

Article

Monitoring Spatiotemporal Dynamics of *Spartina alterniflora*–*Phragmites australis* Mixed Ecotone in Chongming Dongtan Wetland Using an Integrated Three-Dimensional Feature Space and Multi-Threshold Otsu Segmentation

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Highlights

What are the main findings?

- An integrated method combining a three-dimensional feature space with multi-threshold Otsu segmentation and season-specific indices (NIR/NDVI) enabled high-precision extraction of the invasive–native mixed ecotone, achieving 87.3% overall accuracy.
- The mixed ecotone displayed a distinct seaward expansion trend and a composite pattern of regime shift with internal fluctuations, as revealed by the centroid migration model and the Seasonal Area Ratio (SAR) index, respectively.

What are the implications of the main findings?

- The methodology helps overcome spectral mixing challenges in intertidal zones, providing a technical framework for fine-scale vegetation classification and dynamic monitoring in complex wetland environments.
- The revealed spatiotemporal dynamics and competition mechanisms offer critical insights for targeted management of invasive *Spartina alterniflora* and for the conservation of coastal wetland ecosystems.

Abstract

The Chongming Dongtan wetland, a representative coastal wetland in East Asia, faces a significant ecological threat from the invasive species *Spartina alterniflora*. The mixed ecotone formed between this invasive species and the native *Phragmites australis* serves as a highly sensitive and critical indicator of alterations in wetland ecosystem structure and function. Using spring and autumn Sentinel-2 imagery from 2016 to 2023, this study developed an integrated method that combines a three-dimensional feature space with multi-threshold Otsu segmentation to accurately extract the mixed *S. alterniflora*–*P. australis* ecotone. The spatiotemporal dynamics of the mixed ecotone were analyzed at multiple temporal scales using a centroid migration model and a newly defined Seasonal Area Ratio (SAR) index. The results suggest that: (1) Near-infrared reflectance and NDVI were identified as the optimal spectral indices for spring and autumn, respectively. This approach led to a classification achieving an overall accuracy of $87.3 \pm 1.4\%$ and a Kappa



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coefficient of 0.84 ± 0.02 . Notably, the mixed ecotone was mapped with producers' and users' accuracies of 85.2% and 83.6%. (2) The vegetation followed a distinct land-to-sea ecological sequence of "pure *P. australis*–mixed ecotone–pure *S. alterniflora*", predominantly distributed as an east–west trending belt. This pattern was fragmented by tidal creeks and micro-topography in the northwest, contrasting with geometrically regular linear features in the central area, indicative of human engineering. (3) The ecotone showed continuous seaward expansion from 2016 to 2023. Spring exhibited a consistent annual area growth of 13.93% and a stable seaward centroid migration, whereas autumn exhibited significant intra-annual fluctuations in both area and centroid, likely influenced by extreme climate events. (4) Analysis using the Seasonal Area Ratio (SAR) index, defined as the ratio of autumn to spring ecotone area, revealed a clear transition in the seasonal competition pattern in 2017, initiating a seven-year spring-dominant phase after a single year of autumn dominance. This spring-dominated era exhibited a distinctive sawtooth fluctuation pattern, indicative of competitive dynamics arising from the phenological advancement of *P. australis* combined with the niche penetration of *S. alterniflora*. This study elucidates the multiscale competition mechanisms between *S. alterniflora* and *P. australis*, thereby providing a scientific basis for effective invasive species control and ecological restoration in coastal wetlands.

Keywords: *Spartina alterniflora*; *Phragmites australis*; ecotone; three-dimensional feature space; multi-threshold Otsu segmentation; Chongming Dongtan; spatiotemporal dynamics; wetland monitoring

1. Introduction

Spartina alterniflora, a species indigenous to the coastal zones of North America, has spread extensively following its introduction to China in 1979 [1]. More than two decades after its introduction, it was designated as one of China's first official invasive alien species [2]. In the Chongming Dongtan wetland within the Yangtze Estuary, *S. alterniflora* undergoes intense niche competition with the native dominant species *Phragmites australis* for limited resources [3]. The mixed ecotone formed between these two species constitutes a critical ecologically sensitive zone that maintains the structural and functional stability of the wetland ecosystem [4]. Consequently, precise monitoring of the ecotone's spatiotemporal dynamics is a crucial prerequisite for containing the further spread of *S. alterniflora* [5] and preserving coastal wetland biodiversity [6].

Current research on monitoring the spatiotemporal dynamics of ecotones [7] primarily relies on multi-source remote sensing data and long-term time-series analysis, leading to three typical paradigms. The first paradigm involves long-term monitoring using medium-to-low-resolution imagery, such as analyses of land-use changes in agro-pastoral ecotones in various regions across China based on national land survey data (NLSD) or Wuhan University's CLCD dataset [8,9]. The second paradigm focuses on static boundary extraction using high-resolution imagery. For instance, Yao et al. [10] utilized GF-1 data to extract the *S. alterniflora*–*P. australis* mixed ecotone in the Chongming Dongtan wetland, while Döweler et al. [7] detected the spatial distribution of the alpine treeline ecotone in the Southern Alps of New Zealand using radar data. The third paradigm employs multi-platform collaborative observation, for example, Dong et al. [11], who integrated satellite and unmanned aerial vehicle (UAV) remote sensing to monitor a mangrove–salt marsh ecotone in Guangxi's Dandou Sea.

Although previous studies have established remote sensing methodologies for ecotones [12], significant challenges remain in the high-accuracy spatiotemporal monitoring of

the intertidal *S. alterniflora*–*P. australis* ecotone. Spatially, periodic tidal inundation leads to spectral mixing of vegetation signatures. Additionally, micro-topographic variations across the tidal flat further exacerbate spectral heterogeneity by modulating the duration of tidal immersion [13]. Traditional two-dimensional remote sensing methods [14,15], lacking support from three-dimensional spatial features, therefore exhibit limited accuracy in identifying small-scale mixed ecotones. Temporally, there is a lack of analytical models capable of resolving phenological dynamics across monthly, seasonal, and annual scales [16]. This gap impedes a deeper mechanistic understanding of the competitive reversal in spring and autumn [17], which arises from the earlier sprouting of *P. australis* and the later senescence of *S. alterniflora*. Elucidating this mechanism is a critical step towards achieving precise control of this invasive species.

