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Digital Clustering Method for Coastal Zone Scenes Based on Landscape Character Theory

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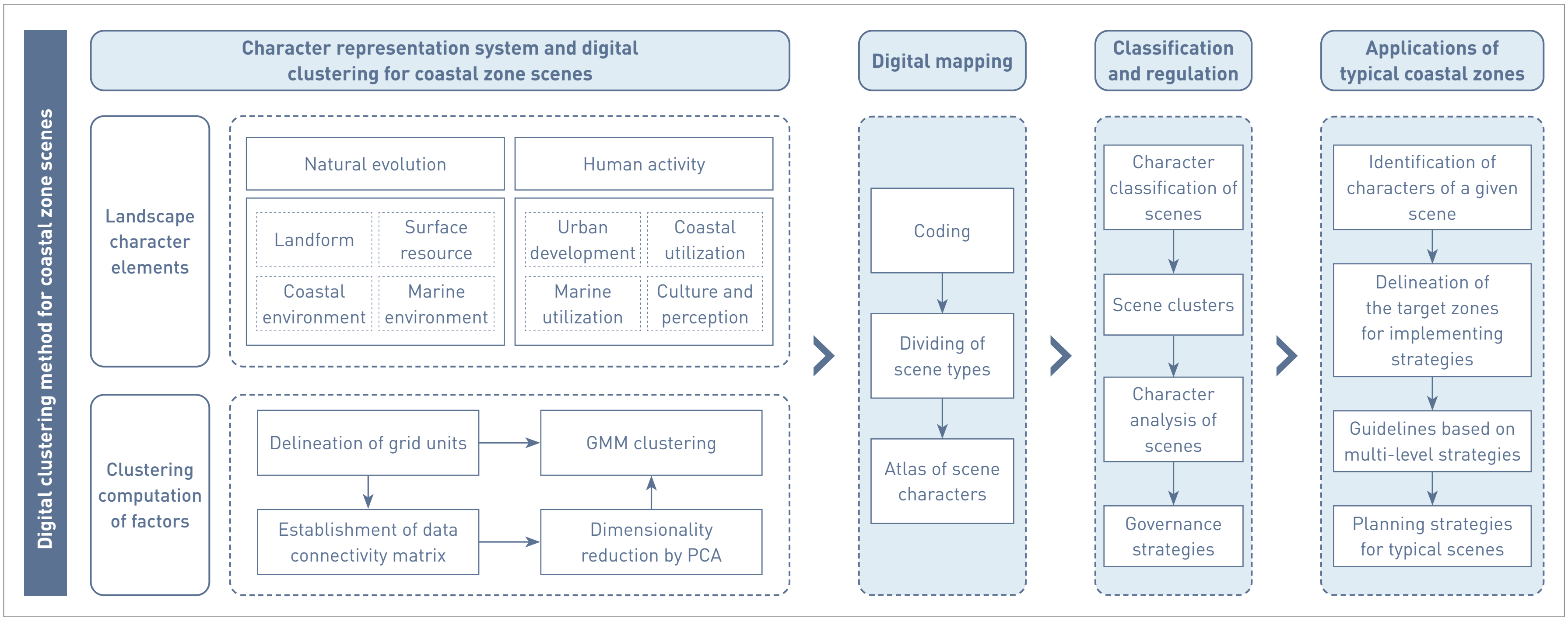
GRAPHICAL ABSTRACT



ABSTRACT

Aiming at the high-quality development of marine landscapes and the needs of accurate assessment and quality improvement of coastal landscapes, systematic digital analysis and quantitative research of typical coastal zone scenes have become one of the prerequisites for the in-depth research on coastal landscapes. This study, based on landscape character theory, constructs an analytical framework and technical path suitable for the digital clustering research on coastal scenes with the Gaussian Mixture Model (GMM). Taking the typical area of Taozi Bay in Yantai as an example, this study collaborates with remote sensing image interpretation and ArcGIS spatial analysis to quantitatively extract basic information of coastal landscapes, establishes a coastal zone scene characterization system, uses the GMM to form a digital clustering analysis process for scene characters, and combines Bayesian Information Criterion and expectation maximization algorithms to optimize key parameters for coastal zone scene clustering. It integrates classification and digital mapping practices for coastal zone scenes, and provides an analytical basis for the formulation of corresponding landscape and environmental management strategies. Proposing an analytical method suitable for the quantitative characterization and digital integration of coastal zone scenes, this study offers

research references and practical implications for the clustering identification and collaborative management of coastal landscape resources.

KEYWORDS

Coastal Zone Scene; Clustering Method; Gaussian Mixture Model; Landscape Character Theory; Coastal Zone; Landscape Planning and Design

HIGHLIGHTS

- A classification framework for coastal scenes is constructed based on landscape character theory
- A GMM-based clustering method is developed for digital analysis of coastal scenes
- A case study in Taozi Bay demonstrates the classification framework with scene typologies and mapping outcomes

RESEARCH FUNDS

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1 Introduction

Precise assessment and refined development of coastal zone landscapes constitute an essential means of highlighting coastal regional identity and sustaining their native landscape characters[1]. Harnessing digital technologies to classify coastal zone scene resources and determine their characters has become the fundamental and pivotal approach in today's marine landscape upgrading initiatives. As a coordinated composite landscape with the land–sea interface, the coastal zone scene serves for purposes of ecological conservation, resource utilization, and cultural inheritance, playing an indispensable role in preserving scene authenticity, strengthening regional distinctiveness, and preventing landscape homogenization[2]. In 2022, China explicitly set the goal of enhancing marine ecological protection and creating "beautiful bays," further propelling coastal zone scene research from traditional macro-scale planning towards refined identification and dynamic regulation[3]. Against the backdrop of rapidly evolving technologies such as big data and machine learning, it is imperative to develop quantitative methods and analytical techniques tailored to the environmental characters of coastal zone scenes. Such methods will assist in scene classification, character analysis, and digital representation, thereby improving the precision of graphical interpretation and the reliability of resource governance.

Contemporary research on landscape characters provides a crucial theoretical basis for scene analysis. Earlier studies dissected the scene essence from the perspectives of element composition, spatial structure, and functional relation, and their findings have been widely applied to scenic and historic areas[4], natural reserves[5], rural landscapes[6], and other scenes. With the research paradigm shifting from static identification to dynamic structural analysis, current coastal zone scene studies commonly face problems such as incomplete cognition of elements[7], dispersed sample-extraction pathways[8], imperfect characterization systems[9], and insufficient clustering accuracy[10]. To overcome these limitations, this study addresses the objective need for comprehensive cognition and refined regulation of coastal zone scenes. Grounded in landscape character theory, it focuses on the multivariate characteristics and spatial differentiation patterns of coastal zone scenes, and systematically integrates the analytical workflow of "sample extraction–character representation–clustering computation–digital mapping." Accordingly, it establishes a digital clustering method and analytical mechanism suitable for studies on coastal zone scenes. The results will advance visually induced scene cognition towards an expressible and assessable quantitative description, and provide technical support for the scientific understanding and resource management of regional, native coastal zone scenes.

2 Theoretical Review of Coastal Zone Scenes Based on Landscape Character Theory

2.1 Landscape Character Theory

Landscape character is defined as "a distinct, recognizable and consistent pattern of elements in the landscape that makes one landscape different from another"[11]. Such patterned character distinguishes one landscape type from others and endows a place with unique spatial perception and cultural identity. Offering an important lens within landscape classification, landscape character theory holds that the attribute, distribution, and morphology of landscape elements determine the statue of a landscape's character; therefore, assessing that status constitutes the landscape classification process[12]. Since the 1990s, studies focusing on the qualification, identification, and classification of landscape characters have increasingly appeared and been widely applied in research on territory landscapes[13] and national parks[14], as well as meso- and micro-scale studies on cultural heritage sites[15], settlements[16], and rural areas[17]. Traditional research—largely grounded in paradigms such as morphological genes and morphological genealogy—has emphasized typology-oriented reasoning: building landscape identification frameworks through graphic language, and extracting and reconstructing element composition relationships in typical environments[18]. In recent years, with the advance of big-data and machine-learning technologies, digital clustering method has become an emerging trend in landscape character research. Digital analytical approaches centered on multi-source data acquisition and machine-learning computation have rapidly become a key technical pathway for the precise analysis of landscape characters and the optimization of spatial decision-making for landscapes.

2.2 Trends in Coastal Zone Scene Research

Scene has become one of the core topics in contemporary landscape character studies: scientifically understanding scene characters is crucial for enhancing the recognized value of a site, optimizing the allocation of spatial resources and fine-tuning landscape strategies[19]. Drawing on existing literature[20], this paper defines a coastal zone scene as the perceptible ensemble of marine, coastline, and land areas—a spatial form of interactions between natural and artificial elements within the land–sea transition zone—and composed of basic units such as shoreline morphology, tidal dynamics, coastal wetlands, and habitat patches. Owing to variations in geographical locations, modes of use, and other factors, coastal zone scenes have not yet converged on a common configurational model. In 2012, Natural England introduced the Seascape Character Assessment (SCA) framework, which established a local-scale mechanism for zoning identification and strategic layering based on visual perception and degrees of human intervention, and has since become an important international reference[21]. From the perspective of geomorphic-system evolution, Carlos E. Nieto et al. devised a cartographic evaluation method suitable for diagnosing coastal zone landscape change[22]. Ziting Bao constructed a local-scale system for landscape character identification and strategic layering that integrates visual perception, cultural intervention, and management requirements, forming a methodological framework that supports spatial identification, zonal evaluation, and management control, and provides scientific guidance for coastal zone scene assessment and resource coordination[23].

Current studies on the landscape character of coastal zone scenes mainly address topics such as coastal style analysis, marine cultural perception, and shoreline change monitoring[24], and have made notable progress with technical pathways such as remote-sensing image analysis and spatial statistical measurement[25]. Yet traditional classification methods, e.g., K-means, hierarchical clustering, see limitations when confronted with complex datasets[26]. By contrast, the Gaussian Mixture Model (GMM), with its ability to cluster high-dimensional, complex data and to assign data points to probabilistic types (which enriches interpretive information)[27], offers more effective technical support for the identification and classification of coastal zone scenes.

In general, research on coastal zone scenes is still situated at the stage of type analysis and character identification. It is now an urgent task to explore clustering methods driven by high-dimensional data and to quantify the character factors and combinational mechanisms of typical scenes, hoping to offer scientific reference for classifying coastal zone scenes and related resource management.

3 The Workflow and Method of Digital Clustering for Coastal Zone Scenes

3.1 Workflow of Digital Clustering for Coastal Zone Scenes

Grounded in landscape character theory, this study constructs a systematic research framework that links the four stages of "sample extraction–character representation–clustering computation–digital mapping" for coastal zone scenes, thereby forming a replicable and expandable digital clustering method (Fig. 1).

1) Sample extraction. Considering the land–sea transitional nature of coastal zone landscapes, coastline vector data are first extracted as the baseline by following the SCA framework. A viewshed analysis is then performed with a digital elevation model (DEM) to delimit the initial study area[28]. Subsequently, boundary accuracy is refined by integrating contour lines, road edges, depth contours, and watershed limits, culminating in a comprehensive sample library of coastal zone scenes.

