Research Paper

Revealing the mismatch between urban green space equity and residents' subjective well-being through explainable machine learning:

A case study of Shanghai, China

Hao Gong[1], Gold Mantis School of Architecture, Soochow University, CHINA

Leilei Sun[2]*, Gold Mantis School of Architecture, Soochow University, CHINA

Abstract

The limited nature of green space resources in urbanized areas cannot meet the happiness needs of residents in a balanced way, which is a global problem. However, the current research on the spatial mismatch between the fairness of green space and the subjective happiness of residents (SWB) is still insufficient. Taking Shanghai as an example, this study evaluates the accessibility of SWB and urban public green space (UPGS) by integrating social media data and improving the traditional GA2SFCA method. The study analyzes and compares the spatial distribution differences of various UPGS accessibility under different travel modes, and uses machine learning to reveal the potential impact of the mismatch between SWB and UPGS accessibility. The study also compared the spatial distribution differences of various UPGS accessibility under different travel modes, and used machine learning to reveal the nonlinear effects and interaction of different environmental factors on their spatial mismatch. The research results are as follows: (1) Shanghai's UPGS accessibility shows obvious spatial heterogeneity; residents' use of high-speed travel can significantly alleviate the inequality of UPGS, while community parks (the lowest Gini coefficient) can alleviate the inequality of other types of urban parks; (2) The accessibility of urban green space and residents' main There is a certain spatial correlation between the sense of happiness, especially in the inner ring area. The accessibility of urban green space and the subjective happiness of residents show an obvious "high-high" clustering mode; (3) The accessibility of road networks, house prices and enterprise clustering are the three most significant variables that affect the spatial mismatch of different dimensions, and show obvious The threshold effect of. These findings link the equity of urban green space with the subjective happiness of residents and provide a basis for targeted interventions to improve social welfare and promote sustainable urban development.

Keywords

Green space accessibility; Environmental justice; Social media data; Machine learning

1. Introduction

The World Urbanization Outlook for 2024 points out that by mid-2024, the global population will be close to 8.2 billion, and it is expected to increase by 2 billion in the next 60 years. The population of 63 countries and regions, including China, has reached its peak (United Nations, 2024). With the advancement of urbanization, human health is facing many challenges. On the one hand, urban residents have to cope with

increasingly serious environmental problems, such as air pollution, noise pollution and water pollution; on the other hand, the risk of declining quality of life among residents is also increasing (Bhattarai & Budd, 2019). Urban park green space is an important public infrastructure to maintain urban ecology and social systems (Lee & Kim, 2015), as an important part of urban green space, urban parks provide residents with a valuable and convenient way to natural areas. Therefore, improving the equity of green spaces to meet the growing public demand is a necessary prerequisite for sustainable urban development (Lu et al., 2024).

UPGS environmental justice research mainly focuses on the differences in the situation between different groups (Rigolon, 2016; Zhang et al., 2024; Liu et al., 2025). On the other hand, the research focuses on the continuous improvement of accessibility assessment methods. Early studies used the cumulative opportunity method to calculate accessibility, but this method was limited by geographical boundaries (Talen, 1997). Later, methods such as spatial syntax and geographic information system (GIS) technology were introduced to improve this defect (Hillier et al., 1993; Wang et al., 2022; Comber et al., 2008). After that, Talen and Anselin (Talen et al., 1998) used the gravity model as a key indicator for accessibility assessment. Subsequent researchers built on this to develop several Floating Catchment Area (FCA) models for improvement, such as the 2SFCA method with Gaussian decay, which incorporates a decay coefficient.Although accessibility assessment methods are becoming more refined, the uncertainty in travel time costs caused by traffic congestion is often overlooked. Later research (Chen et al., 2024) incorporated real-time navigation data to improve the precision of UPGS accessibility assessment. In future research, the limitations of accessibility assessment need to be further addressed.

Research on the relationship between UPGS accessibility and SWB has shown that the more frequently residents visit green spaces, the stronger their sense of well-being (Bertram & Rehdanz, 2015). Subsequent studies have demonstrated that the inequitable distribution of green space can have adverse effects on the SWB of vulnerable groups (Rui, 2025; De Luca et al., 2024). Although UPGS have well-documented public health benefits, their distribution is uneven, and promoting green space equity is therefore an essential component of developing just cities (Sharifi et al., 2021). However, for cities and society as a whole, the potential relationship between UPGS accessibility levels and the spatial mismatch of SWB remains insufficiently understood.