To address these challenges [18,19], this study proposes an integrated methodology that combines a three-dimensional (3D) feature space (X: Longitude, Y: Latitude, Z: Spectrum) with multi-threshold Otsu segmentation. The key innovation lies in the explicit incorporation of geographic coordinates at the pixel level into the feature space. This moves beyond conventional 2D spectral analysis by embedding each pixel within its spatial context [20]. The constructed 3D scatterplots allow for the visualization and quantification of how spatial gradients—primarily driven by tidal inundation frequency and micro-topography—modulate spectral responses. This approach helps mitigate the spectral mixing problem common in intertidal zones, where pixels with similar spectral signatures but different spatial positions (e.g., high vs. low tidal flat) can belong to distinct ecological zones. Furthermore, by leveraging season-specific optimal spectral indices determined through separability analysis within this 3D space, the method establishes adaptive, phenologically aware thresholds for segmentation [21]. Building upon the seasonal spectral index method proposed by Yao et al. [10], this research integrates spatially explicit constraints with multi-temporal adaptive thresholding, establishing a robust dynamic monitoring model centered on the “Spatial–Phenological–Expansion” nexus.

The proposed 3D feature space approach is conceptually distinct from other common spatial-context methods, such as Object-Based Image Analysis (OBIA) and neighborhood filtering. OBIA first segments an image into homogeneous objects based on spectral, spatial, and textural criteria, then classifies these objects [22]. Although powerful, the performance of OBIA depends heavily on segmentation scale and rules, which can be difficult to optimize for dynamic, linear ecotones within heterogeneous tidal flat environments. Neighborhood filtering (e.g., morphological or texture filters) modifies a pixel’s value based on its surrounding pixels [23], typically to reduce noise or enhance features, but does not explicitly retain absolute geographic coordinates as a standalone feature dimension for joint analysis. In contrast, the method proposed here retains the pixel as the basic analytical unit while enriching its feature representation by directly appending its geographic coordinates (X, Y) to its spectral value (Z). This constructs a 3D scatterplot in which spatial patterns—such as seaward gradients and patchiness—and spectral clusters can be visualized and analyzed simultaneously. Rather than smoothing or aggregating information (as in filtering or OBIA) [24], this approach aims to expose and quantify the underlying spatio-spectral structure of the landscape, thereby supporting improved per-pixel, feature-based threshold selection. It offers a transparent framework for diagnosing causes of spectral mixing and establishing classification thresholds that are informed by both spectral separability and spatial context.

Guided by this framework, this study uses the Chongming Dongtan wetland as the study area and a time series of Sentinel-2 imagery (2016–2023) to address two objectives: (1) achieve high-accuracy extraction of the *S. alterniflora*–*P. australis* mixed ecotone; and (2) combine centroid migration with a newly defined Seasonal Area Ratio (SAR) index

(autumn area/spring area) to quantify seasonal competition dynamics and characterize the ecotone's expansion trajectory across multiple temporal scales. This research aims to provide methodological support and a decision-making basis for the dynamic monitoring of invasive species, analysis of competitive mechanisms, and ecological management in coastal wetlands.

2. Study Area, Data Sources, and Methodology

2.1. Study Area

Chongming Island, located in the core area of the Yangtze River Estuary ($121^{\circ}09' - 121^{\circ}54'E$, $31^{\circ}27' - 31^{\circ}51'N$), is the largest alluvial sandbar in China [25]. This study focuses on the Chongming Dongtan wetland (Figure 1). The geomorphology of this area is primarily formed by the long-term deposition of suspended sediments from the runoff [26]. It is characterized by wide and gentle tidal flats with a semi-diurnal tidal regime [27], making it a typical prograding tidal wetland. The region has a northern subtropical monsoon climate [28], with a mean annual temperature of approximately $15^{\circ}C$ and an average annual precipitation of about 1000 mm. The combination of abundant rainfall and warm temperatures creates favorable hydrothermal conditions that promote the development of wetland vegetation [29].

