Research Paper

Study on the Difference of Green Exposure in Urban Communities in Cold Regions based on Multivariate Big Data

Taking the Changbai island in shenyang as an example

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Abstract

In order to study the spatial relationship between green environmental exposure level and house price in different community living circles. this paper selects Changbai island in Shenyang as the research unit to conduct a study in the perspective of humanism, which is grounded on the methods of machine learning and spatial autocorrelation. There is a spatial autocorrelation between the exposure level of green environment and house price in different community living circles, and the perception level of the residents on green environment in different living circles is significantly diverse. The green environmental exposure within the5, 10 and 15 min living circles basically coincides with the spatial distribution of the bivariate cold and hot spots of house prices, and the cold and hot spots of "high-high" and "low- low" are obviously concentrated. Affected by the urban functional structure and the quality of street green environment, the green environment exposure level of the community presents a spatial distribution relationship that is being dispersed first and agglomerative then.

Keywords

multi-source data; machine learning; spatial auto-correlation; green environmental exposure; Moran's I

1. Relevant research progress

1.1. Green environment and health promotion

In the post epidemic era, the society's paying attention to public health has provided unprecedented opportunities and challenges for the discipline of landscape architecture (ENG G, 2020). Scholars also began to focus on the planning and design of neighborhood greening places, street space and reserved space for emergency services from the social living circle. With the fine management and intelligent governance of the city on the agenda, urban streets, as the basic unit of the city, play an important role on health services (Long Y et al.,2019). At present, due to the pressure of life and work, the outdoor activity time of urban residents has been seriously compressed, consequently the street space has become their outdoor activity space with the most frequent daily contact, in which the environmental characteristics have a certain impact on their body and mind due to the high-frequency use of citizens (Ye Y et al.,2018). Especially since the outbreak of the epidemic, the temporary closure and isolation measures have led to a serious shortage of a large number of leisure physical activities, and the public demand for public space is prominent (Yu Y et al.,2021). The high visibility urban street landscape greening environment helps to improve the spatial feeling and walkability, and the more accessible urban greening environment can promote physical activity, relieve pressure, enhance the sense of security, etc. (Yang J et al.,2021; O'BRIEN D T et al.,2019;Li Z; Li CJ et al., 2019). Therefore, the research on the greening environment level of urban street space, especially the analysis of the scope of community living circle, can effectively measure and study the actual urban greening environment level felt by citizens in their daily behavior activities from a humanistic perspective.

1.2. Environmental exposure and green exposure

The relevant researches on environmental exposure derived from the relevant research of medicine. Green environment and blue environment, meteorological factors, noise and air have been proved to have a direct impact on the mental health of urban residents (Li XP. 2016). As an important part of environmental exposure, green exposure has gradually caught the scholars' eye recently (Pei Y et al., 2020; Xu LQ et al.,2019). Traditional researches on urban green environment exposure mainly focused on its area, shape, accessibility, etc. Japanese scholars put forward the green vision rate feeling through adopting the visual reality scene as the research object, and conducted relevant measurement research on the objective space, indicating that the street environment with high green vision rate can replace the park to help citizens release pressure. Scholars' research shows that different exposure times are highly related to mental health, and the frequency of green space visits around residential areas is related to their stress level (Grahn P et al., 2003;Nielsen T S et al., 2006). Due to the practical differences in the living environment of groups with different income levels, the exposure level of green environment may be uneven, which will affect the landscape justice to a certain extent (Liu L et al.,2014). Therefore, measuring and analyzing the exposure level of visual green environment of urban street environment from a humanistic perspective has practical significance to promote landscape justice.

