Analysis of the Spatial Variations of Local Population Distributions from the Viewpoint of Urban Shrinkage Process

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Introduction

The population of Japan is estimated to be 124.09 million in 2024 and will fall below 100 million by 2053. In addition to causing a reduction in society's willingness to develop, such a decline in population makes it difficult to maintain the quality of public services, and may lead to further urban decline. The Ministry of Land, Infrastructure, Transport, and Tourism has been promoting measures to concentrate urban functions and population within walking distance of urban centres, but "urban spongification," in which vacant houses and lots are randomly generated in central city areas, has become an issue. The degradation of local communities and the deterioration of public safety and landscapes due to the urban spongification may hinder the concentration of the population (Ministry of Land, Infrastructure, Transport and Tourism, 2019). The continuous monitoring of urban structure is required to cope with urban spongification. We have focused on the spatial distribution of the population, and have developed a method to statistically define the areas where the population is locally low-density. By iterating the calculation of the size of a locally low-density population area and visualizing the variation over multiple time periods, it was possible to understand the variation in the spatial distribution of the population in detail. On the other hand, there are still few examples that analyse the spatial variation of population distribution on a city-by-city basis. In this study, we analysed the features of spatial variation of population distribution in each city area over a 20-year period, using our method.

Methodology

A spatial analysis method, composed of spatial autocorrelation analysis based on G statistics and overlay analysis, was applied in this study (Getis 1992, Kumagai 2011, Kumagai et al., 2017). Through the statistical tests based on the G statistics, the area of interest was divided into the three kinds of results of the statistical test: a positive spatial autocorrelation, no spatial autocorrelation, and a negative spatial autocorrelation. Positive spatial autocorrelation means that a clustering of larger local populations occurs within the distance d of an observation point i. The spatial analysis we have developed is based on the occurrence of positive spatial autocorrelation areas along the distance parameter d. Fig. 1 shows a conceptual diagram with respect to the detection of the spatial features of local populations. The area being within distance d_{max} of point i, showing positive autocorrelation, generally covers the positive areas being within distance $d_{max\text{-}1}$ or less of i because G statistics are basically derived from the summation of local populations within d of i (see Fig. 1a and Fig. 1b). The change of statistics (from positive spatial autocorrelation to no spatial autocorrelation) occurs in distance d_n at some points as the distance decreases from d_{max} (see Fig. 1b and Fig. 1c). The distance d_n therefore is defined as the Ambiguity of Spatial scale in a densely Populated area (ASP) since the null hypothesis that the set of local populations within d_n of location i is a random sample is not rejected even though positive spatial autocorrelations are consecutively shown in distance between d_{max} and d_{n+1} (Kumagai et al., 2021). There could be lower population density within distance d_n in spite of the fact that there are significantly larger local

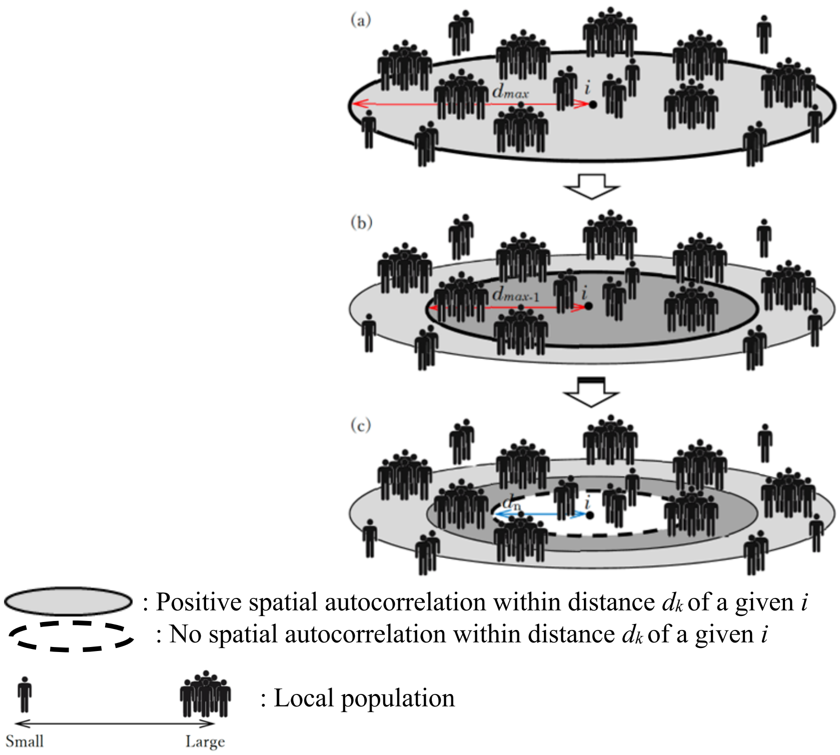
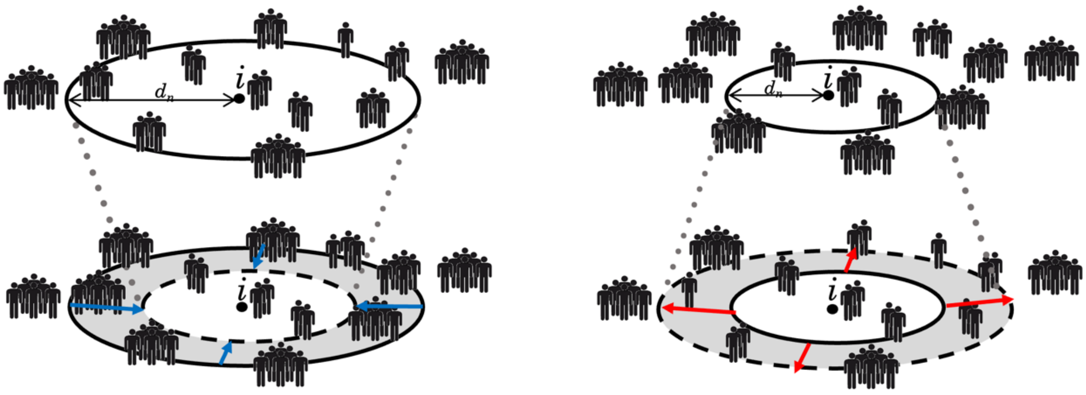


