Supplementary materials

1. Communities and housing prices in study area

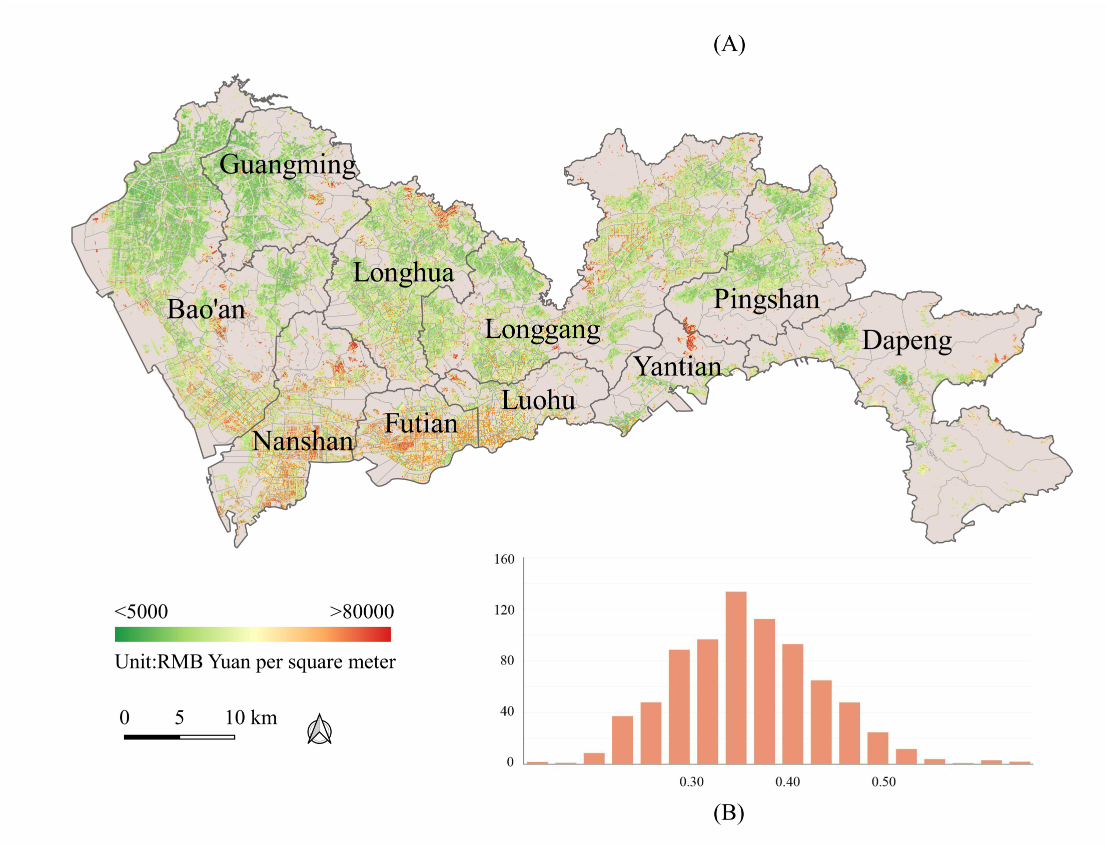

Figure S1. (A) Spatial distribution of housing prices (B) Histogram of CV of House Price in Community (The X-Axis represents the Coefficient of Variation and the Y-Axis represents the number of communities)

1.1 The introduction of community scale

A community is a basic geographic unit and a basic unit of urban governance in China in the 21st century (Bray 2006), and government regulation at the community level has played an important role in improving the quality of residents' lives (Xu and Chow 2006). For each urban space or unit divided by the communities' outline, not only does the space or unit have demographic attributes, but it also exhibits a certain balance in terms of the level of economic development within the area. These properties also make the community scale useful in studying people and city-related issues such as urban construction, planning, crowd travel, and life satisfaction (O'Brien and Ayidiya 1991, Perry 1929, Yue *et al.* 2017). They facilitate researchers in explaining the geographical variability that exists from a practical perspective. As a result, there is no shortage of studies today that analyze the activities of people at different economic levels from a community perspective (Huang and Wong 2016). Considering the above advantages, this study used the community as the minimum research unit. In general, we believe that this scale could help to alleviate the problem of inaccurate population classification caused by the heterogeneity of housing prices. Meanwhile, the abovementioned properties and advantages can preserve the semantic integrity of POIs in the actual geographic area. In our study, the study area, Shenzhen, has a total area of 1997.47 km^2 (Figure 1). It is divided into 781 NCs, with a range of 25420.7 m^2 to 37605370.52 m^2.