1.3. Exposure measurement of built environment

The impact of individual built environment exposure on human health is a key issue in the field of healthy city research. With the development of science and technology, the exposure testing method of urban built environment has gradually transformed from satellite images combined with GIS data to the measurement method of human scale trajectory data and human perspective images (Li WY et al.,2021). Because of the port of the open map data platform, the previously domestic research on urban street view mainly relied on satellite data to measure the greening rate through NDVI index, and then mapped and estimated the greening rate of urban streets subsequently, which has certain technical limitations and systematic deviation. With the rapid development of computer science and technology, machine learning technologies such as convolutional neural network (Li SQ et al., 2021), weakly supervised multi task learning (Li BA et al., 2020) can perform semantic segmentation on image data (Yu XN et al., 2021), then identify the information of roads, buildings, greening and other elements contained in it, and pre clean and pre process the captured data, making Street view data analysis possible (Lin JH et al., 2021). The green environment exposure level and time of urban streets also need to be combined with the algorithm to analyze the actual spatial range of enjoyment, and then the relevant measurement and evaluation can be carried out. Therefore, with the coordinated development of computer science and environmental science (Long Y et al., 2021), it is possible to measure and analyze the green environmental exposure level actually in the perspective of residents use.

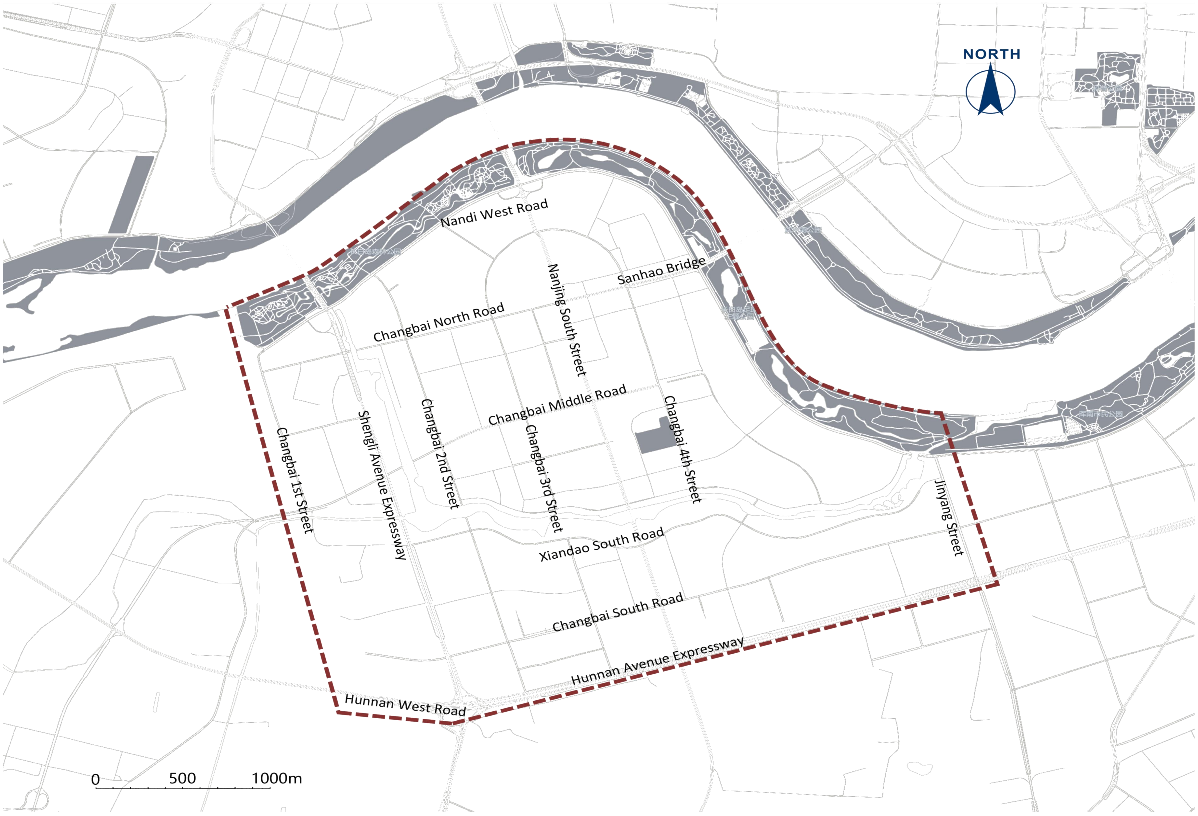

Figure 1. The Map of Changbai Island in Shenyang

2. Data Collection

In this paper, the urban core area, changbai Island area of Heping District of Shenyang, is selected to conduct the study methodically. The area is about 10.8 square kilometers (km2), and the urban roads on the periphery of the area are relatively independent from the roads inside (Figure 1). The island is surrounded by ribbon-like parks, and the urban riverside park is located in the north side of it. The island has been built since 2007, with a large density of buildings and population and a relatively equal distribution of public service facilities. The urban street view has become one of the main environmental exposure factors affecting the daily use of individual residents.

