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Influencing Factors and Spatial Characteristics of Urban Coastal Space Vitality Based on MGWR model: A Case Study of Qingdao

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Abstract Urban coastal spaces serve as critical public resources, where spatial vitality acts as a primary indicator of environmental quality and social functionality. This study aims to quantify the spatial characteristics of coastal vitality and identify its multi-scale driving mechanisms to inform evidence-based urban planning. Focusing on the eastern coastline of Qingdao, we characterized spatial vitality using spatiotemporal crowd distribution data derived from Baidu Heatmaps. Spatial autocorrelation analysis was employed to detect clustering patterns, while a Multiscale Geographically Weighted Regression (MGWR) model was implemented to examine the heterogeneous influence of multi-source spatial factors. The analysis reveals a significant positive spatial autocorrelation in coastal vitality, characterized by a prominent "east-high, west-low" distribution pattern. The MGWR results indicate that the Normalized Difference Vegetation Index (NDVI) of open spaces, shoreline morphology, spatial compactness, transport accessibility, and surrounding residential density are the primary determinants, with their impact varying across different spatial scales. Compared to traditional global and local regression models, MGWR demonstrated superior goodness-of-fit and higher precision in capturing spatial non-stationarity. This research provides a methodological framework for assessing coastal human settlements and offers data-driven insights for the spatial optimization of urban waterfronts. While the study utilizes high-resolution big data, the findings are limited by the seasonal nature of crowd behavior, and future research should incorporate multi-seasonal comparisons to further validate these spatial dynamics.

Keywords Coastal Space, Spatial Vitality, Multi-source Data, Spatial Heterogeneity, Multi-scale Geographically Weighted Regression (MGWR)

1. Introduction

Coastal regions have emerged as premier environments for human habitation and socio-economic advancement, attributed to their abundant marine-terrestrial resources, complex ecological systems, and strategic geographical positioning(Small & Nicholls, 2003). Current United Nations data indicates that approximately 40% of the global population resides within coastal zones as of 2021. Furthermore, two-thirds of the world's megacities are situated in these areas, with coastal population growth rates significantly outpacing those of inland regions (Cicin-Sain & Belfiore, 2005). As pivotal hubs for regional economic prosperity, urban coastal spaces represent some of the most intricate and highly developed functional zones. These areas integrate diverse roles, including economic expansion, tourism development, and ecological conservation, all of which serve to catalyze urban vitality and facilitate

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sustainable growth. Consequently, regional spatial vitality has become a key metric for reflecting the environmental quality and functional vigor of coastal urbanism. Therefore, an in-depth investigation into the mechanisms governing coastal vitality is essential to inform high-quality spatial enhancement and provide a scientific basis for sophisticated planning and management frameworks.

1.1 Urban coastal spatial vitality

Extensive scholarly discourse has addressed urban spatial vitality across diverse disciplines, yielding a robust body of literature regarding its evolutionary trajectory, driving factors, and methodological assessments. The conceptual origins of "urban vitality" are rooted in early theoretical frameworks of urban public space within the planning domain (Nie et al., 2021). Lynch suggests that a good urban form should also include a series of elements such as vitality and diversity, accessibility, control, sense, flexibility, and social equality, among which urban vitality is the primary reference and indicator (Lynch, 1984). The research on urban vitality originally focused on urban morphology, urban policy systems, and macro-management planning; later, some scholars proposed a system of factors influencing urban vitality. Quantitative methods on urban vitality also focus on two dimensions: the representation of the vitality of the crowd and the spatiotemporal distribution of vitality at the spatial scale (Lynch, 1984). At the meso-scale, vitality is predominantly characterized by the intensity of population aggregation. Recent methodological advancements leverage dynamic datasets, including Baidu Heatmaps (Niu et al., 2021), real-time social network check-in data, mobile signaling trajectories, and point-of-interest (POI) densities of catering services, to achieve high-resolution vitality mapping(Niu et al., 2021).

With the wide application of spatial data, the close relationship between urban vitality and urban spatial patterns has been proven (Niu et al., 2021). Investigations into the evolutionary patterns of urban agglomerations, neighborhood-level vitality disparities, and the performance of public realms—such as urban parks and waterfronts—consistently demonstrate that vitality is inextricably linked to the spatial morphology and compositional characteristics of the built environment. For instance, Huang et al. identified recurring spatial attributes across highly dynamic coastal zones in various international contexts(Niu et al., 2021) Similarly, Ying et al. utilized big data to establish a comprehensive framework of street vitality determinants, employing regression analysis to quantify the impact of specific factors across diverse functional street types (Doan & Zhang, 2025). In the context of waterfronts, Jingyi et al. developed a multi-dimensional evaluation system focused on diversity, agglomeration, stability, and public attention (Yin, 2019). while Weiqiang et al. assessed spatial and practical dimensions using GIS and correlation analysis to examine the influence of urban hinterland development on waterfront vigor (Wang & Ma, 2020). Despite the burgeoning literature on waterfront vitality, the current scholarly focus remains predominantly on riverine environments. Empirical research specifically targeting the unique spatial dynamics and vitality drivers of urban coastal spaces remains notably sparse.

1.2 Methodology for research on the correlation between urban vitality and urban space

Studies on the correlation between urban vitality and the built environment mostly use multiple linear regression (MLR) models (Fan et al., 2021; Zhang et al., 2021). However, traditional MLR frameworks often fail to fully demonstrate spatial process heterogeneity and spatial non-stationarity (Fan et al., 2021; Zhang et al., 2021). In this context, the geographically weighted regression model (GWR) was introduced to better accommodate spatial heterogeneity (Liu et al., 2020). Despite its advantages, classical GWR assumes a uniform spatial scale for all independent variables, thereby ignoring the multi-scalar nature of different influencing factors and potentially leading to significant estimation biases. The multiscale geographically weighted regression (MGWR) model improves the classic geographically weighted regression by allowing the bandwidth of each variable to be different, thereby obtaining more credible estimation results and giving the influence scale of different variables (Fotheringham et al., 2017; Shen et al., 2020). At present, MGWR is used in many fields such as research on spatial economic differences (Wang et al., 2022), urban micro-mobility (Huang et al., 2022), urban resilience determinants (Chen et al., 2021), and the nexus between heat island intensity and urban morphology (Huang et al., 2026), etc. However, in terms of revealing the correlation between urban environmental characteristics and the vitality of urban coastal space, currently research is not sufficiently in-depth.

