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Stereotypical ideas in the perception of spatial marginality of urban outskirts

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Abstract. According to the territorial-regional development policy of Russia, a rigid structuring of the country's space is applied through the prism of a hierarchical management system. As a result, the structure of the space of the entire country was fixed through a system of boundaries, the markers of which highlight management objects at the national level, subject of the Russian Federation, territory, region, district. This article will present the main stereotypes that influence the creation of the perception of new territories in the nature of marginality. As is known, the formation of marginal communities can be traced throughout the history of civilizations. It is important to separate geographical marginality from spatial marginality. In geography, there is the concept of “marginal territories”, which can be considered those located on the remote periphery of the region or in isolated places. Such a phenomenon as spatial marginality is characterized precisely by the prevailing stereotypes in society about a specific area. Urban spatial perception critically influences human behavior and emotional responses, emphasizing the need to align urban spaces with human needs to improve the quality of urban life. However, the classification of urban architecture based on functionality is subject to biases stemming from discrepancies between objective representation and subjective perception. These biases can lead to city planning and designs that fail to adequately meet the needs and preferences of city residents, negatively impacting their quality of life and the overall functionality of the city. In this study, we apply machine learning to uncover these biases in urban spatial perception research using a three-step methodology: objective mapping, subjective perception analysis, and perceptual bias assessment. Our results show that machine learning can reveal hidden patterns in this area of research with significant implications for urban planning and design. Of particular note, the study found significant discrepancies in the distribution centroids between commercial buildings and residential or public buildings. This result sheds light on the spatial organization characteristics of urban architectural functions, serving as a valuable guide for urban planning and development. Moreover, it reveals the advantages and disadvantages of different data sources and methods for interpreting urban spatial perception, paving the way to a more complete understanding of the subject. These results highlight the importance of integrating both objective mapping and subjective perspectives when classifying the functionality of urban architecture.

Keywords: marginality, public space, city outskirts, stereotypes of marginality of outskirts, improvement of the area, integrated development of new territories, development of territories, socio-economic efficiency of territories, integrated development

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1. INTRODUCTION

In the modern development of Russian cities (especially their outskirts), a significant factor is their spatial improvement, which affects the improvement of the urban environment and the creation of comfortable (including housing) living conditions. As a result, regional and local communities have formed and are developing in a single geographical space, living in their own production and social fields.

Research interest in the topic of this article is due to the need for qualitatively new approaches in the field of spatial development of cities and especially their peripheral parts for the development of the urban environment. In this regard, there is an urgent need to rethink the role of urban outskirts in the spatial organization of urban and regional systems.

Urban spatial perception, the complex interaction between individuals and their urban environment, greatly shapes human behavior and emotional responses in the fields of architecture and urban design. This psychological process, based on the perception of shapes, structures, colors and aesthetics, emphasizes the importance of aligning urban spaces with human biological structure and meeting human needs, thereby improving the quality of urban life [1]. Within spatial perception research, a widespread phenomenon is “bias,” which refers to the discrepancy between the output of a particular process and its expected outcome [2]. When classifying urban architecture based on functionality, statistical results obtained from objective data may differ from those based on people's subjective perceptions, illustrating an example of bias between observed and true values in the process of city perception. Bias has significant research implications, allowing us to delve deeper into given phenomena and uncover hidden patterns and characteristics within them. For example, semantic differences in the soundscapes of urban open spaces can be explored by understanding differences in sound perception among different demographic groups [3].

This study relies on objective mapping and subjective perceptual distortions of architectural classification to in-depth study the phenomena and characteristics of urban architectural classification. The value of variance research lies in its ability to identify significant differences between expected and actual results.

Objective mapping using statistical methodologies typically uses publicly available city data sets. For example, data from multiple sources, such as geographic information system (GIS) data and points of interest (POI), can be used to facilitate the classification and analysis of the spatial distribution of urban architecture [5]. Such data is typically classified and analyzed based on geographic location, architectural types, and other indicators related to urban functionality. Additionally, subjective perception refers to the awareness of urban architecture, environment and functionality shaped by individual experiences, knowledge, emotions, values and other factors as people perceive and evaluate urban spaces. This perception arises from actual experiences, observations and feelings, as shown in the subjective assessment of thermal comfort in urban open spaces [6]. As part of the research on subjective perception, a machine learning model was constructed that helped map the distribution of people's perceptions of new urban areas throughout the city [7]. Moreover, street images reflect the overall landscape of urban areas, and this new source of graphical data has advantages not only in accurately observing the physical environment but also in social perception [8].

This study acknowledges the potential differences in urban architectural functionality classification and spatial distribution when using objective mapping versus subjective perception methodologies. Objective mapping, "true values" in urban perception, reflects the actual circumstances of architectural structures or spaces. On the contrary, subjective perception, the corresponding "observable values", embodies the individual perception evoked by these structures or spaces. A comprehensive study of the deviation between these “true” and “observed” values in city perceptions could identify sources of bias and improve measurement methods, thereby validating the effectiveness of existing urban planning and design models. At the same time, understanding underlying patterns and characteristics can draw attention to new issues and challenges, providing better data to optimize decision-making and strategy.