Fig. 1: Conceptual Diagram with Respect to the Detection of the Spatial Features of Local Populations (Kumagai et al., 2021).

populations within d_{max} of point i. Then, we applied the ASP calculation to moving window operations for iterating it on a mesh-by-mesh basis over the study area. Consequently, the ASP distributions were mapped with the spatial size of lower population distributions.

In this study, we examine the spatial variation of ASP over a 20-year period. Fig.2 shows the conceptual diagram of the spatial variation of ASP between 2 periods. The spatial variation can be divided into 2 patterns: ASP shrinkage (-ΔASP) and ASP expansion (+ΔASP). The ASP shrinkage means that local population within ASP partially increase, while the ASP expansion implies that local population within ASP partially decrease. Usually, population fluctuations depend on the changes in the state of city, e.g., development, maturity, deterioration, and other issues of city status. We therefore divide the 20 years into a previous decade and a later decade. We then combine the ASP changes for each decade and express them as changes over a 20-year period. In addition, for comparing the distribution of characteristic change locations in different cities, the two patterns, the shrinkage after shrinkage of ASP (--ΔASP) and the expansion after expansion of ASP (++ΔASP), are selected and analysed.



ASP shrinkage：-ΔASP ASP expansion：+ΔASP

Fig. 2: Conceptual Diagram of the Spatial Variation of ASP between 2 Periods.

Results and Discussion

The basic unit block population data of the National Census of Japan, taken in 2000, 2010, and 2020, were applied to the spatial analysis. Before the application, we generated 60m-by-60m mesh data as local population data by counting the basic unit block population data on a mesh-by-mesh basis.

Fig. 3 shows the result of ASP mapping of the study area, Osaka prefecture in Japan, in 2000 as an example. Gradation in colour from red to green denotes the fluctuation of the ASP. ASP_0 denotes that a district showing larger local population exists from the narrowest range to the widest range (d_{max}). Black lines in Fig. 3 indicate represent city, town and village boundaries. We can see the difference between the distributions of ASP by municipality. Fig. 4 reveals the result of mapping of --ΔASP and ++ΔASP: characteristic changes over a 20-year period. We can see the clumps of both ΔASPs are scattered throughout the study area. The size of the ΔASP clumps is also seen to vary from municipality to municipality. We then classify these ΔASP clumps on a city-by-city basis for understanding the spatial variation of the local population over a 20-year period. The relative density of area in the city zone for each size of both ΔASP clump is calculated, and then applied to a hierarchical cluster analysis. As a result, we have 3 groups of municipalities through the classification. Fig.5 displays enlarged ΔASP maps of typical cities in each classified group. It is confirmed that the groups are classified based on the differences of the clumps size of --ΔASP. Referring to Fig 2, --ΔASP implies an increase in the local population, which means that development projects and other activities may be implemented in this area. The clumps of ++ΔASP, however, tend to be