2.1. Road network data collection

In this study, urban road information is obtained through OSM (Open Street Map) platform, and rechecked and completed according to Baidu Map network. By converting and calibrating the road network coordinates obtained by the two platforms, errors of urban road network collected by a single data source can be avoided as far as possible. The research object of this paper mainly considers the influence of street scene exposure in residential areas, so only the urban road network is selected and analyzed. In the process of the study, the missing points which didn't possess the Baidu streetscapes were manually checked and relevant data were supplemented.

2.2. Street View data collection

In this paper, HDRI (360°) street view images were adopted as the source data for subsequent environmental exposure level measurement studies. Through Baidu Map cloud platform API, 193 street nodes within the research area were sampled at an interval of 100 meters, and data of 670 observation points were obtained, covering the whole urban street range of the research object. Through SegNet deep learning, information elements such as sky, buildings and plants can be identified.

2.3. Collection of residential area and housing price data

In this paper, the actual boundaries and main entrances of different residential areas within the research scope are reviewed to provide basic data such as residential areas, entrances and exits for the calculation of subsequent research. In this paper, the Requests module of Python tool was used to simulate the browser to send requests to the housing spectrum network server and obtain page data. After parsing the obtained data with Beautiful Soup library, the data was saved locally, and the historical average housing price data of 85 residential areas in the research range was climbed.

3. Data analysis and model construction

3.1. Machine learning technology for semantic segmentation of street view images

Previous studies generally used photoshop, HSV and other software to calculate the proportion of pixels in images (Xiao X et al., 2018;Zhao Q et al., 2016).In this study, SegNet was applied to extract image features from HDRI images of street view for semantic segmentation (Badrinarayanan V et al., 2015), quantitatively identify the proportion of plant elements in different directions in street view images of the same point, and calculate the average green visual rate of this point (Figure 2).

