 1974 and 1996, published by the Geospatial Information Authority of Japan, together with the Land Use Fragmented Mesh Data (2021) from National Land Numerical Information. We use these land-use status data to extract land-use transitions.

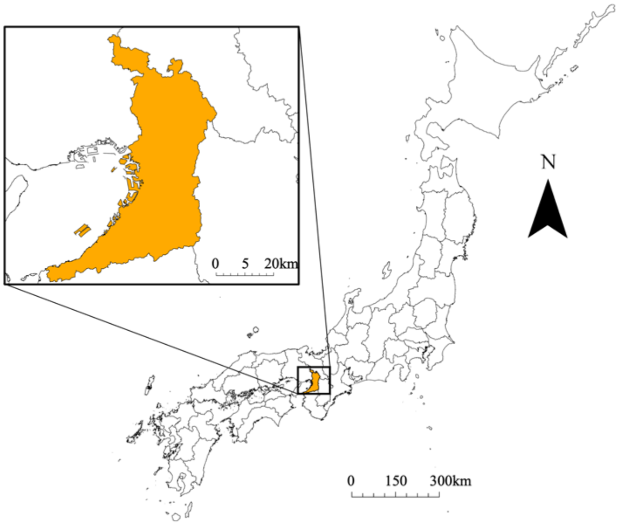

Figure 1. Study area and its location. The orange area in the enlarged view of the map shows Osaka Prefecture.

2.3 Methodology

2.3.1 Spatial analysis of local population distributions: The spatial analysis method applied in this study comprises spatial autocorrelation analysis based on the G statistic and a moving-window analysis (Getis and Ord, 1992, Ord and Getis, 1995, Kumagai, 2011, Kumagai et al. 2017). By applying the G statistic described in Equation (1), we can detect clusters of large local values (here, large local population) and the size of those clusters.

$$G_i(d) = \frac{\sum_i w_{ij}(d) h_j}{\sum_i h_i} \tag{1}$$

where G_i is a G statistic, h_j is local population at the point i, w_{ij} is a symmetric binary spatial weight matrix with ones for all links defined as being within distance d of a given i; all other links are coded zero, including the link of a point i to itself. Under the null hypothesis that the set of local population values, h_j, within distance d of location i is a random sample, we derive the standardized Z value. Depending on whether the Z value is large and positive or large and negative at the chosen significance level, we obtain positive spatial autocorrelation (hotspot) or negative spatial autocorrelation (cold spot). At the 10% significance level, the study area is classified into three types according to the Z value: positive spatial autocorrelation, no autocorrelation, and negative spatial autocorrelation. Positive spatial autocorrelation means that higher local populations are concentrated within distance d, while negative spatial autocorrelation indicates the area of lower local population distributions.

In order to identify locally low-population portions within urban agglomerations, we utilise the occurrence of positive/no spatial autocorrelation. The cluster size is represented by the distance parameter d. The maximum distance, d_{max}, is determined by gradually changing d, computing Z values, and observing the convergence of the areal difference between positive autocorrelation and no autocorrelation regions. The distance parameter d was increased stepwise from 60 m to 1,200 m in 60 m increments. The areal difference between positive and non-correlated regions decreased monotonically and stabilised beyond 720 m. At approximately 750 m, the rate of change fell below 0.5% of the total study area, indicating convergence. Therefore, d_{max} was fixed at 750 m, beyond which further increases produced negligible changes in clustering patterns (Kumagai and Kameda, 2021). To analyse phenomena such as “Urban spongification,” it is necessary to detect locally low-populated subareas within otherwise dense agglomerations. We therefore analyse the occurrence of positive spatial autocorrelation as a function of the neighbourhood distance d. Figure 2 shows a conceptual diagram for detecting spatial characteristics in local populations. Treating the distance parameter d as a variable, we decrease its value stepwise and statistically judge whether there is population concentration within distance d (Figures 2a and 2b). As d decreases, there exists a distance d_n at which the test first judges “no significant concentration.” As illustrated in Figure 2c, the area within d_n around location i that exhibits negative spatial autocorrelation essentially is contained within the area of positive autocorrelation at longer distances d. Where a transition occurs from positive to no autocorrelation at a given location, we define Ambiguity of Spatial scale in a densely Populated area: ASP, that is the size (radius d_n) of a locally lower-populated area embedded within an otherwise higher-populated neighbourhood (Kumagai and Kameda, 2021).