The study aims to explore the differences and causal factors between the actual and observed values of objective mapping and subjective perception in classifying the functionality of urban architecture. This approach contributes to a more complete understanding of the spatial perception of cities. Moreover, the study aims to explore the commonalities and differences between these two methodologies at different spatial scales, carefully analyzing the main factors driving these differences. To achieve this goal, we will use an objective mapping method based on POI data and a subjective perception method based on street view images to analyze the functional classification and spatial distribution of urban buildings. This research aims to contribute to the creation of a more comprehensive theoretical framework and practical recommendations in the fields of architectural design, urban planning and spatial analysis.

The main methodologies of this study include:

(1) Functional classification of urban architecture by applying frequency density coefficient and inverse distance-weighted frequency density methods to POI data.

(2) Using a deep convolutional neural network (DCNN) model to perform functional classification of urban architecture using street view images.

(3) Using spatial clustering analysis and spatial pattern similarity analysis with grid structure to identify discrepancies between objective mapping methodologies and subjective perceptions regarding the categorization of urban architectural functionality and spatial distribution.

(4) Exploring potential factors contributing to differences between objective display and subjective perception, thereby enriching our understanding of urban perception.

2. METHODS AND MATERIALS

The research workflow includes three main steps (Fig. 1). Objective display, subjective perception and perceptual deviation. First, the distribution of building functions at the city scale is determined using the POI mapping method combined with the frequency ratio method and inverse distance weighting. Different types of buildings are identified and classified based on their functions using available POI data. Secondly, subjective perception is carried out by assessing the functions of the building. Street view images are used as a subjective evaluation tool, and domain experts subjectively classify buildings based on these images. In addition, pre-trained models are used to improve the perception of building functions in an urban context. The final step involves calculating perceptual deviation, which quantifies the discrepancy between the objective display and the subjective perception. Spatial clustering analysis is used to identify differences in the distribution of building functions between objective and subjective data sets. In addition, the similarity of the spatial pattern of the grid structure is assessed to determine the degree of agreement between the results obtained from objective mapping and subjective perception.

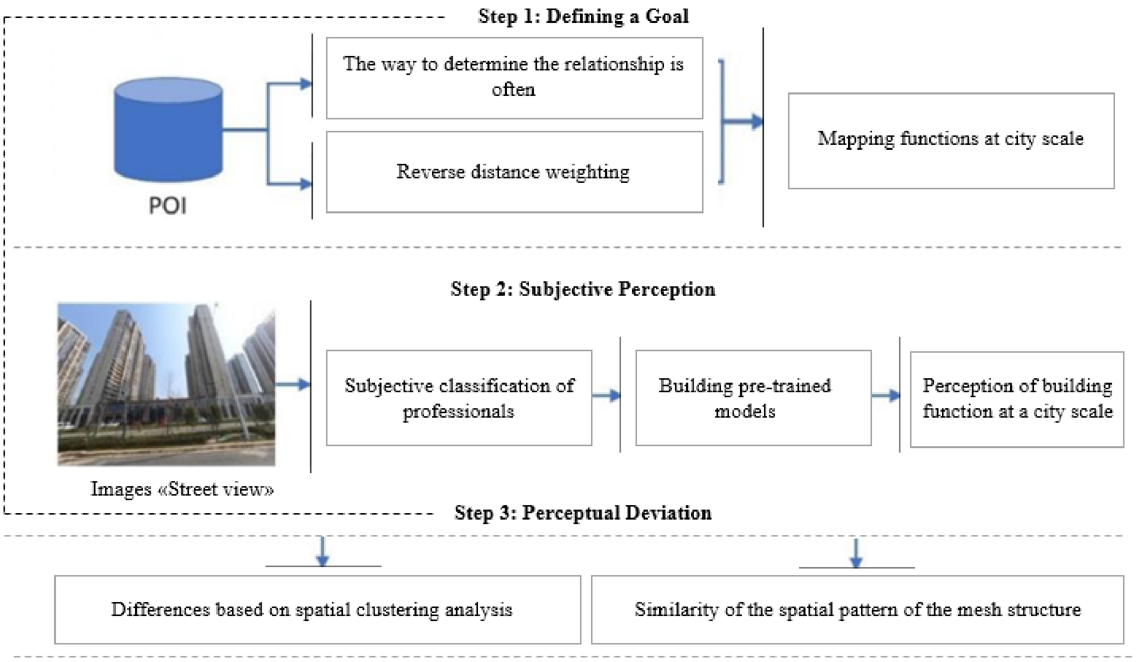


Fig. 1. Research basis for this study.

