Research Paper

Beyond One-Size-Fits-All: Unraveling Spatiotemporal Heterogeneity in Waterfront Living Circle Geographic Environments and Public Emotions for Resilient Urban Growth

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Abstract

During COVID-19, urban waterfront spaces became important blue-green areas, as they gave people a sense of peace and comfort. However, few studies focus on emotional changes within 15-minute living circles, traditional linear models often fail to show the complex links between environment and emotion. We built a spatial machine learning framework to explore the relationship between environmental characteristics and public emotions in Shanghai's "One River One Creek" waterfront living circles. It uses social media emotion data and detailed environmental data to find spatial and temporal variations before and after the pandemic. The pandemic changed how people felt about the waterfront. Emotional hotspots that were once in central areas spread toward the edges of the city, and environmental factors also shifted. After the pandemic, sensory elements became the main influence on emotion. Some key variables showed clear threshold effects. Environmental effects were very different between central and suburban areas, and across different types of shorelines.

Keywords

Environmental resilience, Waterfront living circles, Public wellbeing, Spatiotemporal heterogeneity, Explainable machine learning

1. Introduction

Urban waterfront spaces are key parts of blue-green infrastructure. They offer beauty, recreation, history, social interaction, and emotional comfort (Gascon et al., 2015; Wang & Lin, 2024; White et al., 2019). As cities grow fast, waterfronts have become gateways that show the character of a city. Their quality directly affects people's physical and mental health (Ding et al., 2023). During public health crises like COVID-19, these spaces gained new importance by giving people places for emotional relief (Ugolini et al., 2020). To use waterfronts well, we need to understand how the environment and human behavior interact. The pandemic has changed how people live and how they think about space.

Many studies have explored how the urban environment affects people's emotions (Kaplan & Kaplan, 1989). But most of them look at entire cities or single green spaces. Few focus on emotional changes along the waterfront within small areas such as 15-minute walking circles. The rise of social media now allows researchers to track public emotions on a large scale and in real time (Golder & Macy, 2011; Ma et al., 2020). These data reflect how people truly feel in different places and times (Mitchell et al., 2013). Still, many studies use simple linear models that cannot show complex or uneven relationships in space (Fan et al., 2021). Geographically weighted random forest models can better reveal these patterns (Georganos et al., 2021). Yet few studies have looked at how crises like the pandemic have changed the way people use waterfronts or how they feel about them (He et al., 2024).

This study builds an interpretable spatial machine learning framework. This framework combines Geographically Weighted Random Forest (GW-RF) and Shapley Additive Explanations (SHAP), to examine the ways in which environmental factors relate to public emotions in waterfront living circles. We focus on three main aspects: the influence of environmental features, including built environment factors, perception indicators, and microclimate elements such as temperature, on emotional patterns and their relative importance, the way to measure and explain nonlinear links and threshold effects, and changes of these links across areas and time. By examining these aspects, this study provides insights for health-oriented waterfront planning and design in post-pandemic urban contexts, supporting more human-centered and resilient urban development.

2. Literature Review

2.1. Waterfront Environment and Public Emotion Relationships

Interest in how waterfront environments shape emotional well-being has been sustained for decades, though the depth of explanation varies across studies. Early research, largely grounded in restorative environment theory, suggests that water-based landscapes can reduce mental fatigue and support attentional recovery (Gascon et al., 2015; White et al., 2016). However, these studies rely on general theories and do not test how different waterfront features shape emotions in real urban settings.

Later studies take a broader view of the built environment. Mouratidis (2021) links well-being to travel, recreation, work, social life, residential comfort, emotional response, and health. Cooper, Crase and Burton (2023) show that accessibility, water quality, and facility design all affect psychological benefits. While these studies include more factors, they often treat them as independent variables and do not examine how they interact. Some researchers begin to use new data and methods. Ma et al. (2020) , using geolocated Weibo data, identify gendered emotional patterns along Wuhan's waterfront; however, the analysis largely remains descriptive, offering limited insight into the mechanisms behind these differences.