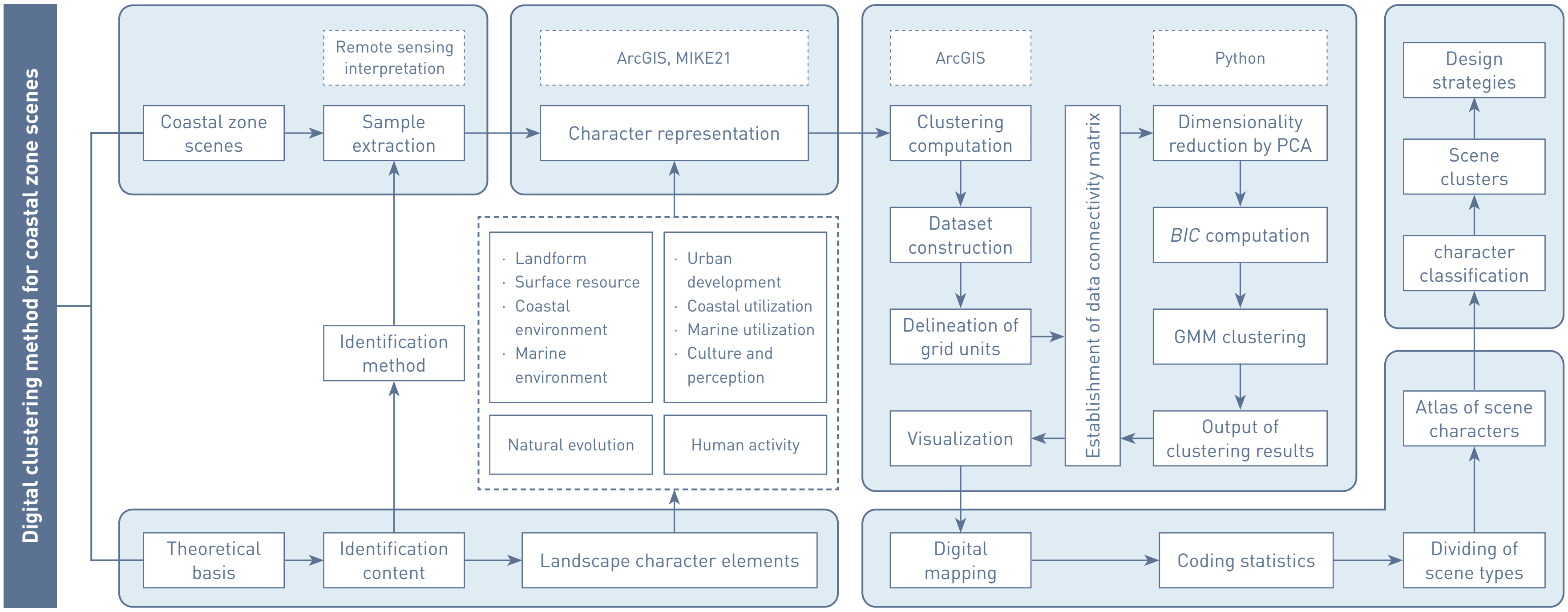

Fig. 1 Digital clustering analysis workflow for coastal zone scenes.

2) Character representation. Natural and artificial landscape character elements for the study area are consolidated to establish a scene character database that covers key factors such as landforms, surface resources, urban development, coastal utilization, and culture and perception. ArcGIS spatial-analysis tools are used to disaggregate these character factors, while the MIKE 21 platform generates tidal dynamics and marine environment datasets, together forming the input for subsequent clustering statistics.

3) Clustering computation. Principal Components Analysis (PCA) is applied for dimensionality reduction and for extracting core character variables. The Bayesian Information Criterion (BIC) is invoked to determine the optimal number of clusters and hence the classification dimensionality. GMM then performs the clustering, with parameters iteratively refined via the Expectation Maximization (EM) algorithm, yielding precise classification results for coastal zone scenes.

4) Digital mapping. Naming and coding rules are scripted in Python; GIS and eCognition multi-scale segmentation are employed to enhance boundary precision and to map the gridded classification of scene types, producing an atlas of coastal zone scene characters. Finally, the hierarchical clustering is used to further classify scene types and scene clusters, supporting decision-making for the classification management and landscape control of coastal zone scenes.

3.2 Digital Clustering Methods for Coastal Zone Scenes

3.2.1 Character Representation System for Coastal Zone Scenes

Establishing a character representation system for scenes, screening core landscape elements, and performing data transformation are the key steps for accurately quantifying landscape characters[29]. Coastal zone scenes are formed jointly by natural evolutions and human activities[30]; hence the selection of landscape elements must accommodate the combined influence of both. Drawing on existing research[31] and using remote-sensing interpretation, spatial analysis and hydrodynamic modelling to disaggregate element characteristics, this study—based on the hierarchical division and type combination of landscape elements—constructs a two-dimensional characterization system (natural attributes and artificial attributes) suitable for coastal zone scenes. The system contains seven landscape elements and sixteen character factors (Table 1).

3.2.2 Clustering Method for Coastal Zone Scenes

The GMM-based digital clustering method for coastal zone scenes comprises six steps: construction of factor/variable dataset; delineation of grid units; establishment of data connectivity matrix; data dimensionality reduction and *BIC* computation; clustering analysis with the GMM algorithm; and digital mapping of the clustering results.

Table 1: Coastal zone scene characterization system

Characterization dimension	Landscape element	Factor
Natural	Topography	Elevation: offshore plain, low plain, terrace, hill, mountain
		Fluctuation: micro, slight, small, moderate, large
		Slope: flat, gentle, incline, steep, precipitous
	Surface resource	Landcover: forest, water body, cropland, artificial surface, grassland, sand
		Vegetation coverage: low, medium, high
	Coastal environment	Coast type: bedrock, sandy, artificial
		Coast morphology: straight, curved, tortuous
		Intertidal type: rocky-reef, sandy, muddy
	Marine environment	Bathymetry: shallow, relatively shallow, moderate, relatively deep, deep
		Velocity: low, relatively low, moderate, relatively high, high
Artificial	Urban development	Building density: low, medium, high
		Landuse: public service, park, residential, industrial, logistics and warehousing, protective green space
	Coastal and marine use	Coast use type: urban development, port/terminal, tourism and recreation, fishery, industrial, unused
		Marine use type: general fishing zone, important fishing zone, port shipping zone, key coastal tourism zone, sandy coastal zone, marine special protection zone
	Cultural points and visibility	Cultural points: theme park, historic site, cultural landmark, museum/exhibition, religious site
		Visibility: non-visible, low, medium, high

Given the high dimensionality, heterogeneity, and spatially non-uniform distribution of coastal zone scene data, the GMM treats the data as a composite of several Gaussian distributions, thereby adapting dynamically to the distribution patterns of landscape elements. In addition, by coupling the model with *BIC* to optimize both the number of clusters and the covariance structure, the GMM gains a greater stability and classification accuracy. Iterative optimization via the EM algorithm ensures that the model converges on the optimal solution[32]. The accuracy of a GMM depends heavily on the appropriate setting of its clustering parameters. Among these, the *BIC* balances model goodness-of-fit against complexity and is calculated as:

$$BIC = -2\ln(likelihood) + k\ln(N), \tag{1}$$

where *likelihood* denotes the likelihood function, $k\ln(N)$ is the penalty term, with N being the sample size and k the number of model parameters. The *BIC* is applied to compare training models that differ in covariance structure or in the number of cluster centers—the smaller the *BIC* value, the better the model fit.

The GMM assumes a random variable x in an unspecified (potentially high) dimensional space, whose probability-density function is defined as:

$$p(x)=\sum_{k=1}^{k} \mathrm{w}_k g(x \mid \theta_k), \tag{2}$$

where k is the number of clusters in the Gaussian mixture; w_k is the mixing weight of the kth component (with $\sum_{k=1}^{k} \mathrm{w}_k=1$); g denotes the probability density function of the kth Gaussian distribution; θ_k represents the parameters of the kth Gaussian distribution—specifically its mean vector and covariance matrix.

The EM algorithm alternates between an E-step (expectation) and an M-step (maximization). These two steps are iterated to maximize the likelihood function and refine the clustering until convergence, with the parameter estimates obtained in each M-step fed back into the subsequent E-step.

E-step:

$$w_i(k)=\frac{\pi_k p_k(x \mid \mu_k, \sum_k^2)}{\sum_{i=1}^{k} \pi_i p_i(x \mid \mu_k, \sum_i^2)}, \tag{3}$$

where $w_i\ (k)$ is posterior probability that data point x_i belongs to cluster k; π_k is the priori (mixing proportion) of cluster k; $p_k\ (x \mid \mu_k, \sum_k^2)$ is Gaussian probability-density function of cluster k.

M-step:

$$\mu_k=\frac{\sum_{i=1}^{n} w_i(k) x_i}{n}, \tag{4}$$

$$\sum_k^2=\frac{\sum_{i=1}^{n} w_i(k)(x_i-\mu_X)(x_i-\mu_X)^{\mathrm{T}}}{n_k}, \tag{5}$$

$$n_k=\sum_{i-1}^{n} w_i(k), \tag{6}$$

where μ_k is updated mean vector of cluster k, i.e., the weighted average of all data points in that cluster; $\sum_k^2$ is updated covariance matrix of cluster k, capturing the spread of data in each dimension; n_k is weighted sample count for cluster k, i.e., the total responsibility mass of the cluster; x_i denotes the ith observation, which captures the values of a sample across multiple dimensions; and T denotes the transpose of a vector.

3.2.3 Digital Mapping of Coastal-Zone Scenes

To enhance the spatial visualization of the clustering results, it is necessary to clarify the dominant characters and the factor structure of each scene unit. Using Python, this study established a standardized cartographic coding scheme: "LCT*n*" denotes a landscape character type, and "LCA*n*" denotes a landscape character area, where n is the serial number. The factor notation was based on the proportional area of each factor: when the factor X occupies an area ≥ 60%, it is recorded as X; when it covers between 30% and 60%, it is recorded as [X]; when it accounts for no less than 10% and no more than 30%, it is shown as (X); and it is omitted if it occupies less than 10% of the area[33].

Because the visual output of coastal zone scene clustering often takes the form of fragmented mosaic patches, multi-level image segmentation in eCognition adopted in this study was combined with remote-sensing imagery to refine the cluster boundary and improve the precision and integrity of classified areas. The similarity among different scene types was then assessed with Pearson correlation coefficients so that compatible clusters can be merged, after which hierarchical clustering was applied to build scene clusters and to refine scene zoning. Finally, drawing on the dominant characters of each coastal zone scene, the study proposed targeted strategies for conservation and utilization, supporting fine-grained regulation of coastal zone landscape planning and management.

4 Case Study on the Digital Clustering of Coastal Zone Scenes: The Case Study on Taozi Bay, Yantai

4.1 Study Area

Taozi Bay is located in the northwestern coastal area of Yantai City, Shandong Province, China. It is a semi-enclosed secondary bay characterized by complex geomorphological conditions and a variety of coastal zone scenes, including mountainous areas, rivers, urban development areas, and marine environments[34]. In this study, Taozi Bay was selected as the study area to verify the applicability of the proposed digital clustering method based on landscape characterization theory under conditions of diverse scene types and heterogeneous terrains.