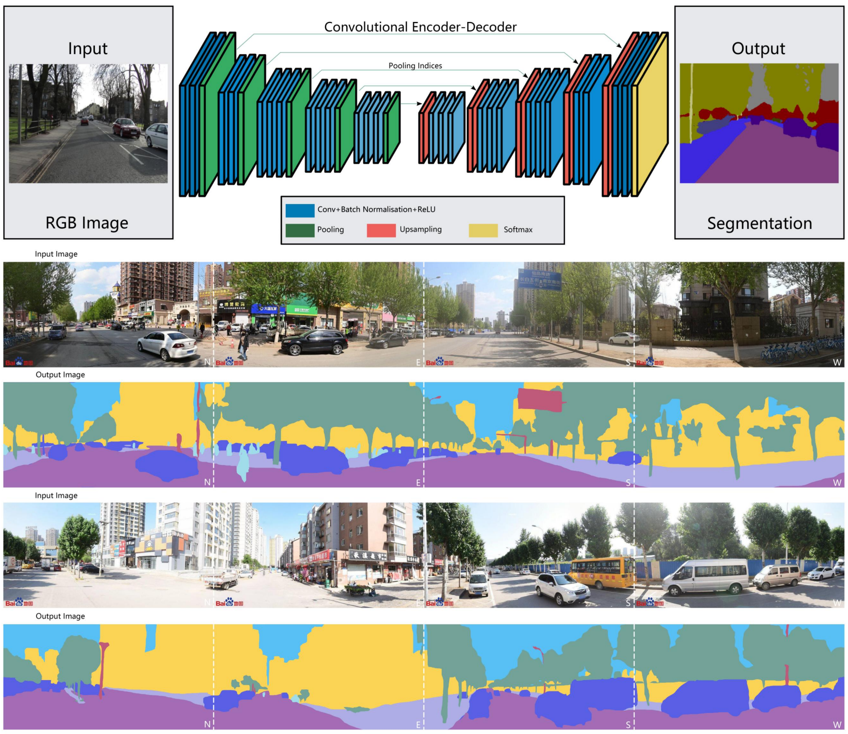

Figure 2. Semantic Segmentation Technology Framework for Street View Images based on Machine Learning

The green visual acuity of the observation point is defined as the average of the green visual acuity of the four lines of sight (Li ZX et al., 2020). Due to incomplete data of sampling points at individual points, the green visual acuity of the sampling point is calculated as 0.

$$G_v = \frac{G_{vN} + G_{vE} + G_{vS} + G_{vW}}{m} \quad (1)$$

Where Gv represents the average green visual rate of sampling points, GvN and others represent the green visual rate of sampling street view images in different directions, and *m* represents the number of images of effective sampling points.

3.2. Calculation of green environmental exposure levels in different living circles

When the living circle of a fixed residence is taken as the calculation object, the range of its living circle is calculated according to the network analysis method in GIS, and the sampling points in different ranges are figured up (Figure 3). Average green visual acuity of different living circles can be obtained subsequently, and its value approximately represents the intensity of exposure to green visual environment (Li ZX et al., 2020).

$$\overline{G_v} = \frac{\sum_{i=1}^{N} G_{vi}}{N} \quad (2)$$

Where $\overline{G_v}$ represents the average green visual acuity in different living circles; G_{vi} represents the green visual rate of a single sampling point; N indicates the number of observation points.