Because the population data are on a 60-m mesh, the step of the distance parameter d is also 60 m. Accordingly, ASP values are discrete (e.g., 150 m, 210 m, …). If no d_n is detected, we deem small local population pockets to be not identifiable at the given resolution and denote this as ASP_0. Conversely, where no positive spatial autocorrelation occurs at any distance, e.g., mountainous or agricultural areas, we consider the local population to be broadly low and denote this as $\mathrm{ASP}_{\mathrm{inf}}$. With the aim of detecting potential locations where “Urban spongification” could arise, we compute ASP across the entire study area using a mesh-based moving window. The ASP value at each location is stored in its corresponding grid cell, and the resulting ASP distribution is mapped as the spatial extent of locally low-population areas (Kumagai and Tokoi, 2023).

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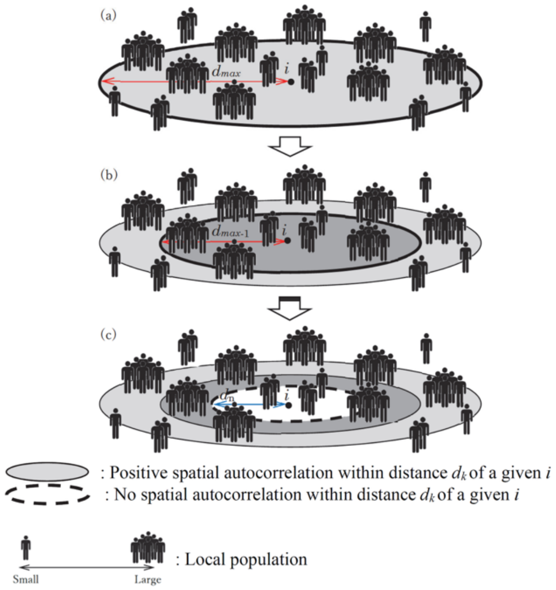

Figure 2. Conceptual diagram with respect to the detection of the spatial features of local populations (Kumagai et al., 2021).

2.3.2 Statistical analysis: We analyse changes over the past 25 years by examining statistical properties of population density. Specifically, we apply a two-sample t-test for the mean and the Kolmogorov-Smirnov (K-S) test for distributional differences (Massey, 1951). Using these in combination makes it possible to grasp characteristics of change in population density from both central tendency and distributional shape. We also apply a χ^2 test of independence to the relationship between the spatial extent of low-population areas and Use District categories and land-use histories and analyse differences among ASP categories using adjusted standardized residuals with Bonferroni correction (Snee, 1974, Miller, 1981, Bewick et al., 2004).

3. Results

Figure 3 shows population change in Osaka Prefecture. After steady growth, the total population peaked around 2011 and has since entered a period of decline. Thus, the 25-year period under consideration here includes both a growth phase and a decline phase. Comparing 1995 and 2020 totals reveals that the overall population is not drastically different. It is necessary to examine whether spatial differences in population distribution emerged before and after the peak.

3.1 Changes in population density

Here, we examine how population density by district has changed over a 25-year period. As the 1995 point data did not contain area information for the basic unit blocks, we utilise the Use District classification, which serves as a benchmark for regulating residential and business activities. Table 1 shows the Use District classifications adopted in this study. Although the City Planning Act defines 13 land use zones, this study consolidates them into five broad categories of the Use District according to activity type and regulatory strength. Note that commercial and industrial districts are regulated to facilitate those activities and, with some exceptions, can also be used for residential purposes. Population density for each classification was calculated by aggregating local population data within areas designated by Use Districts and dividing this sum by the area of that district.

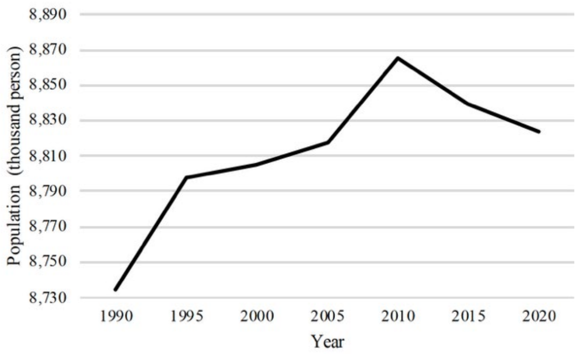

Figure 3. Population dynamics in the study area. The total population from 1990 to 2020 is displayed with a general increase from around 8,730,000 to around 8,870,000, peaking 2010.

Land use zone	Use District defined in this study
Category 1 low-rise exclusive residential zone	Low-rise exclusive residential districts
Category 2 low-rise exclusive residential zone	
Category 1 medium-to-high-rise exclusive residential zone	Mid-to-high-rise exclusive residential districts
Category 1 medium-to-high-rise exclusive residential zone	
Category 1 residential zone	Other residential districts
Category 2 residential zone	
Quasi-residential zone	
Rural residential zone	
Neighborhood commercial zone	Commercial districts
Commercial zone	
Quasi-industrial zone	Industrial districts
Industrial zone	
Exclusive industrial zone	

Table 1. Use District based on Land use zone defined by the City Planning Act.

