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City centers really lived up to the hype? Evidence from human perceptions of over 4000 communities in China

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ABSTRACT

The way how to form well-being cities has been a longstanding challenge in urban planning. Existing studies often assume that residents of urban centers experience more pleasant environments than those living in suburban areas. This study critically investigates whether this assumption holds true by examining the perceptions of pleasantness across over 4000 communities in six major cities within the Pearl River Delta region in China. Using the "Six-Type-Perception" model, we analyze community perceptions across different urban settings by delineating urban-suburban-rural boundaries through nighttime lighting data and leveraging deep learning on street view images for perception measurement. The results reveal a significant center-suburban disparity in environmental pleasantness perception, providing new evidence that "suburbs" are perceived as more pleasant than city "center" across multiple spatial scales in the Pearl River Delta: peripheral cities significantly outperform core cities, peripheral districts generally surpass core districts and suburban communities also fare better than central one. Regression analysis further identifies key environmental factors associated with higher pleasantness perceptions, including a higher sky view index, greater green space density, lower densities of buildings, residential areas, and transportation infrastructure, and higher densities of institutional and commercial facilities. These findings highlight that residents' perceptions of pleasantness are closely associated with specific urban environmental features, offering new perspectives for the planning and design of well-being cities.

1. Introduction

The enduring challenge of providing global citizens with living environments conducive to well-being has become increasingly critical, particularly as the world experiences rapid population growth across diverse regions (Mouratidis & Yiannakou, 2022). Over the past decades, communities around the globe have shifted from predominantly rural settings to urban settlements (Shekhar et al., 2019; Tonne et al., 2021). This trend has spurred a growing body of scientific research focused on creating more livable and pleasant environmental perceptions (Elmqvist et al., 2019; Mouratidis, 2020). Environmental perception is defined as the sense of living in an urban environment with a comprehensive definition and theoretical framework proposed by Ittelson (1973). Specifically, environmental perception involves multidimensional interactions between humans and both the natural and built environments. As it is inherently related to and shaped by the environmental context, understanding environmental perception remains a complex and evolving topic in urban studies.

Traditional research on environmental perceptions has primarily focused on two levels: the individual (subjective) level and the community (collective) level, largely based on limited sociological surveys of human interactions with the urban environment (Shekhar et al., 2019). These early studies typically established various dimensions of urban perception by identifying positive and negative sentiments toward neighboring environments (Leyden et al., 2011; Marks & Shah, 2004). Questionnaires and interviews were then conducted to collect residents' experiences and opinions. However, constrained by the absence of extensive urban big data, these earlier approaches can only provide an overall evaluation of cities, rather than offering fine-grained insights into specific community spaces or examining how particular urban environmental factors influence residents' perceptions (Gim, 2020).

With the increasing availability of rich and fine-grained urban big

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data related to environmental perceptions, recent studies have increasingly integrated traditional social survey methods with geospatial information, remote sensing imagery (Gu, Tang, et al., 2024; Liu, Gu, et al., 2024), and urban street scene analysis (Larkin et al., 2021; Zhang et al., 2018). These studies typically began by administering questionnaires to collect perceptual ratings, followed by employing statistical analyses and machine learning techniques to predict human perceptions of environmental spaces over large spatial extents (He & Li, 2021). For example, Zhang et al. (2018) utilized a large-scale annotated urban street view dataset to infer people's perceptions of their local environment through machine learning models. Similarly, Jeon and Jo (2020) recruited voluntary participants and constructed controlled experimental settings to analyze how different environmental factors influence community perceptions. These studies have significantly advanced the understanding of factors shaping environmental perceptions (He & Li, 2021) and have laid the modeling foundation for subsequent large-scale urban perception analyses (Kruse et al., 2021; Larkin et al., 2021).

To foster environmental perceptions and enhance residents' sense of pleasantness, the characteristics of the socio-economic, built, and natural environments are considered critical by many studies (Leyden et al., 2011). For instance, Gim (2020) examined the relationships between urban public services and perceived pleasantness based on a social survey of 46,000 citizens in Seoul, concluding that convenient public transportation along with access to cultural and recreational facilities were key drivers of residents' pleasantness. Similarly, Putnam (2000), through extensive surveys across American cities, found that fostering safer and more vibrant social spaces can significantly enhance positive environmental perceptions. However, these relationships are often spatially complex and non-linear, meaning that traditional linear models may be insufficient to capture the intricate and multifaceted nature of these relationships. Therefore, recent studies advocate for the use of machine learning regression models (Verma et al., 2020), which can better model these complexities and provide a more nuanced understanding of how various urban environments shape human perceptions.

Despite these initial efforts, most existing studies still conduct perception experiments and factor analyses within a single city or a specific region (Arellana et al., 2020; Sumantri et al., 2022), resulting in conclusions that are less generalizable and lack broader applicability across diverse urban contexts (Kruse et al., 2021). Moreover, research on environmental perceptions has often focused solely on urban settings, implicitly assuming that urban settlements inherently offer better conditions for a livable life, without sufficient critical reflection or breakthrough insights. This has gradually raised important questions: Do residents living in city “centers” have the better environmental perceptions as those in “suburbs”? How should cities be designed to create more pleasant environments for all citizens? These questions highlight the urgent need for more pragmatic, comparative, and critical investigations.

In practice, the construction, development, and renewal of urban environments often unfold in a localized and fragmented manner due to variations in social context, policy priorities, and financial investment. As a result, even within the same city, built environments can exhibit significant spatial heterogeneity across different neighborhoods, projects, and time periods (Chen, Yu, et al., 2023; Gu, Wu, et al., 2024; Xu et al., 2021). This highlights the importance of shifting environmental perception research from broad urban-level analyses to more fine-grained, community-level investigations of spatial disparities. In response to these concerns, this study aims to address the following key research questions:

1) Do residents of city “centers” perceive higher levels of environmental pleasantness compared to those in “suburban” areas?
2) How do specific urban environmental features influence residents' perceived pleasantness?
3) How can insights from communities with higher levels of perceived pleasantness inform future urban planning and design practices?

To systematically address these questions, this study conducts a large-scale empirical analysis across six major cities in the Pearl River Delta region of China, one of the most rapidly urbanizing areas in the world. First, the “urban-suburban-rural” boundaries are delineated through K-means clustering of the Nighttime Light (NTL) data. Subsequently, over 800,000 street view images are collected and evaluated using a deep learning-based “Six-Type-Perception” model that quantifies six dimensions of community-level environmental perception. These perception scores are then visualized and analyzed at the city, district, and community scales. To pinpoint the environmental features that most strongly influence perceived pleasantness, we train an XGBoost regression model and interpret feature contributions using SHAP values. Finally, we conduct qualitative case studies of communities with contrasting pleasantness levels to clarify how specific environmental features drive perceptual disparities.

This study contributes to the field of urban planning in three key ways. First, it provides empirical evidence that challenges the common assumption that urban “centers” inherently offer higher levels of environmental pleasantness. Second, through the integration of deep learning and machine learning approaches, the study identifies specific natural and built environmental features significantly influence residents' perceived pleasantness. Third, by synthesizing findings from high-performing communities, the study proposes evidence-based planning and design recommendations to enhance well-being in urban environments, offering practical guidance for future development and renewal strategies.

2. Study Area and Data

2.1. Research area

This study focuses on six major cities in the Pearl River Delta (PRD) region: Guangzhou (GZ), Shenzhen (SZ), Dongguan (DG), Foshan (FS), Zhongshan (ZS), and Zhuhai (ZH), as shown in Fig. 1. Located in southern China, the PRD is both a geographic and economic hub, recognized as one of the country's three largest urban agglomerations. It is characterized by a dense population, a concentration of innovation centers, and a relatively high GDP compared to other regions. As early as 2015, a World Bank report indicated that the PRD had surpassed Tokyo to become the world's largest urban agglomeration in terms of population and spatial extent (Bie et al., 2015; Gu, Tang, et al., 2024). According to the United Nations Human Settlements Program's World Cities Report, the PRD metropolitan area, anchored by its core cities of Guangzhou, Hong Kong, and Shenzhen, has become the world's largest super-metropolitan region.

We selected these six cities in the Pearl River Delta for their representativeness of diverse urban development levels across different geographic contexts, encompassing both coastal and inland areas, as well as varying urban hierarchies officially defined by the government. Specifically, Guangzhou (GZ) and Shenzhen (SZ) are classified as “core cities,” while Foshan (FS), Dongguan (DG), Zhuhai (ZH), and Zhongshan (ZS) are considered “peripheral cities” (Fang et al., 2024; Haynes & Stough, 2020). Administrative boundary data for all 5475 communities within these cities were obtained from MineData. Based on the availability and completeness of street view images and built environment data (as detailed in Section 2.2), 1286 communities were excluded from the analysis due to their classification as non-residential or undeveloped. As a result, 4189 communities were included as the final units for subsequent analysis.