Recent work starts to model perception more directly. Cao et al. (2022) classify coastal landscapes into natural, artificial, and sensory types and test their effects on tourist emotions. Yan et al. (2024) build a pathway model that links landscape features, water-friendly preference, and emotional outcomes. Compared with earlier work that centers on general environmental benefits, these approaches introduce a more structured understanding of perception. Still, by reducing experience to a few predefined categories, they may overlook the more subtle and layered ways in which emotions are formed in complex waterfront settings.

2.2. Social Media Data for Public Emotion Analysis

The use of social media data has reshaped how urban emotions are studied, offering larger samples, lower costs, and finer temporal resolution than traditional surveys. Li, Goodchild and Xu (2013) and Reece and Danforth (2016) map emotional patterns across cities and find clear spatial differences. However, these studies depend on text data and may suffer from bias in user groups and expression styles. Wu (2019) and Shi (2024) combine spatial and textual data, but they mainly describe patterns and do not model causal relationships.

Recent studies focus on changes under external shocks. Lai (2023) show that COVID-19 shifts park use toward nearby community spaces with good walkability. He (2024) find that people in dense and low-green areas report stronger feelings of helplessness during the pandemic. These studies highlight the importance of contextual factors, yet they are often tied to specific events and do not readily translate into more generalizable analytical frameworks.

2.3. Breaking Traditional Heterogeneity and Nonlinearity Parallel Processing

Many studies treat spatial heterogeneity and nonlinear relationships separately. This limits model performance. Zhou (2023) identify threshold effects in green space that vary by scale and season, which shows clear nonlinearity. However, traditional regression models cannot capture these patterns well. Machine learning models such as random forests can model nonlinear effects, but they often lack interpretability. Global models also ignore spatial variation.

Urban systems show nonlinear and spatial effects at the same time. Georganos (2021) first proposed this method and improved spatial modeling accuracy. Recent work improves interpretability. SHAP methods explain how each variable contributes to model output. Chen (2024) combines geographically weighted random forests (GW-RF) with SHAP to analyze factors influencing green view rates. Even so, applications remain largely confined to visual environment indicators, with limited extension to emotional outcomes—leaving a gap that this study seeks to address.

3. Methodology

The overall workflow consists of four main stages (Figure 1), moving from data construction to modeling and interpretation.

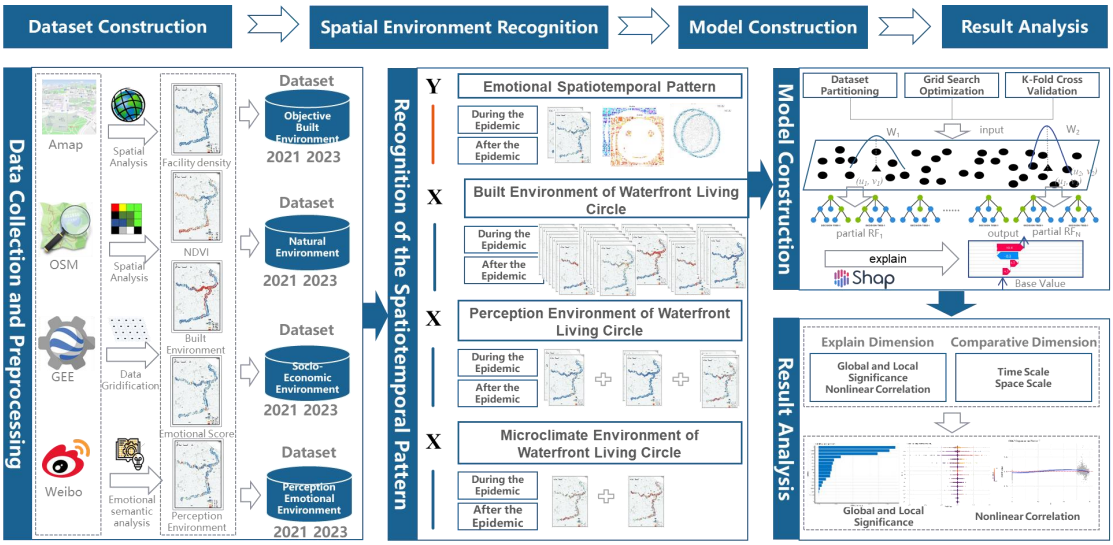


Figure 1. Workflow. Source: Authors.