1.2 Average house prince and the SES index

Since we need to obtain the SES index from the average house price of the user's residence, it is worth considering whether the average house price is a good representation of the house price in the whole community. It is also worth considering whether the house price can reflect all the residents in the community, whether they are house owners or renters.

For the former consideration, we calculated the coefficient of variation of the house prices within the community to analyze whether the average house price is representative of the whole community. The coefficient of variation (CV) is the ratio between the standard deviation and mean value. Generally, if the average level of the variable value is high, the measured value of its dispersion degree is larger, and vice versa. As seen from Figure S1 (A), the variation coefficient of housing prices in the community is between 0.4 in 71% and 0.3 in 28%. This means that average home prices in most neighborhoods mirror local home prices well. However, in a few areas, due to the large total area of the community and the large proportion of nonbuilding land, the housing prices are different to some extent, although the proportion of people who live in these places is also low. Therefore, the overall impact of socioeconomic heterogeneity within each neighborhood committee in the study is small, and the average house price is a good representative of the house prices in the community. For the latter, references show that there is a positive correlation between the price of buying and the price of renting (Hanink *et al.* 2012), and rents are a fundamental determinant of the value of housing (Gallin 2008). Therefore, we believe that if a person can afford to live in the community, the average house price is a good reflection of his or her SES.

2. *Workflow of the research*

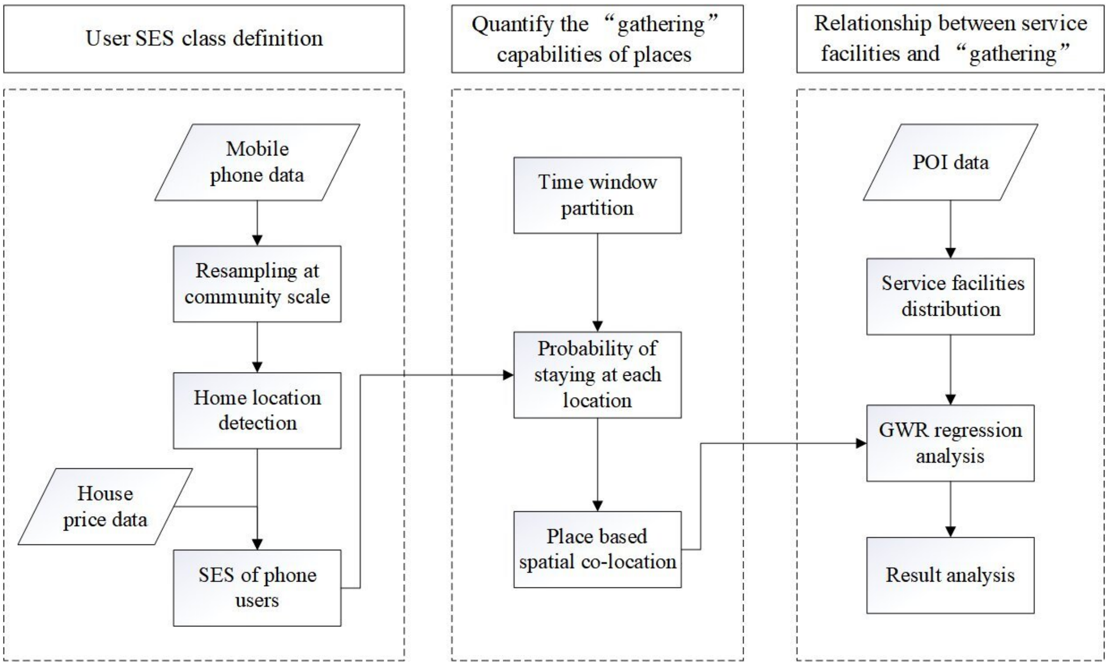

Figure S2. Workflow of research on the impact of service facilities on the social segregation of people of different SESs

3. *Classification of the population*

Table S1. SES classification results of population

Class	Number	Range of house price
High SES people (H)	2931609	[35679.13, 72323.29]
Medium SES people (M)	3998650	[27234.49, 35669.69]
Low SES people (L)	5755527	[11584.73, 27233.84]

4. *Descriptive statistics of the sample*

Table S2. Descriptive statistics of the sample

Variable	Numbers	Explanation
H-M (nighttime)	781	Community's "gathering capacity" between people with a high SES and people with a medium SES during 1:00-7:00
H-M (daytime)	781	Community's "gathering capacity" between people with a high SES and people with a medium SES during 7:00-18:00
H-M (evening)	781	Community's "gathering capacity" between people with a high SES and people with a medium SES during 18:00-1:00
H-L (nighttime)	781	Refer to the previous lines
H-L (daytime)	781	Refer to the previous lines
H-L (evening)	781	Refer to the previous lines
M-L (nighttime)	781	Refer to the previous lines