2.2. Research data

This study primarily utilizes three types of data: 1) street view images, which represent the physical appearance and human perceptions of the community environment; 2) multi-source urban environment datasets, which encompass a wide range of geographic features

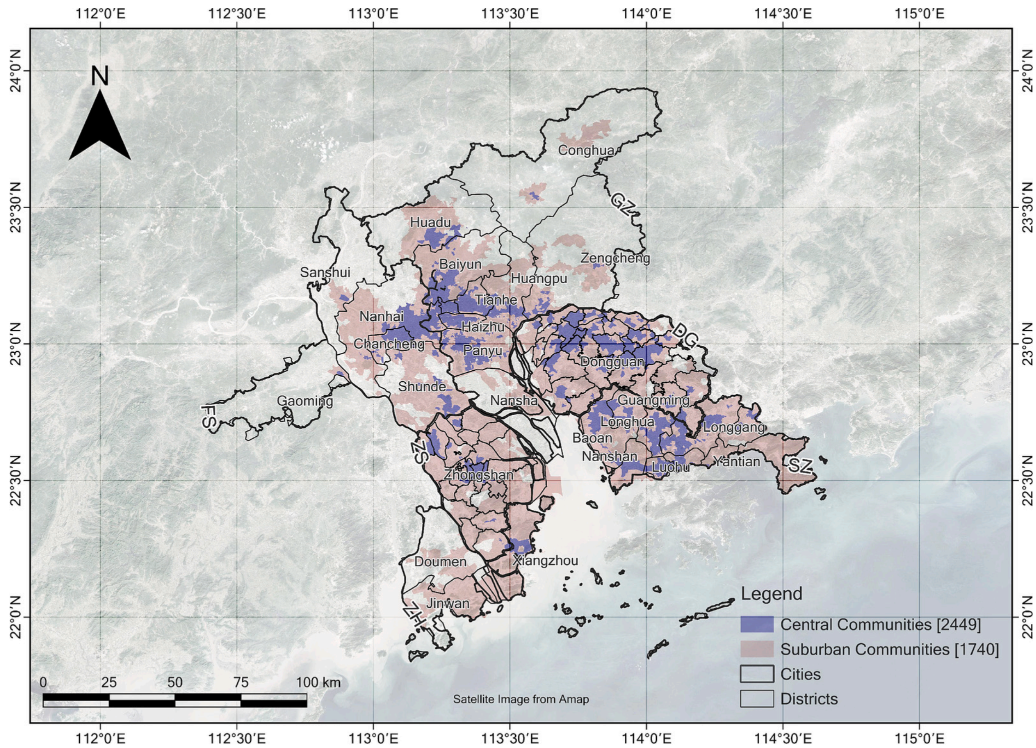


Fig. 1. Location and distribution of the nine research cities in the Pearl River Delta

characterizing the built environment; and 3) socio-economic data. Together, these datasets enable a comprehensive analysis of the relationships between various urban characteristics and perceived community pleasantness.

2.2.1. *Street view images*

The emergence of large-scale geotagged image datasets has significantly enhanced the ability to accurately capture and represent urban visual environments, owing to their rich spatial and topographic information. Moreover, human cognitive and visual perception, as the most direct and intuitive channels through which individuals interact with their surroundings, offer inherent advantages in the holistic comprehension of natural and built scenes. Consequently, street view images serve as a powerful tool for both the quantitative analysis and qualitative interpretation of urban environmental perception (Yao et al., 2019; Zhang et al., 2018).

In this study, street view images were obtained through the application programme interface (API) of Baidu Map Open Platform. Baidu Map is one of the most comprehensive and widely used map services in China, covering mainland China, Hong Kong, Macao, and Taiwan, with high spatial accuracy (Xue & Li, 2020). The data collection process began with extracting the complete road network within the study area, followed by the exclusion of less relevant segments such as overpasses. The remaining road network was segmented at 50-m intervals to generate sampling points. Panoramic street view images were collected at each sampling point between 2019 and 2022. If street view images were unavailable for a given point during this period, historical imagery from the preceding five years was retrieved instead. After rigorous quality filtering and validation of the raw images obtained via the Baidu API, a total of 804,063 high-resolution PNG images were retained for further analysis.

2.2.2. *Multi-source urban environment datasets*

Many previous studies have demonstrated that variations in land use and building types are closely associated with differences in urban environmental perception (Wei et al., 2022; Wu et al., 2023). To further investigate which specific spatial environmental factors contribute to disparities in human perceptions across communities, we identified a total of 12 indicators based on previous relevant research, covering both the built and natural environment dimensions (see Table 1). These indicators include building height, floor area ratio, residential facilities, commercial facilities, institutional facilities, transport facilities, natural mix, natural environment, green space density, canopy height, green view index, and sky view index (Gu et al., 2025; Wei et al., 2022).

The built environment data primarily comprises three categories: building morphology, functional facilities, and land use mix. To extract building morphology indicators, vector data from the 3D-GloBFP dataset were utilized to calculate building density, building height, and floor area ratio (FAR) (Che et al., 2024b, 2024a). The floor area ratio is calculated using the following formula:

$$Floor\ area\ ratio = \frac{S_{building}}{S_{site}} \tag{1}$$

where, the $S_{building}$ is the total area of all building floors and S_{site} is the area of the site.

Functional facilities are represented using Points of Interest (POI) data obtained from AMap, covering a wide range of categories, including companies and enterprises, retail and consumption, dining and cuisine, transportation facilities, financial institutions, hotels and accommodations, educational and cultural institutions, and mixed-use residential and commercial zones. In total, 3,038,765 POI records were collected. The city-wise distribution of these records is as follows: Guangzhou has the highest number with 825,997 records, followed by Shenzhen (717,461), Dongguan (635,079), Foshan (503,190), Zhongshan (246,578), and Zhuhai (110,460). Building upon classification methods established in previous studies (Feng et al., 2024; Wu et al., 2021), the POIs in this study are reclassified into four major categories: residential, commercial, institutional, and transport. The specific POI subtypes included in each category are provided in Table 1.

The land use mix is assessed using entropy-based calculations to quantify the diversity of functional facilities within each community. The concept of entropy originates from thermodynamics, where it de-

Table 1
Urban built and natural environment variables collected in the study.

Variable	Abbreviation	Description	Resource	Reference
Built environment ($n = 8$)				
Building density	BD	The proportion of building footprint to total area of the community.	3D-GloBFP dataset (Che et al., 2024b, 2024a)	(Gu et al., 2025; Xiang et al., 2021)
Building height	BH	The average height of buildings in the community.		
Floor area ratio	FAR	The ratio of the sum of the areas of all building floors with respect to that of the site area.		
Residential facilities	RD	The number of residential facilities (e.g., residence, hotel accommodation, etc).	Amap (https://lbs.amap.com)	(Wei et al., 2022; Wu et al., 2023; Yao et al., 2021)
Commercial facilities	CD	The number of commercial facilities (shopping and dining).		
Institutional facilities	ID	The number of general institutional facilities (e.g., corporate, financial institutions, education and culture, etc).		
Transport facilities	TD	The number of transportation facilities.		
Land use mix	LUM	The land use mix based on the above facilities.		(Wu et al., 2023)
Natural environment ($n = 4$)				
Green space density	GSD	The proportion of green space area within the community of all facilities.	2020 Landsat remote sensing satellite data with a spatial resolution of 30 m (Yang et al., 2019)	(Giannico et al., 2021; Xie et al., 2024)
Canopy height	CH	Average vegetation canopy height on land.	ETH Global Sentinel-2 dataset (2020)	
Green view index	GVI	The percentage of green color in the field of view.	Baidu Map	(Wu et al., 2023)
Sky view index	SVI	The percentage of sky in the field of view.		
Socio-economic characteristics ($n = 4$)				
Gross Domestic Product	GDP	The important indicator represents the economic situation and level of development in an area.	Geographic remote sensing ecological network platform	(Giannico et al., 2021; Gu et al., 2025)
Population density	PD	The proportion of total population to total area of the community.	Worldpop, Age and sex structures, constrained individual countries 2020 UN adjusted (Bondarenko et al., 2020)	
Children percentage	CP	The proportion of the children's population (0 to 15) to the total population of the community.		
	Aging percentage The proportion of aging population (≥ 65) to the total population of the community.	AP		

scribes the degree of disorder or randomness in a system (Guiasu & Shenitzer, 1985; Shannon, 1948). Applied in this urban context, a higher entropy value indicates greater functional diversity, whereas a lower entropy value reflects a more ordered or homogeneous land use pattern. The basic idea behind calculating the land use mix is to assign the objective weights based on the variability of the indicators. The formula for calculating land use mix using entropy is given by:

$$Land\ use\ mix = -\sum_{i=1}^{n} P_i \log P_i \tag{2}$$

where i represents each POI function and P_i means the percentage of i in the total number of POI.