3.1. Study Area

The analysis focuses on Shanghai's "One River, One Creek" waterfront system, covering both the Huangpu River and Suzhou Creek (Figure 2). To operationalize spatial units, walking accessibility is first estimated using the MapBox API, with a 15-minute threshold applied over the street network to delineate reachable areas. Based on this, a uniform grid of 150 m × 150 m is generated, resulting in a total of 8,876 analytical units (Figure 3). This grid-based approach allows for consistent comparison across different environmental and social dimensions.

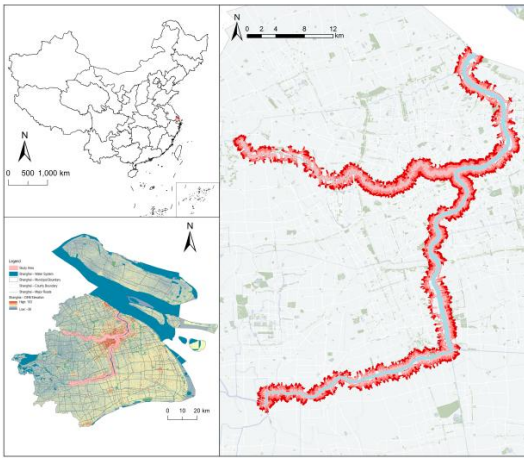


Figure 2. Study area. Source: Authors.

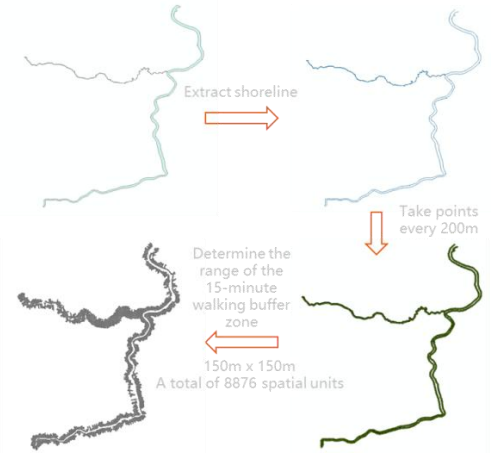


Figure 3. Research area delineation. Source: Authors.

3.2. Datasets

To capture temporal variation, multi-source datasets are constructed for two periods: the pandemic year (2021) and the post-pandemic year (2023). Built environment data—including POIs, road networks, and land use—are compiled from Gaode Map API, the National Geographic Information Public Service Platform, and OpenStreetMap. For the natural environment, NDVI is derived from Google Earth Engine using monthly composite imagery with cloud masking applied, and mean values are calculated at the grid level.

Microclimate conditions are represented by temperature data obtained from the Shanghai Meteorological Bureau and local weather stations, providing a proxy for fine-scale environmental variation. At the same time, social media data are collected from Weibo for September 2021 and September 2023, yielding 40,497 and 84,225 posts, respectively. After filtering for spatial relevance, removing empty entries, and extracting emotionally meaningful content, a cleaned dataset is produced for subsequent analysis.

3.3. Variables

3.3.1. Dependent Variable

We used a dictionary-based sentiment analysis method. This method combines three sources: the Dalian University of Technology Emotion Ontology Library, the HowNet Sentiment Dictionary, and the BosonNLP Sentiment Dictionary. We constructed comprehensive sentiment dictionaries containing positive, negative, and neutral categories totaling over 15,000 vocabulary items. Combined with machine learning techniques, we performed emotion recognition and quantification on Weibo texts, calculating emotional vocabulary scores for each post to generate total emotion scores, then computing emotion environment averages for each grid unit through spatial association.

$$EmotionScore = \sum(PositiveWordScores) + \sum(NegativeWordScores) + DegreeAdverbAdjustmentTerm \quad (1)$$

Where the degree adverb adjustment term modulates emotional intensity based on degree adverbs such as "very," "particularly," "slightly," etc., with adjustment coefficients ranging from 0.5-2.0.

