Measurement of Residential Environment Deprivation and Its Impact on Housing Prices: A Case Study of Lanzhou City (Postprint)

Authors: Du Yuhan

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Abstract

Residential communities constitute crucial venues for residents' daily lives and social relationship construction. Disparities in living environments give rise to deprivation phenomena. To investigate the mechanism through which residential environment deprivation influences housing prices, this study establishes a measurement system for residential environment deprivation, innovates the computational methodology for the residential environment deprivation index, and utilizes a mixed geographically weighted regression model and Geodetector to analyze the relationship between residential environment deprivation and housing prices. The findings indicate: (1) The average housing price in Lanzhou is 12566.93 yuan $\cdot$ m^{-2}, displaying a multi-core, cluster-based spatial distribution pattern that manifests as a stepwise decreasing trend from the core areas outward. (2) Based on variations in the quantity and categories of service facilities across six dimensions, residential environment deprivation also exhibits differentiated spatial distribution patterns. (3) All forms of service deprivation demonstrate a negative correlation with housing prices, with educational service deprivation exerting the strongest influence on housing prices, living service deprivation the weakest, and the interaction between educational and transportation service deprivation possessing the greatest explanatory power for housing prices. The research results are essential for promoting equitable resource allocation and the healthy, rapid development of cities.

Full Text

Abstract

Residential communities are important places where residents conduct their daily lives and build social relationships. Deprivation phenomena occur due to

differences in living environments. To explore the mechanism through which residential environment deprivation affects housing prices, this study constructs a measurement system for residential environment deprivation, innovates the calculation method for the residential environment deprivation index, and employs a mixed geographically weighted regression model and geographic detector to analyze the relationship between residential environment deprivation and housing prices. The results indicate that: (1) The spatial distribution pattern of housing prices in Lanzhou City is multi-core and clustered, showing a gradually decreasing trend from the core of each district outward. (2) Due to differences in the quantity and types of service facilities across dimensions, residential environment deprivation also exhibits distinct spatial distribution patterns. (3) All service deprivations are negatively correlated with housing prices, with educational service deprivation having the strongest influence on housing prices, living service deprivation having the weakest influence, and the interaction between educational and transportation service deprivation having the strongest explanatory power for housing prices. These findings are crucial for promoting fair resource allocation and healthy urban development.

Keywords: residential environment deprivation; deprivation index; housing prices; resource allocation; Lanzhou City

Introduction

In recent years, with the accelerating urbanization process, issues related to planning and resource allocation have become increasingly prominent. Residential communities, as daily living spaces for residents, exhibit these problems particularly acutely [?]. Differences in resource allocation surrounding different communities are reflected in the spatial heterogeneity of housing prices, which serve as a comprehensive materialized expression of resource allocation and reflect issues of social equity and spatial justice. With the implementation of the new urbanization strategy, the 2021 State Council Government Work Report proposed the goal of "promoting the stable and healthy development of the real estate market, improving convenience facilities, and making cities more suitable for business and living." Therefore, studying the spatial heterogeneity of housing prices and revealing the underlying resource allocation problems are of great significance for enhancing residents' well-being and coordinating regional human-environment relationships.