For the multiple population density datasets calculated within each Use District, we conducted two-sample t-tests and K-S tests for the two periods to identify differences overall and within each Use District. The results are shown in Table 2. Table 2 presents the results relative to the 1995 population density. Similar to total population of Figure 3, the overall average population density was significantly higher in 2020. Results by the Use District also indicated either no significant difference or a significantly higher value, except for the mid-to-high-rise exclusive residential districts. Table 2 also lists the results of the K-S test. When the K-S test indicates a significant difference, the nature of the distributional change can be interpreted in two ways: as shown in Figure 4, either the cumulative frequency curves are parallel and separated, or they intersect due to a change in variance (standard deviation). Therefore, the outcomes of the mean and K-S tests are summarised in the “distribution difference” column. As shown

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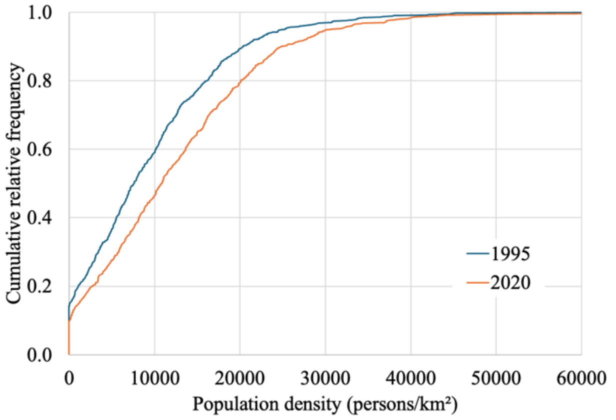
in Figure 4(a), when the cumulative frequency curve shifts to a higher or lower value, this is denoted as “++” or “--”. As shown in Figure 4(b), when the curves intersect, cases where variance increases are denoted as “sd+”, and those where it decreases as “sd-”.

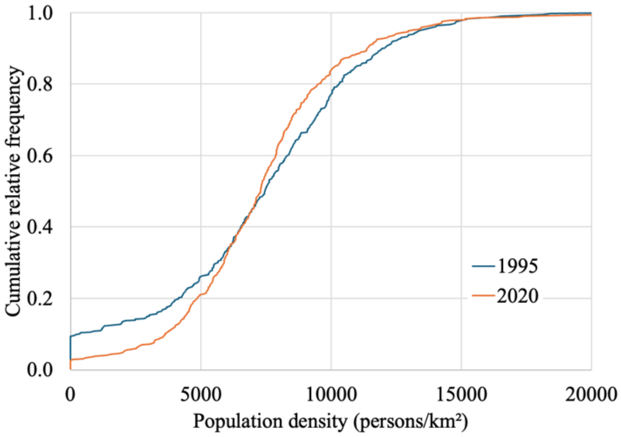
		Two-sample t-test t value	K-S test Z_{ks}	Distribution difference
Use Districts	Low-rise exclusive residential districts	1.066	1.421 *	sd-
	Mid-to-high-rise exclusive residential districts	-3.777 ***	2.444 ***	--, sd-
	Other residential districts	0.741	1.264	
	Commercial districts	6.273 ***	1.756 **	++
	Industrial districts	3.788 ***	3.032 ***	++
	All districts	3.477 ***	2.710 ***	++

***0.001, **0.001-0.01, *0.01-0.05

Table 2. Comparison of population density between 1995 and 2020 by two-sample t-tests and K-S tests.



(a) Commercial districts



(b) Low-rise exclusive residential districts

Figure 4. Cumulative frequency of population density distributions as instances.

Consequently, across all districts, the commercial districts, and the industrial districts, the mean population density in 2020 is significantly higher, and the distribution of population density is also elevated overall. As shown in Figure 3, although population decline is progressing across the study area, the population density of 2020 in all regions and these districts has not yet reached those of 1995. Distinct patterns, however, appear in the low-rise exclusive residential, the mid-to-high-rise exclusive residential, and the other residential districts, differing from the overall population-density trend, as shown in Table 2. While no significant changes were observed in either mean or distribution for the other residential districts, the low-rise exclusive residential districts exhibited decreased variance, and the mid-to-high-rise exclusive residential districts showed a significantly lower mean value in addition to decreased variance.

3.2 ASP analysis

Figure 5 shows the ASP map. Locations with large ASP occur frequently near the edges of the coloured areas. These locations tend to be situated in suburban areas, where land use status such as farmland and forest is common. ASP_0 values, which indicate the absence of a locally low-population extent, are most often distributed in central urban areas. Thus, it can be confirmed that ASP exhibits a characteristic reflecting the low-density state of population distribution dependent on the land use status.