In summary, although the academic community has explored urban waterfront vitality using various methodologies, several research gaps remain. First, existing studies on urban vitality predominantly focus on riverine environments, leaving coastal spaces significantly under-researched. Furthermore, these studies often rely on fragmented spatial segments, lacking a holistic analytical perspective within a contiguous region. Second, conventional analytical frameworks—such as Pearson correlation, Multiple Linear Regression (MLR), and Geographically Weighted Regression (GWR)—fail to accurately reflect multi-scalar spatial indicators and complex spatial processes. Therefore, this study focuses on urban coastal vitality by utilizing Baidu Heatmap data and spatial autocorrelation to analyze spatial differentiation, while employing the Multiscale Geographically Weighted Regression (MGWR) model to examine its driving factors. The research objectives of this article are as follows:

(1) Characterize the spatial configurations and distributional heterogeneity of coastal vitality.

(2) Identify the influencing factors of coastal vitality and

quantify the spatial heterogeneity of their impacts.

(3) Propose relevant planning strategies and suggestions for the construction and renewal of urban coastal space.

This study seeks an in-depth understanding of the impact of the spatial and temporal characteristics of the vitality of the coastal space on the east coast of Qingdao and the factors influencing it. By doing so, it attempts to provide a theoretical basis for enhancing the impact of urban coastal space and ultimately improving the quality of urban life and public environmental conditions.

2. Case and methods

2.1 Study case

Qingdao, located in East China, is an important coastal central city, a coastal tourism city and an international port city in China. Qingdao's coast is divided into the west and east coast with Jiaozhou Bay as the dividing line. The east coast has a mature urban construction, stable spatial element distribution, and diverse coastal space types. Therefore, this study focuses on the entirely open coastal space on the east coast of Qingdao (about 43 kilometers along the coast from Tuandao Island to Baoyu Island), based on the Qingdao City Coast. Based on the relevant content of the Regulations on the Management of Belt Protection and Utilization, the 1,000m buffer zone extending from the coastal municipal road to the inner hinterland is used as the research scope, with a total area of 50.57km² (Figure 1). The latest version of the coastline to the first urban arterial road on land is used as a coastal open public space research unit at intervals of 500m, with a total of 82 units. A buffer zone will extend from the municipal road to the hinterland and be surrounded by urban secondary arterial roads and branch roads. The resulting areas are peripheral environmental research units, with a total of 208, and 290 research units.