2.1. Functional classification of urban buildings based on POI data

2.1.1. Collection and pre-processing of POI data

This study mainly classifies architectural types based on POI data. Despite the abundance of spatial information contained in POI data, inconsistencies in data quality and positional shifts pose significant challenges. Therefore, before starting the architectural classification experiment, it is necessary to process the obtained POI data. The initial steps include selecting POI data from Shanghai, vectorizing it on an online map, and extracting the required POI data for the study.

After data verification, data cleaning is carried out; Excel files with 12 categories of POIs are converted to vector data, and POI data with low public recognition, such as newsstands and public toilets, are excluded from the original data. The processed POI data is then reclassified according to building type and purpose. In accordance with the “National Standard of the Russian Federation - the current Order of the Federal Service for State Registration, Cadastre and Cartography dated November 10, 2020 N P/0412, all functions of buildings are divided into commercial, public and residential categories (as shown in Fig. 2). Considering that the architectural type classification extends to the area of interest (AOI) of the building, it is also necessary to obtain the building area data required by the study.Finally, the geographic coordinate system of all files is converted to a projection coordinate system, and the spatial coordinates of the collected data are uniformly converted to the coordinate system WGS-84 for subsequent general spatial structural analysis.

2.1.2. Frequency ratio method

First of all, frequency methodology is used for calculation. The fundamental principle of the frequency method is to calculate the amount of scattered POI data on an architectural façade, classifying architectural features based on frequency density and the proportion of architectural façade POI types in the spatial scale.

$$F_i = \frac{n_i}{N_i} (i = 1,2,3, \dots, n) \tag{1}$$

$$C_i = \frac{F_i}{\sum_{i=1}^{n} F_i} (i = 1,2,3, \dots, n) \tag{2}$$

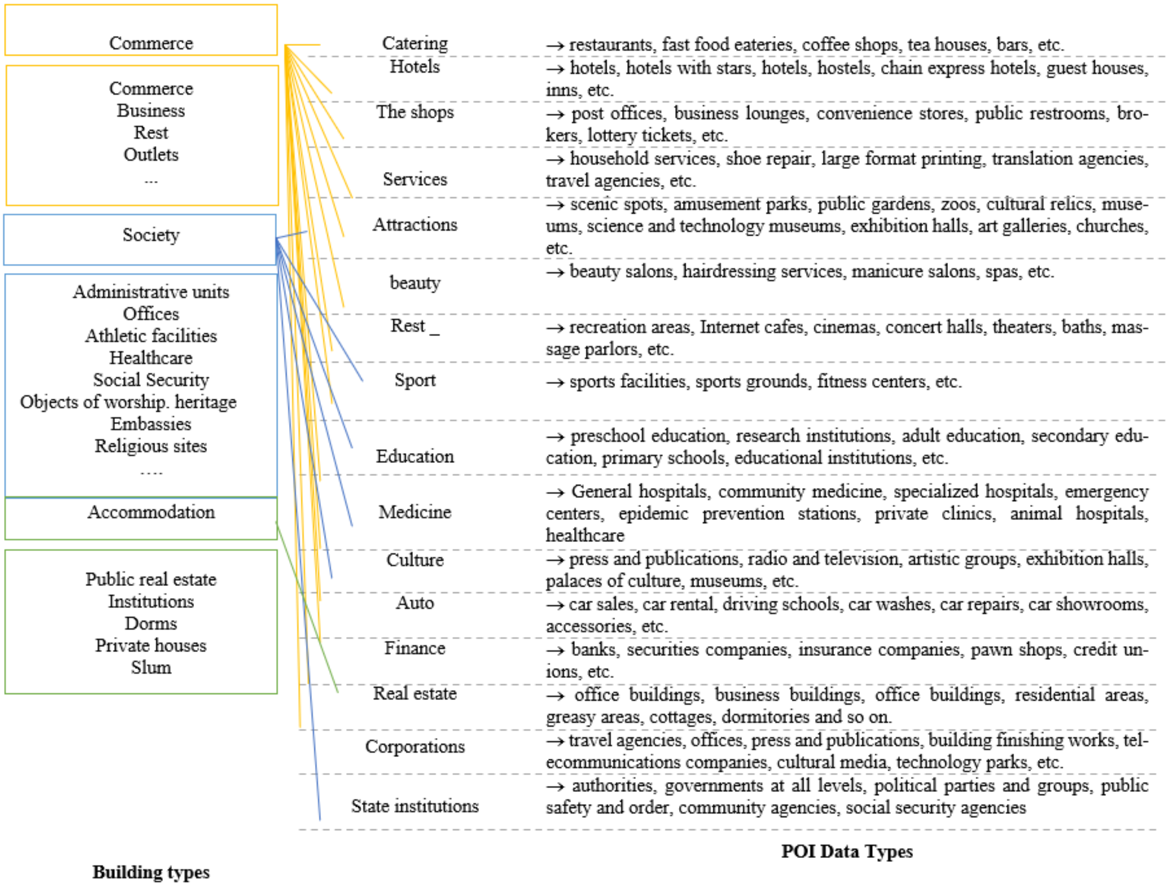


Fig. 2. Functions of buildings and categories of buildings.