This study takes the Shanghai metropolitan area as a case, employing natural language processing (NLP) to analyze 360,979 geotagged Weibo check-in records as an objective measure of SWB. An improved GA2SFCA method is applied to assess spatial inequality in UPGS accessibility. The study makes three key contributions: (1) integrating supervised classification with UPGS quality ratings to generate a composite supply index, enhancing accessibility estimates with real-time travel data, and evaluating spatial disparities using the Gini coefficient; (2) operationalizing SWB measurement from social media content via NLP to examine correlations and spatial mismatches with UPGS accessibility; and (3) applying SHAP and XGBoost models to identify nonlinear effects, thresholds, and interaction patterns among determinants across built environment, infrastructure, and socioeconomic dimensions. The findings provide actionable insights for urban planners to design targeted interventions that improve social well-being and support the sustainable development of urban green infrastructure.A research paper is an academic contribution to a specific field, discipline, or topic. It should be between 3,000 and 5,000 words, including the manuscript and references. The text should be accompanied by tables and figures to enhance clarity. Photographs illustrating a case study context may also be included. When applicable, please add acknowledgements and information about research funding.

2. Methodology

The theoretical framework of residents' SWB and UPGS accessibility is illustrated in Figure 1. We quantified the SWB of residents within the study area and assessed UPGS accessibility using an improved GA2SFCA method. Prior to data analysis, we aggregated the data into hexagonal grids with a 300m (5-minute living circle) range, and used GeoDa to analyze the correlation and mismatch between SWB and UPGS accessibility. Furthermore, SHAP was used to interpret the results of the XGBoost model in order to reveal nonlinear factors influencing mismatch outcomes and to explore their potential mechanisms. The subsequent subsections provide a detailed description of the datasets employed and the methodological approaches adopted in this study.

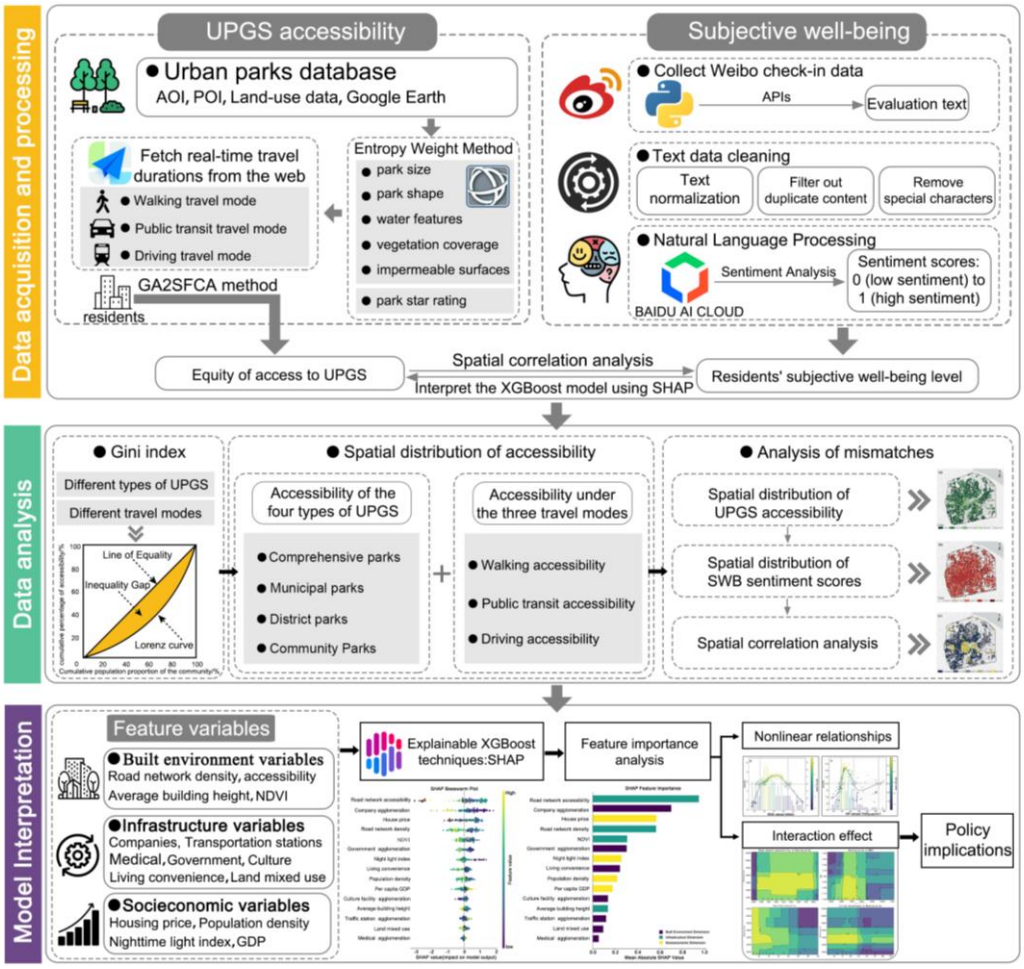


Figure 1. The reserch framework. Source: ISOCARP.