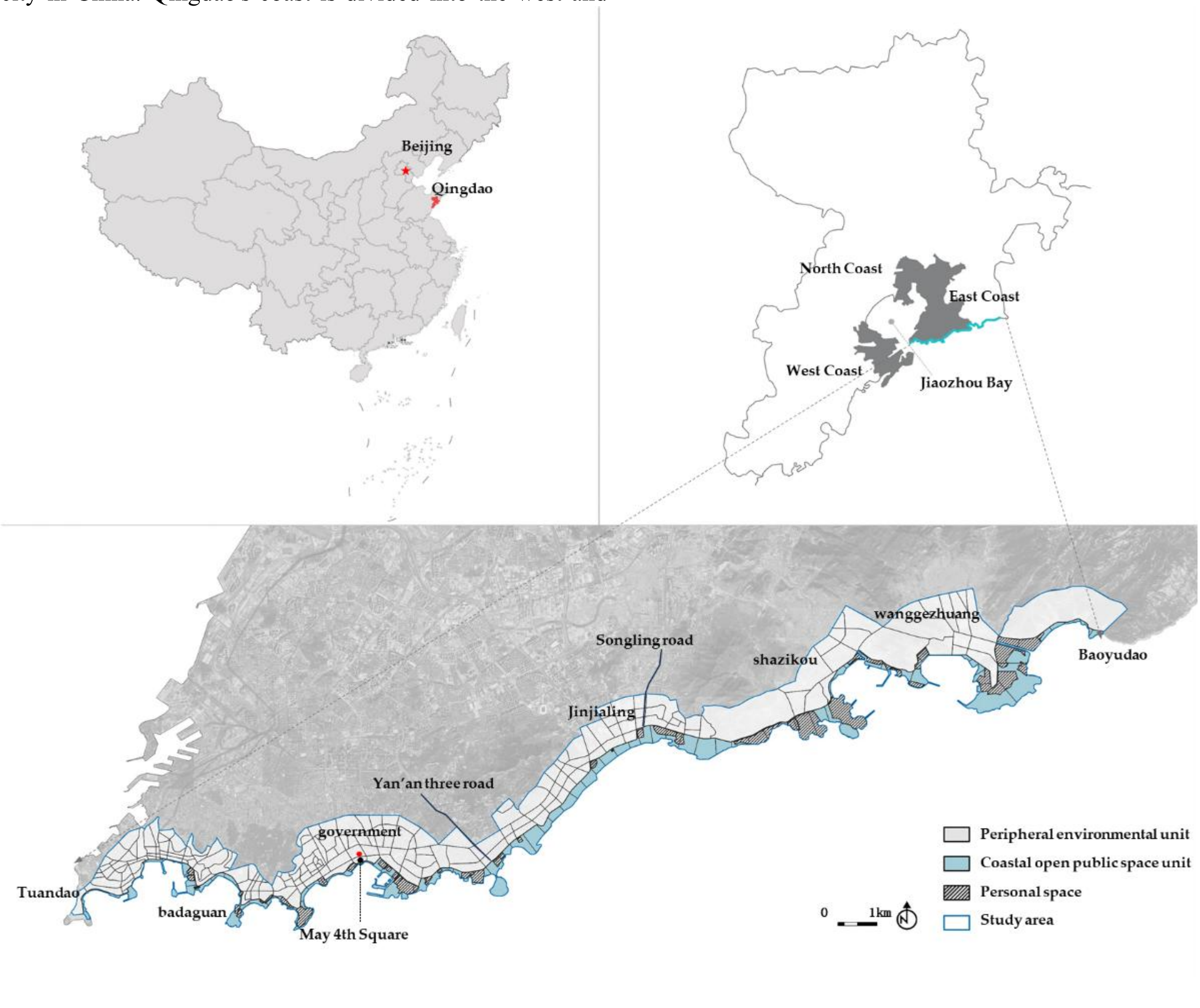


Figure 1. Study area: coastal space along the east coast in Qingdao

2.2 Study data

Consistent with established literature and spatial scale considerations, this study utilizes population aggregation intensity as a proxy for coastal spatial vitality. Real-time crowd distribution data were retrieved via web crawling of Baidu Heatmaps across seven consecutive days, from May 13 to May 19, 2023. This period encompassed both weekend (May 13–14) and weekday (May 15–19) dynamics, with specific sampling intervals at 10:00, 15:00, and 19:00 daily. The selection of May was intentional, as Qingdao's temperate spring climate encourages stable outdoor activities, thereby facilitating the capture of representative behavioral averages. Furthermore, the sampling period consisted exclusively of clear weather conditions, effectively mitigating the confounding effects of extreme weather or peak tourist surges on vitality measurements. To derive a comprehensive vitality index, raw data from different time steps were homogenized and averaged. The resulting dataset was spatially visualized and processed within ArcGIS, during which data points outside the designated research perimeter were filtered to ensure analytical precision.

Integrating established theoretical frameworks with considerations of data availability and quantitative feasibility (Chen & Deng, 2021), the two dimensions of internal characteristics and external environment were selected as the main factors influencing vitality. Among them, the internal characteristics of the coastal area were based on the division principles of natural elements, landscape elements and humanistic elements respectively. Eight indicators were selected, the external environment screened nine indicators based on existing research, and finally all data were normalized. This study uses the standardized normalization method here. The calculation formula is:

$$U = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

where U represents the value after dimensionless processing, X_i represents the original value, and X_{max} and X_{min} represent the maximum and minimum values in the original value respectively.

The data used to study the impact mechanism of coastal space and vitality include Qingdao POI data from 2023 Qingdao point-of-interest (POI) records, road network morphologies, building footprints (vector format), and public transportation inventories (including bus stops and subway stations), Furthermore, vector data detailing Qingdao's 2023 green infrastructure and hydrological systems were incorporated to characterize the natural landscape matrix. To ensure rigorous data fidelity, all vector layers were cross-referenced and calibrated against 2023 high-resolution satellite imagery through a ground-truthing process. This multi-step validation ensured the spatial accuracy and temporal synchronicity of the datasets, providing a reliable foundation for the subsequent MGWR analysis.

Table 1. Urban coastal space environment elements and quantitative measurement

	Index		Explanation
External environment	Residential density		Ratio of total residential area in the statistical unit to the area of the statistical unit
	Attraction density		Ratio of the area of attractions within the statistical unit to the area of the statistical unit
	Number of leisure facilities		Number of POIs for recreation, sports, attractions, shopping spots, dining spots
	Number of public service facilities		Number of POIs for government, education, healthcare, and hotels
	Road network density		Ratio of road length to study unit area in the statistical unit
	Accessibility	Bus stop density	Mean kernel density of bus and subway stops within the statistical unit
		Metro station density	
	Location centrality		Distance of the center of the statistical module from the administrative center of the district
	Resident population density		Ratio of the total population to the area of the street (administrative division) to which the statistical unit belongs
Internal environment	NDIV		Normalized vegetation index within spatial units of coastal landscape zones
	Artificial vertical shoreline		Proportion of shoreline within the spatial unit of the coastal landscape zone to the total shoreline of the unit
	Number of leisure facilities		Number of POIs for fitness facilities, seating, etc. within the spatial unit of the coastal landscape zone
	Number of public service facilities		Number of POIs such as public toilets, washrooms,

		stagecoaches, cafes, etc. in the spatial unit of the coastal landscape zone
	Greenway density	Ratio of total length to area of walking paths, cycle paths and running paths within the spatial unit of the coastal landscape zone
	Parking density	Ratio of parking lot area to spatial unit area within the coastal landscape zone spatial unit
	Compactness	Compactness of the spatial form of spatial units in the coastal landscape zone
	Attraction density	Ratio of the area of attractions within the spatial unit of the coastal landscape zone to the area of the spatial unit

2.3 Study methodology

2.3.1 Spatial vitality density

The Vitality Density Index measures crowd intensity by dividing the instantaneous population count by the respective research unit area. As a positive indicator, higher values denote more robust spatial vigor. For the MGWR analysis, we utilize the diurnal average density to capture characteristic spatial vitality patterns. (Formula 1):

$$\overline{D_j} = \frac{\sum_{i=1}^{m} P_{i,j}}{A * m} \quad (1)$$

where $\overline{D_j}$ is the average crowd density on day j; $P_{i,j}$ is the number of crowds on day j at hour i; A is the area of the research unit (unit: hm2); and m is the number of people in one day's total hours calculated.

2.3.2 Spatial autocorrelation

Spatial autocorrelation analysis is divided into global correlation and local correlation. Global spatial autocorrelation, typically quantified by Global Moran's I, is employed to evaluate the clustering tendencies of the research object across the entire study area, determining whether an overall spatial dependency exists. In contrast, local spatial autocorrelation, specifically Local Indicators of Spatial Association (LISA), facilitates a multi-scalar correlation analysis between a specific spatial unit and its immediate neighbors. Compared to global metrics, LISA provides a more granular reflection of spatial heterogeneity and local clustering patterns, identifying specific "hot spots" or "cold spots" that the global index may obscure.

2.3.3 Multiscale geographically weighted regression

In contrast to classical Geographically Weighted Regression (GWR), which is constrained by a uniform bandwidth for all independent variables, Multiscale Geographically Weighted Regression (MGWR) allows each variable to operate under its own optimal bandwidth. This flexibility effectively addresses the challenge of spatial non-stationarity and varying operational scales across different determinants (Fan & Zhang, 2022). Specifically, MGWR assigns smaller bandwidths to variables exhibiting significant local variations, while selecting larger bandwidths for factors that remain relatively stable or manifest global-scale influences. By deploying the MGWR framework, this study captures the multi-scalar impacts of diverse urban environmental elements on coastal vitality. This approach not only elucidates the nuanced spatial heterogeneity of the drivers but also significantly mitigates the estimation biases inherent in single-scale models. (Formula 2).