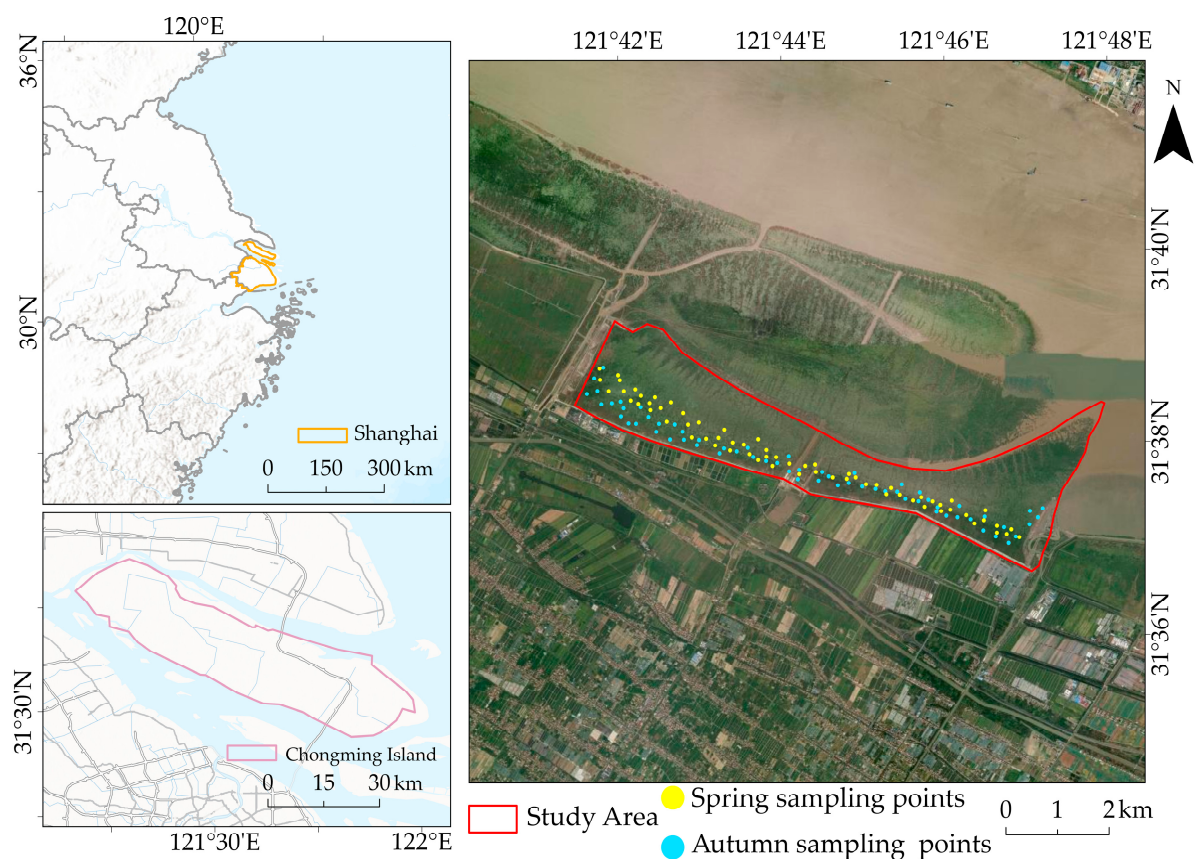


Figure 1. Location of the study area.

Prior to the invasion of *S. alterniflora*, the native salt marsh vegetation in this wetland was co-dominated by *P. australis* and *Bolboschoenoplectus marigueter*. Since the introduction of *S. alterniflora* in the 1990s, its continuous expansion has led to a significant decline in the coverage of *B. marigueter* (by 60–80%) [30], gradually forming a new vegetation pattern centered on a competitive *P. australis*–*S. alterniflora* ecotone. Therefore, the Chongming Dongtan wetland is an ideal area for investigating competitive mechanisms between

invasive and native species and is well-suited for studying the dynamic succession of ecotones under the coupled “Spatial–Phenological–Expansion” framework.

2.2. Data Source and Preprocessing

The Sentinel-2A/2B satellites, equipped with the Multispectral Instrument (MSI), acquire data across 13 spectral bands spanning the visible to shortwave infrared regions. Among these, the blue, green, red, and near-infrared bands offer a 10-m spatial resolution and a 5-day revisit cycle [31], which enables high-frequency, dynamic monitoring of wetland vegetation. Leveraging the distinct phenological differences between *P. australis* (early sprouting) and *S. alterniflora* (late senescence) [32,33], this study selected Sentinel-2 Level-2A imagery, specifically targeting the key phenological windows of spring green-up (April) and autumn senescence (November) for each year from 2016 to 2023. A total of 16 scenes with cloud cover of less than 10% were obtained from the Copernicus Data Space Ecosystem (<https://dataspace.copernicus.eu/>). Their key specifications are provided in Table 1. All Sentinel-2 images were uniformly reprojected to the WGS84 UTM Zone 51N coordinate system and clipped to the study area extent, establishing a standardized spatial framework for subsequent analysis.

Table 1. Data specifications.

Year	Spring Image Date	Cloud Cover	Autumn Image Date	Cloud Cover
2016	25 March 2016	7.8%	07 December 2016	0.2%
2017	29 April 2017	6.9%	15 November 2017	3.1%
2018	01 April 2018	7.3%	12 December 2018	6.0%
2019	06 April 2019	0.6%	15 November 2019	0.0%
2020	13 April 2020	4.9%	29 November 2020	1.4%
2021	18 April 2021	4.6%	14 November 2021	0.0%
2022	20 April 2022	2.8%	16 November 2022	8.4%
2023	28 April 2023	6.5%	24 November 2023	8.7%

Furthermore, field surveys were conducted in April and November 2023 to collect ground-truth data for accuracy validation. A total of 127 sample points were acquired using Real-Time Kinematic (RTK) GPS positioning, with a horizontal accuracy better than 0.05 m (Figure 1). The sampling strategy was designed to ensure representativeness: points were systematically distributed along the transitional ecotone boundaries, within pure stands of *P. australis* and *S. alterniflora*, and across distinct geomorphic contexts—such as areas adjacent to tidal creeks in the northwest, higher tidal flats, and zones near anthropogenic linear features in the central region. Concurrently, UAV-based aerial photography was conducted to obtain high-resolution orthophotos of the sampled areas. These orthophotos, together with field photographs and notes, were visually interpreted to label the 2023 validation points.

2.3. Methodology

2.3.1. Delineation of the Mixed Ecotone

- Spectral Feature Extraction and 3D Feature Space Construction.

Spectral reflectance from the blue (B2), green (B3), red (B4), and near-infrared (B8) bands was extracted pixel-by-pixel from the preprocessed Sentinel-2 images for both spring (April) and autumn (November) 2023. The Normalized Difference Vegetation Index (NDVI) was subsequently calculated using the following formula [34]:

$$\text{NDVI} = (\rho_8 - \rho_4) / (\rho_8 + \rho_4) \quad (1)$$

where ρ_8 and ρ_4 represent the reflectance of the B_8 and B_4 bands, respectively. To utilize both spatial and spectral information for vegetation distribution analysis, a three-dimensional feature space scatter plot was constructed (Figures 2 and 3). In this plot, a pixel's geographic coordinates (X, Y) define the planar axes, and a spectral index (reflectance or NDVI) forms the vertical Z-axis [35]. By fusing geographic and spectral dimensions [36], this approach helps distinguish tidal and micro-topographic influences on spectral signatures, providing an integrated spatial-spectral basis for threshold segmentation.