3.3.2. Independent Variables

Guided by the "5D" framework (Ewing & Cervero, 2010), the built environment is described through a combination of development density, service diversity, transportation provision, design characteristics, and openness, rather than treating these dimensions separately. To capture how space is actually experienced, three perception-based dictionaries are constructed, covering natural elements (e.g., vegetation, water, and weather), artificial features such as buildings and infrastructure, and sensory expressions related to sight, sound, smell, and touch. In addition, temperature is selected as the key microclimate indicator, given its central role in shaping outdoor comfort and its direct influence on emotional responses, particularly in waterfront settings.

Collinearity tests show that all selected variables have variance inflation factors below 7 (Table 1), indicating acceptable levels for model estimation. Descriptive statistics are presented in Table 2.

Variable	T	GSR	BSC	DFS	FSI	MSC	FAR	RND	sense	CFD	nature	CulFD	PSFD	PSD	SSD	manmade
2021	4.24	4.13	3.83	3.73	3.02	2.96	2.48	2.27	1.81	1.6	1.55	1.38	1.18	1.18	1.08	1.01
2023	4.97	4.01	3.85	3.87	2.94	3.08	2.47	2.3	1.81	1.88	1.66	1.57	1.73	1.28	1.1	2.03

Table 1. Results of the VIF analysis. Source: Authors.

TYPE	CATEGORY	VARIABLE INDICATORS		INSTRUCTIONS	MEAN VALUE	VARIANCE
Dependent Variable	2021(during the epidemic)	2021 Emotional Score			1.532	2.634
	2023(after the epidemic)	2023 Emotional Score			1.300	2.006
Independent Variable: Built Environment	Overall Transportation Infrastructure	Bus Station Coverage, BSC, %	2021	bus station 300m buffer zone area /unit area	0.579	0.460
			2023		0.586	0.458
		Metro Station Coverage, MSC,%	2021	subway station 800m buffer zone area /unit area	0.417	0.483
			2023		0.421	0.484
		Parking Facilities Density, PFD, per km²	2021	number of parking lots/unit area	5.249	19.310
			2023		39.887	8010.563
		Road Network Density, RND, km/km²	2021	total length of road network within the unit /unit area	13.028	13.207
			2023		13.384	13.451
	Waterfront Design Features	NDVI(Normalized Difference Vegetation Index)	2021	green area within the unit/unit area	0.376	0.148
			2023		0.380	0.027
		Distance From Shoreline, DFS, m	2021	the vertical distance between the centroid of the unit and the shoreline	492.379	306.928
			2023		492.379	306.928
	Density of Waterfront Development	Floor Space Index, FSI, %	2021	total area of building foundation within the unit/unit area	0.089	0.114
			2023		0.062	0.079
		Floor Area Ratio, FAR	2021	total building area within the unit /unit area	0.562	0.986
			2023		2.288	4.036
	Waterfront Functional Services	Public Service Facilities Density, PSFD, per km²	2021	number of public service POI within the unit/unit area	5.470	23.074
			2023		32.381	129.486
		Commercial Facilities Density, CFD, per km²	2021	number of commercial facilities POI within the unit/unit area	86.492	248.138
			2023		237.339	678.586
		Cultural Facilities Density, CulFD, per km²	2021	number of cultural facilities POI within the unit/unit area	28.144	100.355
			2023		23.169	75.629
	Quality of Waterfront Openness	Park Square Density, PSD, %	2021	area of park square within the unit /unit area	0.049	0.192
			2023		0.072	0.220
		Scenic Spots Density, SSD, per km²	2021	number of scenic spots POI within the unit/unit area	2.122	22.026
			2023		5.265	39.785
Independent Variable: Perception Environment	Perceived Atmospheric Environment	Nature Features, nature	2021	perception level of natural elements in Weibo text	0.090	0.166
			2023		0.087	0.156
		Manmade Features, manmade	2021	perception level of manmade elements in Weibo text	0.003	0.035
			2023		0.129	0.182
		Sense Features, sense	2021	perception level of sensory elements in Weibo text	0.114	0.180
			2023		0.107	0.163
Independent Variable: Microclimate Environment	Climate	Temperature, T,℃	2021	unit average temperature	18.910	12.870
			2023		18.108	12.277