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i \quad (2)$$

where x_{ij} is the jth predictor variable, (u_i, v_i) is the centroid coordinate of each block i, and β_{bwj} represents the bandwidth of the regression coefficient of the jth variable. This study uses MGWR 2.2 software to calculate the model, and combines this with ArcGIS software to assist with visual analysis.

2.4 Study framework

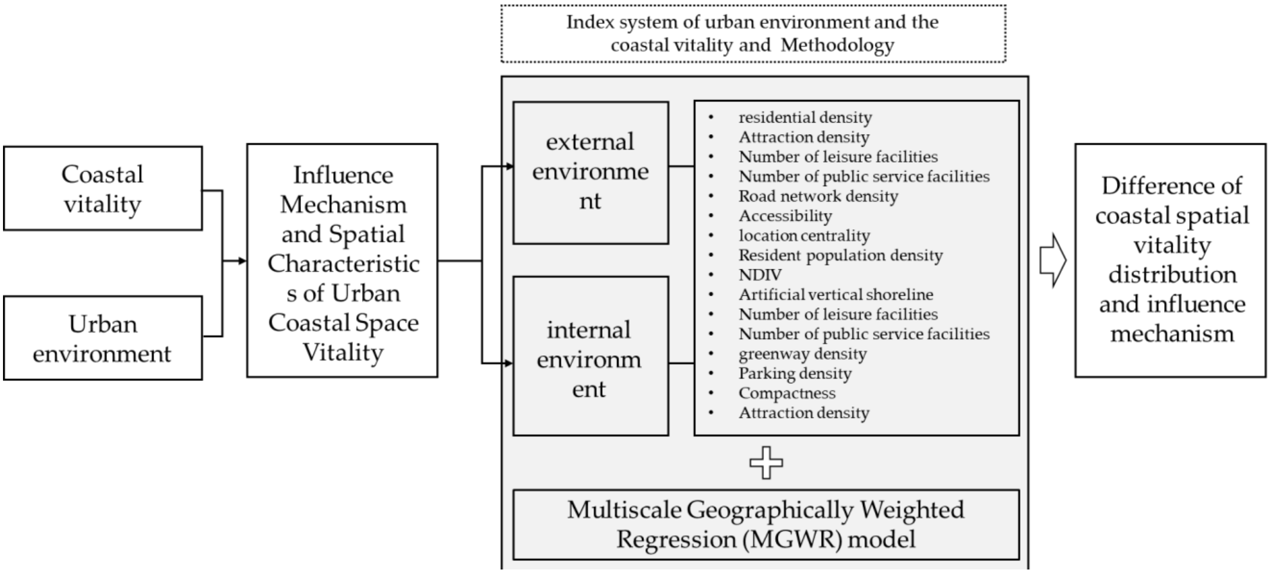


Figure 2. The theoretical framework of coastal vitality

3. Analysis of spatial differentiation characteristics of coastal space vitality

3.1 Distribution pattern of coastal space vitality

The overall vitality of Qingdao's eastern coastline exhibits a discernible "east-high, west-low" distribution pattern, characterized by significant spatial differentiation. Demarcated by Yan'an Third Road, the study area displays a pronounced polarized structure along the east-west axis (Figure 2). In contrast, the distribution of vitality density remains relatively homogeneous. With Yan'an Third Road and Songling Road serving as geographic boundaries, vitality density manifests as a tri-sectional configuration, where the central segment significantly outpaces the eastern and western peripheries in intensity (Figure 3). Specifically, within the eastern Laoshan District—primarily Shazikou and Wanggezhuang Streets—the landscape is dominated by rural settlements with lower road network densities. Consequently, the spatial pattern in these areas is uniquely defined by high vitality values coupled with low vitality density, reflecting a distinct mode of spatial performance compared to the highly urbanized core.

ArcGIS was employed to analyze the development of vitality value and vitality density in the coastal space. The geographic centers of vitality value and vitality density are situated in the central section of the studied coastline, at the boundary between Shinan District and Laoshan District. Furthermore, a discrepancy was observed between the geographic centers of development for vitality value and vitality density. Specifically, the vitality value exhibits a greater eastward shift compared to the vitality density, and its development center encompasses a larger spatial extent, with the development direction extending eastward along the coast.