4.2 Boundary Delimitation and Extraction of Character Factors in the Study Area

Multispectral imagery from the Gaofen-1 (GF-1) satellite was employed as the primary data source. After radiometric calibration, atmospheric correction, and orthorectification, coastline vector data were extracted. Using the ArcGIS platform, a 1-kilometer buffer was generated on both the landward and seaward sides of the coastline. Along the buffered coastline, a 300-meter interval grid of observation points was established to perform viewshed analysis,

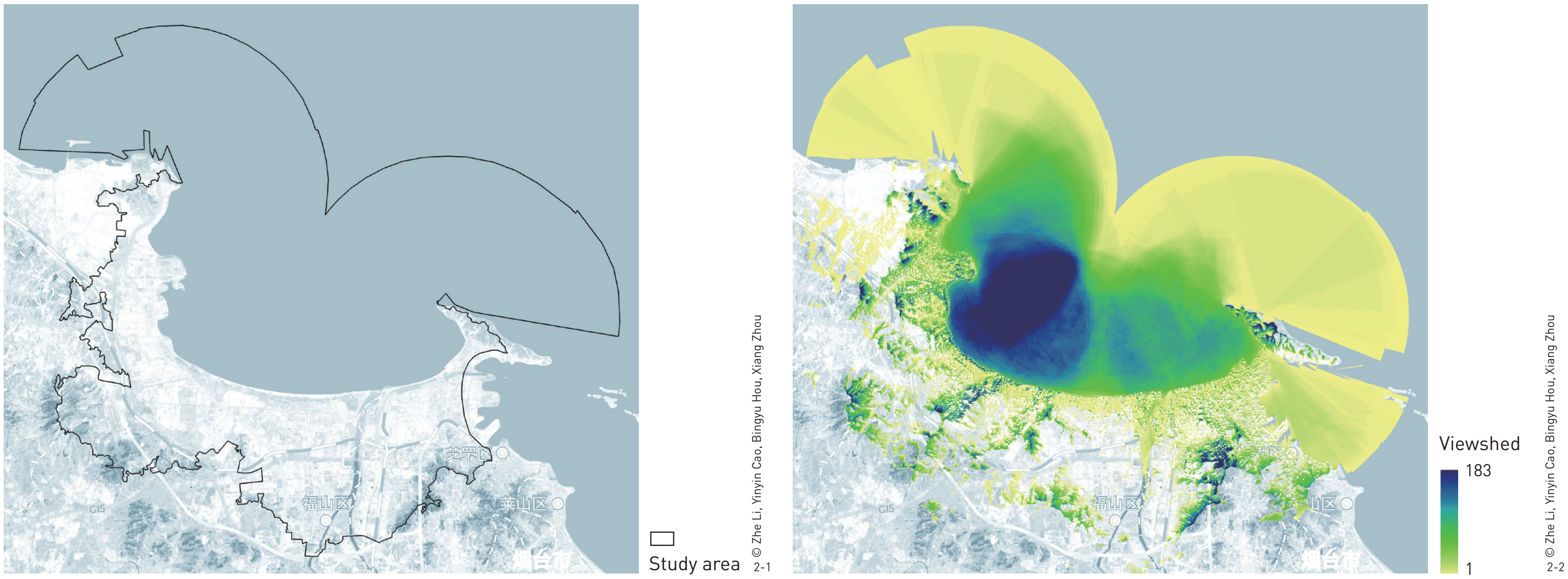

Fig. 2 Study area and the cumulative viewshed (source: Standard Map Service of Yantai City, Shandong Province, map No. Lu SG [2024] 035).

and the resulting cumulative viewshed was used to delineate the boundary of the study area, where the numerical value represents the number of times the area is seen by the observation points (Fig. 2). The final delineated area covers 770.35 km^2, including 264.89 km^2 of terrestrial areas and 505.46 km^2 of marine areas, with a total coastline length of 75.32 km.

Two types of grid units—500 m × 500 m for terrestrial areas and 100 m × 100 m for marine areas—were used, and a total of 108,715 terrestrial grid units and 51,510 marine grid units were obtained. The character factors of coastal zone scenes within the study area were derived from 3 primary data sources (Table 2): 1) vector data, including building footprints and heights, used to

Table 2: Data types and sources

Data type	Data name	Precision	Year	Source
Vector	Building footprints and heights	—	2023	OpenStreetMap
Raster	DEM	12.5 m	2009	Alaska Satellite Facility Data Center
	Remote sensing imagery	1 m	2022	Gaofen-1 (GF-1) Satellite
Text	Taozi Bay nautical chart	—	2023	ChuanXun Electronic Nautical Chart
	Yantai Architectural Style and Control Planning	—	2021	Yantai Natural Resources and Planning Bureau
	Yantai Marine and Coastal Special Planning	—	2023	
	Yantai Overall Urban Design	—	2021	
	Historical and Cultural City Protection Planning for Yantai	—	2021	
	Tidal data	—	2023	MIKE 21 Tide Prediction of Heights

derive urban construction indicators such as building density and functional zones; 2) raster data, including remote sensing imagery and DEMs, used to calculate NDVI, slope, terrain relief, and other natural geographic features; 3) text data, consisting of planning documents and tidal data, from which cultural perception, land-use planning, and marine environmental factors were extracted. Specifically, marine environmental factors were derived using MIKE 21 by simulating tidal flow fields during spring and neap tides to extract current speed and direction. All measured character factors were subsequently reclassified using the Natural Breaks method in ArcGIS, and area-weighted statistics were compiled for each variable (Table 3, Fig. 3).

Table 3: Coastal zone scene characteristic factors and variables in the study area

Category	Code	Proportion
Elevation (m)		
Offshore plain ≤ 37	H1	58.97%
Low plain (37, 81]	H2	23.37%
Terrace (81, 145]	H3	12.58%
Hill (145, 260]	H4	4.22%
Mountain > 260	H5	0.86%
Fluctuation (m)		
Micro (0, 2]	F1	62.80%
Slight (2, 5]	F2	24.31%
Small (5, 10]	F3	9.14%
Moderate (10, 16]	F4	3.10%
Large (16, 54]	F5	0.65%
Slope (°)		
Flat ≤ 2	S1	21.66%
Gentle (2, 6]	S2	51.78%
Incline (6, 15]	S3	20.18%
Steep (15, 25]	S4	5.25%
Precipitous > 25	S5	1.13%

(Continued)

Table 3: Coastal zone scene characteristic factors and variables in the study area (Continued)

Category	Code	Proportion
Landcover		
Forest	LC1	15.25%
Water body	LC2	3.07%
Cropland	LC3	10.20%
Artificial surface	LC4	35.54%
Grassland	LC5	25.70%
Sand	LC6	10.24%
Vegetation coverage		
Low (0, 0.28]	V1	43.36%
Medium (0.28, 0.60]	V2	34.29%
High (0.60, 1.00]	V3	22.35%
Coast type		
Bedrock	CT1	3.75%
Sandy	CT2	22.65%
Artificial	CT3	73.60%
Coast morphology		
Straight (1.01, 1.03]	CM1	38.47%
Curved (1.03, 1.06]	CM2	29.34%
Tortuous (1.06, 1.26]	CM3	32.19%
Intertidal type		
Rocky-reef	IT1	11.64%
Sandy	IT2	68.66%
Muddy	IT3	19.70%
Bathymetry (m)		
Shallow (−11.74, 3.98]	B1	4.39%
Relatively shallow (3.98, 9.31]	B2	5.22%
Moderate (9.31, 15.42]	B3	28.62%
Relatively deep (15.42, 20.19]	B4	60.47%
Deep (20.19, 24.38]	B5	1.30%

(Continued)

Table 3: Coastal zone scene characteristic factors and variables in the study area (Continued)

Category	Code	Proportion
Velocity (m/s)		
Low (0, 0.03]	VE1	9.64%
Relatively low (0.03, 0.06]	VE2	17.48%
Moderate (0.06, 0.10]	VE3	18.15%
Relatively high (0.10, 0.13]	VE4	28.60%
High (0.13, 0.28]	VE5	26.12%
Building density (number of buildings per km^2)		
Low (0, 0.0025]	BD1	74.82%
Medium (0.0025, 0.0077]	BD2	18.27%
High (0.0077, 0.0238]	BD3	6.91%
Landuse		
Public service	LU1	20.81%
Park	LU2	11.73%
Residential	LU3	36.80%
Industrial	LU4	23.03%
Logistics and warehousing	LU5	0.61%
Protective green space	LU6	7.02%
Coast use type		
Urban development	CU1	35.35%
Port/terminal	CU2	20.57%
Tourism and recreation	CU3	28.93%
Fishery	CU4	5.79%
Industrial	CU5	3.63%
Unused	CU6	5.73%
Marine use type		
General fishing zone	MU1	24.57%
Important fishing zone	MU2	4.39%
Port shipping zone 1	MU3	25.94%
Port shipping zone 2	MU4	23.32%

(Continued)

Table 3: Coastal zone scene characteristic factors and variables in the study area (Continued)

Category	Code	Proportion
Key coastal tourism zone	MU5	15.67%
Sandy coastal zone	MU6	5.28%
Marine special protection zone	MU7	0.83%
Visibility		
Non-visible (0)	VP1	15.00%
Low [1, 28]	VP2	52.99%
Medium (28, 74]	VP3	22.16%
High (74, 183]	VP4	9.85%

NOTES

1. In the marine use types, port shipping zone 1 and port shipping zone 2 pertain to different routes and ports; they remain separate to ensure scientific classification.
2. Visibility is determined by the viewshed analysis results of the study area, indicating a given location can be seen by how many observation points.

4.3 Clustering Analysis of Coastal Zone Scenes

Based on the above classification results, PCA was used to perform dimensionality reduction on both land and marine units. For the land units, 49 variables were reduced to 20 principal components, explaining 79.20% of the total variance. For the marine units, 24 variables were reduced to 11 principal components, with a cumulative variance explanation of 78.91%. Subsequently, the *BIC* was used to determine the optimal parameters for GMM—a lower *BIC* value indicates better model fit. The optimal *BIC* value for land units occurred when the covariance type was “full” and the number of clusters was 18. For marine units, the optimal *BIC* value was reached when the covariance type was also “full” with 7 clusters.

According to the optimal cluster numbers, the initial clustering labels generated by the GMM were further optimized via the EM algorithm. After 42 rounds of iteration, the model converged and produced the final clustering results, generating a total of 25 typical coastal zone scene types. Thus, a corresponding dataset containing these 25 scene types was then constructed (Fig. 4), including 18 land scene types (LCT1 to LCT18) and 7 marine scene types (LCT19 to LCT25). Following the preliminary classification, boundary correction was applied by adjusting parameters of scale, shape, and compactness to 140, 0.3, and 0.2, respectively. The