M-L (daytime)	781	Refer to the previous lines
M-L (evening)	781	Refer to the previous lines
Food and Beverage	15124	Restaurants, grand hotel snack bars, cake shops, liquor stores, etc
Business	27373	Companies, factories and production bases, etc
Shopping	29967	Markets, shopping malls, supermarkets, general commercial shops, etc
Traffic Facilities	7794	Subway stations, bus stops, car parks, airports and train stations, etc
Finance and Insurance	7075	Banks, ATMs, insurance services, stock exchanges, etc
Science and Education	4046	Schools, libraries, museums, cultural palaces, training places, scientific research institutions, etc
Sports and Leisure	3539	Gymnasiums, sports venues, fitness centers and bars, amusement parks, KTV, cinemas and other entertainment venues
Health Care	6805	Hospitals, clinics, pharmacies, centers for disease prevention and healthcare services
Hotels and Resorts	2884	Guesthouses, hotels, apartments and guest houses, etc

Table S3. Variance inflation factor of variables

	Food and Beverage	Business	Shopping	Traffic Facilities	Finance and Insurance	Science and Education	Sports and Leisure	Health Care	Hotels and Resorts
H-M (nighttime)	7.002	2.509	4.574	3.029	4.336	1.998	3.783	2.975	3.169
H-M (daytime)	7.009	2.51	4.579	3.031	4.339	1.999	3.787	2.977	3.171
H-M (evening)	7.004	2.509	4.576	3.029	4.337	1.999	3.784	2.976	3.169
H-L (nighttime)	7.03	2.51	4.57	3.031	4.344	1.998	3.793	2.975	3.171
H-L (daytime)	7.009	2.51	4.579	3.031	4.339	1.999	3.787	2.977	3.171
H-L (evening)	7.004	2.509	4.576	3.029	4.337	1.999	3.784	2.976	3.169
M-L (nighttime)	7.035	2.511	4.572	3.033	4.346	1.998	3.796	2.976	3.173
M-L (daytime)	7.009	2.51	4.579	3.031	4.339	1.999	3.787	2.977	3.171
M-L (evening)	7.009	2.51	4.579	3.031	4.339	1.999	3.787	2.977	3.171

Table S3 summarizes the variance inflation factor (VIF) for each of the nine models (VIF). Except for the food and beverage variable, which has a VIF of approximately 7, all variables are less than 5. At the aggregate level, the VIF of all the variables involved in the regression is less than 10, indicating that all potential confounders are sufficiently independent to satisfy the independence assumptions.

5. *Detailed information of GWR model in the study*

The first law of geography suggests that "everything is related to everything else, but near things are more related than distant things" (Tobler 2004). There is also a clear aggregation of people's activities in the city. In addition, our distribution map of the "gathering capacity" of communities (Figure 2) shows a significant spatial variability in the "gathering capacity", and the distribution of services in the city is also spatially unstable. The traditional OSL regression method has the limitation of global regression, which cannot model the spatial relationship between variables. Therefore, OSL cannot be used well to explain the relationship between the distribution of service facilities and the "gathering capacity" of communities. As a statistical technique, GWR can measure the relationship between predictors and outcome variables in space within a single modeling framework (Fotheringham *et al.* 2003, Wheeler and P A Ez 2010). In contrast to other spatial analysis methods that consider spatial autocorrelation but are global regressions (e.g., spatial lags, spatial errors, etc.), GWR is particularly suitable for situations where the level of influence of surrounding values on the observation varies with the location of the observation. As a result, GWR has been widely used in similar geographic research.

As shown in the manuscript, the GWR model in this study can be expressed as:

$$\gamma_{\mathrm{i}} = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$$

It constructed the spatial relationship between the "gathering capacity" and the distribution pattern of service facilities in communities. Specifically, in the formula, γ_{i} is the observation value, that is, the value of the "gathering capacity" of communities; (u_i, v_i) is the coordinate of sample point i, where the coordinates of the center of gravity of each community unit are taken; $\beta_0(u_i, v_i)$ for the region is the regression constant at point i; $\beta_k(u_i, v_i)$ is the kth regression parameter at point i, which is a function of geographic location; p is the number of independent variables, which is 9; x_{ik} is independent variable x_k at point i, that is, the frequency of the A_{k}-type POI in the community unit corresponding to point i; and ε_i is the random error.