2.1. Study Area

Shanghai is a municipality directly under the central government of China and one of the most developed cities in the country. As of the end of 2024, Shanghai's permanent population was approximately 24.8026 million (Shanghai Municipal Bureau of Statistics, 2024), the UPGS covers an area of 4,726.64 hm^2, with a marked intensification of social inequality (Li & Wu, 2008). Meanwhile, Shanghai has recorded 31.974 million internet users (Shanghai Municipal Bureau of Statistics, 2024), which reflects the widespread penetration of social media among the urban population. Considering the integrity and consistency of data

collection, it is an ideal choice for this study to delimit the central area of Shanghai (within the outer ring road) as a research area. However, since residents living near the border of the outer ring road may choose public toilets outside the outer ring road, this study added a 3-kilometer buffer zone outside the outer ring road to more accurately reflect the potential choices of residents when choosing public toilets. As of May 2025, there are 257 public toilets in the study area. These public toilets are rated by the Shanghai Landscaping and Urban Landscape Bureau using a star rating system (i.e., 5, 4, 3, 2, 1 stars and basic level).According to China's "Standards for Classification of Urban Green Space" (CJJ/T85-2017)(Ministry of Housing and Urban-Rural Development of China, 2018) and Shanghai's "Shanghai Ecological Space Planning (2021-2035)" (Shanghai Bureau of Planning and Natural Resources, 2021), urban green space is divided into four categories according to area: comprehensive parks (⩾50 hm^2, 20 parks), municipal parks (10-50 hm^2, 51 parks), district-level parks (4-10 hm^2, 76 parks) and community parks (0.3-4 hm^2, 109 parks).

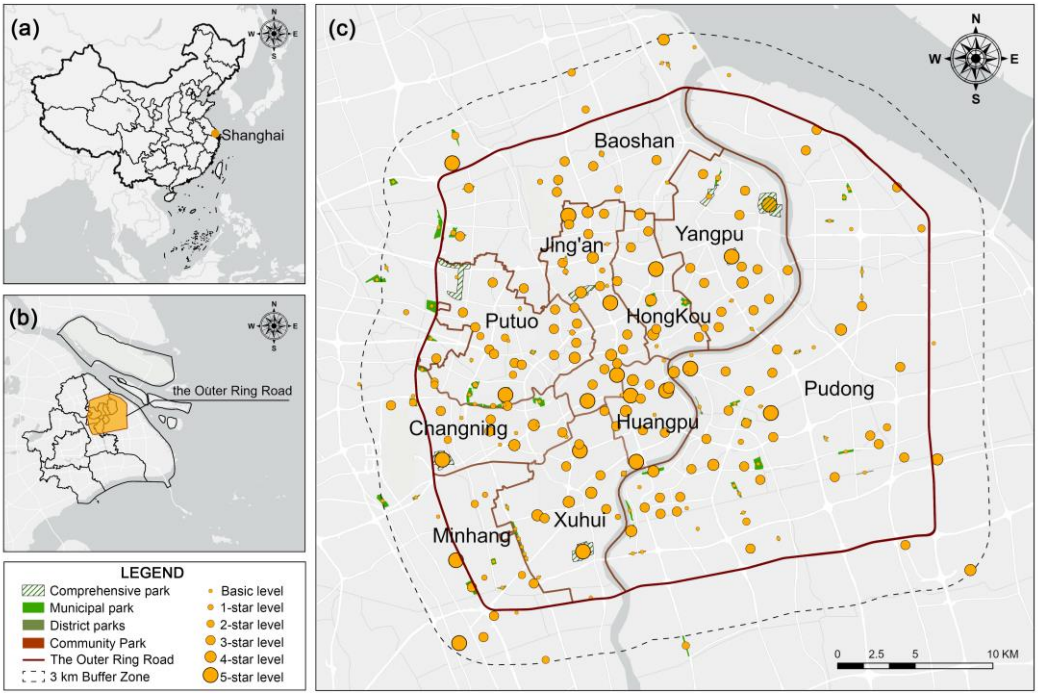


Figure 2. Study area. Source: ISOCARP.

2.2. Data source and processing

We have collected the following types of data: (1) urban park data, (2) social media data, (3) real-time navigation data, and (4) explanatory feature data.

The first type of data is urban park data. In December 2024, we used the Python script to capture the AOI data of urban parks in the research area from the Gaode Map API (https://gaode.com/) and refer to Google Maps (https://maps.google.com/) Get more information. Through cross-checking with the Shanghai Park List, the vector data of 257 urban parks were finally identified in the research area.

The second type of data is social media data. We have captured 980,216 microblog check-in records in Shanghai from September 1, 2023 to August 31, 2024 (https://m.weibo.cn/). After preliminary screening, including de-duty, regularization and removal of hyperlinks and empty data, we further screened the data and retained 360,979 valid records containing geographical latitude and longitude information. Then, we

use Baidu Natural Language Processing (NLP) tools to process these effective microblog data and get a happiness index between 0 and 1.