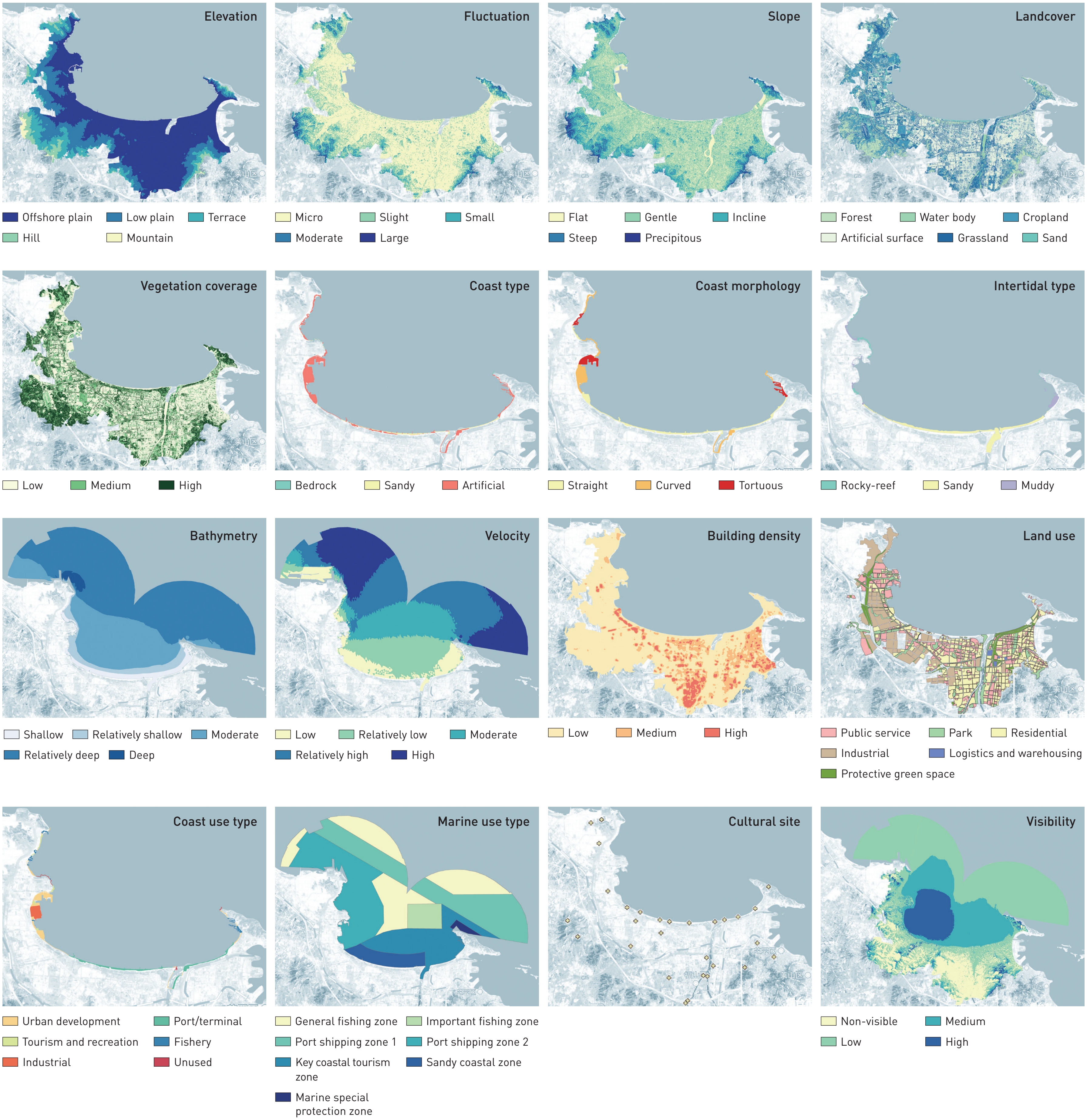

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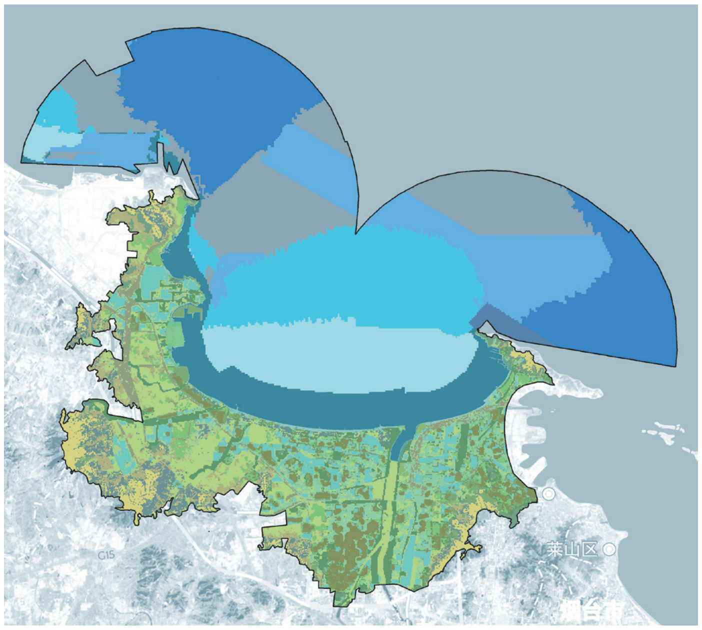
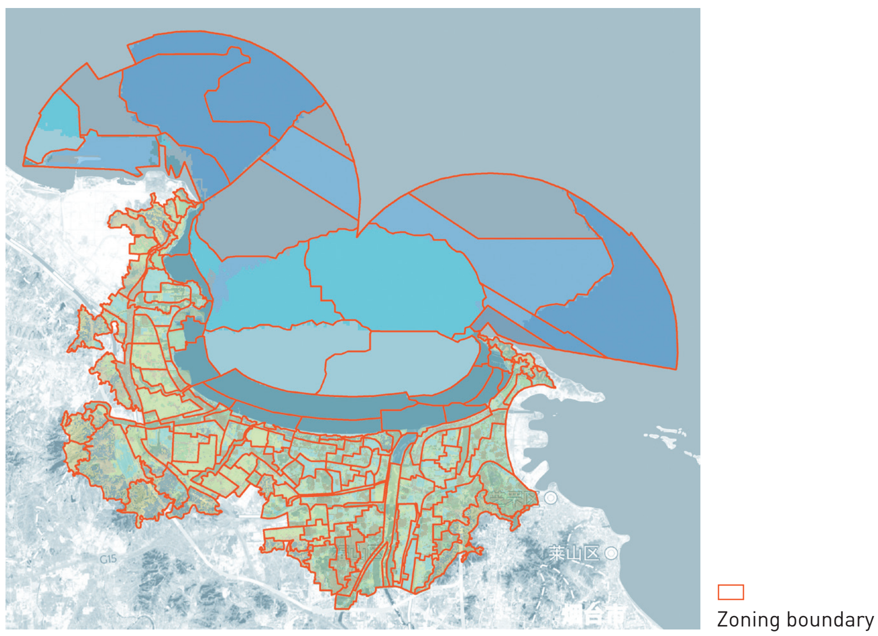
Fig. 3 Character factors of coastal zone scenes (source: Standard Map Service of Yantai City, Shandong Province, map No. Lu SG [2024] 035).



Code	Character code
LCT1	[H1][H2].F1(F2).(S1)S2(S3).(LC1)(LC3)(LC4)[LC5](LC6).[V1][V2](V3).BD1.(LU4)LU6.[VP1][VP2](VP3)
LCT2	H1(H2).F1(F2).(S1)S2(S3)[LC4](LC5)(LC6).V1(V2).[BD1][BD2].[LU3][LU4].[VP1][VP2](VP3)
LCT3	H1(H2).F1(F2).[S1]S2.[LC4](LC5)(LC6).[V1][V2](V3).BD1(BD2).LU1.[VP1][VP2](VP3).
LCT4	[H3][H4](H5).[F3][F4](F5).[S3][S4](S5).LC1(LC3)(LC5).[V2]V3.BD1.(VP1)(VP2)[VP3](VP4)
LCT5	(H1)(H2)H3.(F1)[F2](F3).[S2]S3.[LC1](LC3)(LC5).[V2]V3.BD1.[VP1][VP2](VP3)
LCT6	H1(H2).F1(F2).(S1)[S2](S3).(LC1)(LC3)(LC4)[LC5](LC6).[V1][V2](V3).BD1(BD2).LU2(LU3).[VP1][VP2](VP3)
LCT7	[H1][H2](H3).F1[F2].(S1)[S2](S3).(LC1)(LC3)(LC4)[LC5](LC6).[V1][V2](V3).BD1.[LU1](LU2)(LU3)(LU6).[VP1][VP2](VP3)
LCT8	H1.F1(F2).(S1)[S2](S3).(LC2)(LC4)(LC5)(LC6).V1(V2).CT3.(CM1)CM2.BD1.[LU2](LU4).[CU1](CU4).[VP2][VP3]
LCT9	H1.F1(F2).[S2].[LC4](LC5).[V1](V2).[CT3].(CM2)(CM3).BD1.(LU2)LU4).[CU2](CU3).[VP2](VP3)
LCT10	H1.F1(F2).[S1](S2)(S3).[LC4](LC5)[LC6].V1(V2).[CT2][CT3].CM1.BD1.(CU1)CU3.[VP2][VP3]
LCT11	H1(H2).F1(F2).[S1]S2.[LC4](LC5).V1(V2).[BD2]BD3.(LU1)LU3.[VP1][VP2]
LCT12	[H1][H2].F1(F2).(S1)S2.(LC3)[LC4](LC5)(LC6).[V1][V2](V3).BD1.(LU3)[LU4].[VP1][VP2]
LCT13	(H2)[H3](H4).(F1)(F2)[F3](F4).(S2)[S3][S4].[LC1](LC3)(LC5)(LC6).(V1)[V2][V3].BD1.(LU2)(LU4).(VP1)[VP2](VP3)(VP4)
LCT14	[H2][H3].(F1)F2(F3).[S2][S3].(LC1)(LC3)(LC4)(LC5)(LC6).[V1][V2].BD1.[LU4].[VP1][VP2](VP3)
LCT15	[H1](H2)(H3).[F1][F2](F3).(S1)[S2][S3].[LC4](LC5)(LC6).[V1][V2](V3).(CT3).(CM3).[BD1][BD2](BD3).(LU1)[LU3].(CU1).(VP1)[VP2][VP3](VP4)
LCT16	H1.F1.[S1]S2.LC4(LC5).V1(V2).[BD1][BD2].LU3.VP1[VP2]
LCT17	H1(H2).[F1](F2)(F3).(S1)[S2](S3)(S4).(LC1)(LC4)(LC5)(LC6).[V1](V2)(V3).(CT3).(CM1)(CM2).BD1.(BD2).(LU5)(LU6).(CU3).(VP1)[VP2](VP3)
LCT18	H1.F1(F2).[S1](S2)(S3).[LC4](LC5)(LC6).V1.CT3.CM2.BD1.LU1(LU2).CU5.(VP2)(VP3)[VP4]
LCT19	B4.VE4(VE5).MU1[MU4].VP2[VP3]
LCT20	B4.VE5.(MU1)[MU3](MU4).VP2
LCT21	[B3][B4].(VE2)VE3.[MU1](MU2)(MU4)(MU5).[VP2][VP3](VP4)
LCT22	(IT2).[B1][B2](B3)(B4).VE1[VE2].(MU4)[MU5][MU6].(VP2)VP3(VP4)
LCT23	(B3)B4.(VE1)VE4.MU3(MU4).VP2
LCT24	B3.VE2.(MU1).(MU4)MU5.[VP3][VP4]
LCT25	(B2)[B3][B4].[VE3][VE4][VE5].(MU5)MU7.VP2

NOTE
The categories listed in the table are presented in the order generated by the GMM model clustering analysis.

Fig. 4 Coastal zone scene types (source: Standard Map Service of Yantai City, Shandong Province, map No. Lu SG [2024] 035).
Fig. 5 Coastal zone scenes (source: Standard Map Service of Yantai City, Shandong Province, map No. Lu SG [2024] 035).



final result yielded 161 aggregated typical sections of coastal zone scenes (Fig. 5).

4.4 Interpretation of Coastal Zone Scene Clustering Results

Based on the above analyses, it was found that the mountain–sea configuration constitutes the most prominent landscape character of the study area, with the overall spatial structure exhibiting a "mountain–city–shoreline–sea" pattern. Using Pearson correlation analysis, the aggregated coastal zone scene types were divided into two major groups: the land group (LG) and the marine group (MG). Among them, the forest–mountain scene group (LG4) is distributed as linear, fragmented patches along the urban periphery, exhibiting strong natural characteristics. The urban fringe scene group (LG2) and the urban built-up scene group (LG3) are interwoven throughout the study area. The coastal scene group (LG1) is primarily concentrated along the shoreline. MGs include nearshore shallow sea group (MG1) and offshore deep sea group (MG2) according to sea depth and current velocity. Through hierarchical clustering based on Euclidean distance and the Ward method, spatially adjacent and character-similar areas were grouped into 8 landscape character area groups (LCAG1 to LCAG8) (Figs. 6 ~ 8).

A systematic interpretation on the spatial distribution characteristics and composition of the eight resulting scene clusters was conducted from both perspectives of natural and artificial landscapes, and the following spatial differentiation patterns were identified:

1) Natural coast cluster (LCAG1): covering 5.55% of the total study area, primarily composed of MG1 and LG1; this cluster is characterized by natural shorelines and intertidal zones, with rich ecological resources and high ecological value.

2) Artificial coast cluster (LCAG2): accounting for 3.07% of the total study area, mainly consisting of MG1, LG1, and MG2; it includes urban shorelines, fishing ports, docks, and industrial coastal zones, with a high degree of functional development.