In these equations, i denotes the architectural type, n denotes the number of architectural types, and ni represents the number of the i-th type of POI in the architecture.

In addition, Ni denotes the total number of i-th POI category in the POI data, Fi represents the frequency density considering quantity i type POI and Ci means the ratio of the frequency density of the i-th category of POI to the frequency density of all types of POI data inside the architectural object area.

Calculations for the three POI categories are performed using the frequency density distribution method, which gives the number of three POI categories in each architectural façade file. Observations of the calculation results using the frequency density ratio method show that a significant number of architectural elevation files did not achieve statistical results for POI data. This is primarily due to the lack of data about POI points in the architectural facade file. The advantage of the frequency density ratio method is its ability to account for the number of POIs within each building façade. However, its disadvantage is the relatively high demand for the quality of POI data. The quality of the obtained POI data is often difficult to ensure, which primarily manifests itself in spatial position shifts, data losses, and the like. For elevation files with POI point values, calculations can be performed using the frequency density ratio method. However, for facades where quantity is not taken into account, additional calculations must be performed using the kernel density method or the inverse distance weighted frequency density method.

2.1.3. Reverse Distance Weighting

Due to inherent quality distortions in POI data, some architectural elevation files cannot obtain POI values. These gaps require the use of the inverse distance weighted frequency density method to complement architectural surface area, since conventional methods for calculating the frequency density ratio are found to be insufficient for architectural typology studies. The inverse distance weighted frequency density method incorporates a Gaussian function that provides a fast decay for a given distance factor, thereby significantly reducing the impact of distant POI data on the results. Initially, architectural façade data that can be calculated using the frequency density ratio method is discarded in favor of using the inverse distance weighted frequency density method for the calculation.

The key difference between the inverse distance weighted frequency density method and the frequency density ratio method is the handling of unaccounted architectural façade data. This data uses the surrounding POI data to determine the type classification. For architectural zones that lack POI data, POIs within the surrounding 100 m buffer are counted and the weight of the POI is limited. Consequently, areas closer to the architectural façade carry more weight.

$$f(x) = ae^{-\frac{(x-b)^2}{2c^2}} \tag{3}$$

Compared to the commonly used inverse form of the inverse function, the Gaussian function is a smoother curve and is more applicable to POI data characterized by high uncertainty. The one-dimensional form of a Gaussian function is a bell-shaped curve, where a represents the peak value, b indicates the value of the independent variable at the peak ($x = b$ also serves as the axis of symmetry of the bell), and c denotes the standard deviation, depicting the circle of latitude. True value of dependent variable in x is the distance from the POI to the geometric center of the building polygon. As the POI approaches the architectural facade, the weight approaches 1, and as the POI moves away from the architectural surface, the weight decreases, infinitely approaching 0 but never reaching a negative value, as shown in Fig. 3. Therefore, we assign $a = 1$ and $b = 0$.

For settlements lacking POIs within their catchment area, this study calculates POI categories within a 100-m development buffer zone and evaluates the classification of settlement types.

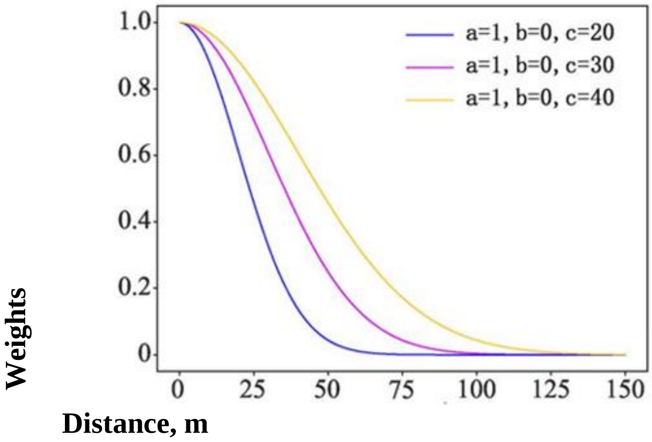


Fig. 3. Reverse Distance Weighting.

2.2. Functional classification of buildings based on visual perception of street view images

2.2.1. Obtaining and pre-processing “street view” images (with a view of the street)

In this study, we extract images from Street platforms view , getting a wide coverage of photographs of city streets. Initially, urban road networks, equipped with geographic coordinate information, are selected and obtained from OpenStreetMap (OSM). Following this, we simplified the road network to linear forms with an average distance of 25 meters between adjacent points, based on the urban street design method proposed by J. Gehl [9]. We subsequently obtained sample points with geographic coordinate information displayed within the spatial distribution. It is noteworthy that not all sampling points in street services view have corresponding street images view . Ultimately, to obtain building elevations, we download two images perpendicular to the road from Street View services for each sample point (left and right respectively, with a viewing angle of 90 degrees, a horizontal angle of 0 degrees, and an image size of 760 × 480 pixels). as shown in Fig. 4. We received a total of 102,046 images of the central city streets of Moscow.