The natural environment data primarily reflect the greenness and openness of urban areas. Urban greening is characterized by three key indicators: green space density, canopy height, and green view index. Green space density is derived from the Normalized Difference Vegetation Index (NDVI), calculated using Landsat satellite imagery from 2020 with a spatial resolution of 30 m (Yang et al., 2019). Canopy height refers to the wall-to-wall height of tree canopies and is obtained from the ETH Global Sentinel-2 dataset (2020), with a ground sampling distance of 10 m. This dataset was accessed via the Google Earth Engine platform and has a spatial resolution of 30 m. The Green View Index and Sky View Index, which reflect the openness and visibility in the street-level environment, were calculated from street view images using a pre-trained DeepLabV3+ semantic segmentation model implemented in GluonCV. The model was trained on the Cityscapes dataset, a benchmark dataset for urban street scene understanding.

Based on these indicators, we compiled comprehensive statistics for all community units within the study area to capture the characteristics of the urban environment. These data were then used to further examine the relationships between specific environmental features and residents' perceived pleasantness.

2.2.3. Socio-economic data

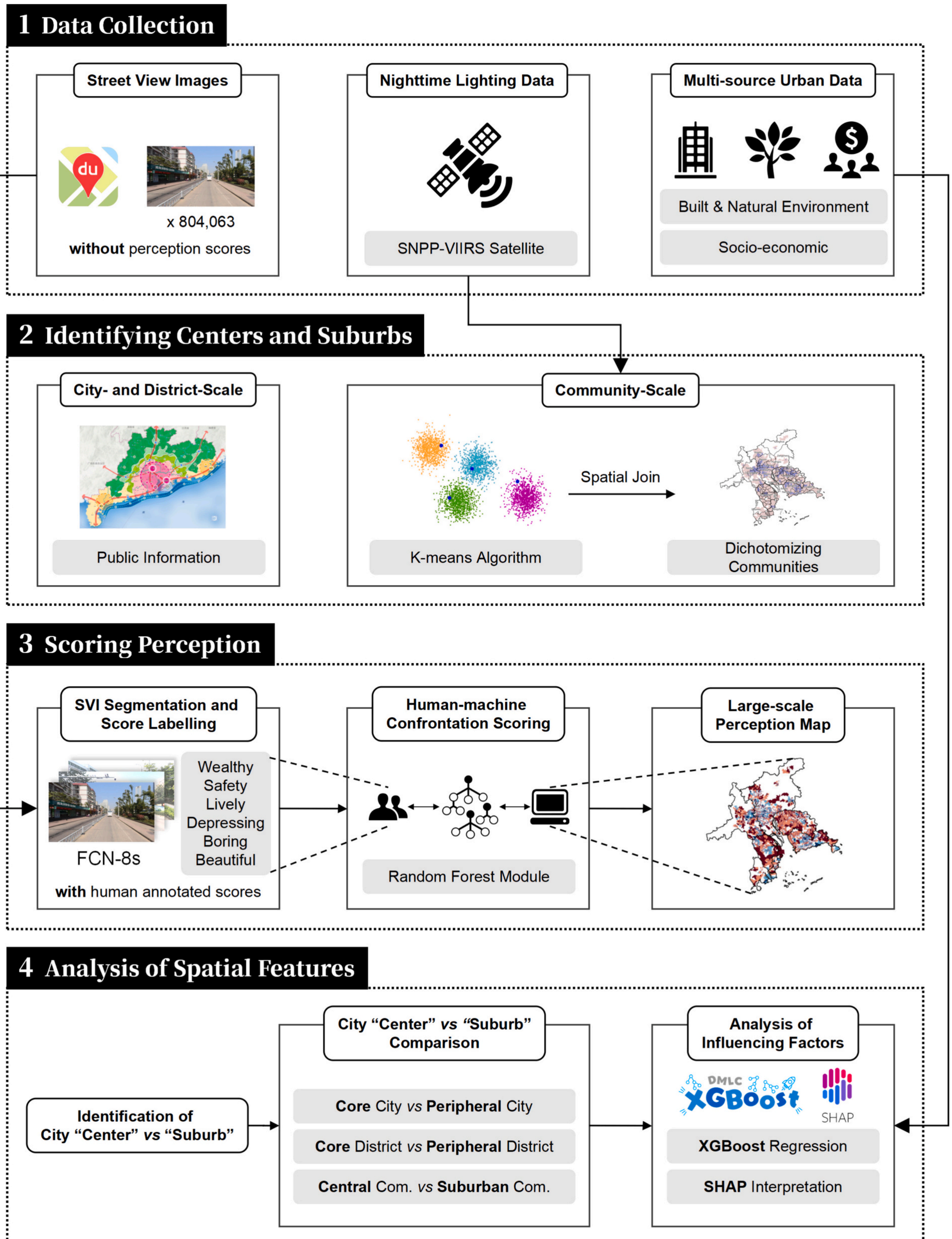
To account for the influence of socio-economic characteristics on residents' perceptions within each community, this study incorporates four indicators: GDP, population density, percentage of children, and percentage of the elderly. As detailed in Table 1, all indicators are sourced from open-source datasets rather than census data, as the latter typically lack the spatial resolution required at the community level.

The GDP data, with a spatial resolution of 1 km, were estimated from national county-level GDP statistics by incorporating multiple proxies for economic activity, such as land use types, nighttime light intensity, and population density. Population data were obtained from the WorldPop database, featuring a spatial resolution of 100 m, adjusted using official United Nations population estimates. All raster values were extracted and aggregated at the community level using ArcGIS Pro.

3. Research Methods

3.1. Research framework

As illustrated in Fig. 2, this study adopts a four-stage research design



Note: Core city, core district, peripheral city, and peripheral district are official definitions by the government that are widely recognized and used.

Fig. 2. The research framework of data collection and analysis in this study.

to investigate the spatial distribution and influencing factors of perceived pleasantness, integrating multi-source data with machine learning techniques:

The first stage involves data collection, including street view images, nighttime lighting data, and multi-source urban datasets covering built and natural environment, and socio-economic variables. This data provides a comprehensive foundation for the subsequent spatial classification and perception modeling.

In the second stage, the study identifies “centers” and “suburbs” across multiple spatial levels. At the city and district scales, center areas are delineated based on official public information. At the community level, a K-means clustering algorithm is applied to relevant features, and spatial join operations are used to classify each community as either a central or suburban community. This spatial categorization establishes the framework for comparing environmental perceptions.

The third stage focuses on scoring environmental perception. Street view images are semantically segmented and annotated with perceptual attributes such as “Wealthy,” “Safe,” “Lively,” “Depressing,” “Boring,” and “Beautiful.” A neural network is trained on a crowd-sourced dataset of labeled images and then applied across the entire study area to predict perception scores, thereby generating a large-scale urban perception map that reveals the spatial distribution of perceived pleasantness.

In the final stage, the study analyzes spatial features and identifies key factors influencing perception disparities between urban “centers” and “suburbs.” An XGBoost regression model is employed to quantify the relationship between environmental variables and pleasantness scores. SHapley Additive exPlanations (SHAP) values are used to interpret the contribution of each variable, offering insights into how different environmental characteristics shape residents' perceptions and revealing spatial inequality in exposure to pleasant urban environments.

3.2. Identification of urban “center” and “suburb”

Using government public information, it is relatively straightforward to distinguish core cities and districts from peripheral ones in the Pearl River Delta. However, to further account for spatial heterogeneity within each city or district, this study further classifies communities as either central or suburban. We adopt the methodology proposed by Liu et al. (2022) to determine the boundaries of central and suburban communities for the six selected cities.

Specifically, we apply the K-means clustering algorithm to 500-m resolution SNPP-VIIRS nighttime light data obtained from NASA satellites to differentiate light intensity patterns. The underlying rationale is that urban “centers” are typically characterized by concentrated, continuous, and homogeneous human socio-economic activity (Shi et al., 2023). Previous studies have proved nighttime light intensity to correlate closely with such activities, effectively capturing the spatial aggregation of urban functions and reflecting distinctions between urban “centers” and “suburbs” (Fan et al., 2014; Liu et al., 2020).

The clustering results are then cross-validated with urban area classifications from the MCD12Q1 dataset (500-m resolution), a globally recognized land cover product derived from MODIS satellite imagery (He et al., 2019; Liu et al., 2022). The resulting urban “center” boundaries align well with established classifications. Finally, we spatially overlay the identified urban “center” extents with the community-level administrative boundaries using the spatial join tool in ArcGIS Pro, classifying the 4189 communities into 2449 central and 1740 suburban units, as illustrated in Fig. 1.