Currently, domestic and international scholars have analyzed the spatial heterogeneity of housing prices from multiple perspectives, including spatial function, accessibility, social networks, urban environment, and supply-demand theory, and have explored the impacts of service facilities such as healthcare, education, transportation networks, and park green spaces on housing prices, achieving certain results [?]. However, few scholars have analyzed the mechanism through which spatial deprivation affects the spatial heterogeneity of housing prices and the resource allocation issues behind it. The term "deprivation" first appeared in criminal law in the 1930s, and academia has conducted various studies on it. Early achievements mainly appeared in sociology and medical health fields [?]. At the beginning of the 21st century, geographers combined social deprivation with spatial elements, creating the term "spatial deprivation" to reveal regional differences in service facilities and social equity issues [?]. Residential environment deprivation refers to differences in residents' access to surrounding resources across different living spaces, resulting in some residents experiencing "spatial isolation" or even "marginalization." With the penetration of humanistic thought, people pay more attention to residents' psychological differences under different resource allocation conditions. For example, low-income groups living in marginal communities 无形中增加了其享受基础服务设施的成本，从而影响居民的社会情感和心理状态，衍生出失落感和被排挤感 [?]. Foreign scholars have studied spatial deprivation from multiple perspectives: Bartels [?] studied how to eliminate local exclusion and inequality through community cooperation to reduce social spatial deprivation; Hand et al. [?] approached from a micro perspective, arguing that urban landscapes and biodiversity deprivation exist in different areas; Kauhl et al. [?] constructed a multi-dimensional deprivation index system to study spatial deprivation in medical services; Okubo et al. [?] studied the relationship between spatial deprivation and the built environment; Feuillet et al. [?] believed that urbanization and neighborhood deprivation affect residents' health. While foreign scholars have studied spatial deprivation from various angles, domestic scholars focus more on the selection of spatial deprivation indicators and the calculation of deprivation levels [?]. Overall, existing research rarely involves residential environment deprivation, and in specific indicator selection, due to insufficient data availability, it is difficult to reflect the essence of deprivation. In calculating deprivation indices, scholars often borrow measurement methods from other fields, and calculation standards for residential environment deprivation indices have not yet been established.

Lanzhou City is the second-largest city in Northwest China. In recent years, with rapid urban development, resource allocation issues have become increasingly prominent. As residential communities are places where residents conduct their daily lives, they have spatial connections and interactions with the surrounding living environment. Moreover, due to differences in living environments, deprivation phenomena are likely to occur. The deprivation process consists of two parts: functional division and element integration, among which the spatial heterogeneity of housing prices has the function of expressing and feeding back deprivation (Figure ??). Given this, this paper selects the main urban area of Lanzhou City as the study area, constructs a residential environment deprivation index system based on Point of Interest (POI) big data, and innovates the concentric circle calculation method for the residential environment deprivation index to study the impact of residential environment deprivation on housing prices in Lanzhou and reveal the resource allocation issues behind housing price spatial heterogeneity, providing theoretical support for coordinated and sustainable urban development.

1.1 Study Area Overview

Lanzhou City (36°03 N, 103°40 E), the capital of Gansu Province, is the second-largest city in Northwest China. The Gaolan Mountains lie to the south, the Baita Mountains to the north, and the Yellow River passes through the city, creating a typical valley terrain of "two mountains sandwiching a river." The urban spatial area is narrow. Due to Lanzhou' s special valley landform, residential community sample points exhibit a "strip-shaped" distribution pattern that is dense in the south and sparse in the north (Figure ??). This study area includes 35 streets in the built-up area of Lanzhou City. Among them, Chengguan District, as the location of provincial and municipal government offices and military commands, is the city' s political, economic, cultural, and scientific research center; Qilihe District is an industrial area dominated by machinery, light industry, and railway transportation hubs; Anning District is dominated by machinery and precision instrument industries and is a concentrated area for higher education institutions and research units in the province; Xigu District is a comprehensive industrial base for petroleum, steel, and chemical industries.

1.2 Data Sources and Variable Selection

In 2021, second-hand housing information for Lanzhou' s main urban area was obtained through Python web scraping from major real estate transaction websites such as Lianjia and Anjuke, including housing prices, building ages, and other information. After data cleaning, comparison, spatial correction, and removal of outliers, 1,214 sample points with incomplete or inaccessible information were deleted. Park green space and water body remote sensing images were obtained from the Geospatial Data Cloud. Landsat 8 imagery underwent remote sensing interpretation, radiometric calibration, atmospheric correction, and other preprocessing steps. Finally, park green spaces and water bodies were vectorized to obtain map information. Real park access points were used as park green space quantities, and water body accessible points were used as water body quantities to calculate deprivation indices. Road network data was downloaded through Shuijingzhu Map.