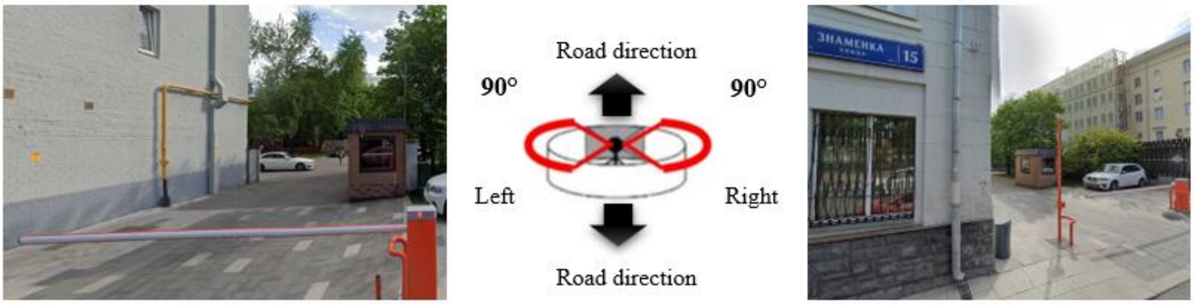


Fig. 4. Obtaining images of the street view at the sampling point.

This study uses a methodology that segments building facades from street-view images, improving the accuracy of façade color recognition and building function classification. In recent years, high-accuracy semantic segmentation models based on convolutional neural networks, such as U - Net [10], PSPNet [11], and DeepLabV 3 [12], have been widely developed. We use DeepLabV 3 to segment building facades in street images view due to its high accuracy and ease of implementation. DeepLabV 3 achieved 93.5% accuracy for buildings on the Cityscapes test set . To improve the accuracy of the experiment, we need to exclude images with a small fraction of buildings, since the computer cannot identify building features from these images. By feeding street view images into a pre-trained semantic segmentation model, we can measure the area ratio of building facades. After calculating the proportion of buildings in each selected image, we exclude images with a proportion of buildings below 15%.

2.3. Discrepancy between objective display and subjective perception of building functions at the city scale

2.3.1. Analysis of variance of spatial distribution based on K -means clustering

This study aims to perform a cluster analysis of image pixels corresponding to a target color, followed by visualization of the results. Initially, to find pixels in an image corresponding to a given target color, we quickly determined all pixel coordinates corresponding to the target color using the NumPy library [13]. After this, the Mini algorithm was used BatchKMeans , part of the scikit - learn library [14], to perform cluster analysis of pixels of the target color. MiniBatchKMeans , a variant of the K -means algorithm, uses a subset of data samples (called mini-batches) during each iteration, thereby speeding up calculations. This algorithm seeks to find optimal cluster centers, thereby minimizing the subsequent objective function:

$$J(C) = \Sigma(\Sigma\|x_i - \mu_j\|^2), \text{где } x_i \in C_j \tag{4}$$

In this context, J (C) stands for clustering error, C_j represents the jth cluster, x_i de marks the data point and μ_j is the center of C_j . By minimizing J (C), we can obtain more compact and representative clusters.

Finally, we use the seaborn library [15] to generate a scatter plot to visualize the clustering results. For each cluster, a dotted circular frame is drawn, the radius of which is equal to the distance from the center to the farthest point inside the cluster. Additionally, the center point of each cluster is illustrated. When calculating the distance, the Euclidean distance formula is used:

$$d(x, y) = \sqrt{\Sigma(x_i - y_i)^2} \tag{5}$$

Thanks to the implementation of these methods, we can compare and conduct cluster analysis of architectural functions both in subjective perception and in objective statistics.

2.3.2. Analyzing the similarity of the spatial pattern of the mesh structure

In this study, we proposed a methodology based on the spatial overlap metric, Jaccard similarity [15], to analyze and visualize the differences between two RGB images of spatial distribution at the city scale. Below we detail the steps involved in implementing this approach:

We initially adjusted the two input RGB images to an appropriate size to make it easier to partition them into a given number of grids. Each image was segmented into 100 x 100 grids. To achieve this, we first split the images along the vertical axis (axis=0), then merge the split image blocks and further split them along the horizontal axis (axis=1).

For each pair of corresponding meshes, we calculated their Jaccard similarity. The specific steps are as follows: First, calculate the unique colors in each grid and their frequencies of occurrence. Second, identify the colors appearing in both grids. For each common color, calculate the minimum amount of it in each grid. Add these minimum values to determine the size of the intersection. Third, calculate the total number of colors in both grids and subtract the size of the intersection to determine the size of the union.