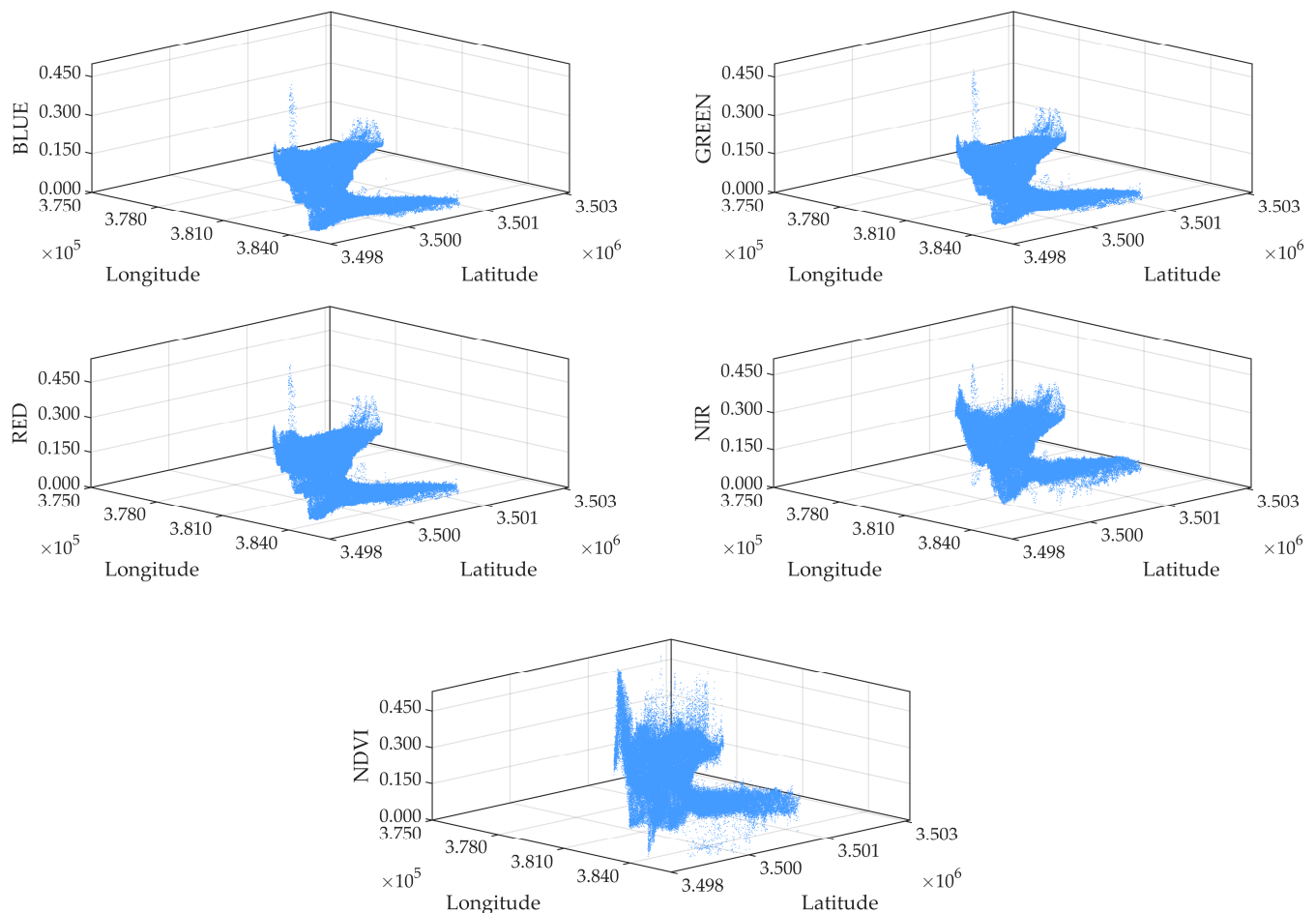


Figure 2. 3D feature space representations of spectral indices for spring (April 2023).

The 3D feature space functions primarily as a visual diagnostic tool rather than as a direct component of the classification algorithm. Geographic coordinates (X, Y) and the spectral index (Z) are not merged into a composite feature vector for segmentation. Instead, the 3D scatter plot visually illustrates how spectral values (Z) are distributed across the spatial domain (X, Y). This aids in selecting the most discriminative single spectral index—for example, near-infrared reflectance—under which vegetation types separate into distinct clusters or spatial gradients. Multi-threshold Otsu segmentation is then applied only to this chosen one-dimensional spectral layer. This avoids potential issues regarding normalization between coordinates and spectral values, as thresholding relies solely on spectral data and is unaffected by absolute coordinate magnitudes. In this workflow, geographic coordinates (X, Y) serve solely as diagnostic and feature-selection aids and are not incorporated as input features into the subsequent classification algorithm. This approach maintains the simplicity and interpretability of the univariate Otsu segmentation, while ensuring that the selected spectral index is optimally discriminative and minimally confounded by underlying spatial gradients.