Examining the change in ASP between 1995 and 2020 (hereafter referred to as ΔASP) reveals the pattern shown in Figure 6. This visualises the changes illustrated in Figure 7; $\Delta ASP = ASP_{2020} - ASP_{1995}$ in this study. Diverse changes are spreading across various regions in Figure 6, yielding results distinct from the ASP distribution in Figure 5. We analyse the relationship between the ΔASP and the Use District classification. Table 3 presents the results of a cross-analysis of these variables. The χ^2 test rejected the null hypothesis, indicating that independence

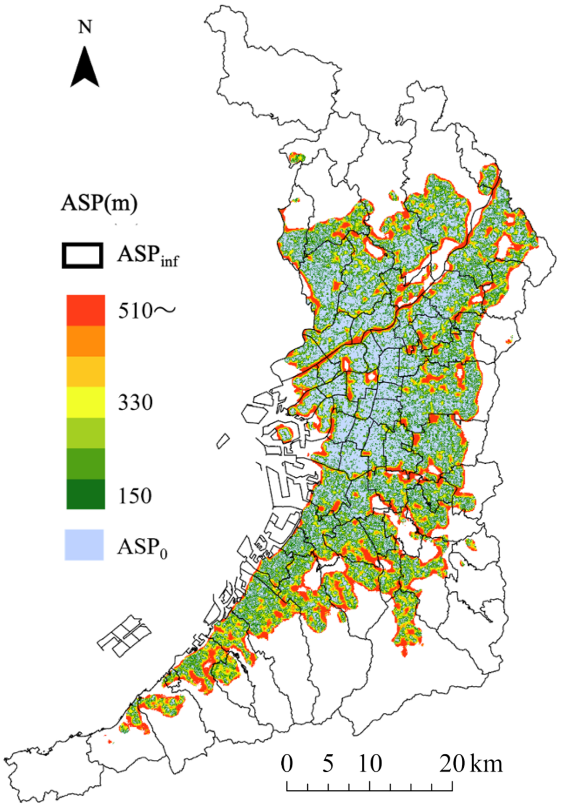


Figure 5. ASP map in 2020.

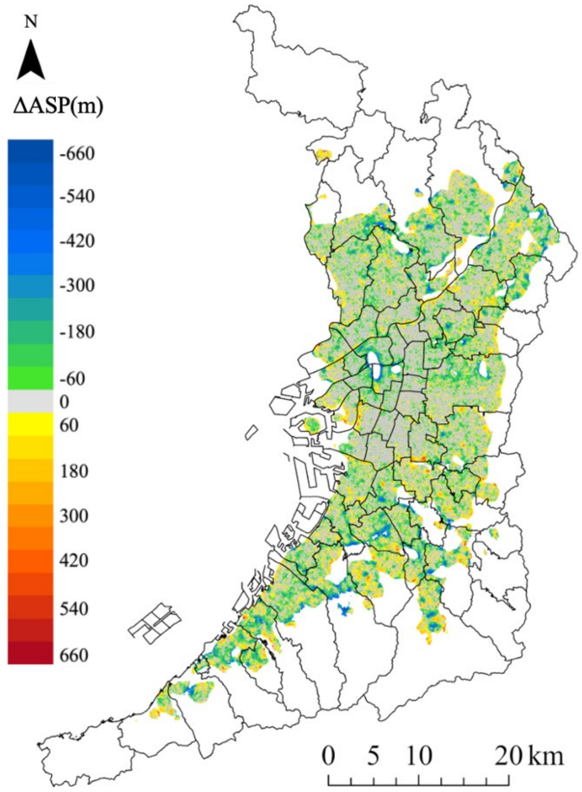
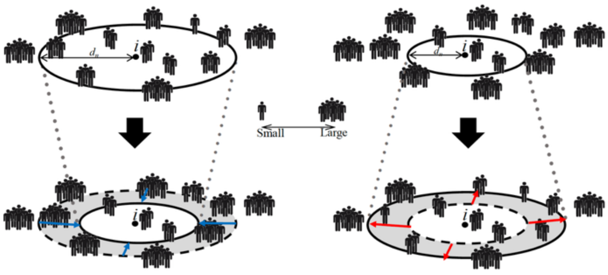


Figure 6. ΔASP map based on the difference in ASP between 1995 and 2020.



(a) ASP shrinkage：-ΔASP (b) ASP expansion：+ΔASP

Figure 7. Concept diagram of ΔASP between 2 periods.

cannot be assumed. This suggests that ΔASP and the Use Districts exhibit a certain degree of correlation. An examination of the residual analysis results in Table 3 reveals distinct patterns across the Use District categories. In the industrial districts, areas where low-population extents expand and contract both occurred at levels significantly higher than expected. In the commercial districts, marked fluctuations are observed at multiple locations, with many areas exhibiting a contraction of low-population extents and few showing expansion. Meanwhile, in the mid-to-high-rise exclusive residential districts and the other residential districts, locations showing no change in low-population extents are considerably more numerous than expected, while those showing expansion or contraction are fewer. In the low-rise exclusive residential districts, although there are a certain number of locations where the extents of low population contract, the areas where these extents expand occur in significantly greater numbers than expected, irrespective of the degree of expansion. These findings indicate that variations in land-use regulations impose diverse constraints on urbanisation and associated human activities, resulting in heterogeneous transformations in the spatial extent of sparsely populated areas.