Table 2. Description of dependent and independent variables. Source: Authors.

3.4. Methods

3.4.1. Geographically Weighted Random Forest (GW-RF) Model

Random Forest is a global model based on all training data where each data point has equal weight for coefficient estimation. However, RF ignores spatial heterogeneity, unable to reveal spatial variations in spatial data associations. To address this limitation, we introduce GW-RF models incorporating GWR

model core ideals into traditional RF models. The equation of the bi-square weighting kernel function is as follows:

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{bandwidth}\right)^2\right]^2, d_{ij} \le bandwidth \\ 0, d_{ij} > bandwidth \end{cases} \quad (2)$$

Where d_{ij} is the distance between grids. Each grid's neighborhood is selected(where $w_{ij} \neq 0$)and used as input for establishing local RF.

The local variable importance for each grid is then estimated. Thus, GW-RF regression equation modified from RF can be expressed as follows:

$$Y_i = f_{(u_i, v_i)}(x^*) + \varepsilon_i \quad (3)$$

where $f_{(u_i,v_i)}(x^*)$is the prediction of GW-RF on gridi, and u_i, v_i denotes the coordinates of the center of grid.

3.4.2. SHAP Interpretability Analysis

SHAP models, based on game theory Shapley value concepts, quantify each feature's marginal contributions to model predictions. The Shapley value formula for feature i is:

$$\phi_i(x) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(x_S \cup \{i\}) - f(x_S)] \quad (4)$$

Where N represents the set of all input features, S represents a subset of N, X_S represents the input vector with feature values in the set.

4.Results

4.1.Model Performance Comparison

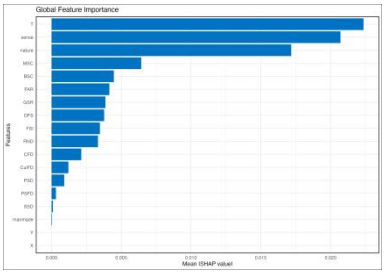
We established two models for 2021 and 2023 emotion scores, adopting grid search methods and 3-fold cross-validation for optimal hyperparameters to prevent overfitting. Using R^2, RMSE, and Mean Absolute Error (MAE) evaluation indicators, we compared two GW-RF models with OLS, GWR, and RF models. Results demonstrate that compared to other models, GW-RF models show lower RMSE and MAE values with higher R^2 values, reflecting their superiority in considering spatial heterogeneity.

4.2.Nonlinear associations Interpretations

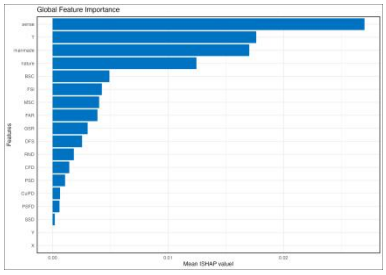
4.2.1.RI of variables

Global RI is measured through global SHAP values, calculated using ratios of each variable's mean |SHAP| to all variables' mean |SHAP| sums after computing absolute SHAP value averages (Figure 4). Waterfront area public emotion influencing factors demonstrate significant changes between pandemic and post-pandemic periods. During pandemic, temperature was the primary emotion influencing factor, with September's suitable temperature conditions positively impacting emotions, followed by sensory elements and natural elements, subway station coverage, bus station coverage, and floor area ratios.