We calculate the Jacquard similarity using the formula:

$$J(A,B) = |A \cap B| / |A \cup B| \tag{6}$$

Where A and B denote two sets, | $A \cap B$ | indicates the size of the intersection of sets A and B, and | $A \cup B$ | represents the size of the union of sets A and B. Jaccard similarity serves as a measure of the similarity between two sets, with values ranging from 0 to 1. The closer the similarity value is to 1, the more similar the two sets are; conversely, the closer the similarity value is to 0, the greater the discrepancy between them.

Store the calculated Jaccard similarities in a matrix whose row and column numbers match the number of grids. Finally, visualize the Jacquard similarity matrix as a heat map using the Seaborn library's " heatmap " function .

With these steps, we can generate a heat map illustrating the similarities between RGB images of spatial distributions at the city scale with two inputs. This method allows us to compare and analyze similarities and differences in urban spatial patterns in a quantitative manner.

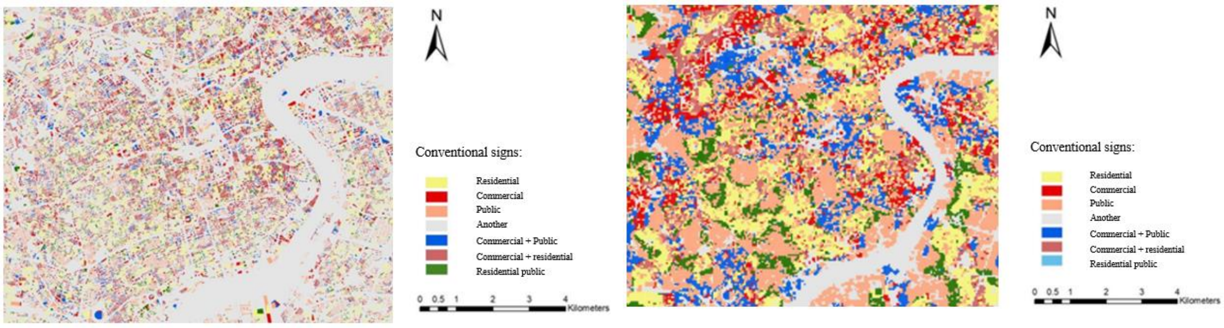
3. RESULTS AND DISCUSSION

3.1. Building classification results based on POI

By applying the above-mentioned frequency density ratio and inverse distance-weighted frequency density methods, we classified structures in the Shanghai epicenter, resulting in the creation of an urban architectural classification map based on AOI data (Fig. 5A).

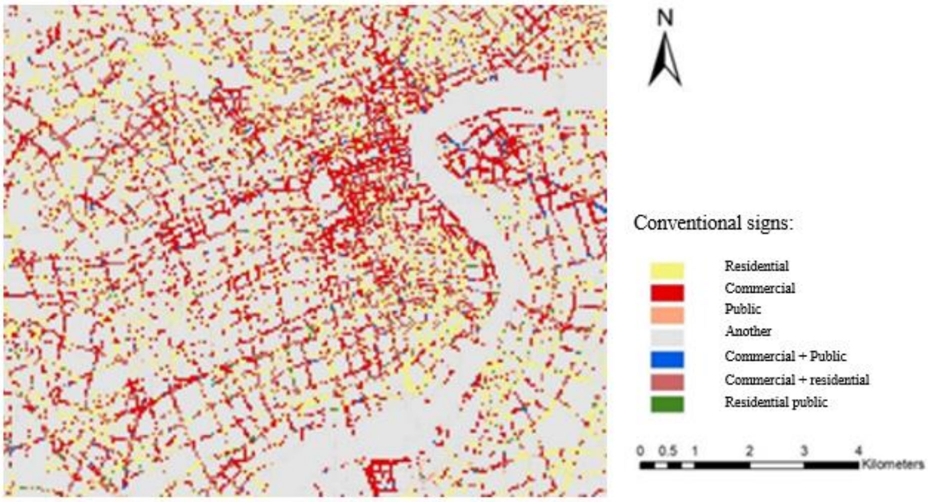
To facilitate subsequent comparison with subjective visual perception, we have included a reference to established standards related to the observation of architectural facades.

People can usually discern the general shape and complex features of a building at close range (approximately 25 meters). Conversely, at a greater distance (approximately 250 meters), attention is primarily focused on the prominent building and spatial relationships in the urban environment. Recognizing that people may scrutinize architecture from different distances during actual viewing, we chose an average distance of 50 meters (with a field of view extending 25 meters in either direction) as the appropriate measurement standard. This distance sufficiently takes into account both the overall shape and the individual complex characteristics of the building, while reflecting its spatial relationships in the urban environment. Accordingly, a 50-meter buffer analysis of the buildings was carried out and a visualization of the spatial distribution of the architectural classification results based on the POI data was performed (Fig. 5B).



A. Urban building classification map based on AOI data.

B. Building classification results based on POI data.



B. Results of visual perception of the functions of urban buildings classification of streetscape images at the street scale.

Fig. 5. Visualization of building classification results.