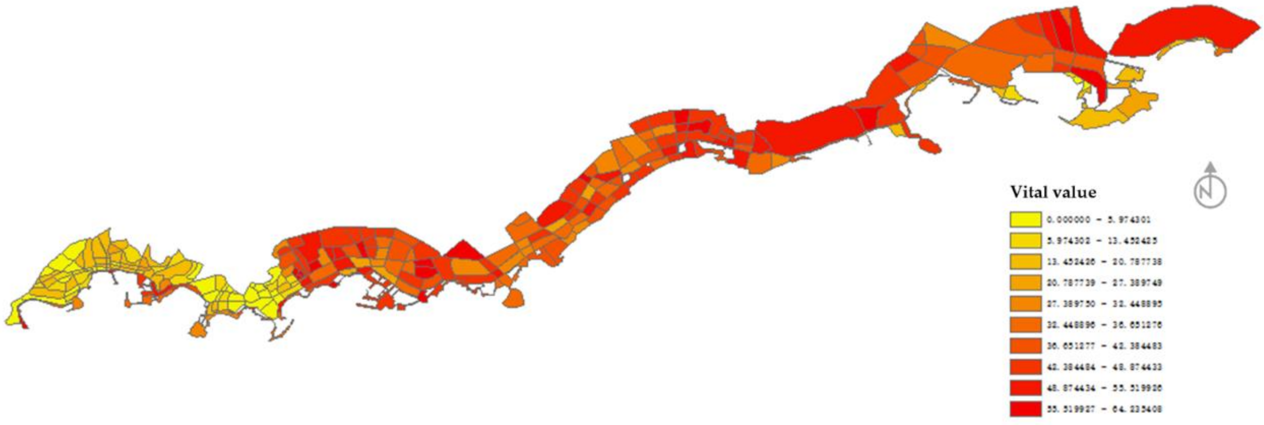


Figure 3. Distribution of the coastal vitality

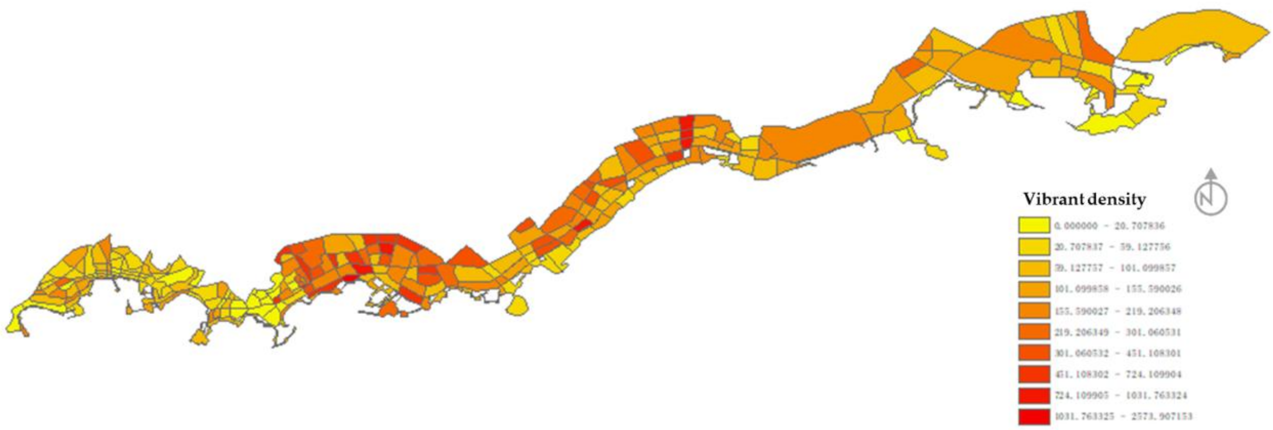


Figure 4. Distribution of the coastal vitality density

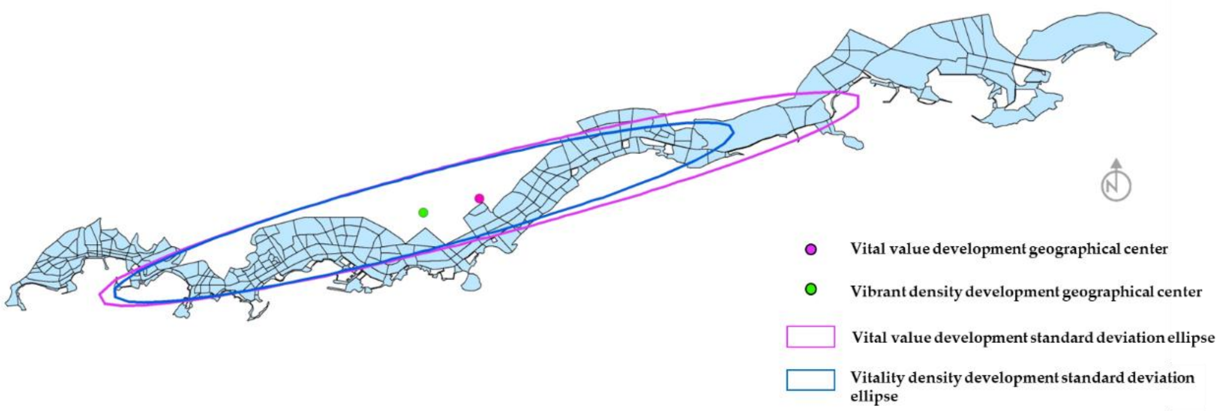


Figure 5. Geographic distribution of spatial vitality development

3.2 Vitality clustering characteristics of coastal space

According to the Moran's I statistical results of spatial vitality within the study area on Qingdao's east coast (Figure 5), the P-value is close to zero, and all values are significant at the 0.01 level. This indicates that the distribution of vitality in the coastal space is not random but exhibits a high degree of clustering. In other words, the vitality value of a given research unit exerts either a positive or negative influence on the vitality values of adjacent units. The LISA measurement results further confirm that the spatial vitality distribution on Qingdao's east coast possesses significant spatial autocorrelation and displays a non-uniform spatial pattern, characterized by four distinct types of agglomeration areas: high-high, high-low, low-high, and low-low.

As shown in Figure 6, 22.11% of the regions exhibit high vitality values, which in turn positively or negatively affect the vitality values of surrounding units. These high-vitality areas are mainly concentrated in the central section of the Wusi Square Business District (where the municipal government is located) and the Jinjia District of the Laoshan District Government, including the Ridge Financial Center. In contrast, 13.36% of the area has low vitality values, which similarly influence adjacent units; these low-vitality areas are primarily concentrated in the old city near Qingdao Railway Station and the Badaguan Historical District. Figure 7 reveals that the spatial clustering pattern of vitality density is broadly similar to that of vitality values. Specifically, 8.84% of the area belongs to the "high-high" cluster, while 19.37% belongs to the "low-low" cluster. Notably, the easternmost unit within the study area exhibits an anomalous pattern: it shows a "high-low" clustering for vitality values but a "low-low" clustering for vitality density. This unit corresponds to a village located near the Laoshan Scenic Area, where the division of spatial units follows a consistent principle based on road networks. However, the permanent population in this unit is relatively large, resulting in higher vitality values but lower vitality density. Overall, the spatial vitality distribution along Qingdao's east coast demonstrates a pronounced two-level differentiation, characterized by clear "high-high" and "low-low" clustering patterns.