The third type of data is travel time navigation data. This study mainly discusses the accessibility assessment of residents' daily short-distance leisure travel to UPGS. In order to obtain the travel time of residents under the actual traffic conditions, we collected the travel time data of residents walking, taking public transportation or driving to UPGS from the Gaode Open Platform(https://gaode.com/). We excluded the impact of strong winds (Shanghai encountered strong winds on April 13, 2025, so the data on that day was excluded), rainy days, and weekends and morning and evening rush hours. The data collection period is selected as a sunny working day from April 9 to 16, 2025.

The last type of data is explanatory characteristic data. In order to further explore the potential factors of urban planning and residents' subjective happiness (SWB) spatial mismatch, we selected a total of 15 indicators from three dimensions. In the built-up environment dimension, we have incorporated urban road network data, building height data and normalized vegetation index (NDVI) data. In the socio-economic dimension, we have incorporated house price data, night light data, GDP data and population data. We collected the house price data of 4,292 residential communities in the research area through Anjuke API (https://shanghai.anjuke.com/). The infrastructure dimension mainly includes point of interest (POI) data. We have collected a total of 343,391 POIs through the Gaode Map Open API.

2.3. Analysis methods

2.3.1. Measuring UPGS accessibility based on improved GA2SFCA

Based on the traditional GA2SFCA model, we improved the spatial impedance and the attractiveness level of green space catchment areas, and used Python scripts to scrape the real-time status of different travel modes of residents along the Amap planned routes to accurately measure the UPGS accessibility of each residential location.

Next, we use the prepared data to start calculating the accessibility of UPGS within the study area. The first step is to calculate the supply-demand ratio: for each *j*, all communities *k* search from *j* at time t_0, forming the catchment area of *j*. M_j represents the attractiveness of j within its catchment area, and the total population of each community within the catchment area, after weighting, is P_k. The weighted population in catchment area *j* is considered the potential users of urban park *j*. This study assumes that within the walking-mode search radius, residents can all reach the park and green space by walking, so the proportion of the population using walking mode is set to 1. Only beyond the walking search radius will public transport or driving modes be used. Based on the "2024 Shanghai Statistical Yearbook" (Shanghai Municipal Bureau of Statistics, 2024), the number of private cars and total households in Shanghai are obtained, yielding approximately 42 private cars per 100 households. Therefore, the travel population proportions for public transport and driving are set to 0.58 and 0.42, respectively. The total population of each demand point k is multiplied by the proportion of each travel mode to calculate the population using walking, public transport, and driving modes. Using a Gaussian function for weighting and aggregation, the final supply-demand ratio R_j of UPGS to community population is expressed as follows(1):

$$R_{(j)} = \begin{cases} \dfrac{M_j}{\sum_{k\in\{t_{kj,w}\le t_0\}} G(t_{kj,}t_0)P_k} \\ \dfrac{M_j}{\sum_{k\in\{t_0^w\le t_{kj,p}\le t_0\}} G(t_{kj,}t_0)P_k} \\ \dfrac{M_j}{\sum_{k\in\{t_0^w\le t_{kj,c}\le t_0\}} G(t_{kj,}t_0)P_k} \end{cases} \quad (1)$$

In this formula, $t_{kj,w}$, $t_{kj,p}$ and $t_{kj,c}$ represent the travel times for visitors to travel from *k* to *j* via walking, public transportation, or driving, respectively. t_0 represents the travel time threshold from the origin to the destination. A review of previous studies indicates that 30 minutes is generally regarded as the maximum travel time limit for residents (Wang, 2013). Therefore, in this study, t_0 was set to 30 minutes. In addition, we found that residents tend to prefer walking for trips with destinations located within 500 meters, which aligns well with Shanghai's park development principle of "a park within 500 meters". Accordingly, in this study, we introduced a prerequisite when evaluating accessibility by car and public transport: the travel time to the destination by these two modes must be greater than the walking time for 500 meters. Assuming a walking speed of 4 km/h, the travel time for this distance is calculated to be 7.5 minutes, which we define as t_0^w. $G(t_{kj,}t_0)$ is the distance decay function, expressed as follows (2):

$$G(t_{kj,}t_0) = \begin{cases} \dfrac{e^{\left(-\frac{1}{2}\right)\times\left(\frac{t_{kj}}{t_0}\right)^2} - e^{\left(-\frac{1}{2}\right)}}{1-e^{\left(-\frac{1}{2}\right)}}, & t_{kj} \le t_0 \\ 0, & t_{kj} \ge t_0 \end{cases} \quad (2)$$