4. Discussion

4.1 Urban porosity/fragmentation and spatial characteristics of local population

Analysis of population density revealed that density remains high in non-residential Use Districts even though the population is totally declining, whereas in the residential exclusive Use Districts, the variance (standard deviation) of population density distribution has decreased. Meanwhile, the analysis of ΔASP confirmed a tendency for the number of cases in which lower-populated areas expand at various scales to be higher in the low-rise exclusive residential districts.

Monitoring phenomena such as “Urban spongification” requires analysis at finer spatial units. Regarding the population density in this study, the locations where the basic unit block data are collected vary by survey year, meaning the data can be handled only as figures for the Use Districts. Capturing spatial variations within the Use Districts, therefore, proves difficult.

	ΔASP(m)																						
	-660	-600	-540	-480	-420	-360	-300	-240	-180	-120	-60	0	60	120	180	240	300	360	420	480	540	600	660
Low-rise exclusive residential districts	**	***	***	***	***		(-) **		(-) *	(-) ***	(-) ***	(-) ***	***	***	***	***	***	***	***	***	***	***	***
Mid-to-high-rise exclusive residential districts		(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	***	***	(-) ***	(-) ***	(-) ***	(-) **	(-) ***	(-) **	(-) *			
Other residential districts					(-) *		(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	***	(-) ***	(-) ***	(-) ***	(-) **	(-) *	(-) ***	(-) ***				
Commercial districts				***	**	***	***	***	***	***	***		(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) ***	(-) **	(-) *	
Industrial districts					**	***	***	***	***	***	***	(-) ***	***	***	***	***	***	***	***				

***0.001, **0.001-0.01, *0.01-0.05

Table 3. Results of a cross-analysis between ΔASP and the Use Districts. The results of the residual analysis are also shown. “(-)” indicates that the value is significantly smaller than the expected value.

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It is recognised that development projects, such as land preparation, are not necessarily implemented simultaneously across areas delineated by the land use zone categories. In other words, the timing of development is typically segmented and executed at finer district levels. In the sale of residential plots, for instance, this approach allows equitable sales opportunities and enables adjustment of sales strategies in response to demand trends. Consequently, within areas planned for development, actual building construction is generally staggered over time. From the perspective of spatial extent, even within an area designated as a single land use zone, the timing of urbanisation is often staggered across different parts. Local population fluctuations may similarly occur within these spatial units as population inflows and outflows happen depending on the timing of the urbanisation.

Comparing the past 25 years, by employing the ΔASP shown in Figure 6, it becomes possible to identify both the locations where spatial variation occurs and the scale of that variation within the same Use District at finer spatial resolutions. This offers the potential to understand urban porosity and fragmentation.

4.2 Relationship between changes in local population distribution and district histories

ΔASP derived from localised population inflows and outflows may appear due to the occurrence of urbanisation or the passage of time since urbanisation. We therefore utilise land use data from multiple time periods to categorise the urbanisation history of the districts. This study focuses particularly on land uses directly related to local population fluctuations, such as residential land categories. Table 4 summarises the land use items related to residential land categories within the land use data adopted for this study. Given that the interpretation criteria for aerial photographs and satellite imagery used to generate the land use data differ between datasets, these items were consolidated from the perspective of certain common denominators. We define the Residential land use in Table 4 as a specific land use category for representing local population fluctuations caused by urbanisation. For the Detailed Digital Information (10m Grid Land Use) datasets, the land use category with the highest frequency within each 50-m grid cell, matching the grid size of the Land Use Fragmented Mesh Data, was adopted, and the data were ultimately standardised to a 60 m grid, consistent with the ASP.

Table 5 organises the urbanisation histories of districts from the perspective of changes to the Residential land use of Table 4. Table 5A indicates districts where the Residential land use category has appeared continuously in the land use data for 1974, 1996, and 2021. Then, assuming that the Residential land use has continued since before 1974, we denote this as “-1974”. Table 5B shows districts that corresponded to the Residential land use in both 1996 and 2021, defined as follows: the conversion to the Residential land use occurred between 1974 and 1996, and then the land use has continued to the present (designated as “1974-1996”). For Table 5C, we assume that land use change occurred over the most recent approximately 25 years, roughly matching the period used for the local population analysis in this study. We define this as a shift towards the Residential land use having occurred from 1996 to the present, designated as “1996-2021”.