3.3. Semantic segmentation and perceptual measurement of street view

To efficiently evaluate urban perception at a large scale, this study adopts the high-efficiency “Six-Type-Perception” framework proposed by Dubey et al. (2016). In the process of human-machine interaction scoring, deep learning technology and iterative feedback mechanisms are employed for semantic segmentation and perceptual measurement of a large number of street view images. This method primarily focuses on six dimensions of urban perception: safe, lively, beautiful, wealthy, depressing, and boring. The overall identification and scoring process of street view image is structured into the following steps:

First, the Pyramid Scene Parsing Network (PSPnet) is applied for the semantic segmentation of street view images. This model enables the classification of each image pixel into predefined natural object categories such as vehicles, roads, trees, and buildings. It employs a Pyramid Pooling Module to capture multi-scale contextual information, thereby enhancing the semantic understanding and segmentation accuracy of street scenes. Based on the pixel proportions of segmented categories, a multi-dimensional feature vector is generated to represent each street view.

Second, Dubey et al. (2016) collected a large dataset by recruiting 81,630 respondents with diverse socio-economic backgrounds from 56 cities worldwide (including seven in Asia) to rate street scenes. This dataset, comprising human-labeled perceptual scores, serves as the foundation for model training. By combining crowdsourcing with neural network-based regression, the model simulates the human scoring process. In the early stages, users manually rate a subset of images, which enables the model to establish a prediction function. During subsequent iterations, the system suggests predicted scores, which are then refined through human correction and validation, producing a robust human-machine confrontation scoring dataset.

Lastly, the driving factors behind urban perception are examined from both visual and functional perspectives. Using a random forest-based optimization model embedded within the perception framework, perceptual scores are generated across all street view images at the city scale. This method has been validated in several recent studies on street view-based urban perception (Biljecki & Ito, 2021; Yao et al., 2019; Zhu et al., 2025) and supports the large-scale measurement of the six perceptual dimensions across the studied cities.

3.4. Synthetic score of pleasant environment in communities

Based on the preceding measurements of urban perception, the average values of six perception dimensions, namely safe, lively, beautiful, wealthy, depressing, and boring, are calculated for each community. Among these, safe, lively, beautiful, and wealthy are considered to positively contribute to the perception of a pleasant environment (PE), while depressing and boring are treated as negative indicators.

To ensure that no single perception dimension disproportionately influences the final PE score, all six dimensions are first standardized. This normalization step guarantees that each dimension carries equal importance in the analysis. Furthermore, equal weights are assigned to all six indicators to simplify the calculation process and eliminate potential subjective bias. The final PE score for each community thus reflects a balanced aggregation of both positive and negative perceptual indicators. The calculation of the synthetic PE score is presented in Formula (3).

$$PE = \sum_{i}^{4} positive_i * \frac{1}{6} - \sum_{i}^{2} negative_i * \frac{1}{6} \quad (3)$$

where, PE denotes the overall pleasant environment score of a community, and $positive_i$ and $negative_i$ represent the standardized values of corresponding perception dimensions.

3.5. Relationship between perceived pleasantness and urban environments

To examine the relationship between PE scores and various features of urban environments, this study first establishes regression models to explore these associations. Initially, the Ordinary Least Squares (OLS) method in ArcGIS Pro is employed to model linear relationships and test for multicollinearity using the Variance Inflation Factor (VIF). VIF values below 10 indicate no significant multicollinearity, allowing the variables to be used in further regression analysis.

Among several non-linear modeling approaches, this study adopts the eXtreme Gradient Boosting (XGBoost) algorithm, an advanced machine learning regression method proposed by Chen and Guestrin (2016), after comparing its performance with other commonly used models. XGBoost, an enhanced version of Gradient Boosting Decision Trees, has demonstrated strong predictive capabilities and has been widely applied in spatial analysis studies (Doan et al., 2025; Gu, Wu, et al., 2024; Yang et al., 2024; Yuan et al., 2024).

To ensure comparability, all input indicators are standardized to unify measurement scales. The dataset is then split into a training set (75 %) and a test set (25 %). A grid search with cross-validation is conducted to optimize model parameters, yielding the following configuration: alpha = 0.2, learning rate = 0.2, max depth = 5, and n_estimators = 80. The model's performance is evaluated using standard metrics, including Root Mean Square Error (RMSE), coefficient of determination (R^2), and Mean Absolute Error (MAE).

Although XGBoost exhibits excellent predictive accuracy, like many machine learning models, it functions as a “black box,” identifying feature importance without explicitly explaining how each feature affects the prediction (Gu, Wu, et al., 2024). To address this, the study incorporates SHapley Additive exPlanations (SHAP) to interpret the model output and quantify both the importance and the direction (positive or negative) of each feature's influence.

SHAP is grounded in cooperative game theory and conceptualizes each feature as a “contributor” to the model's output. For each prediction sample, the model outputs a prediction value, and SHAP assigns a value to each feature, indicating its marginal contribution to that prediction. Assuming the i sample is x_i, the j feature of the i sample is x_{ij}, the model's prediction value for this sample is y_i, and the baseline of the entire model (usually the mean of the target variable across all samples) is y_{base}, then the SHAP value adheres to the following formula:

$$y_i = y_{base} + f(x_{i1}) + f(x_{i2}) + \ldots + f(x_{ij}) \tag{4}$$

where, $f(x_{ij})$ is the SHAP value of x_{ij}. Specifically, $f(x_{i1})$ represents the contribution of the first feature in the i sample to the final predicted value y_i. When $f(x_{i1}) > 0$, it indicates that this feature increases the predicted value, i.e., it has a positive effect. Conversely, if $f(x_{i1}) < 0$, it suggests that the feature decreases the predicted value, thus exerting a negative effect.

4. Results

4.1. Core cities/districts vs. peripheral cities/districts

Based on statistical summaries at the city and district scales, this section compares the perceived pleasantness of core versus peripheral cities and districts in the Pearl River Delta. The left panel of Fig. 3 presents differences in scores across six perception dimensions between core and peripheral cities, representing the first level of spatial scale in our analysis. The results show that peripheral cities outperform core cities in all four positive perception dimensions, namely safe, lively, beautiful, and wealthy. For negative perceptions, peripheral cities also score better than core cities on the “depressing” dimension, with a highly significant mean difference of approximately 0.7. The only exception is the “boring” dimension, where peripheral cities score lower. By aggregating the six perception dimensions using Formula (3), the overall Pleasant Environment (PE) scores were computed, revealing that peripheral cities significantly outperform core cities.

The right panel of Fig. 3 compares scores between core and peripheral districts within each of the six cities, constituting the second spatial scale of analysis. Here, administrative divisions are used as the units of analysis (for Dongguan and Zhongshan, which lack formal district divisions, planning zones or sub-districts with comparable spatial scale and delineation are used instead). For the three positive perception dimensions (safe, lively, and beautiful), five cities (excluding Dongguan) report higher scores for peripheral districts. In Dongguan, the score differences between peripheral and core districts across all dimensions are minimal. For the wealthy dimension, peripheral districts in Shenzhen, Foshan, and Zhongshan perform better, while core districts score higher in Guangzhou and Dongguan. In Zhuhai, the two types of districts yield similar results, with a slight edge for core districts.

Regarding the two negative dimensions (depressing and boring), peripheral districts consistently score lower on “depressing” but higher on “boring.” Overall, with the exception of Dongguan, peripheral districts in the other five cities exhibit higher PE scores than their core counterparts. Notably, Foshan and Zhongshan show the most significant disparities, with mean differences in PE reaching approximately 0.9 and 1.0, respectively. In Dongguan, the mean PE difference is about 0.2.

4.2. Central communities vs. suburban communities

This section focuses on the community scale within cities, representing the third level of our analysis. We begin by comparing central and suburban communities across each city using grouped box plots (Fig. 4). The left panel of Fig. 4 illustrates the differences in Pleasant Environment (PE) scores between central and suburban communities in the six study cities. In all cities, the mean and median PE scores of suburban communities are higher than those of their central counterparts, with the most pronounced differences observed in Foshan and Zhongshan.

A Kolmogorov-Smirnov normality test indicates that the PE score distributions for both central and suburban communities approximately follow a normal distribution. Therefore, an independent two-sample t-test was conducted to determine whether the differences in mean PE scores between central and suburban communities are statistically significant. As shown by the p-values in Fig. 4, the differences are

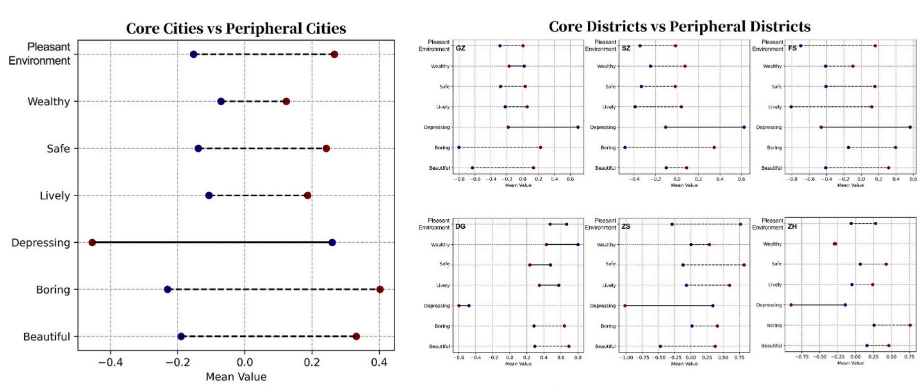


Fig. 3. Statistical comparison between the six research cities in Pearl River Delta.