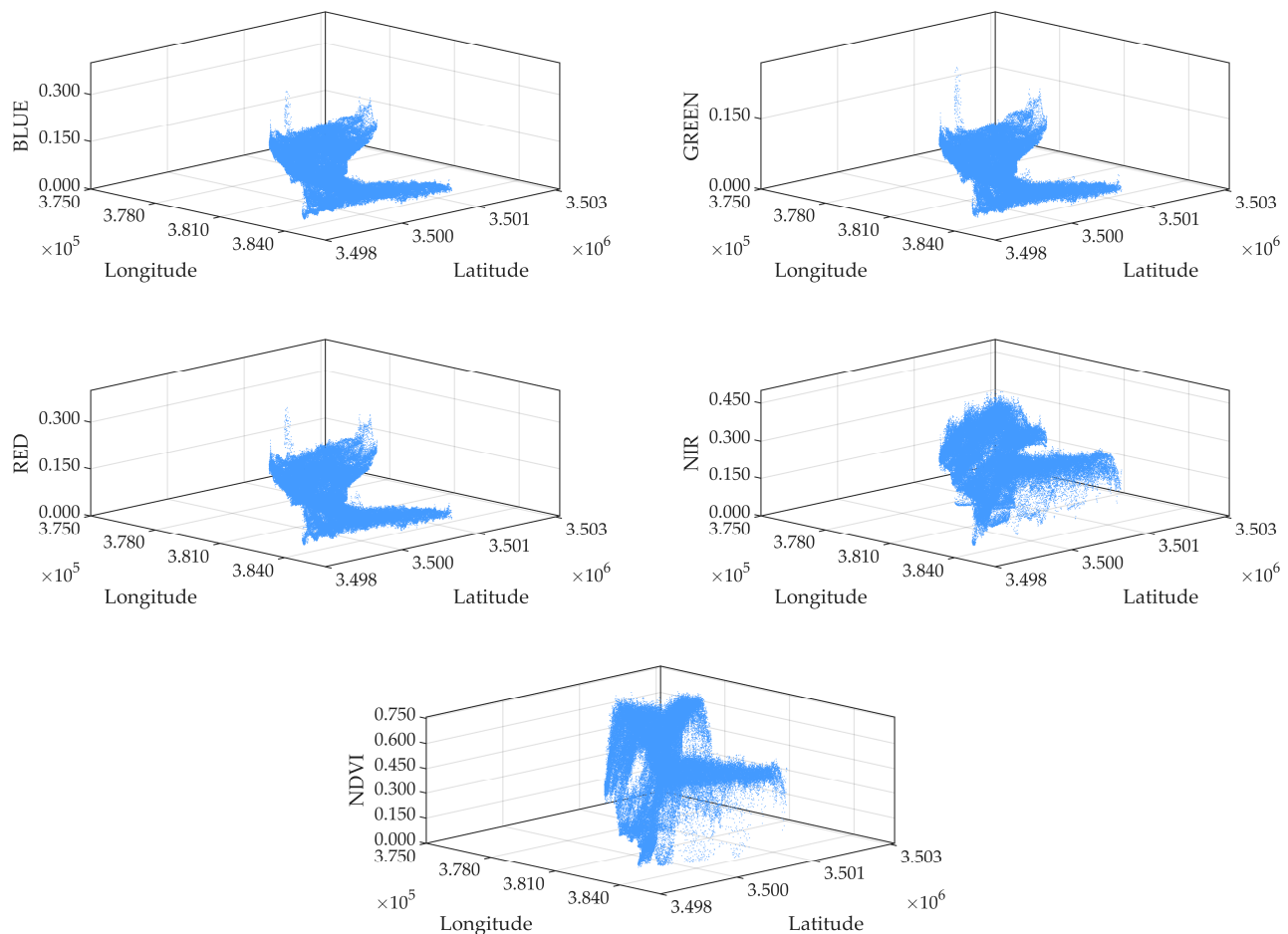


Figure 3. Three-dimensional feature space representations of spectral indices for autumn (November 2023).

The delineation approach follows a pixel-based, three-stage workflow: (1) Spatio-spectral diagnostics: A representative seasonal image (e.g., spring 2023) is used to construct a 3D scatter plot in which geographic coordinates (X, Y) define the base plane and candidate spectral indices (e.g., NIR reflectance, NDVI) are plotted along the vertical (Z) axis (Figures 2 and 3). This visualization illustrates how spectral responses vary along spatial gradients, such as land–sea and elevation. (2) Optimal feature selection: By combining the 3D plots with the quantitative Jeffries–Matusita (JM) distance, the spectral index that provides the greatest separability among the three target vegetation classes—pure *P. australis*, the mixed ecotone, and pure *S. alterniflora*—is identified for that season. (3) Adaptive segmentation: For each image in the time series, the multi-threshold Otsu algorithm is applied exclusively to the pixel values of the preselected optimal spectral index layer. This generates image-specific adaptive thresholds (T_1 , T_2) based on the histogram of each scene. Note that geographic coordinates are not fed into the Otsu algorithm; their function is limited to the diagnostic and feature-selection stage (Stage 1).

- **Optimal Spectral Index Selection and Multi-threshold Otsu Segmentation.**

To ensure accurate and consistent delineation of the mixed ecotone across the eight-year dynamic time series, a two-stage analytical strategy was employed: first, determining the seasonally optimal spectral index, followed by per-image adaptive thresholding.

Stage 1: Determination of Seasonally Optimal Spectral Indices. The spring and autumn images of 2023 were selected as a representative baseline due to their data quality and phenological representativeness. For this baseline period, three-dimensional (3D) feature

space scatter plots were constructed for a suite of candidate spectral indices: blue (B2), green (B3), red (B4), and near-infrared (B8) reflectance, as well as the NDVI. For each index, the multi-threshold Otsu segmentation algorithm was applied to the 3D data structure to preliminarily separate the three target classes [37–39]: pure *P. australis*, the mixed ecotone, and pure *S. alterniflora*. The class separability achieved by each index was then quantitatively evaluated using the Jeffries-Matusita (JM) distance [40], calculated as:

$$JM = 2 \times (1 - e^{-B}) \quad (2)$$

where B is the Bhattacharyya distance. The JM distance ranges from 0 to 2, where increasing values correspond to enhanced class separability [41], and values exceeding 1.80 generally indicate good separability. Through this combined analysis—leveraging both the unsupervised clustering capability of Otsu and the statistical rigor of the JM distance—a systematic comparison of all candidate indices was performed, leading to the identification of one optimal spectral index for each season.

Stage 2: Time-Series Classification with Adaptive Thresholding. Based on the seasonal optimality established in Stage 1, all spring images were classified using the identified optimal index for spring, and all autumn images using the optimal index for autumn. Critically, while the spectral index was fixed per season, the segmentation thresholds were not. For each of the 16 individual Sentinel-2 scenes (2016–2023), the multi-threshold Otsu algorithm was applied independently. The algorithm processed the pixel values of that scene’s designated seasonal index and automatically derived the two optimal thresholds (T_1 , T_2) that maximized the inter-class variance for that specific image. This per-image adaptive thresholding is a core design feature, ensuring that the classification is optimized for the unique spectral histogram of each date, thereby accommodating inter-annual variability in phenology and environmental conditions.

The multi-threshold Otsu algorithm was selected for its suitability in scenarios with limited prior training data, as it provides unsupervised, data-adaptive threshold determination [37–39]. This characteristic is particularly advantageous for long-term time-series analysis in dynamic environments like intertidal zones, where acquiring exhaustive ground truth for every date is impractical. By operating on the preselected, highly separable spectral indices (rather than raw, mixing-prone bands), this two-stage framework enhances the robustness and interpretability of the classification across the entire temporal dataset.