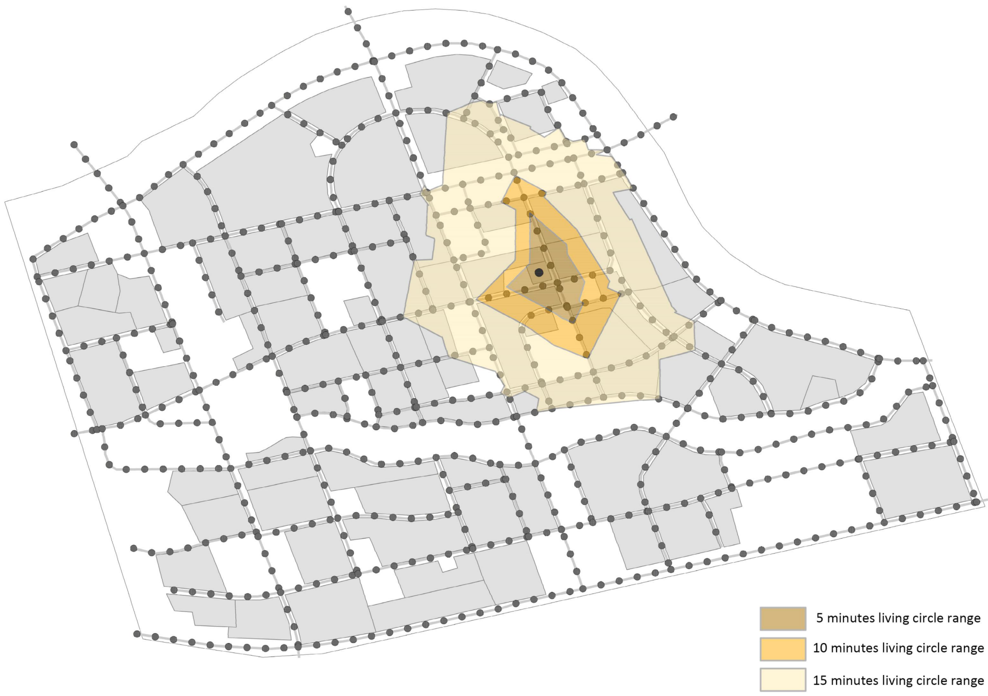

Figure 3. Measured range of exposure level sampling points in different living circle ranges (5, 10, 15min)

3.3. Bivariate spatial autocorrelation analysis model

Spatial autocorrelation analysis includes global spatial autocorrelation and local spatial autocorrelation. Global spatial autocorrelation can be used for describing the average correlation degree, spatial distribution pattern and significance of all objects on the whole Changbai Island. Local spatial autocorrelation statistical variables can identify the possible spatial correlation patterns in different spatial locations, therefore, the local spatial instability can be discovered, the obtainment of aggregation and differentiation characteristics of local spatial elements can be more accurate, which can provide a basis for classification and decision-making. Spatial autocorrelation analysis can determine whether a variable is spatially correlated and how it is correlated. Among them, global spatial autocorrelation focuses on describing spatial aggregation state and correlation degree, while local spatial autocorrelation can judge spatial hot spots (Anselin L, 1995). The author introduced Moran's I and Local Moran's I indices to describe global and Local spatial autocorrelation (Ord J K et al., 1995). Where, the calculation formula of Moran's I index is

$$I=\frac{\sum_{i}^{n}\sum_{j\neq i}^{n} w_{ij}(Y_i-\overline{Y})(Y_j-\overline{Y})}{S^2\sum_{i}^{n}\sum_{j\neq i}^{n} w_{ij}} \tag{3}$$

In the formula: For a single space unit I, its Local Moran's I index is

$$I_{\mathrm{i}}=\frac{Y_i-\overline{Y}}{S_i^2}\cdot\sum_{i=1,j\neq \mathrm{i}}^{\mathrm{n}} W_{ij}\cdot(Y_i-\overline{Y}) \tag{4}$$

$$S^2=\frac{1}{\mathrm{n}}\sum_{i}^{n}(Y_i-\overline{Y})^2 \quad \overline{Y}=\frac{1}{\mathrm{n}}\sum_{i=1}^{n}Y_i \tag{5}$$

Where Y_i and Y_j represent the attribute values of unit I and unit J respectively. n is the number of spatial units;W_{ij} is a spatial weight matrix based on European distance and K-nearest Neighbor (KNN) algorithm. In order to describe the spatial correlation between multiple variables, relevant scholars (Wartenberg D,1985;Lu RC et al., 2012) further expanded the global and local autocorrelation of bivariate based on Moran's I index, providing a feasible method for revealing the correlation of spatial distribution of different elements (Zhou X, 2020). It is defined as:

$$I_{lm}^{p}=z_{l}^{p}\cdot\sum_{q=1}^{\mathrm{n}} W_{pq}\,\mathrm{z}_{\mathrm{m}}^{\mathrm{q}} \tag{6}$$

$$\mathrm{z}_{\mathrm{l}}^{\mathrm{p}}=\frac{X_l^p-\overline{X_l}}{\sigma_l} \tag{7}$$

$$\mathrm{z}_{\mathrm{m}}^{\mathrm{q}}=\frac{X_m^q-\overline{X_m}}{\sigma_m} \tag{8}$$

Where X_{l}^{p} is the value of attribute L of space unit P; X_{m}^{q} is the value of the attribute M of space unit Q; $\overline{X}_{\mathrm{l}}$ and $\overline{X}_{\mathrm{m}}$ are the average values of attributes L and M respectively; σ_{l} and σ_{m} are the variances of attributes L and M, respectively.