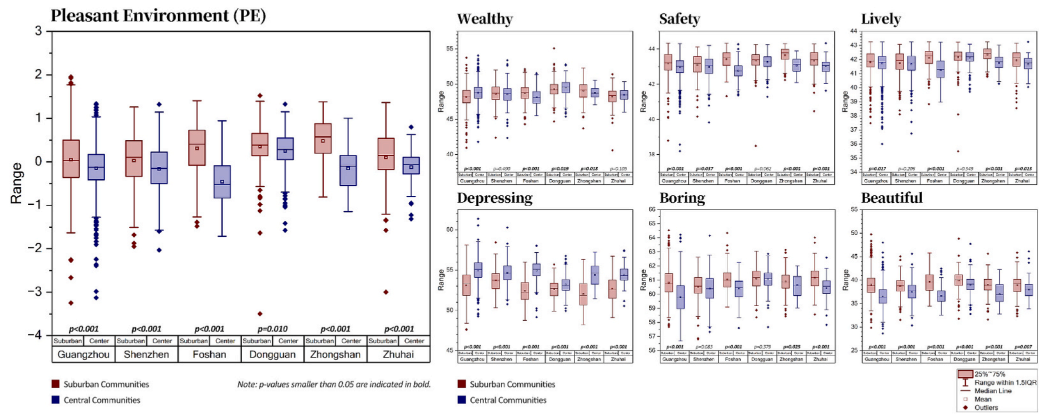


Fig. 4. Statistical comparison between the central and suburban communities in six research cities.

significant at the 0.01 level in all six cities.

The right panel of Fig. 4 provides a breakdown of the six perception dimensions between central and suburban communities. For positive perceptions (safe, lively, and beautiful) and the negative perception of "boring," all six cities show that suburban communities have higher mean and median scores than central communities. For the negative perception of "depressing," suburban communities consistently show lower scores across all cities. Regarding the "wealthy" dimension, suburban communities outperform central ones in Foshan and Zhongshan, while the opposite pattern is observed in Guangzhou and Dongguan. No statistically significant differences in wealthy perception are found between central and suburban communities in Shenzhen and Zhuhai ($p >$ 0.05).

The statistical results from the 4189 community study units are further illustrated in the spatial map in Fig. 5. In this map, communities within the red urban boundaries are defined as central communities. The scores for the three positive perception dimensions (beautiful, lively, and safe) demonstrate similar spatial distribution patterns: communities located near the urban "center" tend to have lower scores, whereas those in "suburban" areas score higher. Interestingly, the spatial distribution of lively and safe perceptions shows almost identical patterns. The wealthy perception exhibits a less consistent spatial distribution. For the negative perception dimensions, depressing and boring display contrasting spatial patterns. Communities in urban "centers" tend to have higher depressing scores, with a noticeable gradient of decreasing values toward the "suburbs." In contrast, boring scores are generally lower in central communities. Regarding overall PE, all six cities show that suburban communities have higher scores. In particular, Zhongshan, Guangzhou, and Foshan exhibit a tree-ring-like spatial distribution pattern, indicating that the further a community is located from the urban "center," the higher its overall PE tends to be.

4.3. *Influencing environmental features of perceived pleasantness*

To further investigate the factors contributing to the spatial heterogeneity of urban perception across the six cities, this study constructed a regression model relating pleasantness scores to urban environmental characteristics, using 4189 communities as the analysis units. Initially, an Ordinary Least Squares (OLS) model was employed to capture linear relationships, with the results summarized in Table 2. Although the OLS model provides regression coefficients for the relationship between each variable and PE, the model's overall fit is relatively weak, with an adjusted R-squared value of only about 0.12. This suggests that the relationship between PE and the selected features is complex and non-linear, thus making the OLS model inadequate for accurate prediction. Consequently, a non-linear modeling approach is warranted.

The performance of the XGBoost regression model significantly outperforms that of OLS, as shown in Table 3. Fig. 6 presents the

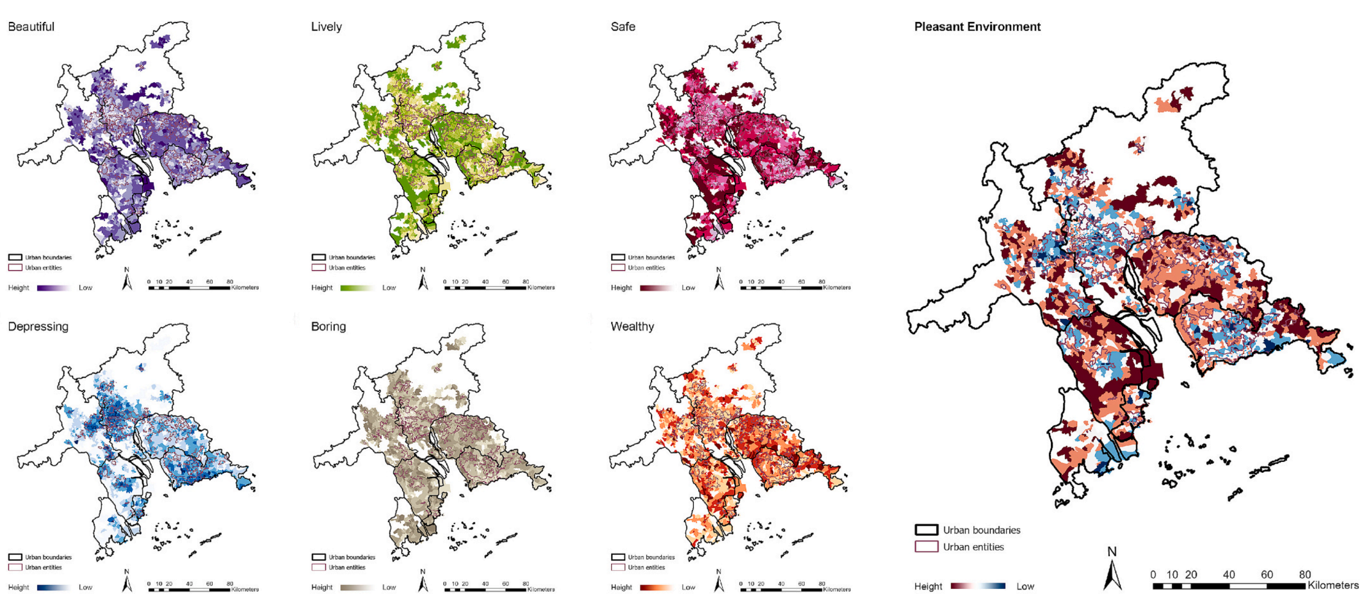


Fig. 5. Spatial distributions of human perceptions in the 4000+ research communities.

Table 2
Coefficient and VIF results of Ordinary Least Square (OLS) model in the study.

Variable	Coefficient	Probability	VIF
Built environment (n = 8)			
Building density	−1.514331	0.000000*	6.800350
Building height	−0.015265	0.000000*	4.060027
Floor area ratio	0.166315	0.000000*	9.649716
Residential density	−0.000569	0.365703	2.283246
Commercial density	0.000047	0.441695	4.384526
Institutional density	0.000178	0.022244*	3.678936
Transport density	−0.000274	0.026519*	4.861066
Land use mix	−0.021575	0.916830	1.139898
Natural environment ($n = 4$)			
Green space density	0.000197	0.679873	2.901994
Canopy height	−0.001454	0.768021	4.376454
Green view index	−0.915778	0.000000*	1.475656
Sky view index	0.879674	0.000000*	2.366893
Socio-economic characteristics (n = 4)			
Gross Domestic Product	−0.000000	0.001106*	1.816967
Population density	−0.031525	0.062244	1.004765
Children percentage	−3.417164	0.000001*	1.246376
Aging percentage	0.846321	0.006020*	1.616641

Note: Asterisk (*) indicates a coefficient is statistically significant ($p < 0.01$)

Table 3
Model performance results of the eXtreme Gradient Boosting (XGBoost) model.