3) River and urban park cluster (LCAG3): covering 2.75% of the total study area, mainly formed by LG2 and LG3; this cluster is distributed along the urban-natural transition zones, showing

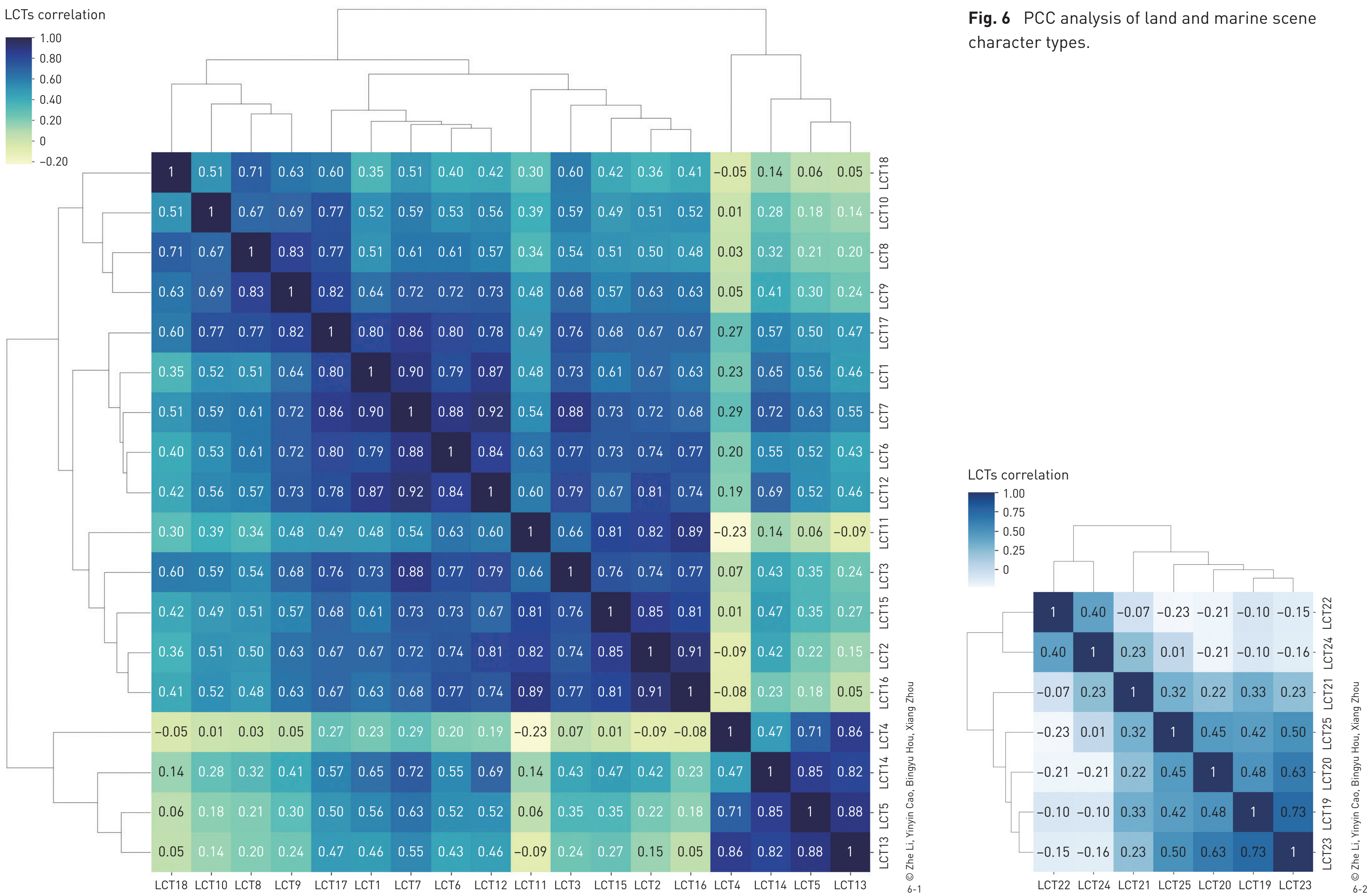


Fig. 6 PCC analysis of land and marine scene character types.

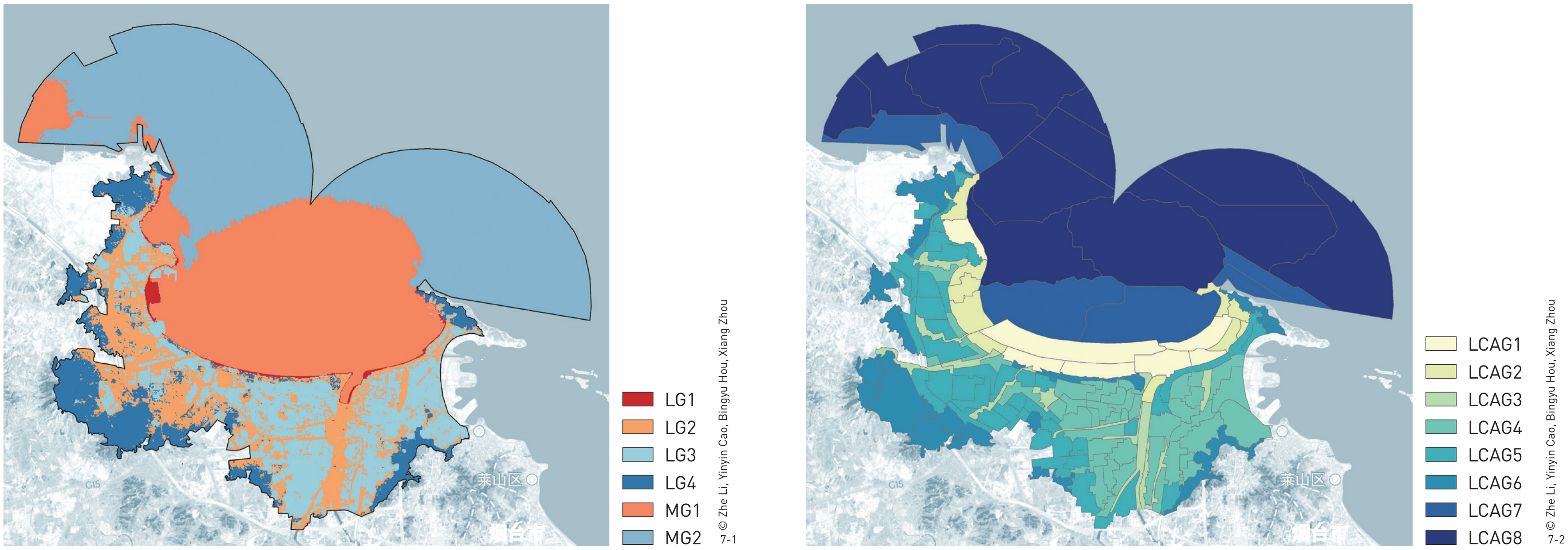
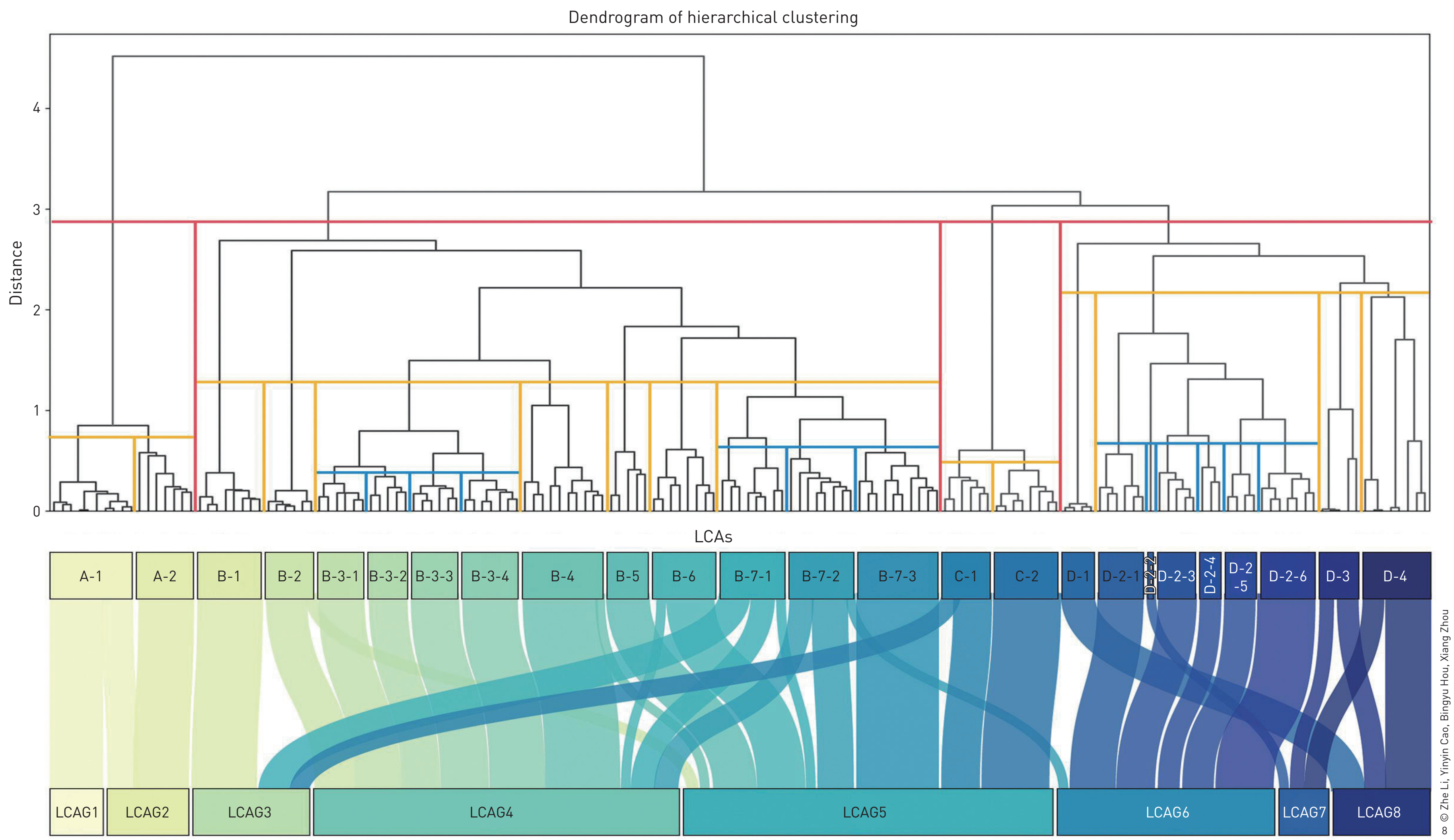


Fig. 7 Scene type groups (LCT GROUP) and scene clusters (LCA GROUP) in coastal zones (source: Standard Map Service of Yantai City, Shandong Province, map No. Lu SG [2024] 035).

Fig. 8 Hierarchical clustering tree of scenes.



corridor-like patterns but high fragmentation of landscape patches.

4) Urban built-up landscape cluster (LCAG4): representing 11.09% of the total study area, dominated by LG3 and LG2, concentrated in the core urban area; it is characterized by high building density, low greening rate, and poor spatial continuity.

5) Urban fringe landscape cluster (LCAG5): accounting for 11.24% of the total study area, scattered in block-like patterns; acting as a buffer zone between urban development and natural landscapes, it offers protective functions but suffers from insufficient green coverage.

6) Mountain–forest landscape cluster (LCAG6): occupying 8.06% of the total study area, primarily composed of LG4 and LG2; it forms a significant ecological barrier surrounding the urban areas.

7) Nearshore marine landscape cluster (LCAG7): covering 12.31% of the total study area, dominated by MG1; this cluster is concentrated in inner bay zones with low velocity and shallow water depth, exhibiting ecological sensitivity yet high biodiversity.

8) Offshore marine landscape cluster (LCAG8): the largest cluster, covering 42.78% of the total study area, primarily composed of MG2; although biological productivity is relatively low, this zone plays a critical role in regional fisheries and shipping trade.

4.5 Strategies for the Conservation and Utilization of Coastal Zone Landscapes

Based on the differentiated characteristics of typical coastal scene clusters, reference to both international practical cases, and considerations on the ecological background of the study area, this research proposed a series of conservation and utilization strategies for promoting the sustainable development of multifunctional coastal landscapes.

1) Conservation and ecological restoration of natural coasts. For natural coast clusters, strategies may draw inspiration from the Great Barrier Reef ecological conservation project in Australia[35]. Measures such as periodic ecological monitoring, comprehensive habitat restoration, vegetation replanting, and sandbar stabilization can be adopted to strengthen the ecological buffer functions of natural shorelines.