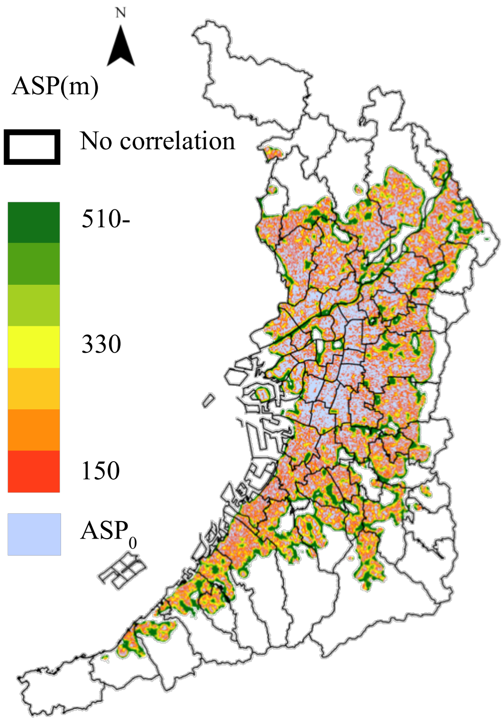


Fig. 3: Result of ASP Mapping of the Study Area, Osaka Prefecture in Japan, in 2000 as an Instance.

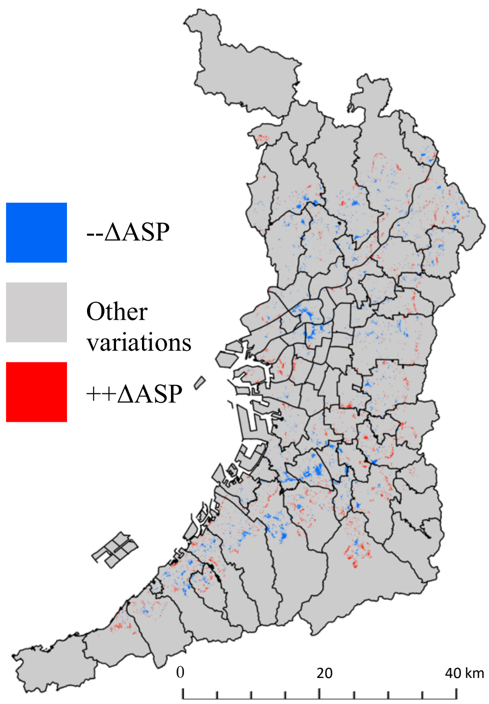
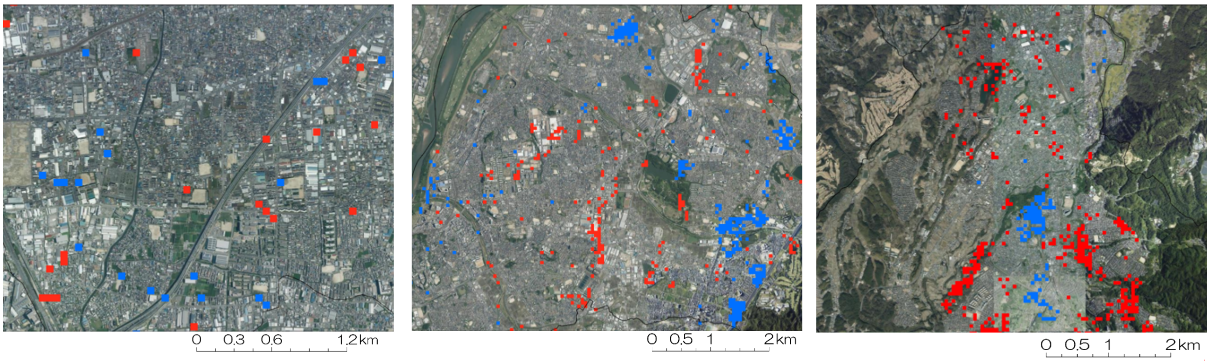


Fig. 4: Result of ΔASP Mapping of the Characteristic Changes between 2000 and 2020.



a) Group [1] b) Group [2] c) Group [3]

Fig.5: Enlarged Maps of Classified Cities as Instances. The Legend is the Same as in Fig.4

small and scattered. This tendency is common across the three groups classified. Further detailed analysis of demographic and urban transitions is required in the future because ++ΔASP areas may contain an urban spongification phenomenon.

Conclusions

We examined the spatial variations of local population distributions over a 20-year period to apply the fluctuations of ASP on a city-by-city basis. It was shown the municipalities were classified according to the size of the area with decreasing the low-density population range. On the other hand, regardless of classification class of municipalities, the clusters of areas with increasing the low-density local population ranges tended to be small and scattered.

References

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