Variable	R2	RMSE	MAE
Trained XGBoost model	0.801502	0.234092	0.179637
Tested XGBoost model	0.738501	0.195782	0.151798

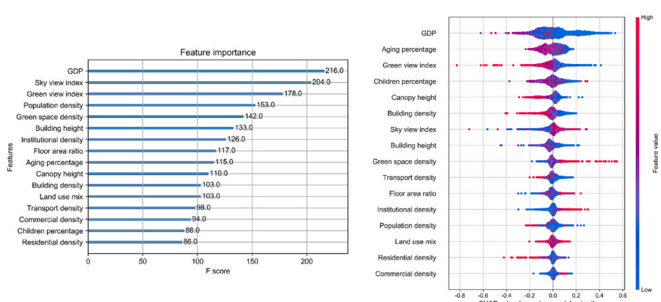


Fig. 6. Contribution of each urban environment to the pleasant environment.

XGBoost model results, including the feature importance ranking derived from the model training process and the direction and magnitude of feature impacts on predicted PE scores, as interpreted using SHAP values.

As illustrated in Fig. 6, the predictors of perceived pleasantness can be grouped into three major dimensions. Socio-economic characteristics rank as the most influential. Among these, Gross Community Product (GCP) emerges as the most important factor (F = 216), reflecting the strength of local economic activity, followed by population density (F = 153). In contrast, demographic indicators such as aging percentage (F = 115) and children percentage (F = 88) exert relatively limited influence. Natural environmental features represent the second most influential dimension. The sky view index (F = 204), which captures spatial openness, along with the green view index (F = 178) and green space density (F = 142), together shape visual perceptions of the urban environment. In the built environment category, physical form indicators such as building height (F = 133), floor area ratio (F = 117), and building density (F = 103) exhibit moderate predictive power. Among functional facilities, only institutional density (F = 126) shows a strong association with PE, whereas other types, like transport and residential facility density, play a weaker role. These findings reflect a layered structure of influences, with socio-economic vitality and natural openness emerging as the primary contributors to perceived pleasantness.

The SHAP analysis further reveals distinct directional patterns. First, higher values of socio-economic indicators such as GDP, population density, aging percentage, and children percentage are consistently associated with lower pleasantness scores. Second, natural environmental features demonstrate mixed effects: While higher sky view index and green space density positively contribute to pleasantness, the green view index and canopy height exhibit diminishing or even negative effects beyond certain thresholds. Third, built environment indicators also show divergent trends. Densities of buildings, transport facilities, and residential facilities are negatively correlated with PE, whereas higher floor area ratio, institutional facility density, and commercial facility density contribute positively. Notably, building height and land use mix display non-linear relationships with PE, suggesting context-dependent impacts rather than simple directional trends.

Based on these findings, certain environmental features can be inferred as characteristics of communities with higher or lower perceived pleasantness. Communities with higher PE tend to feature greater sky openness, greater green space density, and lower canopy height in terms of natural elements. From a built environment perspective, they typically exhibit lower densities of buildings, transport, and residential facilities, coupled with higher floor area ratios, institutional facility density, and commercial facility density. Importantly, in contrast to green space density, a high green view index does not necessarily correspond to higher perceived pleasantness, suggesting that the visual presence of greenery alone may not always translate into positive environmental perceptions.

4.4. Case studies of communities with disparate pleasantness scores

Based on the preceding analysis, this study selects communities with the highest and lowest Pleasant Environment (PE) scores across three spatial scales (core cities vs. peripheral cities, core districts vs. Peripheral districts, and central communities vs. Suburban communities) to conduct in-depth case studies. These selections enable a comparative exploration of the differences in perceived pleasantness between urban "centers" and "suburbs," as well as the underlying environmental factors that drive these disparities. In total, 24 communities are identified across the six cities, with four cases selected per city, as shown in Fig. 7.

The typical street view images in Fig. 7 are manually selected to illustrate the key functional and environmental characteristics of each community. These images are taken from public municipal roads rather than internal residential roads, such as those found in gated communities, which tend to have limited public accessibility. However, it should be noted that each street view image is not intended to represent the overall or average perception of the entire community but rather to convey typical visual scenes.

To facilitate comparison, communities are classified into four categories: those located in core districts of core cities, peripheral districts of core cities, core districts of peripheral cities, and peripheral districts of peripheral cities. Within each category, both central and suburban communities are selected, resulting in eight representative communities for detailed comparative analysis. This classification helps to better understand how different spatial contexts influence residents' perceptions of pleasantness and the contributing environmental features.

Overall, suburban communities tend to achieve higher pleasant environment (PE) scores than central communities, regardless of whether they are located in the core or peripheral districts of core or peripheral cities. For example, Shiliugang Community in Haizhu District, Guangzhou (PE = 1.928), and Yangguang Community in Nanshan District, Shenzhen (PE = 1.041), both suburban communities in core districts of core cities, exhibit high PE scores. In contrast, some central communities in peripheral districts of peripheral cities show lower PE

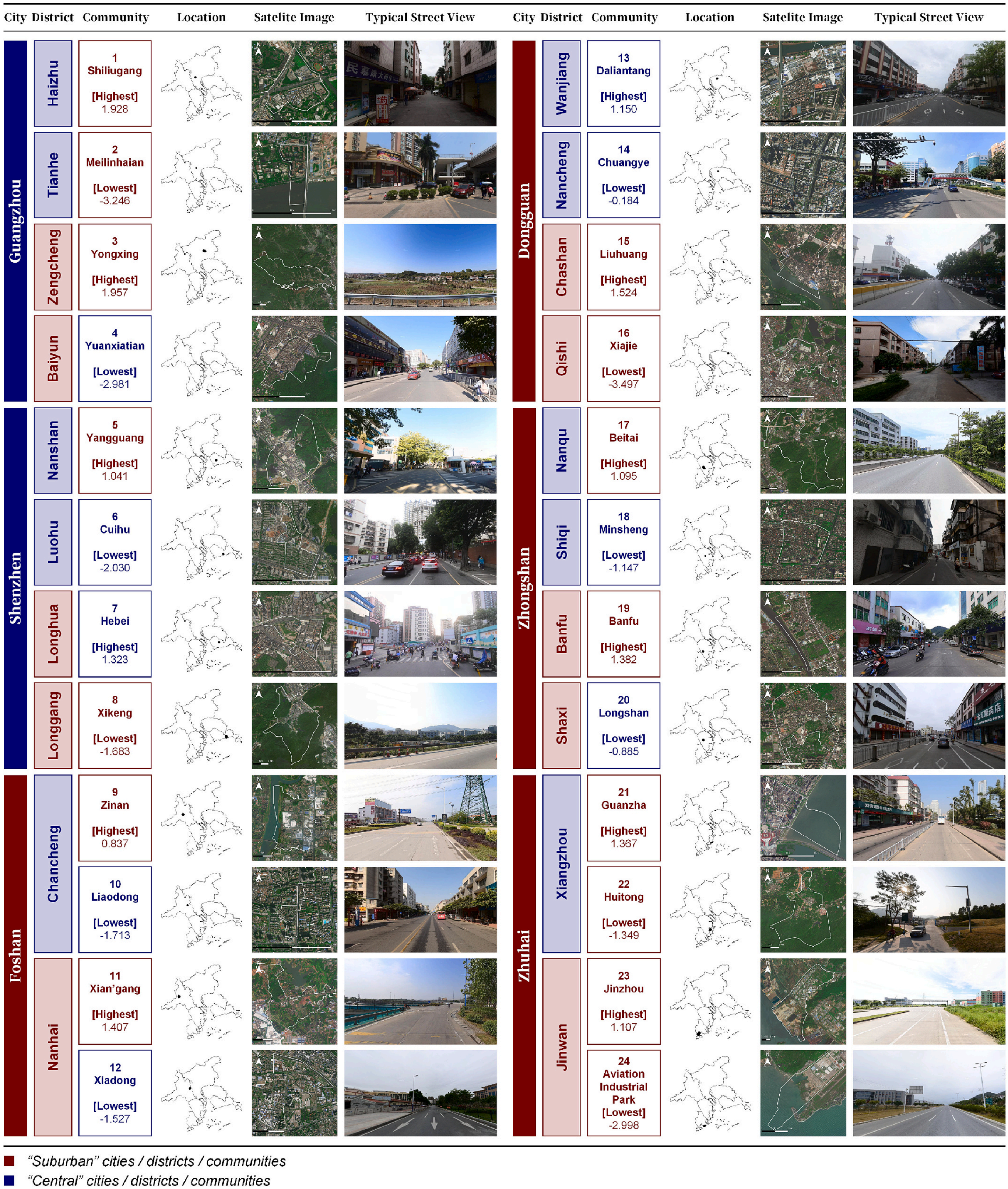


Fig. 7. Typical communities selected for detailed urban perception analysis.

scores, such as Xiadong Community in Nanhai District, Foshan (PE = −1.527), and Longshan Community in Shaxi District, Zhongshan (PE = −0.885). However, exceptions exist, where some central communities achieve higher PE than nearby suburban communities, such as Hebei Community in Longhua District, Shenzhen (PE = 1.323). The environmental characteristics of these typical communities are summarized as follows.