2) Renovation and structural optimization of artificial shorelines. For artificial coast clusters, examples such like the construction experience of artificial coastlines at the Yongding New River estuary in Tianjin[36] can be referred. Emphasis should be placed on the construction of eco-friendly embankments, and the ecological remediation of ports and industrial waterfronts to enhance the ecological functionality and aesthetic value of artificial shorelines.

3) Enhancement of urban built environment and landscape quality. For river and urban park clusters, as well as urban built-up clusters, lessons can be drawn from the Tokyo Bay wetland optimization project in Japan[37]. Strategies include the integration of fragmented land parcels, expansion of green space coverage, and the construction of ecological greenways and pedestrian networks to improve the spatial continuity of urban green infrastructure. In addition, wetland and intertidal habitat restoration should be prioritized to strengthen local ecological resilience.

4) Protection of urban fringe green spaces and mountainous landscapes. For urban fringe landscape clusters, reference can be made to the greenbelt planning model of the Ruhr region in Germany[38], focusing on native plant species configuration and urban heat island mitigation. For mountainous and forested clusters, strategies may refer to mountain conservation practices in the Alpine region[39], implementing zoning-based protection and low-intervention recreation planning, balancing ecological restoration with scenic development.

5) Resource optimization and sustainable use of nearshore and offshore marine areas. For nearshore and offshore marine clusters, the intertidal ecological restoration practices of Auckland, New Zealand[40] can provide a valuable reference. Emphasis should be placed on ecosystem protection, development threshold control, and the implementation of restricted fishing and aquaculture policies. Establishing a comprehensive environmental impact assessment mechanism is also essential to ensure the long-term sustainability of coastal resources.

5 Conclusions and Discussion

In response to the current demand for precise assessment and categorized governance of coastal zone scenes, this study constructed a digital clustering methodology grounded in landscape character theory. Taking the coastal zone of Taozi Bay in Yantai as an empirical case, the study explored the application path of this method and provided both theoretical and technical demonstrations for the fine-grained classification and governance strategies of coastal landscapes. By integrating multi-source data, this research established a representation system for coastal scenes, optimized clustering parameters using the *BIC* and EM algorithm, and developed a systematic clustering analysis process consisting of "sample extraction–character characterization–clustering computation–digital mapping." The feasibility of GMM-based digital clustering for coastal zones was thereby validated.

The findings indicate that the spatial distribution of coastal scenes in the Taozi Bay area is jointly shaped by natural landforms, oceanic dynamic processes, and human activities, exhibiting a typical "mountain–city–shoreline–sea" spatial pattern. Among them, scene units such as urban built-up environments, artificial shorelines, and ecological buffer zones show a clear spatial structure and well-defined boundaries, while scenes related to marine resource utilization display notable variation under different bathymetric conditions. The empirical results demonstrate that the scene classification system developed in this study effectively encompasses the representative landscape types within the study area, indicating the method's potential for further expansion and cross-regional application. China's vast coastline harbors abundant coastal landscape resources. With the rising demand for high-quality development and refined spatial governance of coastal zones, the application of digital clustering methods in coastal scene research remains in its early stages. This study, grounded in landscape character theory, explores a pathway for scene classification, analysis, and regulation in coastal zones. By digitally decoding land–marine characteristics and reshaping scene recognition through landscape structure logic, the study contributes to the establishment of a scientific evaluation framework for coastal and marine landscapes.

Nevertheless, this study primarily focused on the spatial distribution patterns of coastal scenes and did not sufficiently incorporate the influence of social and economic driving forces, which constrains the systemic scope of conservation and utilization strategies. Moreover, various coastal types exhibit significant spatial heterogeneity due to differing oceanic dynamics, climatic conditions, and anthropogenic pressures. Future research should further refine classification variables and discriminant criteria based on specific coastal contexts, enhance the methodological adaptability, and expand applications across typical coastal zones to distill universal patterns, thereby supporting the synergistic development of landscape conservation and refined spatial governance for coastal areas.

ELECTRONIC SUPPLEMENTARY MATERIAL

Supplementary material is available in the online version of this article at https://doi.org/10.15302/J-LAF-0-020037.

Competing interests | The authors declare that they have no competing interests.

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基于景观特征理论的海岸带场景数字化聚类方法

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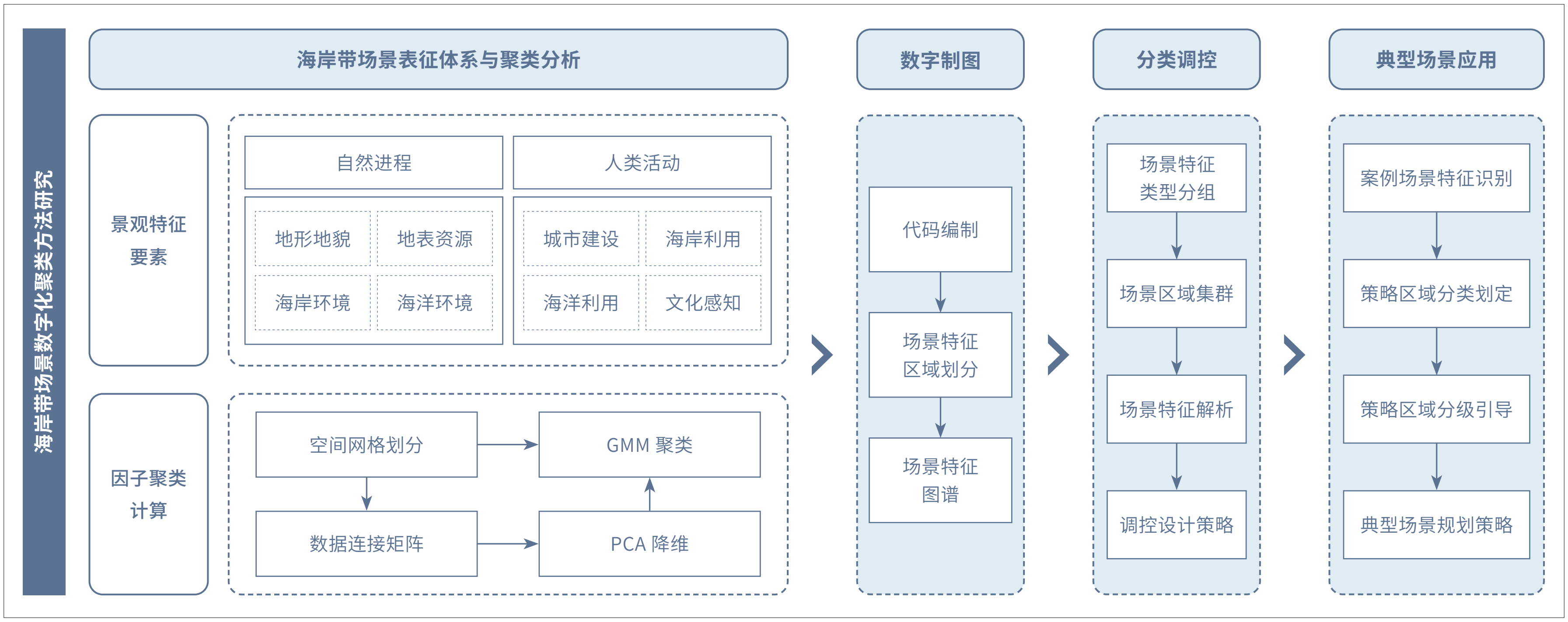
图文摘要



摘要

面向海洋景观高质量发展，针对海岸带景观精准研判与提质增效的需求，系统开展海岸带典型场景数字化解析与定量研究已成为当前海岸带景观研究纵深发展的前置问题之一。本研究结合景观特征理论相关成果，构建适用于海岸带场景聚类研究的分析框架与技术路径，依托高斯混合模型开展海岸带场景数字化聚类方法与技术解析。研究以烟台套子湾典型区域为例，协同遥感影像解译、ArcGIS空间分析等量化提取海岸带景观基础信息，建立海岸带场景表征体系，采用高斯混合模型组建场景特征数字化聚类分析流程，结合贝叶斯信息准则与期望最大化算法优化海岸带场景聚类关键参数，集成开展海岸带场景的协同分类与数字制图实践探索，为景观环境治理相应策略制定提供分析依据。研究提出了一种适用于海岸带场景量化表征与数字集成的分析方法，为海岸带景观资源的聚类识别与协同治理提供研究参考与实践案例。

关键词

海岸带场景；聚类方法；高斯混合模型；景观特征理论；海岸带；景观规划设计

文章亮点

- 基于景观特征理论研究，构建海岸带场景分类解析框架
- 形成一种基于高斯混合模型的海岸带场景聚类分析方法
- 以套子湾为例开展实证研究，编制海岸带场景特征图谱

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- 国家自然科学基金面上项目“基于脑电‘唤醒－效价’情绪模型的生活街区消极空间数字制图及其景观提质研究——以南京为例”（编号：52278051）
- 教育部人文社会科学基金青年项目“人本尺度城镇历史地段河流生物文化多样性测度与管理机制研究”（编号：22YJCZH145）

编辑 田乐，马锡栋

1 研究背景

精准研判与精细化发展海岸带景观是彰显滨海地域特色、赓续原生风貌的重要手段[1]。以数字技术助力海岸带场景资源分类与特征判定已成为当前海洋景观提质建设的基础和关键方法。海岸带场景作为海陆交互范围内协调统一的复合景观空间，兼具生态保育、资源利用和文化传承等多重功能，在凸显场景原真性、增强地域特色、避免景观趋同化方面发挥着不可或缺的作用[2]。中国于2022年明确提出加强海洋生态保护、建设美丽海湾的目标，进一步推动海岸带场景研究由传统宏观规划向精细识别与动态调控演进[3]。在大数据、机器学习等技术快速更新的时代背景下，亟须发展契合海岸带场景环境特征的量化方法与分析技术，以此辅助海岸带场景景观分类、特征解析和数字表达，提升图像解析精度和资源治理信度。

当代景观特征研究的发展为场景解析奠定了重要理论基础。既往研究注重从要素构成、空间结构、功能关系等视角剖析场景内涵，且相关成果已广泛应用于风景名胜区[4]、自然保护地[5]、乡村景观[6]等场景。伴随研究范式由静态识别转向动态结构剖析，当前海岸带场景研究普遍面临着要素认知不全面[7]、样本提取路径分散[8]、特征体系不完善[9]、聚类精度不足[10]等问题。为突破这些局限，本研究面向海岸带场景综合认知与精细调控的客观需求，基于景观特征理论，聚焦海岸带场景的多变量特征及其空间分异模式，系统融通场景“样本提取—特征表征—聚类计算—数字制图”的分析流程，建立了一种适用于海岸带场景的数字化聚类方法与解析机制。研究成果有助于将视觉归纳的场景认知推进至可表达、可研判的量化描述，为地域性、原生性海岸带场景的科学认知与资源调控提供技术支持。

2 基于景观特征理论的海岸带场景理论综述

2.1 景观特征基础理论

景观特征指景观要素在特定区域内依据一定组合方式形成的，具有独特性、一致性和可识别性的格局。该种格局特征可使其有别于其他类型的景观，并赋予场地特定的空间感知与文化认同[11]。作为景观分类学的重要视角，景观特征理论认为景观要素的属性、分布及形态决定了景观的特征状态，故对特征状态展开评估即为景观分类过程[12]。20世纪90年代以来，针对景观特征的定性、识别和分类研究陆续涌现，广泛应用于国土景观[13]、国家公园[14]等宏观尺度，以及文化遗产[15]、聚落[16]和乡村[17]等中微观尺度。其中，传统研究大多依托形态基因、形态谱系等理论范式，侧重类型学导向下的归类逻辑，以图示语言构建景观类型识别框架，强调典型环境中景观要素构成关系的提炼与重构[18]。近年，随着大数据与机器学习技术的发展，数字化聚类方法逐步成为景观特征研究的新兴趋势。以多源数据采集、机器学习计算为核心的数字化分析途径迅速成为精准解析景观特征、优化景观空间决策的技术路径。