Step 2: Calculating accessibility. Taking each community point *k* as the center, the supply-demand ratio R_j of UPGS located within the spatial catchment defined by the time threshold t_0 is weighted using the Gaussian function $G(t_{kj,}t_0)$, The accessibility of community point *k*, denoted as $A_{(k)}$, is then obtained as follows (3):

$$A_{(k)} = \begin{cases} \sum_{j\in\{t_{kj}\le t_0\}} G(t_{kj,}t_0)R_j \\ \sum_{j\in\{t_0^w\le t_{kj,p}\le t_0\}} G(t_{kj,}t_0)R_j \\ \sum_{j\in\{t_0^w\le t_{kj,c}\le t_0\}} G(t_{kj,}t_0)R_j \end{cases} \quad (3)$$

2.3.2. XGBoost model analysis

We employed the XGBoost model to assess the influence of 15 features across the urban built environment, urban infrastructure, and socioeconomic factors on the mismatch between UPGS accessibility and SWB. XGBoost is a machine learning algorithm that leverages gradient boosting to enhance model performance (Chen & Guestrin, 2016), offers several advantages, including fast training speed, high accuracy, strong capability in handling missing values, and effective prevention of overfitting. In this study, the dataset was divided into 70% for training and 30% for testing. Model parameters were tuned using five-fold cross-validation and a grid search method. To avoid bias in evaluating model performance due to class imbalance, the ROC curve was used as the primary metric for assessing predictive ability, as it is unaffected by sample proportions and better reflects the true performance of the model. After training and fine-tuning, the optimal model achieved an AUC of 0.85 and an F1 score of 0.858, demonstrating good generalization ability.

2.3.3 SHAP interpretation

Machine learning models are often criticized as black-box approaches because it is difficult to intuitively understand the relationship between features and prediction outcomes. To address this limitation, Lundberg and Lee (Lundberg & Lee, 2017) introduced SHAP, a game-theory-based method for interpreting machine learning results. The Shapley value represents the contribution of a particular feature to a specific

prediction relative to the baseline prediction, which is defined as the model output when all features are set to their average values. We adopted this method to interpret the output of the XGBoost model, as shown in the following formula (4):

$$\emptyset_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|(|F|-|S|-1)!}{|F|!} \left(f(s \cup \{i\}) - f(s) \right) \quad (4)$$

Where $\emptyset_i$ represents the Shapley value of feature *i*, *F* is the set of all features, *S* is the subset of other features excluding feature *i*, $f(s)$ is the prediction result of feature subset *S*, and $f(s \cup \{i\})$ is the output result when feature *i* is added to the feature subset *S*. $|S|$ and $|F|$ are the sizes of the feature subset *S* and the full set of features *F*, respectively.In this study, we initialized the interpretation using a grid-level dataset representing the mismatch between residents' subjective well-being (SWB) and UPGS accessibility. The Shapley values for all test samples were then calculated as follows, let $f(x)$ be the prediction value, and $\emptyset_0$ be the model's baseline prediction. Then, we have (5):

$$f(x) = \emptyset_0 + \sum_{i=1}^{d} \emptyset_i \quad (5)$$

Where $f(x)$ is the model's prediction for input *x*, $\emptyset_0$ is the baseline value (the expected value or mean of the model output), $\emptyset_i$ is the contribution of feature *i* to the prediction result, and *d* is the dimensionality of the features.

2.3.4 PDP interpretation

The PDP algorithm visualizes the marginal effects of one or two specific features on the predictions of a machine learning model (Friedman, 2001). Its principle is to hold all other features constant, vary the values of the target feature, and record the resulting changes in predictions (Zhao et al., 2022). In this study, the PDP algorithm was implemented using a Python open-source toolkit, and partial dependence plots together with interaction plots were employed to reveal the potential relationships between the features and the predicted outcomes. The explanation is as follows (6):

$$\hat{f}_S(x_s) = E_{X_C} = \left[\hat{f}(x_s, X_C) \right] \int \hat{f}(x_s, X_C) dP(X_C) \quad (6)$$

x_s denotes the feature used to plot the partial dependence and interaction functions, and $X_C$represents the remaining features. $P(X_C)$ is the probability distribution of the complementary features X_C. $\hat{f}$ refers to the predictive model used in this study.

3. Discussion

3.1. Equity assessment of green space planning based on the improved GA2SFCA

According to the results of the accessibility distribution (Figure 3), we found that the accessibility of UPGS under low-speed travel mode (walking and public transportation) is significantly lower than that of high-speed travel mode (private car). This may be due to the limited number of large green spaces in the study area, especially in the inner ring area, resulting in more uneven green space searches in a smaller range. In addition, the Gini coefficient of public transportation accessibility indicates the underdevelopment of public transportation facilities around UPGS, which significantly reduces the actual accessibility level of UPGS. Judging from the UPGS type, the comparison of the Gini coefficient shows that the performance of community parks is obviously better than that of the other three categories. This shows that small green spaces such as community parks can effectively make up for the shortcomings of the other three types of UPGS in achieving green space equity. Therefore, under the circumstances that the construction of the other three types of parks is restricted, priority can be given to the development of community parks to improve the accessibility of residents to UPGS.