However, post-pandemic, influencing factor importance rankings underwent fundamental adjustments. Sensory elements became the most important influencing factors, surpassing temperature as primary, followed by temperature, perceived natural and artificial elements, bus station coverage, and building density. This change's core lies in artificial element influence substantial increases, directly reflecting post-pandemic waterfront activity frequency significant increases, making artificial facility richness more importantly impact emotional experiences.



(a) 2021 Variable relative importance ranking



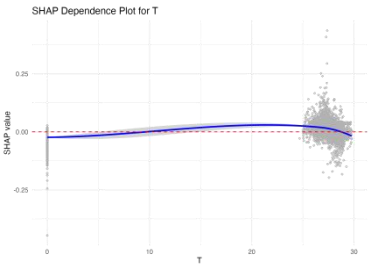
(b) 2023 Variable relative importance ranking

Figure 4.The global and local RI of environmental factors from the SHAP model. Source: Authors.

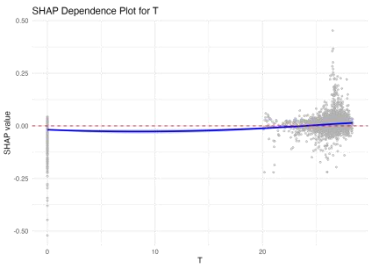
4.2.2.Nonlinear Association Analysis

The SHAP results reveal pronounced nonlinear relationships and threshold effects between waterfront environmental factors and public sentiment.

For **microclimatic conditions**, temperature exhibits an overall inverted U-shaped effect (Figure 5). During the pandemic period, its influence turns negative when exceeding approximately 28–29°C. In the post-pandemic stage, the high-temperature constraint weakens, while the negative effect of low temperature becomes more prominent, with a threshold around 20°C, indicating a shift in thermal comfort preferences.



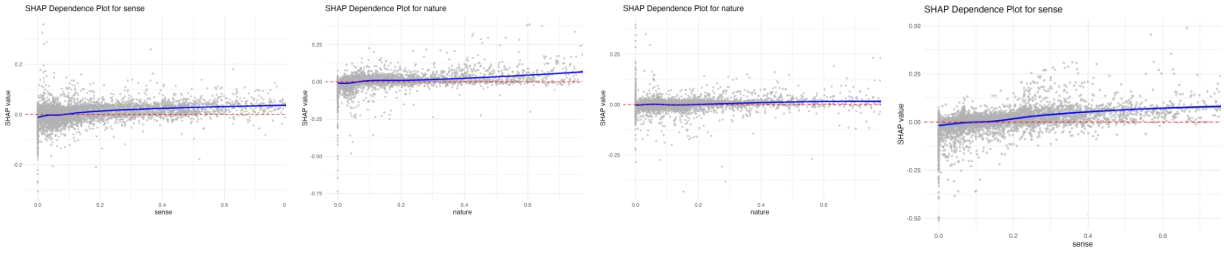
(a) 2021 temperature



(b)2023 temperature

Figure 5. SHAP value for microclimate environmental variables. Source: Authors.

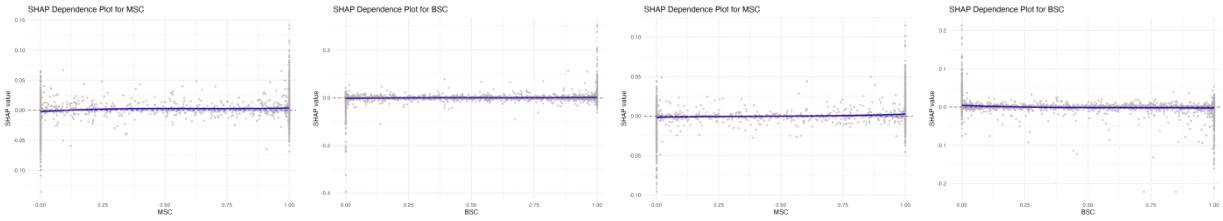
Perceptual environmental variables also show clear threshold patterns (Figure 6). Natural and sensory elements generate positive effects at relatively low levels (around 0.1), whereas artificial features require higher intensities (around 0.4) to produce comparable benefits. This suggests that emotional responses are more sensitive to natural stimuli, while built features exhibit a higher activation threshold.