4. Analysis of spatial distribution relationship

4.1. Global spatial autocorrelation analysis

In this paper, the green environmental exposure levels of different living circles within the research range were calculated on average according to distance cost, and ArcGIS was used to make visual presentation (Figure 4). According to scholars' relevant studies on Global autocorrelation, Moran's indexes can be divided into Global Moran's I and Local Moran's I. The former was proposed by PAP Moran to measure whether the space has agglomeration or outliers. The latter was proposed by Luc Anselin to measure where clustering or outliers occur (Ord J K et al., 1995). Therefore, the author conducted global autocorrelation statistics on green environmental exposure levels and housing prices in different communities' living circle ranges respectively to satisfy the bivariate local autocorrelation research in subsequent studies. The statistical results showed that the global autocorrelation index increased gradually with the increase of the community living circle, which were 0.158, 0.263 and 0.625 respectively, and the Z values were 2.47, 3.96 and 9.06 respectively (see Figure 5). The results indicated that with the expansion of the living circle, the concentration degree of community green environmental exposure increased continuously. In addition, the global autocorrelation index of housing price is 0.29, and the Z-value is 4.39, which conforms to the standard of positive spatial correlation and can be carried out in the follow-up multi-variable spatial autocorrelation research.

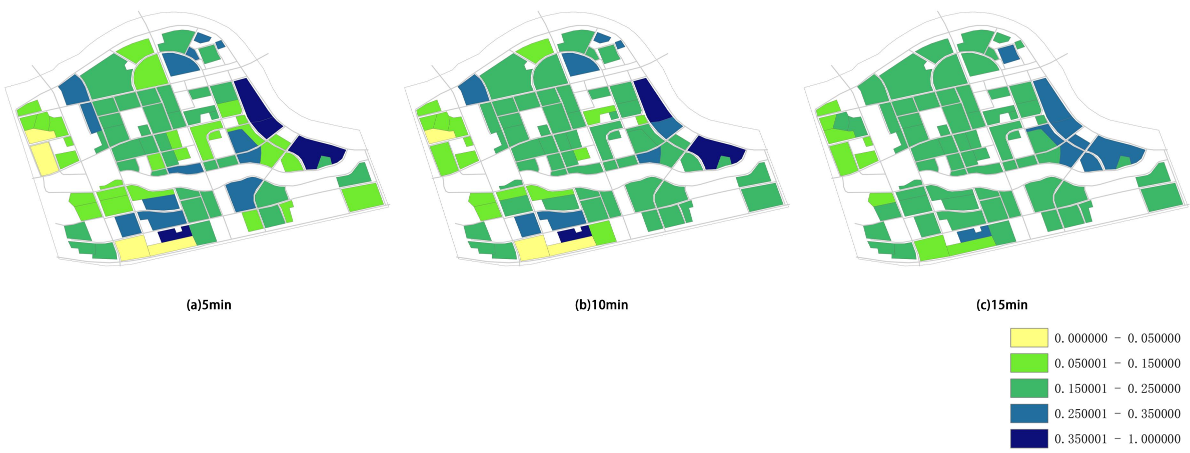

Figure 4. Spatial distribution map of the green environmental exposure levels in different living circles

(1) With the continuous expansion of the living circle, the concentration of hot and cold spots in green environmental exposure tends to be obvious. Hot spot agglomeration gradually changed from scattered distribution in the northeast of the island to concentrated distribution in the west. The concentration distribution of cold spot gradually moved from northwest to west. As for the local spatial autocorrelation of housing price level, hot spots are mainly distributed in the east area adjacent to the central axis of the island, such as Zhonghai Longwan and the East area of The Second Phase of Zhonghai International Community. The cold spot cluster is mainly distributed in the northwest, southwest and west of the central axis of the island, such as SHANGhewan of MCC and Changbai New City.