Commercial buildings within this range tend to be located in areas with optimal transport accessibility, often in the center of neighborhood clusters. Most residential buildings have a cluster distribution within the range, which is consistent with the characteristics of the aggregate distribution of residential space in most Chinese cities, taking the form of residential communities. Apart from large public service institutions such as hospitals and schools concentrated in clusters, public buildings in the central research area of Shanghai are quite scattered, mainly administrative offices, cultural and sports facilities, often located in separate buildings. They occupy vast areas of land and are numerous.

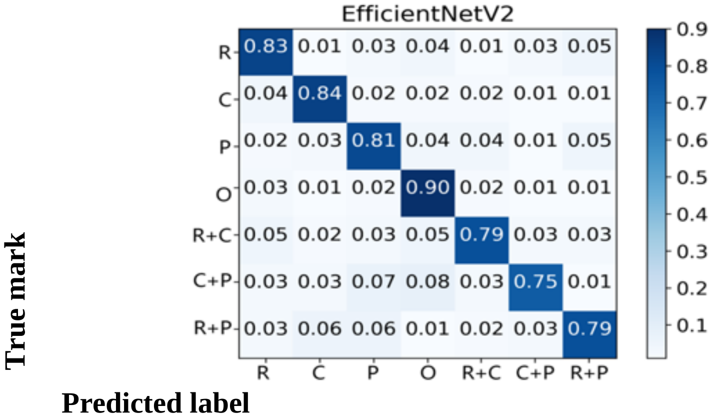
3.2. Results of building classification based on street view images

3.2.1. Classification Accuracy of Deep Learning Models

Figure 6 shows the normalized chaos matrices of seven architectural feature classifications estimated from our testing data using the trained Efficient Net V2 model. The F1 score (F1), a reliable criterion for evaluating classification accuracy, is an average value that includes both precision (p) and recall (r). It is formulated as:

$$\mathrm{F1score} = 2 * (\mathrm{p} * \mathrm{r})/(\mathrm{p} + \mathrm{r}) \tag{7}$$

The determined F-score value for the trained Efficient Net V2 model is 0.82.



	R	C	P	O	R+C	C+P	R+P
R	0.83	0.01	0.03	0.04	0.01	0.03	0.05
C	0.04	0.84	0.02	0.02	0.02	0.01	0.01
P	0.02	0.03	0.81	0.04	0.04	0.01	0.05
O	0.03	0.01	0.02	0.90	0.02	0.01	0.01
R+C	0.05	0.02	0.03	0.05	0.79	0.03	0.03
C+P	0.03	0.03	0.07	0.08	0.03	0.75	0.01
R+P	0.03	0.06	0.06	0.01	0.02	0.03	0.79

Fig. 6. Normalized chaos matrices for seven classifications of architectural functions.

3.3. Building function classification results and spatial distribution

The study area covers 102,046 estimated street-view images.

Figure 5B shows the distribution of building functionality within these street view images of the study area.

From a subjective human point of view, the main functional capabilities of buildings in the central region of Moscow are predominantly residential and commercial premises. These two features occupy important positions in the visual landscape. Residential buildings are likely to represent the dominant function, reflecting the high population density and urban residential areas in the central area. Commercial structures such as shopping malls and retail stores are also widespread, reflecting the vibrant economic activity and commercial hubs in the city.

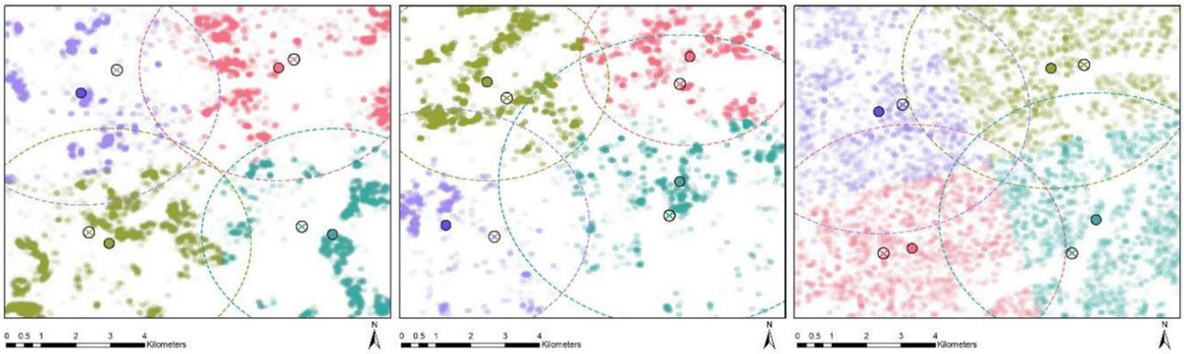
In contrast to the previous figure, it is notable that office buildings can be misidentified as commercial buildings. This misperception can arise from various factors such as architectural design, signage and visual appeal, all of which influence the perceived distribution of different functionalities in an urban environment.