- **Time-Series Classification and Accuracy Validation.**

Using the selected optimal spectral indices and their corresponding Otsu thresholds, automated classification was conducted on all 16 spring and autumn scenes from 2016 to 2023. This process produced seasonal and annual vegetation distribution maps featuring three distinct classes: pure *P. australis*, the mixed ecotone, and pure *S. alterniflora*. Accuracy validation relied primarily on the 127 ground verification points collected in 2023 (Figure 1). To evaluate classification results for historical years (2016–2022), a back-interpretation procedure was used. High-resolution UAV orthophotos from 2023, along with available historical high-resolution imagery (e.g., from Google Earth Pro), were examined to identify the apparent positions of stable vegetation patches and ecotone boundaries. Sample points for each historical year were then generated based on this interpretation, under the assumption that the core spatial structure of major vegetation zones remained relatively consistent at the 10 m Sentinel-2 pixel scale during the study period, in the absence of major disturbances. This approach produced a multi-temporal validation dataset encompassing all three vegetation types [42]. A confusion matrix was generated to evaluate the reliability and consistency of the classification results by calculating the overall accuracy, Kappa coefficient, producer’s accuracy, and user’s accuracy [43].

2.3.2. Spatiotemporal Dynamics Monitoring of the Mixed Ecotone

Accordingly, quantitative models were developed to examine the spatiotemporal dynamics of the mixed ecotone across inter-annual and intra-annual scales. At the inter-annual scale, the ecotone area was quantified from the annual classification results to determine its yearly change rate [44], and linear regression was used to evaluate the statistical significance of the observed trend [45]. Meanwhile, the centroid migration model was applied to delineate the evolutionary trajectory of its spatial configuration [46]. To capture intra-annual variations, the Seasonal Area Ratio (SAR) index was used to quantify seasonal dynamics of the vegetation community.

- Centroid Migration Model.

The centroid migration model was used to analyze the spatial trajectory and stability [47] of the mixed ecotone. The centroid (spatial first-order moment) of the ecotone patches was calculated annually, and its migration trajectory was tracked over the study period. The centroid coordinates [48] are computed as follows:

$$X_t = (\sum_i (A_i \times x_i)) / \sum_i A_i, Y_t = (\sum_i (A_i \times y_i)) / \sum_i A_i \quad (3)$$

where (X_t, Y_t) represents the centroid coordinates in year t , A_i is the area of the i -th patch, and (x_i, y_i) denotes the geometric center coordinates of that patch. The centroid migration trajectory can be used to identify the dominant direction of spatial expansion for the entire ecotone.

- Seasonal Area Ratio (SAR) Index.

To quantify seasonal competitive dynamics within the vegetation community [49], the Seasonal Area Ratio (SAR) was defined as the ratio of ecotone area in autumn to that in spring within the same calendar year. This metric serves as an indicator of phenology-mediated competition by reflecting shifts in the relative spatial dominance of the two species across seasons.

$$SAR_t = (Area_{autumn, t}) / (Area_{spring, t}) \quad (4)$$

where $Area_{autumn, t}$ and $Area_{spring, t}$ denote the ecotone area in autumn and spring of year t , respectively. Inter-annual SAR variations capture phenologically mediated competitive shifts between *P. australis* and *S. alterniflora*, providing a metric to quantify the seasonal dynamics of their competition.

3. Results and Analysis

3.1. Selection of Optimal Spectral Indices

To determine the optimal spectral indices for mixed ecotone delineation, 2023 was selected as a representative year for detailed analysis. Three-dimensional scatter plots were constructed for key spectral indices—comprising the blue, green, red, and near-infrared reflectance along with NDVI—during both spring (April) and autumn (November) seasons (Figures 2 and 3). The multi-threshold Otsu segmentation algorithm was applied to determine the optimal thresholds for distinguishing the three classes: pure *P. australis*, the mixed ecotone, and pure *S. alterniflora*. Table 2 summarizes the classification thresholds derived for each spectral index by season. In addition, the Jeffries-Matusita (JM) distance, as summarized in Table 2, was used to evaluate the classification performance of each spectral index, quantifying separability among the three vegetation classes. The analysis showed that near-infrared reflectance yielded the strongest separability in spring (average JM value = 1.99). This is supported by its 3D scatter plot (Figure 4a), which shows clear clustering and distinction among vegetation types. In contrast, for autumn, NDVI (average

JM = 1.93) was identified as the most effective index, with its scatter plot (Figure 4b) showing a well-defined gradient pattern.

Table 2. Otsu segmentation thresholds and inter-class separability (JM distance) of spectral indices for spring and autumn 2023.

Season	Spectral Index	Threshold T ₁	Threshold T ₂	JM Distance (Average)
Spring	ρ_{BLUE}	0.040600	0.094005	1.50
	ρ_{GREEN}	0.066416	0.123075	1.60
	ρ_{RED}	0.075696	0.129511	1.70
	ρ_{NIR}	0.149945	0.190183	1.99
	NDVI	0.174555	0.282613	1.86
Autumn	ρ_{BLUE}	0.066783	0.104831	1.40
	ρ_{GREEN}	0.043947	0.074789	1.50
	ρ_{RED}	0.072376	0.119112	1.60
	ρ_{NIR}	0.181992	0.258286	1.80
	NDVI	0.311753	0.513176	1.93

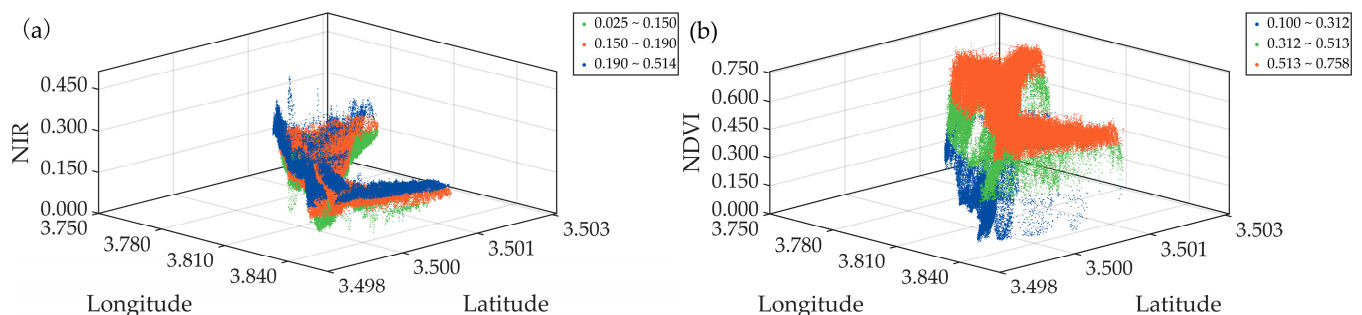


Figure 4. Three-dimensional scatter plots based on the optimal spectral indices for 2023: (a) Spring, using near-infrared reflectance; (b) Autumn, using NDVI.