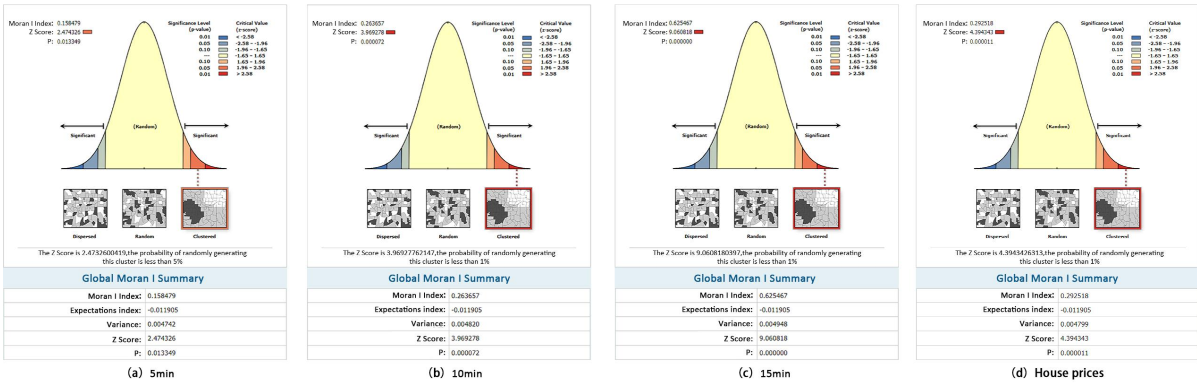

Figure 5. Global spatial autocorrelation analysis of green environmental exposure levels and housing prices in different community living circles

(2) There were outliers in the cold and hot spot cluster within the living circle of 5 minutes and 10 minutes, and the outliers disappeared within the 15- minute living circle. The "low-high" outliers of 5 minutes and 10 minutes mainly appeared in the Two river basins of No. 3 bund and China Aviation City. The "high-low" outliers mainly appeared in the second phase of Xinjiapei City. The outliers were mainly affected by the street green environment within the living circle, and the outliers disappeared after 15 minutes, indicating that the green environment in changbai Island showed a spatial positive correlation with the housing price level in a larger range.

(3) There is a significant coupling between the exposure level of green environment in the community within the 15-minute living circle and the cold-hot agglomeration of housing price. The hot agglomeration of housing price is included in the hot agglomeration within the 15-minute living circle, and there is no obvious coupling relationship with the hot agglomeration within the 5-minute and 10-minute living circle. The results indicate that green environmental exposure within the 15-minute living circle has a significantly positive impact on housing price. On the other hand, the cold spot agglomeration of housing price is partially coupled with different living circles, indicating that the negative impact of housing price only has a partial impact relationship.

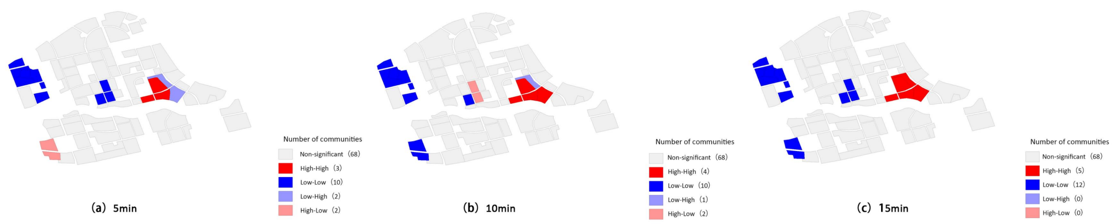

Figure 6. Spatial distribution map of community green environmental exposure levels and housing prices based on univariate local spatial autocorrelation

4.2.2 Analysis of autocorrelation in bivariate local space

The spatial visualization analysis of local Moran index of green exposure level and housing price was carried out by using the bivariate autocorrelation LISA diagram, and then the paper discussed whether the income compensated by housing price had a significantly positive or negative influence on the equity of green environmental exposure level. GeoDa is used to analyze the spatial autocorrelation of bivariate (34), and the spatial weight matrix based on Euclidian distance and K-nearest Neighbor (KNN) algorithm is established. Bivariate local spatial autocorrelation analysis was conducted between green environmental exposure level and housing price within the living circle of 5minutes, 10minutes and 15 minutes (see Figure 7).