In addition, the GWR model is solved by applying a weighted linear least squares approach to the model for each regression analysis point i $s$eparately:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i)\mathrm{X})^{-1}\, X^T W(u_i, v_i)\mathrm{y}$$

where X is the sampling matrix of the independent variable, whose first column takes the value of 1 and is used to estimate the intercept term $\beta_0(u_i, v_i)$; y is the column vector of sampling values of the dependent variable; $\hat{\beta}(u_i, v_i) = (\beta_0(u_i, v_i)\beta_1(u_i, v_i) \cdots \beta_{\mathrm{m}}(u_i, v_i))^T$ is the vector of regression analysis coefficients at the analysis point (u_i, v_i); and $W(u_i, v_i)$is a diagonal matrix whose diagonal element values are the spatial weights of each data point (u_i, v_i) to the regression analysis point, which is defined as follows:

$$W_i = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{bmatrix}$$

where the diagonal value w_{ij} $(j = 1,2,\cdots,n)$ represents the weight value of the $j\,th$ data point to the regression analysis point i. According to the first law of geography, the basic principle of the GWR model to calculate the weights is as follows. The closer the distance is, the higher the value of the weight assigned, and the farther the distance is, the lower the value of the weight assigned (Fotheringham *et al.* 2003). Therefore, the weights can be calculated by a monotonically decreasing function of spatial distance with an arbitrary value range of $[0, 1]$, which is called the kernel function. In this study, the Gaussian kernel function is used to play the role of the kernel function, establishing the spatial weight matrix. Its weights are defined as follows:

$$w_{ij} = e^{\frac{(d_{ij}/b)^2}{2}}$$

where d_{ij} denotes the spatial distance or proximity measure between position i and position j and b is the bandwidth value. The bandwidth size directly determines the decay rate of the weights with increasing distance as follows. The larger the bandwidth is, the faster the weight decay, and the smaller the bandwidth is, the slower the weight decay. Our experiment determines the bandwidth h according to the minimum information criterion (AIC) proposed by (Akaike 1987).

6. The "gathering capacity" of communities and its reflection of social segregation

This study calculated the interaction intensity of people of different economic levels at the community scale—the "gathering capacity" of communities. The results show that interactions between people with a high economic level and people with a low economic level in the study area are the least frequent. Specifically, downtown areas (such as Futian District and Nanshan District) have a strong ability to gather people at high and middle economic levels. High-tech industrial zones successfully gather all kinds of people. However, the "gathering capacity" of communities in suburban areas is very weak. Since segregation and gathering between groups are relative concepts, observing the differences in the ability of the communities to gather different groups of people can reflect the phenomenon of social segregation in Shenzhen. In other words, the areas with a weak ability to bring together people of different economic levels and the two types of people who are not easily brought together present a strong degree of segregation.

We found that the most severe segregation existed in the suburban areas of Shenzhen. Few communication activities among people of different SESs occur in these areas. The second most serious segregation is in the downtown areas, where H and M people have more interaction, but there is less interaction with L people. Overall, segregation between people with high and low economic levels occurs frequently and to a serious degree. This is consistent with the findings of many scholars (Le Roux *et al.* 2017, Xu *et al.* 2019, Zhou *et al.* 2021). People with the most advantaged socioeconomic level are more inclined to go to areas with better living conditions, while those with generally disadvantaged economic levels usually visit areas that are more disadvantaged than their own areas of residence (Krivo *et al.* 2013, Xian *et al.* 2022). The most advantaged social groups gathered during both day and night and were most seriously isolated from other groups (Le Roux *et al.* 2017). In other words, the communication between M and L is mutual, so it happens more frequently in cities. However, the H group showed a weak tendency to go to areas with low economic development, so the segregation between H and L is more serious than the segregation among other groups in the city.

This study also found that the community has the strongest ability to gather people during the day, so the degree of social segregation is reduced compared to other time periods. Similar to the study of Silm and Ahas (2014), activities that are conducive to crowd communication mostly occur during the day. Our results show that the distribution of different social groups during the day and working days is more even than the distribution of their residences in China's megacities. Specifically, since the differences in economic level between H and M and between M and L are smaller, their probability of generating colocation during daytime—when people work as their main activity—is greater, so the communities show a significant increase in "gathering capacity" during the daytime hours. In contrast, the H-L population, although it is also capable of interactions during out-of-home activities, has a relatively smaller degree and a weaker effect of alleviating regional residential segregation, thus showing quite a similarity in the figure.

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