Note that this classification based on district history cannot reflect changes from densely built-up residential areas to redeveloped residential areas, or shifts from low-rise to mid-to-high-rise residential areas. This approach focuses on changes from land uses other than those in Table 4 to the Residential land use and the continuation of that land use state. Furthermore, it cannot reflect changes occurring within a single period, such as where land changed from residential land to another land use and then back to residential land during the single period (around 22 to 25 years). For example, an area that changed from low-rise housing to developed land and then to mid-to-high-rise housing would not be included.

Specific land use	Detailed Digital Information (10 m Grid Land Use) (1974, 1996)	Land Use Fragmented Mesh Data (2021)
Residential land use	General low-rise residential area	Low rise building area (non-dense areas)
	Densely packed low-rise residential area	Low rise building area (dense areas)
	Mid-to-high-rise residential area Commercial and business area	High-rise building area

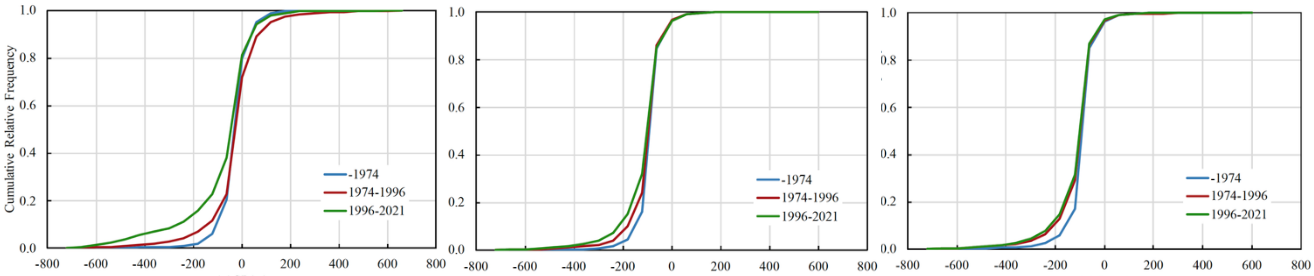
Table 4. Definition of Specific land use areas based on residential land categories of land use datasets.

History of land use transition	Residential land use			Assumed land use conditions	Designation
	1974	1996	2021		
A	✓	✓	✓	The Residential land use has continued since before 1974.	-1974
B		✓	✓	The conversion to the Residential land use occurred between 1974 and 1996, and then the land use has continued to the present.	1974-1996
C			✓	A shift towards the Residential land use has occurred from 1996 to the present (2021).	1996-2021

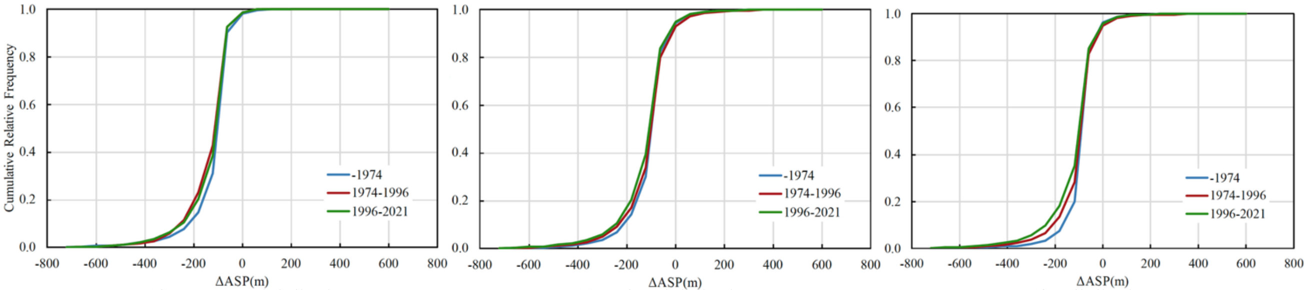
Table 5. Urbanisation history defined in this study approach.

Figure 8 shows the occurrence state of ΔASP for each Use District in Table 1, represented by the cumulative relative frequency distribution for the three land use histories in Table 5. In Figures 8b to 8e for the mid-to-high-rise exclusive residential districts, the other residential districts, the commercial areas, and the industrial areas, we can see that regardless of land-use history, the peaks tend to occur at negative ΔASP, indicating that over the 25 years the extent of locally low population has contracted. ΔASP, however, peaks near zero in Figure 8a for the low-rise exclusive residential districts, which have the strictest land use restrictions. Meanwhile, locations in Table 5B that changed to the Residential land use between 1974 and 1996 show a higher occurrence of significantly positive ΔASP values compared to any other Use District category. This implies that there are relatively many places where the extent of locally low population expanded between 1974 and 1996.