3.4. The result of the deviation between objective statistics and subjective perception of building functions

Comparing the color block centroids of different building functionalities in two diagrams illustrates the differences in spatial distribution between objective statistics and subjective perceptions. We calculated the differences in the distribution of architectural features between the spatial clustering analysis of subjective perception and objective statistics, as shown in Fig. 7. Particular attention was paid to the differences in the centroids of the distribution of residential, commercial and public buildings.

The results show the greatest difference in the centroid of the distribution of commercial buildings, which indicates significant variability in the spatial distribution of commercial functionality within the central region of Moscow. Further analysis shows that this centroid difference in the distribution of commercial buildings may be closely related to factors such as urban planning, land use and market demand. This discrepancy may reflect trends in commercial agglomeration and changes in urban development.

In addition, the differences in the distribution centroids of residential and public buildings are relatively minimal, implying a stable spatial distribution of these two functions within the main area. Studying these discrepancies contributes to a deeper understanding of the spatial organization characteristics of urban architectural functions, providing guidance for urban planning and development. Future research could delve into the underlying causes and influencing factors, including the economic dynamics of business activities, changes in citizen needs, and the direction of government planning, to promote smarter and more sustainable urban development.



○ Clustered display center. ⊗ Grouped center of perception. ● Group 1 ● Group 2. ● Group 3 ● Group 4

Residential cluster. Commercial cluster. Public cluster.

Fig. 7. Differences in the distribution of construction functions based on spatial clustering analysis.

3.5. Results of the similarity analysis of the spatial pattern of the grid structure

Subjective perception results and objective building functionality display results were obtained and their similarity to the grid-based spatial pattern was visualized in a new image. Areas of the grid with higher similarity are illustrated in blue, while areas with lower similarity are illustrated in red. The results of the spatial similarity analysis of the grid structure are shown in Fig. 8.

In terms of overall similarity, subjective perceptions and objective statistics show a certain degree of similarity in their spatial distribution at the urban scale. For example, areas located near the Moscow River tend to show higher similarity. In terms of local differences, despite the general similarities between the two maps, significant differences remain in some local areas.

Through grid-based similarity analysis of spatial patterns, we can gain greater insight into the characteristics of these two spatial perception distributions and the differences between them. This helps urban planners and relevant stakeholders better understand urban development patterns, thereby enabling the development of top-down planning strategies and interventions.

Grid structure Spatial pattern similarity

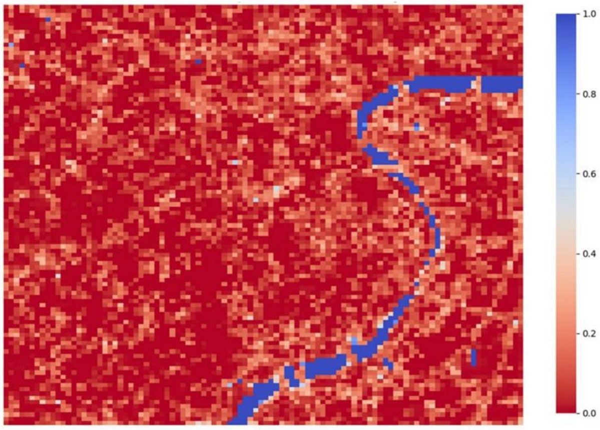


Fig. 8. Similarity of the spatial pattern of the grid structure.

The importance of perceptual bias in urban science is that it challenges the perception of human activities and the socio-economic environment of cities using traditional computer vision functions. Traditional image analysis methods and automated algorithms often find it difficult to accurately capture perceptual subjectivity, multiple backgrounds, and the complex layout of urban functions. This limitation requires the development of superior computational tools and methods capable of holistically learning and interpreting the visual content of urban environments.

By understanding perceptual biases, researchers can strive for more precise and quantitative measurements of architectural functional layout and socioeconomic conditions. Extracting high-level representations from street view images is key to this endeavor. These representations provide insight into the functional distribution of urban architecture. By analyzing visual data and taking into account perceptual biases, researchers can identify indicators that reflect people's perceptions of the functional distribution of architecture, such as commercial activity and residential experience. This information is of paramount importance for optimizing transport planning and infrastructure development. Understanding perceptual bias facilitates the integration of urban science with data science, opening new opportunities for innovative solutions in evidence-based decision making, efficient resource allocation, and sustainable urban development.

4. CONCLUSIONS

In summary, this study sheds light on the impact of the discrepancy between objective display and subjective perception on the functional classification of urban architecture.

By using machine learning methodologies to identify hidden patterns and signatures within urban spatial perception research, we have effectively addressed this challenge and achieved a more complete understanding of urban design and planning. The implications of these findings lie in their ability to guide the development of more effective and sustainable urban strategies. In particular, by integrating both objective mapping and subjective perception, we can provide a deeper understanding of the needs and preferences of heterogeneous communities in urban contexts, thereby facilitating the development of more inclusive and livable urban plans. Taken together, this study highlights the critical role of interdisciplinary research in addressing complex issues related to urban space perception and design.

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