By observing the accessibility level of green space in the geographical spatial distribution, we found that the accessibility of urban green space in the inner ring area of Shanghai is relatively high and concentrated. However, due to the limited land available for development in the region, the plan should pay more attention to improving the availability of urban green spaces in the inner ring area.In contrast, there are fewer buildings in the south and north of the central area of Shanghai, and there are fewer commuters, which provides enough space for large-scale construction of urban green space resources to alleviate the shortage. In addition to improving the accessibility of residents to urban green spaces by increasing the number of green spaces and changing the mode of travel, we also suggest that the municipal government further improve the service level of supporting facilities in urban green spaces during the construction process. This includes the reasonable arrangement of transportation, parking and other facilities for users who drive to urban green spaces, so as to significantly improve the convenience of vulnerable groups and green spaces. This can improve the frequency of use of green space and the convenience of driving to a certain extent.

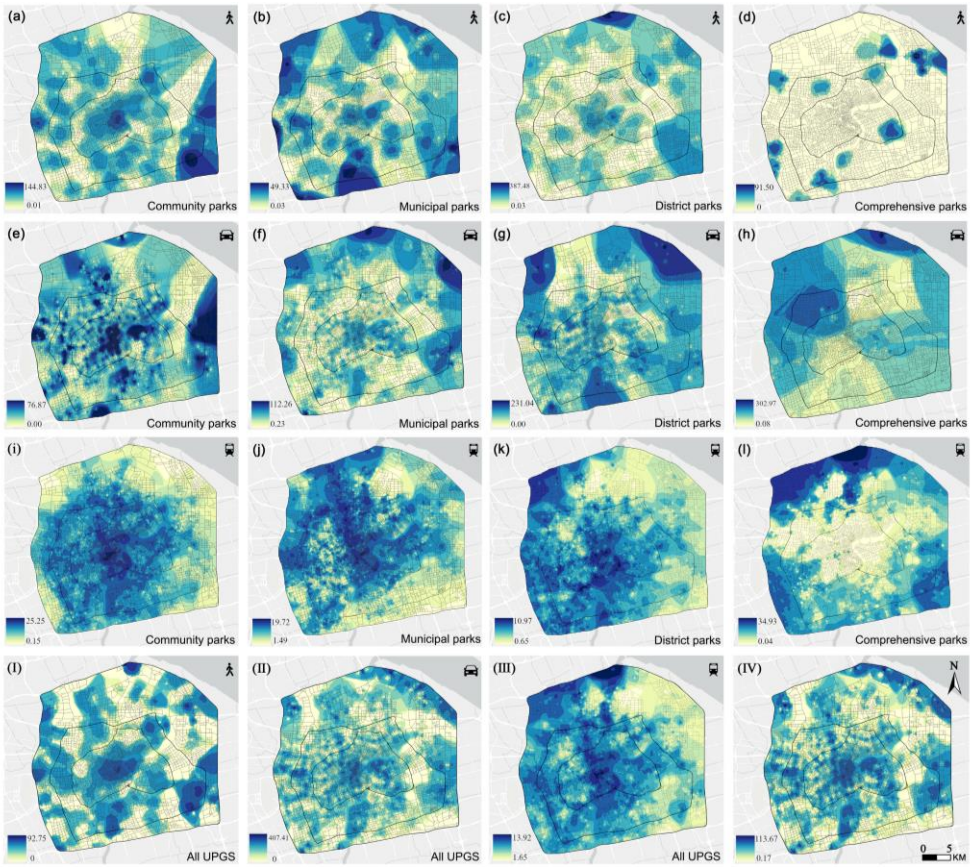


Figure 3. Spatial distribution of UPGS accessibility in central Shanghai. Source:ISOCARP.

3.2. Impacts of environmental variables on green space planning

Using SHAP and XGBoost analysis, we found that in the urban environment, road network accessibility, convenience of life, NDVI and house prices have a positive impact on the spatial mismatch of residents' subjective happiness, while the concentration of enterprises, night light pollution index and population density have a negative impact on the subjective happiness of residents(Figure 4). Through specific analysis, we find that in terms of building an urban environment, improving the accessibility of road networks is

crucial to improving commuting efficiency and social equity. The improvement of NDVI is crucial to alleviating the urban heat island effect, but attention must be paid to the threshold effect to prevent the waste of green resources (Navarrete-Hernandez et al., 2024). Therefore, under the condition of limited urban greening resources, urban planners should focus on balancing urban transportation development and environmental greening.