2.2 海岸带场景研究趋势

场景是当前景观特征研究的核心内容之一，科学认知场景特征对提升场地认知价值、优化空间资源配置、精细调控景观策略具有重要意义[19]。参考既有文献[20]，本文将“海岸带场景”定义为人类可感知的海洋、海岸线和陆地区域的综合体，是陆海过渡区中自然、人工要素相互作用的空间产物，包括海岸线形态、潮汐动态、滨海湿地、生境斑块等基本单元。受地理区位、利用方式等因素影响，海岸带场景尚未形成统一的构型模式。2012年，英格兰自然署提出海景特征评估（Seascape Character Assessment，SCA）体系，基于视觉感知和人为干预关系构建地方尺度的分区识别与策略分层机制，已成为国际有关研究的重要参照成果[21]。卡洛斯·E. 尼托等从地貌系统构型演变视角出发，建构了一套适用于海岸带景观演化研判的图谱评价方法[22]；鲍梓婷则构建面向地方尺度的景观特征识别与策略分层体系，融合视觉感知、人文干预与管理需求，形成支持景观空间识别、分区评价与管理调控的方法体系，为海岸带场景评估、资源统筹提供了科学参考[23]。

现有海岸带场景景观特征研究多围绕滨海风貌解析、海洋文化感知、海岸线变化监测等议题展开[24]，并在遥感影像分析、空间统计测度

等技术路径维度取得了重要进展[25]。相较于K-means、层次聚类等在处理复杂数据方面存在局限的传统分类方法[26]，高斯混合模型（Gaussian Mixture Model，GMM）因其适用于高维、复杂数据的聚类算力[27]，可输出属于不同概率类型的数据点使聚类结果信息更加丰富等优势，为海岸带场景识别和分类解析提供了有效技术支持。

总体来看，既有海岸带场景研究尚处于类型剖析和特征辨识的发展阶段，探索高维数据驱动下的海岸带场景聚类方法、量化解析典型场景的特征因子与组合机制已是当务之急，这于科学提升海岸带场景分类识别能力和资源调控水平具有积极意义。

3 海岸带场景数字化聚类分析流程与方法

3.1 海岸带场景数字化聚类分析流程

本研究基于景观特征理论，构建了贯通海岸带场景“样本提取—特征表征—聚类计算—数字制图”的系统性研究框架，形成一套可复制、可拓展的海岸带场景数字化聚类方法（图1）。

1）样本提取：依据海岸带景观的陆海过渡特性，参照SCA方法体系提取海岸线矢量数据作为基准，结合数字高程模型进行可视域分析，界定初始研究范围[28]；进而整合场地等高线、道路边界、等深线、流域范围等地理标示信息优化边界，集成构建海岸带场景样本库。

2）特征表征：整合研究区自然属性和人工属性的景观特征要素，建立涵盖地形地貌、地表资源、城市建设、海岸利用、文化与感知等关键因子的场景特征数据库；运用ArcGIS空间分析工具解构特征因子，并结合MIKE21平台生成潮汐动力与海洋环境特征数据，为后续聚类统计提供数据集。

3）聚类计算：采用主成分分析进行数据降维，提炼核心特征变量，引入贝叶斯信息准则（Bayesian Information Criterion，BIC）计算最优聚类数以确定分类维度；应用GMM模型进行聚类计算，并利用期望最大算法迭代调整参数，输出海岸带场景精准分类结果。

4）数字制图：借助Python平台构建名称及代码规则，基于GIS平台和eCognition多尺度分割技术提升分类边界精度，对场景类型划分空间网格进行空间映射，生成海岸带场景特征图谱；而后借助层次分析法，进一步划分场景类型和场景集群，为海岸带场景分类管理及景观管控提供决策依据。

3.2 海岸带场景数字化聚类分析方法

3.2.1 海岸带场景表征体系

建立场景表征体系、筛选核心景观要素并进行数据转换，是实现景观特征科学量化的关键环节[29]。海岸带场景的形成受自然进程与人类活动的共同驱动[30]，故其景观要素选取需统筹二者综合影响。参考既有研究[31]，结合遥感解译、空间分析、水动力模拟等技术手段拆解要素特征，并基于景观要素的层级划分和类型组合，本研究从自然属性和人工属性两个维度构建适用于海岸带场景的表征体系，共含7个景观要素及16个特征因子（表1）。

表 1：海岸带场景表征体系

表征维度	景观要素	特征因子
自然属性	地形地貌	高程：近海平原、低平原、台地、丘陵、山地
		地形起伏度：微起伏、缓起伏、小起伏、中起伏、高起伏
		坡度：平地、缓坡、斜坡、急坡、陡坡
	地表资源	土地覆盖类型：林地、水体、耕地、人造表面、草地、沙地
		植被覆盖度：低覆盖度、中等覆盖度、高覆盖度
	海岸环境	海岸类型：基岩海岸、砂质海岸、人工海岸
		海岸形态：平直海岸、弯曲海岸、曲折海岸
		潮间带类型：岩礁质潮间带、砂质潮间带、淤泥质潮间带
	海洋环境	海水深度：浅海、较浅海、中海、较深海、深海
		海水流速：低流速、较低流速、中等流速、较高流速、高流速
人工属性	城市建设	建筑密度：低密度、中密度、高密度
		用地类型：公共服务设施用地、公园绿地、居住用地、工业用地、物流仓储用地、防护绿地
	海岸与海洋利用	海岸功能用途类型：城镇海岸、港口码头、旅游娱乐、渔业、临海工业、未利用
		海洋功能用途类型：一般渔业海域、重要渔业海域、港口航运、重要滨海旅游区、重要砂质岸线临近海域、海洋特别保护区
	文化节点与视觉感知	文化节点：主题公园、历史遗址、文化地标、博物展览、宗教圣地
		视觉感知：不可视、低可视度、中等可视度、高可视度

3.2.2 海岸带场景聚类方法

基于GMM的海岸带场景数字化聚类方法涵盖因子／变量数据集构建、网格单元划定、建立数据连接矩阵、数据降维及*BIC*计算、GMM算法聚类分析、聚类结果数字映射6个步骤。

由于海岸带场景数据呈现高变量、异质性及非均匀分布等复杂特点，GMM将数据视为由多个高斯分布的混合体组成，能动态适配景观要素的分布模式；且该模型可结合BIC优化聚类数和协方差类型，增强稳定性和分类精度，并通过期望最大化EM算法进行迭代优化，确保模型收敛至最优解[32]。GMM的准确性依赖于聚类参数的合理设定。其中，*BIC*用于权衡模型拟合度和复杂性，计算公式如下：

$$BIC = -2\ln(likelihood) + k\ln(N), \tag{1}$$

其中，*likelihood*表示似然函数，$k\ln(N)$表示惩罚项，N表示样本数量大小，k表示模型参数数量。该参数用以评价多个不同协方差及聚类中心数量的训练模型，其数值越小，表示模型拟合效果越好。

GMM模型假设某个维度不定的随机变量为x，计算公式如下：

$$p(x) = \sum_{k=1}^{k} \mathrm{w}_k g(x \mid \theta_k), \tag{2}$$

其中，k是高斯混合中分类簇的个数；w_k是各子分布的混合权重（$\sum_{k=1}^{k}\mathrm{w}_k=1$）；$g$表示第$k$个高斯分布的概率密度函数；$\theta_k$代表控制第$k$个高斯分布的参数，包括均值和方差。

EM算法包含求期望E步和最大似然估计M步两个步骤。两个步骤不断迭代计算，以此最大化似然函数并优化聚类结果。随后继续将M步得到的参数值用于E步中计算，迭代直至收敛。

E步公式如下：

$$w_i(k) = \frac{\pi_k p_k(x \mid \mu_k, \sum_k^2)}{\sum_{i=1}^{k} \pi_i p_i(x \mid \mu_k, \sum_i^2)}, \tag{3}$$

其中，$w_i(k)$表示数据点x_i属于类别k的后验概率；π_k为类别k的先验概率；$p_k(x \mid \mu_k, \sum_k^2)$为类别$k$的高斯概率密度函数。

M步公式如下：

$$\mu_k = \frac{\sum_{i=1}^{n} w_i(k) x_i}{n}, \tag{4}$$

$$\sum_k^2 = \frac{\sum_{i=1}^{n} w_i(k)(x_i - \mu_X)(x_i - \mu_X)^{\mathrm{T}}}{n_k}, \tag{5}$$

$$n_k = \sum_{i-1}^{n} w_i(k), \tag{6}$$

其中，μ_k是第k类别的均值向量，即所有数据点在该类别的加权平均值；$\sum_k^2$是类别k协方差矩阵，衡量数据在各维度的分布；n_k是第k类别的加权样本数，衡量类别中数据点的权重总和；x_i表示第i个观测数据点，代表样本在各维度上的取值；T表示向量的转置。

3.2.3 海岸带场景图谱表达

为强化聚类结果的可视化空间表达，还需明确各类场景单元的主导特征及因子构成结构。本研究借助Python平台构建名称及代码规则，制定了一套标准化制图编码体系：LCT*n*（landscape character type）为场景特征类型，LCA*n*（landscape character area）为景观区域，*n*为编号。其中，以因子变量*X*在某一场景特征类型中的面积占比为例，$X≥60\%$记作X，$30\%<X<60\%$记作$[X]$，$10\%≤X≤30\%$记作(X)，$X<10\%$则省略不计[33]。

海岸带场景聚类结果的可视化常呈现为分散破碎的马赛克式图斑。本研究依托eCognition软件执行多层次图像分割，结合遥感影像修正聚类边界，以增强分类区域的精准性与完整性；采取皮尔逊相关系数计算不同场景景观类型之间的相似性，优化整合聚类结果；继而引入层次聚类方法，构建场景集群、细化场景分区；最终基于海岸带场景景观主导特征，提出针对性的保护与利用策略，以支撑海岸带景观策略的精细调控。

4 海岸带场景数字化聚类实证研究：以烟台套子湾海岸带为例

4.1 研究区域

烟台套子湾位于中国山东省烟台市西北部海区，是一处开敞式次生海湾，地貌特征复杂、场景类型丰富，涵盖山地、河流、城市和海洋等多种海岸带场景[34]。本研究将其作为研究区域，以验证基于景观特征理论的数字化聚类方法在复杂地貌环境及多样化海岸带场景中的适用性。

4.2 研究区域边界与特征因子提取

本研究采用高分一号多光谱影像作为数据源，经辐射定标、大气校正和正射校正预处理后提取海岸线矢量数据；进而借助ArcGIS平台沿海岸线向陆地和海洋两侧各扩展1 km缓冲区，设置300 m等距离点阵作为观景点开展可视域分析，数值表示研究区域被观测点看到的次数，并根据累积可视域划定研究范围（图2）。所得研究区域总面积为770.35 km²，其中陆地面积264.89 km²、海域面积505.46 km²，海岸线长度75.32 km。

本研究分别采用500 m×500 m、100 m×100 m两类空间网格划定陆域和海域样本单元，共获得陆域空间网格样本108 715个、海洋空间网格样本51 510个。研究区域内各海岸带场景特征因子数据来源如表2所示：1）矢量数据主要包括建筑轮廓、高度等城市建设信息；2）栅格数据主

表 2：数据类型与来源

数据类型	数据名称	数据精度	年份	来源
矢量数据	建筑轮廓及高度	—	2023	OpenStreetMap
栅格数据	数字高程模型（DEM）	12.5m	2009	阿拉斯加卫星设施数据中心
	遥感影像	1m	2022	高分一号（GF-1）
文本数据	套子湾海图	—	2023	船讯网电子海图
	烟台市建筑风貌特色和管控规划	—	2021	烟台市自然资源和规划局
	烟台市海洋与海岸带专项规划	—	2023	
	烟台市总体城市设计	—	2021	
	烟台历史文化名城保护规划	—	2021	
	潮汐数据	—	2023	MIKE 21 潮汐高度预测