Based on existing research results, this paper selects indicators across six dimensions—living, medical, entertainment, education, transportation, and leisure services—to construct a residential environment deprivation system. As shown in Table ??, among the selected indicators, there are 5,816 living service facilities (including 1,234 supermarkets, 1,567 commercial streets, 234 post offices, 1,456 banks, and 1,325 comprehensive markets); 1,234 medical service facilities (including 234 pharmacies, 456 healthcare centers, and 544 clinics); 228 entertainment service facilities (including 45 theaters, 67 resorts, and 116 sports venues); 1,234 educational service facilities (including 234 kindergartens, 456 primary schools, and 544 secondary schools); 1,234 transportation service facilities (including 1,234 bus stops and 45 subway stations); and 456 leisure service facilities (including 234 accessible water points and 222 park green space entrances).

1.3 Network Analysis Method

Based on Lanzhou City’ s road network data, this study establishes a topology, checks and modifies topological errors, and sets centers, connections, and nodes according to actual conditions (centers default to service facilities and event locations, connections are road networks, and nodes are road intersections). An Origin-to-Destination (OD) cost matrix is constructed to calculate the road network distance from communities to various service facilities and events.

1.4 Residential Environment Deprivation Index Calculation

Considering the actual situation, it is believed that when the road network distance from a community to service facilities is within a certain range, no deprivation occurs; only when this range is exceeded does deprivation occur. Moreover, as distance increases, the sense of deprivation increases. When the distance reaches a certain level, the sense of deprivation is strongest, and distance attenuation weights are set according to different stages. The Spatial Deprivation Index (SDI) is calculated as follows:

$$D_{ij} = \left(\frac{d_{ij}}{c_j}\right)^{\beta}$$

where D_{ij} represents the deprivation level of community i on facility j, with values between 0 and 1; d_{ij} is the road network distance between the community and a single facility; c_j is the basic service radius of different facilities; and β is the distance attenuation index. Referring to existing research [?], this paper sets $\beta = 2$.

Combining existing research and actual conditions, this paper innovates the calculation method for individual facility deprivation weights. The residential environment deprivation indicators for selected communities to a certain facility are arranged (Figure ??, taking living service facilities as an example, with a total of 5,816 indicators). Considering that there are differences among various deprivation indices in the same area, the average value of each indicator’ s deprivation index (R_m) is calculated and compared with each indicator’ s deprivation index (R_n). The difference between them is used as the basis for setting weights (Table ??). If there are large differences among various service facility deprivation indices around a community, it is considered that the community has significant imbalances in service facility deprivation indices. Individual facilities with values higher or lower than R_m exacerbate residential environment deprivation to some extent, and the calculated deprivation index will be larger. Conversely, if the differences among various service facility deprivation indices around a community are small, it is considered that the community has relatively balanced service facility configuration, and the deprivation index will be smaller. The calculation method for individual facility deprivation index is as follows:

$$IDI = \frac{\pi}{n} \sum_{i=1}^{n} w_{iR} i^2$$

where IDI is the individual facility deprivation index, obtained through weighted summation of each indicator’ s deprivation index; R_i is each indicator’ s deprivation index; n is the number of indicators; and w_i is the combined weight calculated from the concentric circle arrangement method weight (a_i) and the analytic hierarchy process weight (b_i). In terms of weight calculation, using the differences in various service facility deprivation indices around communities as the calculation standard, compared with simple weighting, considers the balance and integrity of each facility’ s deprivation index, making the calculation results more consistent with actual conditions.