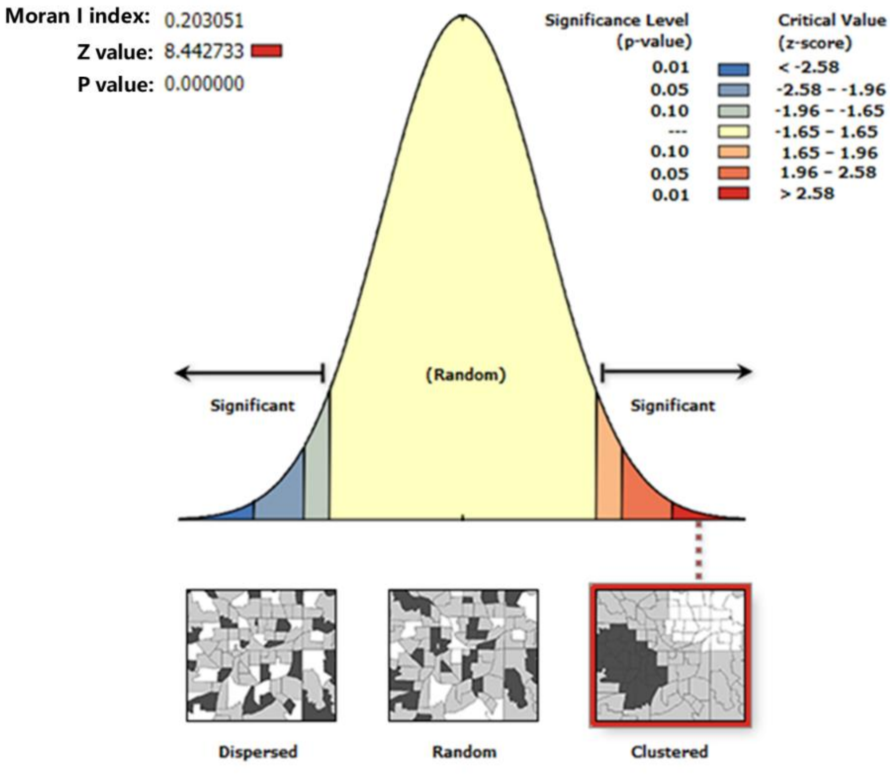


Figure 6. Results of global spatial autocorrelation analysis

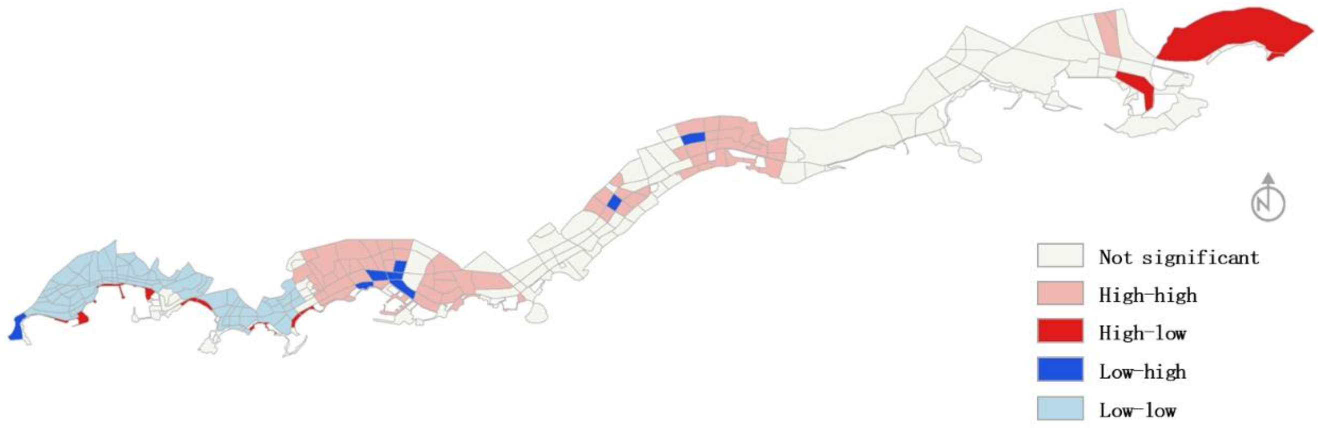


Figure 7. LISA agglomeration of the coastal vitality

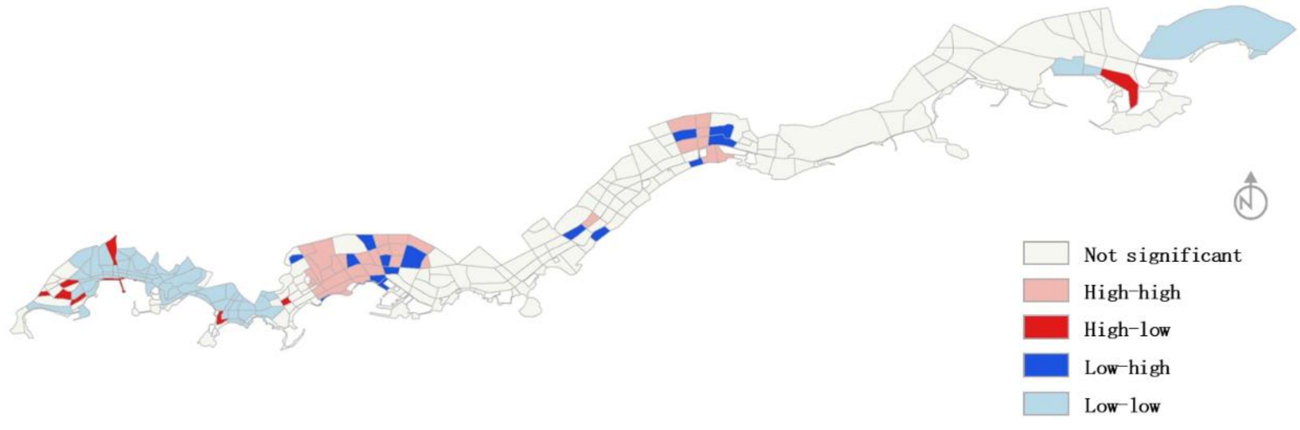


Figure 8. LISA agglomeration of the coastal vitality density

4. Analysis of factors influencing coastal space vitality

To explore the differences in internal characteristics and external environmental factors affecting coastal space, as well as their impacts on vitality value and vitality density, and to simultaneously verify the applicability of the MGWR regression model, this study employed OLS, GWR, and MGWR models to analyze the vitality value and its influencing factors in coastal space. The results (Table 2) show that the MGWR model achieves a significantly higher adjusted R^2, while its AICc value progressively decreases, indicating that the MGWR model has the best overall goodness of fit among the three models. The adjusted R^2 value of the MGWR model is 0.733, meaning that the model explains 73.3% of the variation in coastal spatial vitality values on Qingdao's east coast, demonstrating a good fit. Compared with the GWR model, the MGWR model allows the bandwidth to adapt to the scale of each variable, thereby accounting for differences in the scales at which individual variables affect vitality values. Therefore, the MGWR model was comprehensively considered as the preferred model for analyzing influencing factors in this study.