From a socio-economic perspective, within a certain range, house prices can improve people's subjective happiness (SWB). Changes in house prices will quickly affect the wealth stock of residents, thus directly changing the wealth of families. During the period of rising house prices, the appreciation of real estate can increase the total assets of the family; while the decline in house prices will expose residents to the risk of depreciating real estate. In addition, low-cost areas often lack perfect infrastructure, which has a negative impact on subjective happiness. This reflects the environmental inequality caused by the wealth gap. Therefore, the future green space planning should focus on the development level of green space in low- and middle-income areas, and be alert to the risk of "green gentlemanization". The increase in the intensity of lights at night will lead to noise pollution, light pollution, increased disease incidence and other problems, thus reducing people's subjective happiness.

In terms of urban environmental infrastructure construction, areas with a high concentration of enterprises often lead to a decline in subjective happiness (SWB) due to the high pressure of the employed population. These employees usually work in high-rise office buildings. Therefore, in addition to building small and convenient urban public green spaces (UPGS) on the two-dimensional plane of the city to relieve their mental health pressure, measures such as promoting three-dimensional green space planning can also be implemented. Improving the convenience of daily life within a certain range can quickly meet the needs of residents and improve subjective happiness. Therefore, coordinating urban life service facilities with corresponding landscape and green space infrastructure can further improve people's subjective happiness. In addition, there is a mutual interaction between characteristic variables of different dimensions.

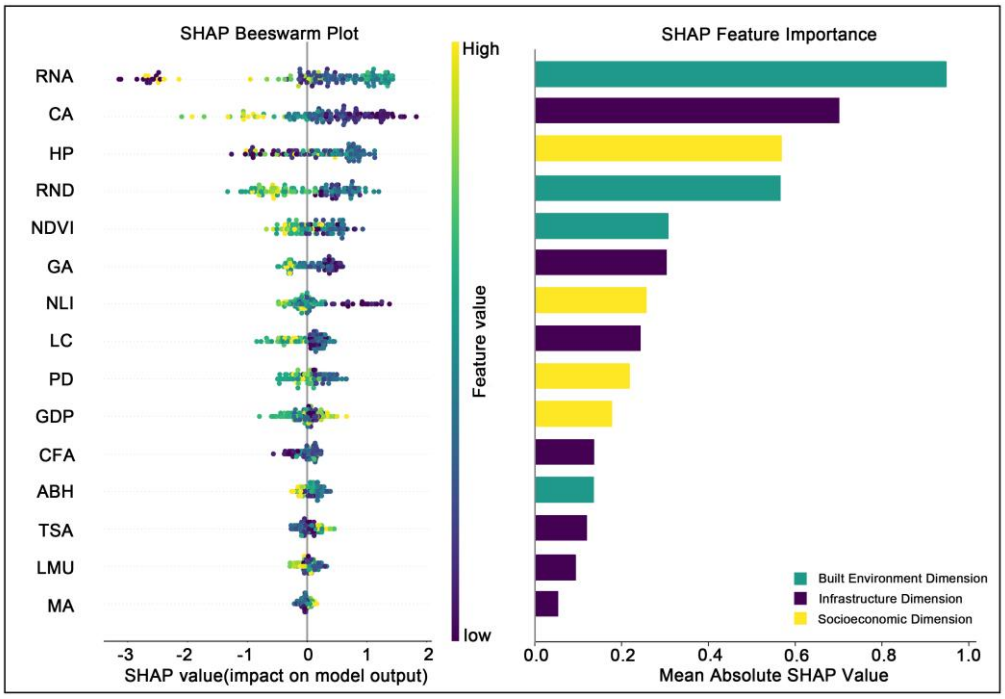


Figure 4. SHAP summary plots. Source:ISOCARP.

3.3. Global perspectives on implications for environmental decision-making

Our research findings have strategic significance for urban sustainable development and environmental decision-making:

(1) From the perspective of green space planning, Shanghai, like Hong Kong, London and other international metropolises, is facing the phenomenon that the infrastructure of the city center is relatively perfect and the suburban green space is insufficient(Shan & He, 2025). The existence of small green spaces (such as community parks) helps to alleviate spatial imbalance (Zhang & Chen, 2024). Therefore, in the central urban areas where land supply is tight and it is difficult to build large parks, community-level green spaces can be used as an effective alternative to solve the problem of spatial inequality; at the same time, the construction of suburban urban green space services (UGPS) should also be strengthened.

(2) From the perspective of resource allocation (Figure 5), similar to cities such as New York and Beijing, the dual effect of housing prices in Shanghai reflects the tension between "green welfare" and "green gentlemanization"(Assaad & Jezzini, 2024; Wu & Rowe, 2022). Research shows that although environmental improvement measures such as urban greening have improved the quality of public space, they have also inadvertently pushed up house prices in these areas, forced vulnerable residents to move out, and attracted high-income and highly educated groups, thus raising land prices and cost of living. Given that studies have shown that the construction of three-dimensional greening in commercial-intensive areas such as central business districts can improve the subjective happiness of office workers(Xie et al., 2025), urban policymakers should actively promote the construction of three-dimensional green infrastructure.