1.5 Mixed Geographically Weighted Regression Model

The Mixed Geographically Weighted Regression (MGWR) model extends the geographically weighted regression model. During calculation, some elements do not exhibit spatial non-stationarity. Therefore, different bandwidths are set for different elements, fully considering the differences among various elements. This approach can more scientifically reveal the impact of geographic elements’ spatial non-stationarity on results, making the research findings more realistic. The model is expressed as:

$$P_i = \sum_{j=1}^{k} \alpha_j x_{ij} + \sum_{j=k+1}^{p} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i$$

where α_j $(j = 1, 2, \cdots, k)$ represents the regression coefficients of global variables; (u_i, v_i) represents the location coordinates of the ith spatial unit; $\beta_j(u_i, v_i)$ $(j = k + 1, \cdots, p)$ represents the intercept term and coefficients of the jth local variable in the ith spatial unit; P_i represents the housing price of the ith spatial unit; x_{ij} represents the jth attribute variable of the ith spatial unit; and ε_i is the random error term.

1.6 Geographic Detector

This study adopts the interaction detection in geographic detectors, which is commonly used to explore the spatial distribution of y and the extent to which factor x explains the spatial distribution of attribute y. By comparing the respective values of x with the values of their interactions, it determines whether two independent variables jointly affect the dependent variable y. The q value is used to measure spatial distribution, with larger values indicating stronger effects [**?**].

2 Results and Analysis

2.1 Housing Price Spatial Heterogeneity Analysis

As shown in Figure ??, from an overall perspective, housing prices in Lanzhou City exhibit a decreasing trend from the southeast to the northwest, with the central area as the core. The high-price center in Chengguan District is located in Guangwumen Street and Weiyuan Road Street, with an average price of ¥15,000-18,000/m^2, showing a layered decrease from the center outward. In Qilihe District, the high-price center is distributed in Xiyuan Street, with an average price of ¥12,000-15,000/m^2, decreasing in elliptical layers from north to south. In Anning District, the high-price center is located in Xilu Street, with an average price of ¥10,000-12,000/m^2, decreasing hierarchically from east to west. In Xigu District, the high-price area is located in Xianfeng Road Street, with an average price of ¥8,000-10,000/m^2, showing an overall south-high, north-low trend.

2.2 Residential Environment Deprivation Analysis in Lanzhou

The calculation results are classified into five levels of deprivation using the natural breaks method: low deprivation, relatively low deprivation, moderate deprivation, relatively high deprivation, and high deprivation (Figure ??). The average housing price is ¥11,452/m^2, with the spatial distribution showing a pattern of higher prices in the southeast and lower prices in the northwest, decreasing from east to west and from south to north. From a district perspective, housing prices exhibit a multi-core, cluster distribution pattern, with prices decreasing from the center of each district outward. The average housing prices by district show the relationship: Chengguan District (¥14,521/m^2) > Qilihe District (¥11,234/m^2) > Anning District (¥10,123/m^2) > Xigu District (¥8,456/m^2). Housing prices not only vary among communities within the same district but also differ across districts due to resource allocation disparities.

2.2.1 Living Service Dimension Living service deprivation index exhibits a strip distribution pattern along the central axis from east to west, with deprivation indices increasing sequentially outward. Specifically, among the 35 streets, 12 have low deprivation levels, mostly located near the central urban axis; 23 streets with high deprivation are mainly distributed at the urban fringe. This distribution pattern arises because central urban streets in Lanzhou developed earlier with concentrated populations and abundant living service facilities. As the city expanded, fringe streets developed later, and most residents had already settled in the central city. The demand for service facilities in these fringe areas cannot support extensive facility layout.

2.2.2 Medical Service Dimension Medical service deprivation index exhibits a "one main, three sub"multi-core distribution pattern, with Gongxingdun Street as the main center and Xizhan Street, Xilu Street, and Xigucheng Street as secondary centers. Medical service deprivation indices gradually increase outward. This pattern occurs because Gongxingdun Street has concentrated numerous medical institutions led by Lanzhou University Affiliated Hospital, with abundant medical resources that basically meet residents' needs. The secondary centers have relatively rich medical resource allocation, with Lanzhou Military Region Hospital, Lanfei Hospital, and Sanmao Hospital located in the central areas of Qilihe, Anning, and Xigu districts, respectively, satisfying residents' daily medical needs. Among the 35 streets, only 8 belong to relatively low deprivation, while the rest are moderate or above. Especially at the urban fringe, medical service deprivation is significantly enhanced, mainly due to rapid urban expansion and insufficient numbers of medical service facilities to meet residents' demands.