要包含遥感影像和DEM数据，用于获取归一化植被指数、坡度、地形起伏度等因子；3）文本数据包括规划文件与潮汐资料，用于提取文化感知、用地规划以及海洋环境类因子。其中，海洋环境因子借助MIKE21软件模拟大潮日和小潮日的典型时刻流场，提取海水流速和流向特征而生成。最终，统一将测度后的特征因子数据在ArcGIS平台中选取自然间断法进行重分类，并结合变量面积占比统计（表3，图3）。

4.3 海岸带场景聚类计算

基于上述分类结果，使用主成分分析方法对陆地和海域样本进行降维处理。陆地样本的49个变量转化为20个主成分，累积总方差解释为79.20%；海域样本的24个变量转化为11个主成分，累积总方差解释为78.91%。随后，通过计算*BIC*以获得GMM最优属性，*BIC*值越小，表示模型拟合程度越好。陆地样本协方差模型为“full”且聚类中心数量为18时*BIC*得分最低；海域样本协方差模型为“full”且聚类中心数量为7时*BIC*得分最低。

基于最优聚类数设定结果，以GMM初次聚类获得的类别标签为基础，通过EM算法对模型进行优化迭代。经42次迭代后，模型达到收敛并最终获得聚类结果，共形成25类典型海岸带场景类型。而后以此构建包含25种特征类型的变量数据集（图4），包括18类陆域场景（LCT1～LCT18）和7类海域场景（LCT19～LCT25）。通过对初划结果进行边界修正，将尺度、形状、紧凑度参数分别调整为140、0.3、0.2，最终聚合为161处典型区域（图5）。

4.4 海岸带场景聚类结果解析与判读

基于上述分析结果，研究发现山海格局是研究区域内最显著的景观特征，场景整体呈“山—城—岸—海”的分布规律。通过皮尔逊相关性计算，将海岸带场景类型划分为陆域场景分组（LG）和海域场景分组（MG）。其中，山林场景组（LG4）沿城市边缘以带状片段式分布，自然特征突出；城市边缘场景组（LG2）与高度人工化的城市建成场景组（LG3）交错分布；海岸场景组（LG1）集中分布于岸线区域；海域场景可依据海域深度与流速进一步划分为近浅海（MG1）和远深海场景组（MG2）。研究进一步结合层次聚类分析、欧式距离与Ward法，将空间邻近、特征相似的区域聚类为8个场景集群（landscape character area group），即LCAG1～LCAG8（图6～8）。

通过对最终所得的8个景观集群的空间分布特征和类型构成展开系统解析，研究从自然景观与人工景观两个视角，发现研究区域内场景特征分异规律如下：

1）自然海岸集群（LCAG1）面积占比5.55%，以MG1和LG1为主，表现为自然岸线与潮间带，生态资源丰富、生态价值显著；

2）人工海岸集群（LCAG2）面积占比3.07%，主要包括MG1、LG1、MG2，以城镇岸线、渔业岸线、港口码头、工业岸线等人工化岸线类型和功能性海域为主，综合开发程度较高；

3）河流及城市公园景观集群（LCAG3）面积占比2.75%，主要由LG2和LG3组成，分布于城市与山海交界处，呈条带状分布，具有廊道功能但斑块破碎化程度较高；

表 3：研究区域海岸带场景特征因子及变量

变量	代码	占比
高程（m）		
近海平原 ≤ 37	H1	58.97%
低平原 (37, 81]	H2	23.37%
台地 (81, 145]	H3	12.58%
丘陵 (145, 260]	H4	4.22%
山地 ＞ 260	H5	0.86%
地形起伏度（m）		
微起伏 (0, 2]	F1	62.80%
缓起伏 (2, 5]	F2	24.31%
小起伏 (5, 10]	F3	9.14%
中起伏 (10, 16]	F4	3.10%
高起伏 (16, 54]	F5	0.65%
坡度（°）		
平地 ≤ 2	S1	21.66%
缓坡 (2, 6]	S2	51.78%
斜坡 (6, 15]	S3	20.18%
急坡 (15, 25]	S4	5.25%
陡坡＞ 25	S5	1.13%
土地覆盖类型		
林地	LC1	15.25%
水体	LC2	3.07%
耕地	LC3	10.20%
人造表面	LC4	35.54%
草地	LC5	25.70%
沙地	LC6	10.24%
植被覆盖度		
低覆盖度 (0, 0.28]	V1	43.36%
中等覆盖度 (0.28, 0.60]	V2	34.29%
高覆盖度 (0.60, 1.00]	V3	22.35%

变量	代码	占比
海岸类型		
基岩海岸	CT1	3.75%
砂质海岸	CT2	22.65%
人工海岸	CT3	73.60%
海岸形态		
平直海岸 (1.01, 1.03]	CM1	38.47%
弯曲海岸 (1.03, 1.06]	CM2	29.34%
曲折海岸 (1.06, 1.26]	CM3	32.19%
潮间带类型		
岩礁质潮间带	IT1	11.64%
砂质潮间带	IT2	68.66%
淤泥质潮间带	IT3	19.70%
海水深度（m）		
浅海 (－11.74, 3.98]	B1	4.39%
较浅海 (3.98, 9.31]	B2	5.22%
中海 (9.31, 15.42]	B3	28.62%
较深海 (15.42, 20.19]	B4	60.47%
深海 (20.19, 24.38]	B5	1.30%
海水流速（m/s）		
低流速 (0, 0.03]	VE1	9.64%
较低流速 (0.03, 0.06]	VE2	17.48%
中等流速 (0.06, 0.10]	VE3	18.15%
较高流速（0.10, 0.13]	VE4	28.60%
高流速 (0.13, 0.28]	VE5	26.12%
建筑密度（个 /km^2）		
低密度 (0, 0.0025]	BD1	74.82%
中密度 (0.0025, 0.0077]	BD2	18.27%
高密度 (0.0077, 0.0238]	BD3	6.91%

（续表见下页）

表 3：研究区域海岸带场景特征因子及变量 （接上表）

变量	代码	占比
用地类型		
公共服务设施用地	LU1	20.81%
公园绿地	LU2	11.73%
居住用地	LU3	36.80%
工业用地	LU4	23.03%
物流仓储用地	LU5	0.61%
防护绿地	LU6	7.02%
海岸功能用途类型		
城镇海岸	CU1	35.35%
港口码头	CU2	20.57%
旅游娱乐	CU3	28.93%
渔业	CU4	5.79%
临海工业	CU5	3.63%
未利用	CU6	5.73%

变量	代码	占比
海洋功能用途类型		
一般渔业海域	MU1	24.57%
重要渔业海域	MU2	4.39%
港口航运区 1	MU3	25.94%
港口航运区 2	MU4	23.32%
重要滨海旅游区	MU5	15.67%
重要砂质岸线临近海域	MU6	5.28%
海洋特别保护区	MU7	0.83%
视觉感知		
不可视（0）	VP1	15.00%
低可视度 [1, 28]	VP2	52.99%
中可视度 (28, 74]	VP3	22.16%
高可视度 (74, 183]	VP4	9.85%

注

1. 海洋功能用途类型中，港口航运区 1 和港口航运区 2 分属不同的航道和港口，为确保场景划分的科学性，研究中保留二者的独立识别与分类，未作合并。
2. 视觉感知一项基于可视域分析结果生成，即某一空间位置可以被不同观察点观测到的次数，反映其在观察体系中的可见程度。

4）城市建成景观区集群（LCAG4）面积占比11.09%，由LG3、LG2主导且集中分布于城市核心区域，建筑密度较高、绿化率较低，景观空间连续性较差；

5）城市边缘景观区集群（LCAG5）面积占比11.24%，呈块状散布，作为城市建成景观区集群与自然环境间的过渡区域，具有缓冲保护作用但绿量不足；

6）山体及林地景观区集群（LCAG6）面积占比8.06%，以LG4、LG2为主，是围绕城市形成的重要生态屏障；

7）近岸海域景观集群（LCAG7）面积占比12.31%，以MG1为主，集中分布在海湾内部流速缓慢、水深较浅的区域，生态系统较敏感但生物多样性较高；

8）离岸海域景观集群（LCAG8）面积占比42.78%，以MG2为主，生物生产力较低，但对区域的渔业和航运贸易经济活动影响显著。

4.5 海岸带景观保护与利用策略

基于典型景观集群的特征分异，并结合国内外实际案例和研究区域本底特征，本研究以实现多功能海岸带景观的可持续发展为目标，提出以下保护和利用策略。

1）自然海岸保护与生态修复：于自然海岸集群而言，可参考澳大利亚大堡礁生态保护项目[35]，开展周期性监测与综合修复，实施植被重建和沙坝稳定化等措施，强化自然岸线生态屏障。

2）人工岸线整治与结构调整：对于人工海岸集群，建议借鉴天津永定新河口人工海岸建设经验[36]，以生态堤岸构建为核心，推进港口与工业岸线整治，增强人工岸线的生态功能和景观价值。

3）城市建成环境与景观提升：针对河流及城市公园景观集群和城市建成景观区集群，可参照日本东京湾河口湿地景观优化案例[37]，在整合零散地块、扩展绿地覆盖范围的基础上，构建生态绿廊与城市慢行系

统，强化绿地结构网络的空间连续性；恢复河口湿地和潮间带生物栖息地，改善区域生态承载力。

4）城市边缘绿地与山体景观保护：对于城市边缘景观区集群，学习德国鲁尔区城市边缘绿地模式[38]，提升乡土植物配置，缓解热岛效应；就山体及林地景观集群而言，可参考阿尔卑斯地区山地保护案例[39]，实施分区保护与低干预游憩规划，统筹生态修复与景观体验。

5）近岸与远海海域的资源调适与利用：针对近岸海域与离岸海域景观集群，借鉴新西兰奥克兰潮间带生态修复实践[40]，推进生态系统保护与开发限度控制，实施限捕限养并建立环境影响评估机制，保障滨海资源可持续利用。

5 结论与讨论

面向当前海岸带场景精准研判和分类治理的需求，本研究基于景观特征理论构建了一套适用于海岸带场景的数字化聚类方法体系，并以烟台套子湾海岸带为实证研究区域探讨该方法的应用路径，为海岸带场景的精细分类和调控策略提供理论和技术基础。本研究集成多源数据构建海岸带场景表征体系，基于BIC和EM算法优化聚类参数，建立了“样本提取—特征表征—聚类计算—数字制图”的聚类分析流程，探讨了基于GMM的海岸带场景数字化聚类方法的可行性。

研究结果显示，烟台套子湾海岸带场景的分布受自然地貌、海洋动力过程与人类活动综合作用，呈现典型“山—城—岸—海”的分布特征。其中，城市建成环境、人工岸线、生态缓冲带等场景单元在空间上呈现结构分布清晰、边界辨识度高等特征，而海洋资源利用场景则在不同水深条件下呈现明显的差异特征。实证结果表明，依据该方法构建的海岸带场景分类体系已基本覆盖研究区域的典型景观类型，具备深化拓展与跨场景推广的潜力。中国拥有广袤的海岸线，蕴藏着丰富的滨海景观资源。随着海岸带景观高质量发展和资源精细化管控需求的不断提升，数字化聚类方法在海岸带场景研究中的应用仍处于探索阶段。本研究基于景观特征理论探索海岸带场景分类、解析与调控，以数字语言解析海陆特征，以景观结构逻辑重塑场景认知，为构建滨海及海洋景观科学评价框架提供重要支撑。

与此同时，本研究聚焦解析场景的空间分布特征，在社会、经济等驱动因素的综合考量方面尚存不足，因而景观保护和利用策略的系统性有待深化。此外，不同海岸类型受海洋动力、气候条件及人类活动强度的影响，呈现显著的空间差异性。未来仍需结合不同海岸带场景优化分类变量及判别标准，提升方法的适应性，并拓展至典型海岸带区域的分类应用，提炼共性规律，助力海岸带场景景观资源保护和空间精细治理的协同发展。

补充材料

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