Figures 9 and 10 focus on districts that exhibited distinctive distributions within the low-rise exclusive residential districts and provide enlarged displays of ΔASP maps, land-use transition histories, and aerial photographs. The lines in Figures 9 and 10 indicate the boundaries of the low-rise exclusive residential districts. In Figure 9, locations with Table 5A histories appear in clusters in the northeast, while Table 5B histories spread across the southwest. It is understood that in this area, residential development proceeded in stages from the 1960s to the 1980s, with the district being subdivided (Nankai

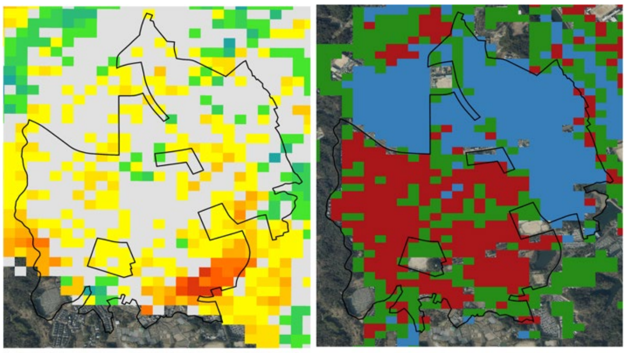


(a) Low-rise exclusive residential districts. (b) Mid-to-high-rise exclusive residential districts (c) Other residential districts

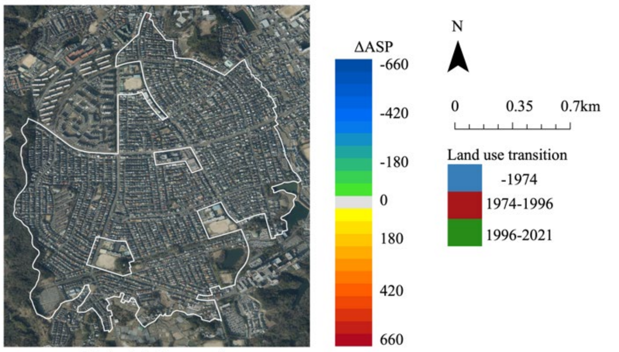


(d) Commercial districts (e) Industrial districts (f) All districts

Figure 8. Cumulative relative frequency ΔASP based on the history of land use transition.

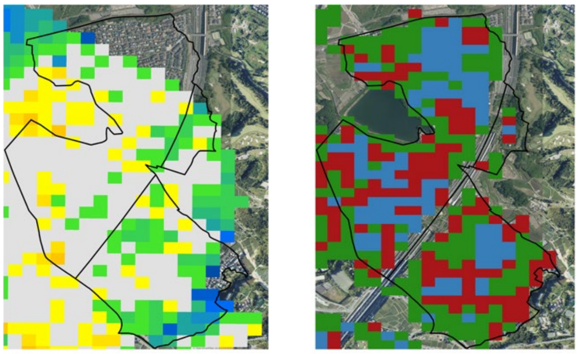


(a) ΔASP (b) Land use transition

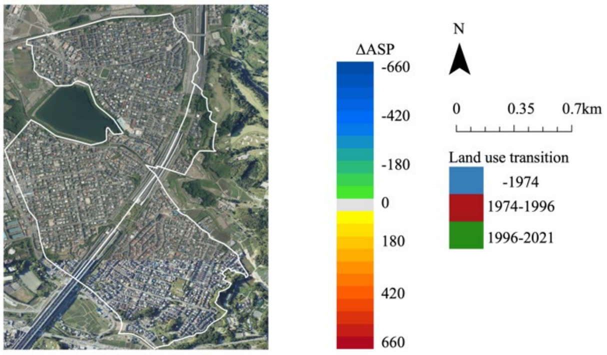


(c) Aerial photograph

Figure 9. ΔASP map, land use transition, and aerial photograph of Osaka Sayama New Town in Osaka Sayama city.



(a) ΔASP (b) Land use transition



(c) Aerial photograph

Figure 10. ΔASP map, land use transition, and aerial photograph of Nagao and Sugi Yamate area in Hirakata city.

Electric Railway, 1985). Regarding ΔASP, small changes, e.g., -60 m, 0 m, +60 m, are scattered in the northeast, whereas in the southwest many locations show positive ΔASP, and there are areas where high values occur in clusters. In Figure 10, the land-use transition histories appear to expand from Table 5A to Table 5C from the center of the district toward its edges. For ΔASP, while locations with Table 5C histories tend to show shrinking low-population extents, we do not observe distinctive patterns like those in Figure 9 elsewhere.