These findings indicate that near-infrared reflectance captures the phenological differences between *P. australis* (higher reflectance) and *S. alterniflora* (lower reflectance) in spring. In contrast, NDVI shows the strongest discriminatory power during autumn, a period characterized by the distinct phenological contrast between senescent *P. australis* and still-verdant *S. alterniflora*. Therefore, near-infrared reflectance and NDVI were selected as the optimal spectral indices for spring and autumn, respectively. The corresponding thresholds were then used to classify the complete time-series dataset.

3.2. Accuracy Validation of Classification Results

Using the selected optimal spectral indices for spring and autumn, an automated processing workflow was applied to the 16 Sentinel-2 scenes from 2016 to 2023. Each scene was processed with its corresponding seasonal index and classified using multi-threshold Otsu segmentation, yielding distribution maps of the three vegetation types for each season and year (Figure 5).

To evaluate the reliability of the classification results, a confusion matrix and derived accuracy metrics were calculated using 127 ground validation points from April and November 2023 (Figure 1), together with a verification sample set based on the visual interpretation of historical high-resolution imagery. The results (Table 3) show that the average overall classification accuracy across all images was $87.3 \pm 1.4\%$, with an average Kappa coefficient of 0.84 ± 0.02 , indicating high consistency of the time-series classification results. For the primary target—the mixed ecotone—the average producers' and users' accuracies

were 85.2% and 83.6%, respectively, indicating the method's effectiveness in delineating this narrow transition zone. Classification accuracies for both pure *P. australis* and pure *S. alterniflora* exceeded 90%, further supporting the robustness of the classification approach.

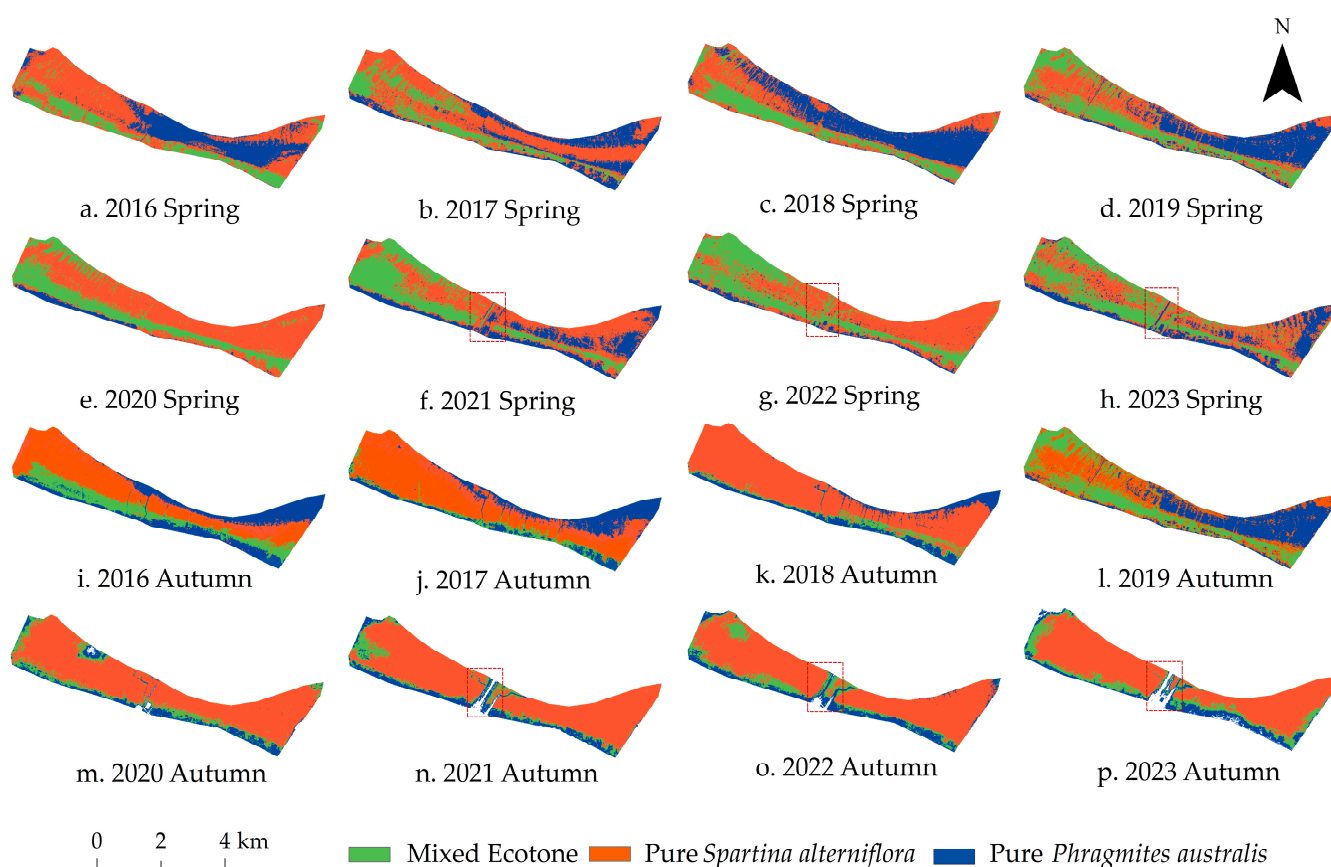


Figure 5. Time-series vegetation classification maps derived from optimal spectral indices and Otsu segmentation (2016–2023): (a–h) Spring, (i–p) Autumn. The red dashed box in the 2021–2023 panels highlights a geometrically regular linear feature of anthropogenic origin.

Table 3. Accuracy assessment of vegetation classification results (2016–2023).