Table 2. Comparison of the results of each model

	OLS	GWR	MGWR	
AICc	2324.673	2258.078	463.112	
Adjust R^2	0.452	0.589	0.733	
Bandwidth	——	88	NDIV	289
			Proportion of artificial shoreline	289
			Number of leisure facilities	289
			Number of public service facilities	289
			Greenway density	289
			Parking density	289
			Compactness	289
			Attraction density	289
			Residential density	123
			Attraction density	289
			Number of leisure facilities	289
			Number of public service facilities	289
			Road network density	47
			Bus stop density	289
			Metro station density	289
			Location centrality	226
			Resident population density	142

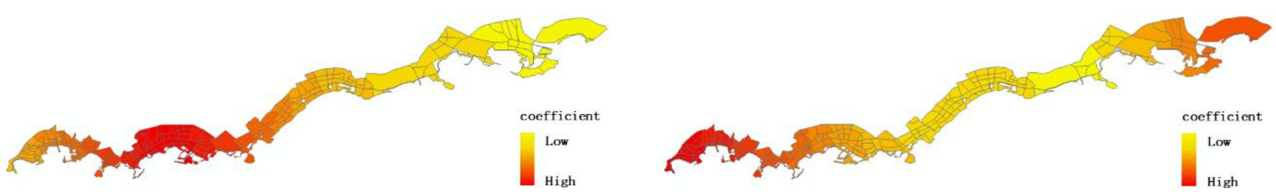
Based on the MGWR model, this study constructed three sets of regression models to analyze the factors influencing vitality value and vitality density in the coastal space of Qingdao's east coast (Table 3). The three sets correspond to: (1) internal characteristics of coastal space; (2) external environment of coastal space; and (3) all indicators combined. The regression results for internal characteristics show that the selected indicators explain approximately 54.6% of spatial vitality. Among these, the proportion of artificial shoreline, the Normalized Difference Vegetation Index (NDVI), and the compactness of spatial form significantly influence coastal spatial vitality, exhibiting a significant correlation and an inhibitory effect. The regression results for the external environment (i.e., buffer space and spatial vitality) indicate that the selected external environment indicators explain about 71.7% of vitality. Within this group, the kernel density of bus stations, the kernel density of subway stations, and residential density within research units have significant effects on spatial vitality. Finally, the regression results combining all indicators (internal characteristics and external environment) demonstrate that these factors collectively have the greatest influence on vitality, explaining 73.3% of the overall vitality value.

Table 3. The regression of each variable in the vitality regression model

		Model 1		Model 2		Model 3	
	Variables	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
Internal environment	NDIV	-4.895	0.000			-3.269	0.001
	Proportion of artificial shoreline	-3.669	0.000			-1.649	0.099
	Number of leisure facilities	0.005	0.996			0.919	0.358
	Number of public service facilities	0.857	0.391			0.780	0.435
	Greenway density	-1.907	0.056			-1.049	0.294
	Parking density	-0.691	0.490			-1.250	0.211
	Compactness	-4.561	0.000			0.588	0.557
	Attraction density	-0.530	0.596			-0.206	0.837

External environment	Residential density			5.743	0.000	5.502	0.000
	Attraction density			-0.795	0.426	-0.942	0.346
	Number of leisure facilities			0.170	0.865	0.289	0.773
	Number of public service facilities			0.477	0.633	0.468	0.640
	Road network density			1.545	0.122	1.279	0.201
	Bus stop density			3.770	0.000	3.796	0.000
	Metro station density			5.972	0.000	4.006	0.000
	Location centrality			0.310	0.757	-0.785	0.432
	Resident population density			0.208	0.835	0.277	0.782
Results	Samples	290		290		290	
	Adjust R^2	0.546		0.717		0.733	
	AICc	606.926		471.184		463.112	

To further understand the spatial differences among the various indicators affecting coastal spatial vitality, this study used ArcGIS software to analyze the spatial distribution of influence coefficients for indicators significantly correlated with spatial vitality values (Figure 8). The results indicate that the NDVI (Normalized Difference Vegetation Index) is negatively correlated with coastal spatial vitality, and its influence exhibits a gradually decreasing trend from west to east. Among the areas, the municipal government and the Hong Kong Middle Road business district are most strongly affected. The proportion of artificial shoreline is also negatively correlated with coastal spatial vitality, and its influence value shows a pattern of increasing from east to west and gradually decreasing toward the middle, with the western end slightly higher than the eastern end. This suggests that the eastern and western ends of the study area—namely the Tuandao to Badaguan area and the Shazikou Laoshan area—are more susceptible to the influence of shoreline type due to their lower vitality values. Moreover, artificial shoreline is inherently more isolated than natural ecological shoreline, which enhances people's contact with the ocean. Thus, it is also confirmed that natural ecological coastlines, such as gravel and bedrock coastlines, can drive and promote the popularity of coastal open spaces.The influence of spatial form compactness on coastal spatial vitality displays a pattern of being high at both ends and low in the middle. Statistical results show that the smaller the degree of spatial form discreteness (i.e., the more compact the space), the lower the vitality value of the coastal space. This implies that populations tend to prefer spatial aggregation along linear or free layouts of the coast; compact spatial forms often induce negative psychological effects, thereby reducing spatial vitality. In contrast, linear or free spatial forms can create a favorable sense of order and thus increase popularity. Regarding the impact of residential density, the results show a basic pattern of being high in the east and low in the west within the research units. (Fan & Zhang, 2022). The primary impact range is concentrated in the area east of Songling Road, mainly covering Shazikou Street and Wanggezhuang Street. In contrast, areas with lower impact coefficients are concentrated around the municipal government and the Hong Kong Middle Road business district. These results also indicate that when land within the coastal space serves only a single use, residential density exerts a greater influence on vitality. Furthermore, the core density of bus stations and subway stations within the study units affects the distribution of coastal spatial vitality, both exhibiting a clear spatial pattern of low values in the west and high values in the east. The improvement of public transportation accessibility thus has a strong impact on enhancing the vitality of coastal space..