(3) From the perspective of fairness, alleviating the uneven spatial distribution of urban green space is conducive to achieving social equity. In the future, it is necessary to strengthen the construction of urban public transportation, improve the convenience of residents' access to urban green space in different modes of travel, and improve the accessibility of residents on foot as much as possible. Research shows that walking has the most significant impact on promoting green space equity. In addition to the impact of objective accessibility on social equity caused by the spatial distribution of urban green space, residents' subjective perception of green space has also become an important indicator for predicting the use mode of green space. There is a difference between residents' subjective perception of green space, objective accessibility and actual accessibility (subjective happiness, SWB), which is affected by factors such as age, gender and socio-economic status. This highlights the importance of creating attractive, safe and inclusive green spaces, not just improving factors such as improving the objective accessibility of urban public transportation, and provides valuable inspiration for urban planners and policymakers.

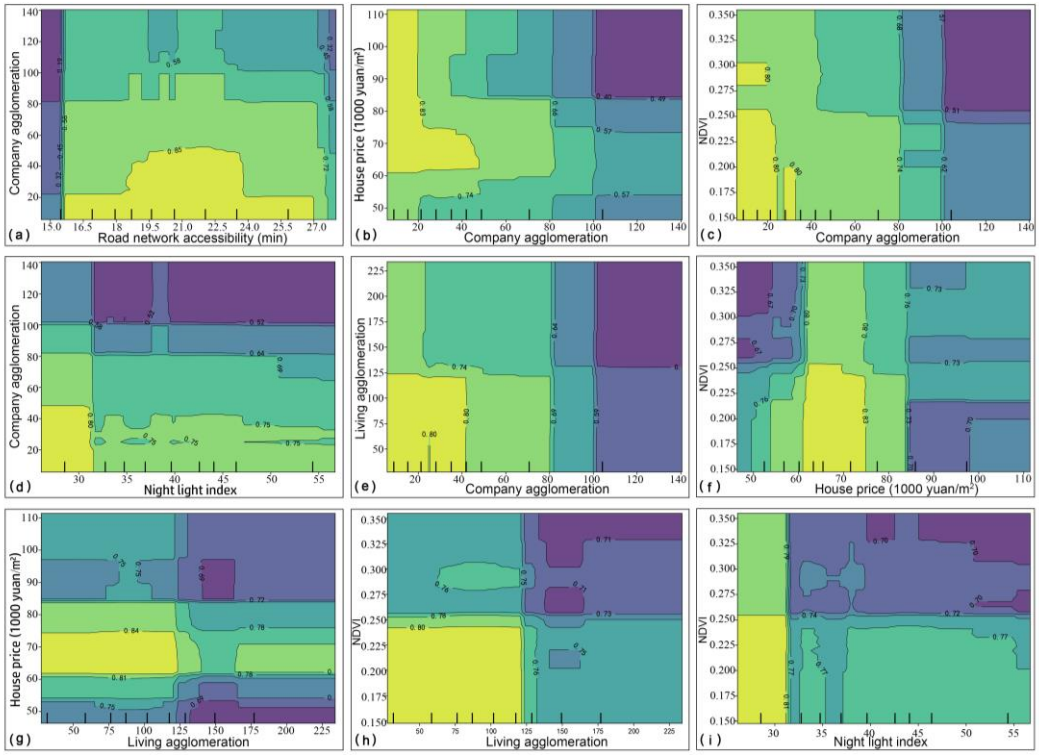


Figure 5. Interaction Plot. Source:ISOCARP.

4. Conclusion

This study puts forward a new research framework with the urban area in the center of Shanghai as an example. First of all, we use Baidu Natural Language Processing (NLP) technology to quantify the subjective happiness of residents based on social media data with geographical tags, and obtain the real-time travel time of urban residents in three modes of walking, public transportation and driving through Airbnb map route planning. Secondly, we use the Gaussian two-step floating watershed method to evaluate the accessibility of the urban built environment. Third, we use the Gini coefficient to evaluate the difference in the fairness of the urban built environment, and evaluate the spatial mismatch between the accessibility of the urban built environment and the subjective happiness of residents through bivariate spatial correlation analysis. Fourth, we use the SHAP method to explain the XGBoost model, reveal the nonlinear impact mechanism of 15 characteristic variables in the three aspects of urban construction environment, infrastructure and socio-economics, and evaluate their contribution level, key feature impact threshold and interaction.

This research can provide an effective reference for future urban planning and social equity decision-making. By identifying areas with weak green space equity, policymakers can allocate resources more effectively. In addition, our research results further establish the connection between urban planning and the public, which helps to achieve environmental justice. This is not only conducive to the sustainable development of Shanghai, but also provides valuable references for other parts of the world.Few studies have previously focused on the geographical mismatch between UPGS accessibility and residents' subjective well-being.

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