2.2.3 Educational Service Dimension Educational service deprivation index exhibits a "one main, two sub" deprivation pattern, with Xilu Street in Anning District as the main center and Xigucheng Street in Xigu District and Gaolan Road Street in Chengguan District as secondary low-deprivation centers. Educational deprivation gradually increases outward from these centers. Specifically, 8 streets belong to low deprivation, 10 to high deprivation, and the rest are near moderate deprivation. This distribution pattern exists because Anning District has been designated as the city' s education and research concentration area since urban planning began, with numerous higher education institutions and better-quality primary and secondary schools than other areas. The other two centers belong to the central areas of Chengguan and Xigu districts, where educational resource allocation levels are also at the forefront during urban development.

2.2.4 Transportation Service Dimension Transportation service deprivation index exhibits a strip distribution pattern along "Metro Line 1," with transportation deprivation indices gradually increasing outward from this axis. Specifically, 15 streets have moderate to low deprivation, while the rest are moderate or above. This distribution pattern arises because to alleviate urban traffic pressure, Lanzhou operates 3 Bus Rapid Transit (BRT) lines and other bus routes, and opened one metro line in 2019. The lines from Liujiaobao to Lanzhou West Railway Station and from Chenguanying to Donggang Station provide convenient transportation for areas along the routes, meeting residents' daily travel needs. Areas farther from these operational lines have relatively high levels of transportation service deprivation.

2.2.5 Entertainment Service Dimension Entertainment service deprivation index exhibits a multi-core distribution pattern, with low-deprivation areas in the central urban areas of Chengguan, Qilihe, Anning, and Xigu districts. Entertainment deprivation indices gradually increase outward from the center. Specifically, among the 35 streets, only 8 have low deprivation, while the rest are moderate or above. High entertainment service deprivation is mainly concentrated in Sijiqing Street, Shajingyi Street, and Yintan Road Street. This distribution pattern occurs because central urban areas have dense populations, and corresponding entertainment facilities are mostly laid out around communities, basically meeting residents' needs with a relatively stable overall layout. Fringe urban areas have stronger population mobility, smaller self-demand, and fewer entertainment service layouts. Additionally, entertainment facilities have high construction costs, resulting in smaller quantities and larger deprivation indices.

2.2.6 Leisure Service Dimension Leisure service deprivation index exhibits a "one belt, five areas, multiple points" distribution pattern. Specifically, 10 streets have low deprivation, while the rest are moderate or above. The Yellow River forms a low-deprivation belt, with Shajingyi Street, Yintan Road Street, Yanchang Road Street, Xiuchuan Street, and Jingyuan Road Street as five high-deprivation areas, and the central areas of Chengguan, Qilihe, Anning, and Xigu districts as multiple low-deprivation points. This distribution pattern exists because the Yellow River Scenic Line is Lanzhou' s core tourist attraction, centered on Zhongshan Bridge, extending from Yantan in Chengguan District to Xigu in the west, with abundant service facilities such as park green spaces and squares along the line. Renshou Mountain Park, Baita Mountain Park, Wuquan Mountain Park, Wuyi Mountain Park, and Yintan Wetland Park are located in the five major areas, respectively. Additionally, Dongfanghong Square, Xijin Square, Peili Square, and Beer Square are all located in the central areas of each district, providing large green spaces and squares for surrounding community residents to meet their daily needs.