(a) (b)

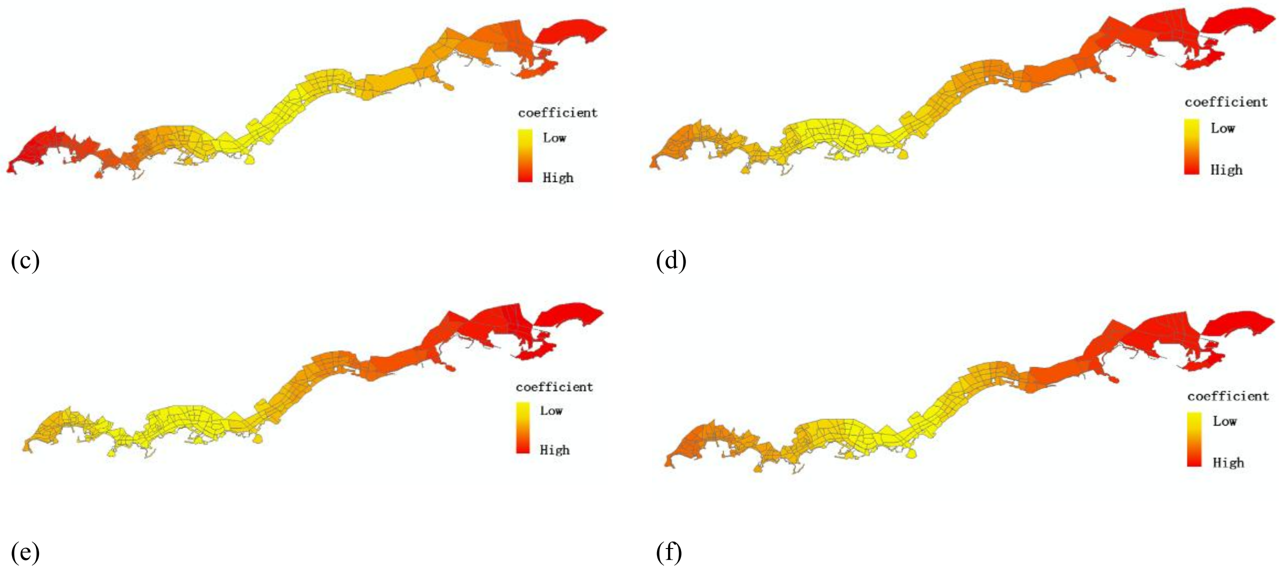


Figure 9. Spatial distribution of coefficients of multi-scale geographically weighted regression model: (a) spatial distribution of NDVI vegetation index coefficients; `(b) spatial distribution of artificial shoreline coefficients; (c) spatial distribution of compactness coefficients; (d) spatial distribution of residential density coefficients; (e) spatial distribution of bus stop density coefficients; (f) spatial distribution of metro station density coefficients

5. Discussion

5.1 Optimization of Internal Spatial Determinants

The empirical results suggest that enhancing the vitality of urban coastal spaces requires a strategic optimization of their intrinsic characteristics. To facilitate crowd gathering, coastal open public spaces must prioritize visual permeability; specifically, reducing dense vegetation that obstructs sightlines is essential to fostering a sense of safety and enhancing hydrophilicity. Furthermore, while adhering to coastal engineering safety protocols and flood control requirements, planning efforts should strive to preserve naturalistic shoreline morphologies. This balance ensures that functional infrastructure does not compromise the high-quality aesthetic experience expected by the public. Additionally, the impact of spatial configuration on vitality must be carefully managed. Planners should evaluate the trade-offs of high-compactness environments and consider avoiding overly rigid linear layouts in favor of more organic, diverse spatial forms that encourage prolonged stay.

5.2 Synergistic Influence of the Urban Matrix

The vitality of coastal spaces is not an isolated phenomenon but is deeply embedded in the surrounding urban fabric. First, transportation accessibility remains a cornerstone of spatial performance. This necessitates a robust multi-modal network that integrates coastal nodes with high-density public transit stations, ensuring seamless connectivity between the waterfront and the inner city. Second, the spatial heterogeneity of vitality is significantly moderated by external factors such as residential density and economic potential. Therefore, the deployment of coastal public nodes should transition toward a dynamic zoning approach. By synthesizing data on land-use types, population density, and development gradients, planners can achieve a more rational and resilient spatial distribution that aligns with the specific socio-economic context of the area.

6. Conclusion

6.1 Summary of Findings

This study implemented a Multiscale Geographically Weighted Regression (MGWR) model to conduct an empirical analysis of urban coastal space vitality, using the eastern coast of Qingdao as a representative case. By examining a multi-dimensional suite of internal and external influencing factors, the research successfully elucidated the spatial differentiation and underlying mechanisms governing coastal crowd distribution. The results confirm that the MGWR framework provides superior precision in capturing the spatial non-stationarity of these drivers compared to traditional global models.

6.2 Academic and Practical Contributions

The findings contribute to the field by addressing the existing research gap concerning the multi-scale drivers of waterfront vitality. Methodologically, this study offers a reproducible framework for evidence-based design (EBD) in coastal environments. Practically, the proposed strategies for spatial optimization and dynamic zoning provide a theoretical foundation for urban planners and policy-makers to enhance the quality and social sustainability of coastal public assets.

6.3 Limitations and Future Research

Despite the insights gained, this research is subject to certain limitations. The reliance on big data from a specific period means the findings may not fully account for seasonal variations in crowd behavior or extreme weather impacts. Future studies should incorporate longitudinal data across multiple seasons and integrate qualitative methods, such as user perception surveys, to provide a more holistic understanding of the social-ecological dynamics of coastal vitality.

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