First, within core districts of core cities, Cuihu Community in Luohu District, Shenzhen, is a typical central community with a relatively low PE score of −2.030. It is mainly composed of large low-rise residential complexes, along with primary and secondary schools and shopping malls. The presence of noise barriers and retaining walls along public roads, combined with high building density, contributes to a less favorable environment. As shown in Table 4, Cuihu Community has the lowest sky view index (0.082) among all cases, while its green space density is moderate (122.605), and both institutional and commercial facility densities are low. In contrast, Yangguang Community, a suburban community though located in a core district of a core city, has a considerably higher PE score (1.041). It features industrial parks and residential areas, is adjacent to extensive mountainous green spaces, has fewer high-traffic roads, and benefits from well-maintained green street interfaces. According to Table 4, it has a much higher sky view index and green space density (157.446), along with lower building density (0.095) and higher institutional and commercial densities.

Second, in the peripheral districts of core cities, Yuanxiatian Community in Baiyun District, Guangzhou, is a central community with a low PE score of −2.981. This area includes urban villages, high-rise office buildings, and industrial zones. While it has the highest green space density (185.061) among all cases, it suffers from a low sky view index (0.092) and a very high transport facility density (345). On the other hand, Yongxing Community, a suburban community in Zengcheng District, Guangzhou, achieves a high PE score of 1.957. Situated in a more remote suburban location, it is surrounded by natural mountainous areas with scattered low-rise residences. Its sky view index is significantly higher (0.415), and it has the second-highest green space density (184.312), with low building, residential, and transport facility densities.

Third, within the core districts of peripheral cities, Liaodong Community, a central community in Chancheng District, Foshan, has a relatively low PE score of −1.713. It is characterized by high-rise residential complexes and a limited number of commercial and office facilities. According to Table 4, it has a moderate sky view index (0.235) and green space density (90.720), but its building density (0.536) is the second highest among all communities analyzed. In contrast, Zinan Community, a suburban community also in Chancheng District, achieves a higher PE score of 0.837. This community features industrial parks, multiple schools, and mid-to-high-rise residential buildings. It is located near the Dongping Waterway and is rich in green and water spaces. Its sky view index and green space density are slightly higher than those of Liaodong Community, while its building density (0.220) is significantly lower. Moreover, its institutional (80) and commercial (241) facility densities are substantially greater than those of Liaodong.

Lastly, as a central community in a peripheral district of a peripheral city, Longshan Village in Shaxi District, Zhongshan, has a relatively low PE score of −0.885. It features low-rise residences, schools, and abundant green spaces and parks. The sky view index (0.263) is moderate, and the green space density is relatively high (104.320). Despite being in a peripheral location, its building density (0.345) remains relatively high. In contrast, Banfu Community in Banfu District, Zhongshan, a suburban community, exhibits a higher PE score (1.382). It comprises mid-to-low-rise and high-rise residential buildings and is located near the Shiqi River, surrounded by ample green spaces. As per Table 4, Banfu's green space density is relatively high (110.744), and its transport facility density (9) is significantly lower than that of Longshan Village (38).

5. Discussion

5.1. Center-suburban perception disparities and underlying mechanism

This study reveals a significant center-suburban disparity in environmental pleasantness perception, providing new evidence that suburban areas are perceived as more pleasant than central areas across multiple spatial scales in the Pearl River Delta. Through statistical and geospatial analyses of large-scale street view images, we further mapped the spatial patterns of these disparities and explored the underlying correlations between environmental characteristics and perceived pleasantness.

"Peripheral cities," "peripheral districts," and "communities in suburban areas" demonstrate statistically superior environmental

Table 4

Statistical results of typical communities with respect to Building density (BD), Building height (BH), Floor area ratio (FAR), Residential density (RD), Commercial density (CD), Institutional density (ID), Transport density (TD), Land use mix (LUM), Green space density (GSD), Canopy height (CH), Green view index (GVI), and Sky view index (SVI).

City	District	Community	PE	Built Environment (n = 8)								Natural Environment (n = 4)			
				BD	BH	FAR	RD	CD	ID	TD	LUM	GSD	CH	GVI	SVI
GZ	Haizhu	Shiliugang	1.928	0.061	9.973	0.221	5	23	16	18	0.566	138.639	9.401	0.328	0.247
	Tianhe	Meilinhaian	−3.246	0.036	4.079	0.057	4	57	34	31	0.538	34.105	0.941	0.076	0.482
	Zengcheng	Yongxing	1.957	0.013	6.707	0.033	0	24	17	5	0.544	184.312	15.431	0.082	0.415
	Baiyun	Yuanxiatian	−2.981	0.020	7.383	0.054	22	366	319	345	0.567	185.061	18.747	0.698	0.092
SZ	Nanshan	Yangguang	1.041	0.095	13.249	0.566	10	122	91	86	0.564	157.446	11.357	0.096	0.285
	Luohu	Cuihu	−2.030	0.048	8.996	0.152	0	18	6	8	0.518	122.605	6.868	0.702	0.082
	Longhua	Hebei	1.323	0.320	17.923	2.207	11	167	81	71	0.569	74.564	1.334	0.057	0.295
	Longgang	Xikeng	−1.683	0.056	12.046	0.276	2	54	68	35	0.532	179.026	16.438	0.271	0.152
FS	Chancheng	Zinan	0.837	0.220	8.105	0.866	6	241	80	50	0.544	94.870	3.562	0.178	0.251
		Liaodong	−1.713	0.536	12.672	2.769	6	86	9	15	0.500	90.720	1.220	0.253	0.235
	Nanhai	Xian'gang	1.407	0.055	7.968	0.270	10	82	90	25	0.532	128.153	7.361	0.138	0.452
		Xiadong	−1.527	0.287	7.280	0.950	19	486	413	170	0.562	91.513	2.748	0.262	0.326
DG	Wanjiang	Daliantang	1.150	0.283	15.033	1.854	26	212	143	119	0.570	96.748	3.679	0.099	0.286
	Nancheng	Chuangye	−0.184	0.564	12.880	3.688	4	165	186	63	0.544	92.696	2.543	0.362	0.194
	Chashan	Liuhuang	1.524	0.207	7.916	0.618	3	32	78	34	0.530	89.854	3.850	0.191	0.323
	Qishi	Xiajie	−3.497	0.248	7.340	0.757	2	42	51	21	0.564	106.850	4.265	0.168	0.297
ZS	Nanqu	Beitai	1.095	0.029	7.165	0.092	8	62	51	32	0.534	168.782	15.154	0.238	0.300
	Shiqi	Minsheng	−1.147	0.323	15.632	2.478	28	484	131	234	0.564	96.473	3.320	0.214	0.128
	Banfu	Banfu	1.382	0.330	10.412	1.328	3	7	18	9	0.530	110.744	5.517	0.140	0.115
	Shaxi	Longshan	−0.885	0.345	9.437	1.265	7	136	133	38	0.558	104.320	4.918	0.156	0.263
ZH	Xiangzhou	Guanzha	1.367	0.001	106.979	0.051	29	97	84	75	0.577	3.295	0.121	0.199	0.171
		Huitong	−1.349	0.014	9.894	0.061	0	20	11	6	0.495	175.087	16.062	0.341	0.208
	Jinwan	Jinzhou	1.107	0.050	13.025	0.251	8	124	292	43	0.509	0.000	6.359	0.155	0.453
		Aviation Industrial Park	−2.998	0.024	22.072	0.125	32	290	141	185	0.567	0.000	4.077	0.170	0.501

Note: Red denotes "suburban" cities, districts, and communities; blue denotes "central" cities, districts, and communities.

pleasantness perception compared to "core cities," "core districts," and "communities in urban core areas," challenging the prevailing assumption that more urbanized areas inherently provide greater pleasantness for residents (Arellana et al., 2020; Kruse et al., 2021; Sumantri et al., 2022). Geospatial analysis reveals a clear concentric gradient pattern, where perceived pleasantness systematically increases with distance from urban cores. This spatial disparity aligns with variations in multidimensional urban characteristics (Fig. 5). Further regression analysis elucidates the underlying mechanisms, highlighting how socioeconomic factors, built environment parameters, and natural environment metrics collectively shape these perceptual differences (Gim, 2020; Leyden et al., 2011; Putnam, 2000; Verma et al., 2020).