In the low-rise residential exclusive districts, locations where land use changed to the Residential land use between 1974 and 1996 tend to exhibit an expansion in the extent of locally low population. Conversely, in locations where land use changed to the Residential land use before 1974, no significant changes are observed in the extent of locally low population. One possible reason for this difference is the degree to which population renewal within the district has progressed. Historically in Japan, newly developed residential areas tended to attract households of similar generations. The districts in Table 5A have now passed more than 46 years, including periods of population growth, suggesting that substantial population renewal has occurred through generational turnover. Meanwhile, in the districts listed in Table 5B no significant population renewal appears to have taken place yet. The expansion of locally low-population extents in these districts may reflect factors such as advancing ageing and increasing solitary living. Figure 11 shows the average household size in Osaka Prefecture. Unlike the population trends in Figure 3, this graph shows that the average household size has been monotonically decreasing and is approaching 2.0 persons per household. To examine variations in the characteristics of average household size across Use Districts, we calculated the average household size for each spatially independent polygonal unit. We then computed the unweighted mean of these values and assessed their distribution within each Use District. Table 6 indicates the results of two-sample t-tests and K-S tests applied to the area-level average household size data for 1995 and 2020, following the same procedure as in Table 2. The K-S test indicates significant differences across all Use Districts, with distributions shifting toward smaller household sizes relative to 1995. Furthermore, in the low-rise residential exclusive districts and mid-to-high-rise exclusive residential districts, the mean values also showed statistically significant declines. Given the rapid demographic ageing in Japan, these results are consistent with an increase in smaller households, particularly single-person households, which may contribute to the emergence of residential vacancy.

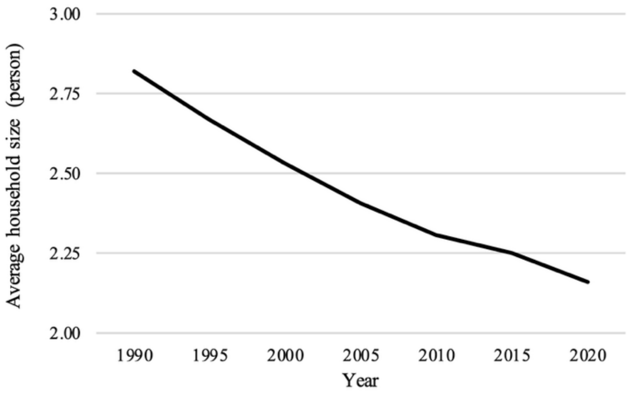


Figure 11. Average household size in Osaka Prefecture.

		Two-sample t-test t value	K-S test Z_{ks}	Distribution difference
Use Districts	Low-rise exclusive residential districts	-7.543 ***	9.673 ***	--
	Mid-to-high-rise exclusive residential districts	-3.942 ***	13.024 ***	--
	Other residential districts	-1.769 *	11.082 ***	-
	Commercial districts	-0.215	7.585 ***	-
	Industrial districts	-0.412	6.097 ***	-
	All districts	-0.339	18.503 ***	-

***0.001, **0.001-0.01, *0.01-0.05

Table 6. Comparison of area-level average household size between 1995 and 2020 by two-sample t-tests and K-S tests.

Under continuing population decline, impediments to the advancement of population renewal may heighten the likelihood of “Urban spongification”. On the other hand, the spatial coexistence of locations with differing land-use transition histories tends to mitigate the expansion of locally low-population extent, suggesting the presence of some form of spatial interaction.

5. Conclusions

This study adopted local population distribution as a core indicator of urban porosity and fragmentation, focusing on the identification and analysis of localised low-population areas within Osaka Prefecture. The results demonstrated that the spatial extent and distribution of localised low-population areas differed across Use Districts and according to long-term land-use transition histories. These patterns revealed spatial and temporal conditions that are considered conducive to the development of urban porosity and fragmentation. Furthermore, the study showed that these conditions could not be captured adequately through population density metrics alone, emphasising the importance of fine-scale spatial analysis.

ASP captures, however, the spatial extent of localised low-population areas rather than the physical configuration of the built environment itself. In this sense, ASP functions as a demographic proxy for potential urban porosity rather than a direct measure of building-level vacancy. Although vacancy data were not applied in this study, the combined analysis of regional population distribution and land-use conversion provided the indirect evidence of demographic processes associated with “Urban spongification”.

Future research should extend the analysis to other Japanese urban clusters and to cities experiencing varying degrees of population decline, in order to evaluate the generalisability of the findings. Furthermore, a deeper examination of the socio-cultural and institutional factors underlying population decline, such as ageing, changes in household composition, housing market dynamics, and zoning regulations, remains necessary (Naganuma, 2006, Shimizu, 2015, Fujigaki, 2022). Future work will also examine the distribution of localised low-population areas both within and outside residential inducement areas designated under Location Optimisation Plans and will explore how this information may support future planning revisions.

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