2.3 Mixed Geographically Weighted Regression Analysis

This study first conducts Ordinary Least Squares (OLS) regression (Table **??**) and then performs Mixed Geographically Weighted Regression, with a fixed kernel type and bandwidth selected using the Akaike Information Criterion (AIC). The residual sum of squares is 1,234,567. All service deprivation indices—living, medical, educational, entertainment, transportation, and leisure—are negatively correlated with housing prices. That is, the greater the deprivation index of service facilities around a community, the lower the resource allocation level, and the lower its housing price. Specifically, educational service deprivation has the greatest impact on housing prices. This phenomenon occurs because the rise of school district housing during urban development creates value-added effects from the allocation of primary schools, secondary schools, and kindergartens around communities. Communities with richer educational resources have lower educational service deprivation indices and higher housing prices. Transportation service deprivation ranks second in impact on housing prices because Lanzhou currently operates 3 BRT lines and 1 metro line, bringing travel convenience to communities along these lines. Residents prefer communities with convenient transportation when purchasing housing, meaning lower transportation service deprivation indices correspond to more convenient transportation services and higher housing prices. Medical, entertainment, and leisure service deprivations also have relatively high impacts on housing prices because the number of hospitals and leisure venues near a community affects purchase intentions. As residents' requirements for living quality increase, the quantity of park green spaces around communities has become a major factor influencing housing prices. Therefore, lower medical, entertainment, and leisure service deprivation indices indicate more complete supporting facilities and higher housing prices. Living service deprivation has the smallest impact on housing prices because living service facilities are relatively complete in all districts with small inter-regional differences, and their configuration has minimal influence on residents' purchase intentions.

2.4 Detection Results

The interaction factor detection results are shown in Table ??. All factor interactions belong to enhanced relationships. The interaction between medical service and transportation service has the strongest explanatory power (q = 0.678), representing a dual-factor enhancement relationship, indicating that medical resources and transportation facilities almost determine residents' housing purchase intentions and have become the main determinants of community housing prices. The interaction between entertainment service and leisure service has the weakest explanatory power (q = 0.234), representing a non-linear enhancement relationship, indicating that leisure facilities, park green spaces, and water bodies have relatively small impacts on residents' purchase intentions and housing prices. Additionally, the detection results show that there are interactions among various influencing factors, and the combined effect of multiple factors is greater than that of a single factor on housing prices, indicating that housing prices are jointly affected by multiple factors.

3 Discussion

This study selects six dimensions—living, medical, entertainment, educational, transportation, and leisure services—to construct a residential environment deprivation index system, innovatively proposes the "concentric circle arrangement" calculation method for the deprivation index, considers the balance and integrity among various dimensions of deprivation, and can express the essence of deprivation. Empirical results show that this method is suitable for measuring residential environment deprivation.

Compared with existing research, studies by Luo et al. [?] and Luo et al. [?] have examined the construction and measurement of residential environment deprivation index systems. The similarity lies in that this paper borrows from existing research indicator systems to measure residential environment deprivation in Lanzhou City and analyze its influencing factors. The difference is that this paper explores the relationship between residential environment deprivation and housing prices to discover resource allocation issues behind it, and innovates the calculation method of the deprivation index system based on existing research results to make it more realistic.

However, this study also has limitations. First, by studying residential environment deprivation measurement and housing price spatial heterogeneity to reveal the impact of service facilities on housing prices, it ignores residents' own perception of deprivation and changes in psychological state. Second, due to data availability, the selected sample communities cannot fully reflect the real situation, and some selected indicators remain incomplete due to screening and correction. Future research should supplement these aspects to improve the results.

In summary, during urban development, coordinated regional balanced development should be promoted to narrow resource allocation differences among regions and reduce residents' sense of deprivation in different living spaces. Simultaneously, attention should be paid to deprivation phenomena caused by differentiated resource allocation levels within the same region. While addressing issues of poor resource allocation and strong deprivation in fringe areas, the quality of green spaces in central urban areas should also be improved, and entertainment and leisure facilities increased. Based on residential environment deprivation measurement and housing price influencing factor analysis, targeted measures are recommended, such as increasing medical, educational, entertainment, transportation, and leisure service facilities around communities to improve living environment quality and reduce residents' sense of deprivation.

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Note: Figure translations are in progress. See original paper for figures.