(a) 2021 sense features (b) 2021 nature features (c) 2023 nature features (d) 2023 sense features

Figure 6. SHAP value for perceived Environmental Variable (During the Pandemic). Source: Authors.

The **built environment** demonstrates more complex dynamics (Figure 7). The effect of transport facilities remains relatively stable across periods: well-served areas are associated with positive sentiment, while poorly connected areas show negative effects, highlighting the role of accessibility. In contrast, preference patterns change markedly. During the pandemic, proximity to water and environmental quality were prioritized, with a “closer is better” tendency; a distance of approximately 125 meters and a green space ratio around 0.4 represent key thresholds.



(a) 2021 Metro station coverage (b) 2021 Bus Station Coverage (c) 2023 Metro station coverage (d) 2023 Bus Station Coverage

Figure 7. SHAP value for built Environmental Variable. Source: Authors.

4.2.3.Spatiotemporal Heterogeneity Analysis

Local relative importance reveals pronounced spatial variation across periods (Figure 8). Temperature and perceptual atmosphere remain the dominant drivers, though their spatial influence shifts after the pandemic. The role of temperature weakens in suburban areas, indicating reduced sensitivity to microclimatic conditions outside the urban core.



(a) The feature variable with the greatest impact in 2021 (b) The feature variable with the greatest impact in 2023

Figure 8. Feature variable local explanation map. Source: Authors.

5.Discussion

5.1.Planning and Policy Implications for Waterfront Emotional Geography

Research reveals fundamental waterfront emotional distributions have shifted from convenience toward comfort, center toward periphery, single functions toward composite experiences. During pandemic, central areas had high population densities, leading to lower public emotion scores, while suburban open

waterfront spaces became emotional havens due to low-density characteristics. Post-pandemic, this "risk geography" influence became weaker. People returned to looking for complete functions. At the same time, they wanted much better spatial quality.

Development intensity has a positive U-shaped relationship. Both extremely low-intensity open spaces and ultra-high-intensity landmark developments create positive emotions. But medium-intensity development causes negative emotions. This suggests waterfront spaces should avoid "mediocre medium development." They should pursue "either completely open or very outstanding" strategies.

Perceptual elements have a low threshold of 0.1. This means that even small amounts of natural experience can make people feel better. It also shows that improving spatial quality can be done at a low cost. However, there are diminishing returns. Planners should focus on creating natural spaces where none exist, instead of only adding more in places that already have them.

The GW-RF model shows clear spatial differences. Environmental factors work differently in central and suburban areas. This means local strategies are more effective than one-size-fits-all approaches.

5.2. Limitations and Future Work

This study has several limitations. The Weibo data may have user bias because most users are young and well-educated. The emotion analysis is based mainly on text mining and does not include physical or behavioral testing. The study also focuses only on Shanghai, so the results may not apply to other cultural settings.

Future research should combine data from different social media platforms with traditional survey methods. It should also use wearable sensors and EEG devices to track emotions in real time. In addition, future work should build cross-city and cross-cultural research networks to compare emotional patterns in different environments.

6. Conclusions

This study built a GW-RF-SHAP framework to explore how the environment affects public emotions in Shanghai's "One River One Creek" waterfront area. The pandemic greatly changed the emotional patterns along the waterfront. The links between environmental factors and emotions are complex and non-linear, and they vary across locations. Development intensity exhibits clear threshold effects, with both low- and high-intensity environments associated with more positive emotions. Waterfront planning should consider spatial differences and avoid uniform strategies. Waterfront development should balance functional provision with higher spatial quality.

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