Figure 7. Spatial distribution map of community green environmental exposure level and housing price based on bivariate local spatial autocorrelation

(1) The green environmental exposure within the living circle of 5minutes, 10minutes and 15 minutes basically overlapped with the spatial distribution of cold- hot spots in the bivariate housing price. The maximum range of cold spots gathering was 15 minutes, including cold spot gathering space of 5 and 10 minutes, indicating that with the expansion of the living circle, the cold spot gathering point is more obvious. The hot spots in 5minutes, 10minutes and 15 minutes are basically the same, indicating that green environment exposure in different living circles is positively correlated with housing price.

(2) The green environment exposure within the living circle of 5minutes, 10minutes and 15 minutes shows obvious clustering with the bivariate hot spot agglomeration of housing price. Analysis results in different living circle ranges "high - high" and "low -low" significant clustering characteristics, including near the island north China shipping international community group as the typical "high -high"

concentrated area, and grew up near the railway, China metallurgical Ma Zong garden, near the center of the plot southwest jiangnan era, plot the tianhe home groups, such as "low - low concentrated area. The "high-high" cluster mainly appeared in the branded real estate community clusters near the two urban strip parks at the same time, while the "low-low" cluster was the relocation cluster and the newly constructed core area distal cluster.

(3) There are outliers in the bivariate hot spot cluster within the living circle of 5minutes to 10 minutes, and the outliers disappear within the 15-minute living circle. 5-minute living circle and 10- minute living circle range appeared "high - low" outliers "low - high", explaining green environmental exposure levels in small scale circle "house prices do not have significant spatial autocorrelation, the reason may be that small scale circle" housing prices are also housing properties (commodity house and economy applicable room, small property right, etc.), brand developers, property maintenance level and so on many aspectsto a certain extent, the surrounding low green rate and high housing price or high green rate and low housing price agglomeration outlier; In a larger scale, due to the time continuity of residential development cycle and the spatial aggregation of quality open brands, the spatial autocorrelation between green environmental exposure level and housing price tends to be stable on a larger scale, and the outliers gradually disappear.

5. Summary

(1) Green environmental quality of urban street space is also an important potential factor affecting housing price. Street green environmental quality in urban built-up space is also a potential factor affecting the environmental exposure level of street green space. The pricier neighborhoods are surrounded by lots of parkland. The location of community and green space is an important factor affecting housing price, and the main structure of city also has a significant impact on housing price. The housing price of adjacent intercity railways and urban expressways is relatively low, which is similar to the quality of green space.

(2) There was a significant difference in the perception level of green environmental exposure in different living circles. With the increase of the living circle, the exposure level approached equilibrium, and the number of residential areas with better perception level increased significantly. The exposure level of the 5min living circle is mainly affected by the urban street greening, and the exposure level of the 15min living circle is affected by the urban ribbon park. Among them, city-level belt parks have a significant impact on exposure level, while other level belt parks have a relatively weak impact on it.

(3) Hot spots and cold spots cluster in green environment exposure level and housing price in different communities. There was one significant hot spot agglomeration and two significant cold spots agglomeration in the 5min living circle. There were three significant cold spot clusters and one significant hot spot cluster within living circle of 5 minutes and 10 minutes. The "high-high" cluster community also has two rich urban parks, which reflects a higher level of street green environmental exposure, and forms a good interaction effect with housing prices.

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