First, the sky view index emerges as a critical determinant of environmental pleasantness, further supporting similar conclusions from previous studies (Buttazzoni & Minaker, 2023; Le et al., 2024; Masoudinejad & Hartig, 2020). Not only does it directly impact residents' visual perception, but it also has a certain relationship with other variables, such as building density, building height, green view index, and canopy height (Chiang et al., 2023; Fujiwara et al., 2024; Gong et al., 2018). A higher sky view index is typically associated with lower building density and more extensive open spaces. Existing studies have shown that these environmental features help reduce urban heat island effects, improve air circulation, and increase natural light (Chen, Meili, et al., 2023; Chiang et al., 2023; Dirksen et al., 2019; Fujiwara et al., 2024; Kim et al., 2022; Yao et al., 2024), while also reducing stress and enhancing subjective comfort, thus positively impacting mental health (Chen et al., 2022; Liu, Yu, et al., 2024; Mohite & Surawar, 2024).

Second, although increasing the green view index and green space density is generally regarded as an effective strategy for enhancing environmental pleasantness, our findings challenge this assumption by revealing substantial variability in their actual effectiveness across different communities (Cheng et al., 2024; Foster et al., 2024; Liu & Liao, 2024; Navarrete-Hernandez et al., 2024; Yao et al., 2024). When the visual aesthetics of green spaces are poor or when their utilization rates and accessibility are low, their contribution to perceived pleasantness becomes limited. For instance, although the Cuihu community in Luohu District, Shenzhen, exhibits a high green view index, its pleasantness score is not notably high. This may be attributed to the predominance of tall and dense street trees, which obstruct sky visibility and negatively affect streetscape visual quality (Chiang et al., 2023). This finding also helps explain the inconsistent conclusions in previous studies regarding the correlation between green exposure and mental health (Helbich et al., 2019, 2021; Liu et al., 2019; Navarrete-Hernandez et al., 2024). Furthermore, the impact of canopy height on pleasantness appears consistent with that of the green view index, suggesting that excessive canopy height would diminish perceived pleasantness.

Third, suburban areas exhibit significantly lower transport facility density, and our findings highlight that higher transport facility density has a pronounced negative impact on environmental pleasantness, which partially reflects the phenomenon of "Not In My Back Yard" (Guo et al., 2015; Wen et al., 2022). On the one hand, increases in the density of commercial and institutional facilities can generally enhance perceived pleasantness, relying on the support of transportation and other infrastructure. On the other hand, however, the presence of high-traffic roads, elevated highways, and subway stations often degrades the surrounding environmental quality and adversely affects residents' perceptions. Previous studies have further suggested that the provision of appropriate compensatory facilities can help mitigate the negative perceptions associated with NIMBY attitudes (Wen et al., 2022).

Lastly, the regression results indicate that residents generally prefer communities with relatively lower building density, greater building height, and higher floor area ratios. This preference suggests a stronger appreciation for visual openness and streetscape quality at eye level (Cheng et al., 2024; Zeng et al., 2024). Such tendencies may partially resonate with Le Corbusier's vision of the "Radiant City," where future urban development would emphasize vertical growth to accommodate high-density living demands while preserving green spaces and public parks rather than promoting unchecked horizontal sprawl (LeGates, 2014).

5.2. Practical suggestions for improving environmental pleasantness

Traditional urban planning often adopts a functionalist perspective, assuming that central urban areas, with their richer amenities and resources, inherently provide higher levels of environmental pleasantness (He et al., 2024). However, our findings suggest that this assumption may overlook key factors related to human perception. Based on the regression analysis of environmental features influencing pleasantness perception, we propose several recommendations for urban planning and landscape design to more effectively enhance residents' perception of environmental pleasantness and overall well-being.

First, our study highlights the critical role of visual elements, particularly the sky view, in shaping residents' perception of environmental pleasantness. Urban planners should therefore reconsider the relationship between building layout and spatial openness, and explore strategies to increase sky visibility and enhance overall spatial quality. Beyond simply reducing building density and height, more refined design approaches are needed. For example, widening streets, incorporating green belts with unobstructed sightlines, and strategically arranging low-rise buildings can effectively expand visual openness while maintaining functional density. In newly developed areas, the planning of visual corridors should be carefully considered. Introducing slight bends along these corridors or integrating key landmarks into the urban fabric can create localized visual expansions and offer residents more diverse and engaging visual experiences.

Second, to improve both the landscape quality and practical utility of green spaces, especially in high-density urban areas, the introduction of multi-layered micro-green spaces, such as street "pocket gardens" and vertical green walls, should be encouraged (Navarrete-Hernandez et al., 2024). These micro-green spaces can offer direct visual benefits and provide more accessible recreational areas, thereby maximizing the aesthetic and functional value of urban greenery (Hsiao & Huang, 2024). In parallel, the accessibility and maintenance of existing street trees, roadside green spaces, and large parks should be systematically re-evaluated to better leverage the potential positive effects of urban green spaces on residents' perception of pleasantness.

Third, based on the urban renewal experiences of developing countries such as China, an important strategy for enhancing residents' perception of pleasantness during the urbanization process is to promote public participation and collaborative governance (Hsiao & Huang, 2024; Musa et al., 2018). Specifically, urban managers should provide policy support and resources to encourage residents' active involvement in community development and decision-making processes. Such a participatory model not only helps to better understand residents' needs and preferences for spatial landscapes and functional facilities, but also facilitates the coordination of interests among residents living in different parts of the community, ultimately contributing to an overall improvement in perceived environmental pleasantness.

5.3. Limitations and prospects

This study primarily focuses on spatial perception as reflected by visual and image features. It is undeniable that the existing model will inevitably have some inaccuracies on the perception of residents of the Pearl River Delta as the model proposed by Dubey et al. (2016), but it can effectively represent the perception from global human beings and has been widely used in related research (Zhang et al., 2018). It is highly recommended that future research utilize the human-machine adversarial scoring framework proposed by Yao et al. (2019) and recruit more respondents from different Chinese cities to understand the perception from a more local perspective.

Furthermore, while visual perception is an important aspect of pleasantness, it represents only one dimension. Cultural and social well-being are also essential components of residents' overall sense of pleasantness (Musa et al., 2018) and can be assessed through alternative data sources such as social media (Cheng et al., 2021; Ma et al., 2024). Therefore, future research could incorporate non-physical features and investigate their heterogeneous distribution between center and suburban areas (Cheng et al., 2021). In addition, individual differences among residents, including age, educational background, and income level, may significantly influence how they perceive pleasantness within the same urban environments (Claris Fisher et al., 2021; Patino et al., 2023; Rui & Li, 2024; Taczanowska et al., 2024). Thus, future studies are encouraged to further explore the differential relationships between diverse demographic groups and urban environments.

Finally, the recommendations proposed in this study for promoting well-being cities are not only applicable to the Pearl River Delta region but also provide valuable references for other rapidly urbanizing areas. However, due to limitations in data availability and computational capacity, this study focuses on six cities within the Pearl River Delta as case studies. Considering the significant differences in urban landscapes across cities with varying geographical and cultural contexts, it is important to adapt these recommendations to local conditions during specific implementations. Future research could further investigate the applicability and potential variations of factors influencing the perception of pleasantness across different geographical and cultural settings.

6. Conclusions

This study conducts an in-depth analysis of perceived environmental pleasantness across over 4000 communities in the Pearl River Delta region based on street view images and multi-source urban big data. The findings challenge the conventional assumption that urban "centers," due to their proximity to amenities and higher levels of development, necessarily offer greater perceived pleasantness than "suburbs." Using interpretable machine learning regression models, the study reveals that the relationship between perceived pleasantness and urban environmental features is complex and non-linear.

First, residents in peripheral cities, peripheral districts, and suburban communities generally report higher levels of pleasantness than those in core cities, core districts, and central communities. Across six perceptual dimensions, "suburban" areas are typically perceived as safer, more lively, more beautiful, and less depressing, though slightly more "boring" than urban cores. Second, the traditional urban-suburban dichotomy does not sufficiently explain spatial disparities in perceived pleasantness. On the one hand, natural environmental attributes such as a higher sky view index, greater green space density, and lower canopy height are positively associated with pleasantness. On the other hand, built environment features, including lower building and infrastructure density, higher floor area ratio, and institutional and commercial facility densities, also contribute positively to perceived environmental pleasantness.

In summary, while suburban communities tend to score higher in perceived pleasantness, this advantage is largely shaped by local conditions, including landscape openness, functional composition, and spatial form. These findings offer practical guidance for urban planners and policymakers, underscoring the importance of community-specific strategies to enhance residents' environmental experience and to promote the development of truly "pleasant cities."

CRediT authorship contribution statement

Xinyue Gu: Writing – review & editing, Software, Project administration, Data curation, Validation, Formal analysis, Conceptualization, Writing – original draft, Methodology, Visualization, Resources. **Wenrui Xu:** Visualization, Writing – original draft, Methodology, Writing – review & editing, Formal analysis, Conceptualization. **Chuanjia Gong:** Software, Methodology, Resources, Writing – review & editing. **Xintao Liu:** Supervision, Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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