Year	Season	Overall Accuracy (%)	Kappa Coefficient	Mixed Ecotone	
				Producer's Accuracy (%)	User's Accuracy (%)
2016	Spring	85.5	0.82	83.8	82.0
	Autumn	86.0	0.83	84.5	82.8
2017	Spring	86.8	0.83	85.0	83.5
	Autumn	85.2	0.81	82.5	80.9
2018	Spring	87.2	0.84	85.5	84.0
	Autumn	87.8	0.85	86.0	84.5
2019	Spring	88.0	0.85	86.3	85.0
	Autumn	87.0	0.84	85.0	83.2
2020	Spring	88.5	0.86	87.0	85.8
	Autumn	87.3	0.84	85.2	83.5
2021	Spring	88.9	0.86	87.5	86.2
	Autumn	88.2	0.85	86.3	84.8
2022	Spring	89.2	0.87	88.0	86.5
	Autumn	88.5	0.86	86.8	85.0
2023	Spring	89.5	0.86	86.2	85.0
	Autumn	88.7	0.87	85.8	84.5
Average $\pm$ StdDev (%)		87.3 $\pm$ 1.4	0.84 $\pm$ 0.02	85.2 $\pm$ 1.5	83.6 $\pm$ 1.7

In summary, this study developed a “seasonally adaptive spectral indices and dynamic threshold segmentation” approach, which provides a robust data foundation for analyzing the spatiotemporal dynamics of the mixed ecotone. By identifying optimal spectral features and validating them across multiple temporal phases, the proposed method enables accurate monitoring of mixed ecotone dynamics and provides technical support for coastal wetland management.

3.3. Inter-Annual Variation in Adaptive Thresholds

Following the per-image adaptive segmentation strategy, a unique set of Otsu thresholds (T_1 , T_2) was generated for each seasonal image. The annual thresholds for both spring (NIR) and autumn (NDVI) are presented in Table 4.

Table 4. Adaptive Otsu thresholds for spring (NIR) and autumn (NDVI) classifications (2016–2023).

Year	Spring (NIR) Threshold T_1	Spring (NIR) Threshold T_2	Autumn (NDVI) Threshold T_1	Autumn (NDVI) Threshold T_2
2016	0.2700	0.2981	0.2865	0.4263
2017	0.2500	0.2722	0.2778	0.3830
2018	0.2383	0.2629	0.3039	0.4149
2019	0.2462	0.2685	0.2402	0.3077
2020	0.2382	0.2982	0.2695	0.3767
2021	0.2531	0.2830	0.2979	0.4096
2022	0.2828	0.3411	0.4533	0.6179
2023	0.1499	0.1902	0.3118	0.5131

The thresholds exhibited considerable inter-annual variation, highlighting the need for the per-image adaptive approach. Notable variations include the lower NIR thresholds in spring 2023 and the higher NDVI thresholds in autumn 2022. These shifts likely reflect inter-annual differences in vegetation biophysical status (e.g., canopy structure, leaf area) and environmental conditions (e.g., temperature, precipitation, tidal regime) during those specific growing seasons.

Despite these variations in absolute threshold values, the classification accuracy remained high across all years (see Table 3, overall accuracy: $87.3 \pm 1.4\%$). This demonstrates the robustness of the proposed framework: the “optimal spectral index + adaptive Otsu” strategy recalculates discriminative decision boundaries for each image, accommodating inter-annual spectral shifts. Therefore, the derived spatiotemporal dynamics are based on a time series of locally optimized classifications, which helps ensure that observed trends reflect ecological changes rather than artifacts of a static classification scheme.

3.4. Spatial Distribution Pattern of the Mixed Ecotone

The high-resolution 2023 classification results (Figure 5) show distinct vegetation zonation patterns in the Chongming Dongtan wetland. Overall, the vegetation shows a distinct land-to-sea ecological sequence, transitioning from pure *P. australis* through the mixed ecotone to pure *S. alterniflora*. The mixed ecotone, serving as a transitional zone of competition between the two vegetation types, forms a continuous, east–west trending strip, which represents an important ecological boundary between the terrestrial and marine environments.

At the local scale, the vegetation distribution pattern shows significant spatial heterogeneity. In the northwestern sector, where tidal creek dissection and micro-topographic variation are common, the mixed ecotone exhibits a patchy mosaic pattern. This spatial pattern is primarily due to hydrodynamic differentiation caused by variations in tidal flat elevation. Elevated patches with infrequent inundation and moderate salinity support *P.*

australis persistence, whereas low-lying areas with frequent waterlogging and high salinity promote *S. alterniflora* establishment. The resulting salinity gradient, influenced by this microhabitat heterogeneity, helps limit the competitive expansion of *S. alterniflora*, thereby allowing *P. australis* to persist in localized patches and resulting in a complex, interwoven distribution of the two vegetation types. In contrast to these naturally driven patterns, a geometrically regular linear feature appeared in the central study area during 2021–2023 (red dashed box, Figure 5). This area has sharply delineated linear boundaries that contrast with the sinuous, continuous formations of the surrounding natural vegetation. Comparison with high-resolution imagery showed that its geometric characteristics are consistent with anthropogenic infrastructure such as embankments or ditches, indicating that human activities are the likely driver of this vegetation pattern.

3.5. Spatiotemporal Dynamics of the Mixed Ecotone

3.5.1. Inter-Annual Variations (2016–2023)

- Analysis of Area Change Trends.

From 2016 to 2023, the mixed ecotone in Chongming Dongtan wetland showed a general trend of expansion, with marked seasonal differences between spring and autumn, as detailed in Table 5 and shown in Figure 6.

Table 5. Summary of mixed ecotone area (km²) and annual change rate (%) from 2016 to 2023.

Year	Spring Area	Annual Spring Change Rate	Autumn Area	Annual Autumn Change Rate
2016	2.2256	—	2.5047	—
2017	2.5783	15.85	0.9311	−62.83
2018	2.7990	8.56	1.0032	7.74
2019	3.6594	30.74	0.9929	−1.03
2020	3.7882	3.52	1.5540	56.51
2021	4.1325	9.09	1.3432	−13.56
2022	4.7836	15.76	1.7050	26.94
2023	4.3959	−8.10	1.8441	8.16

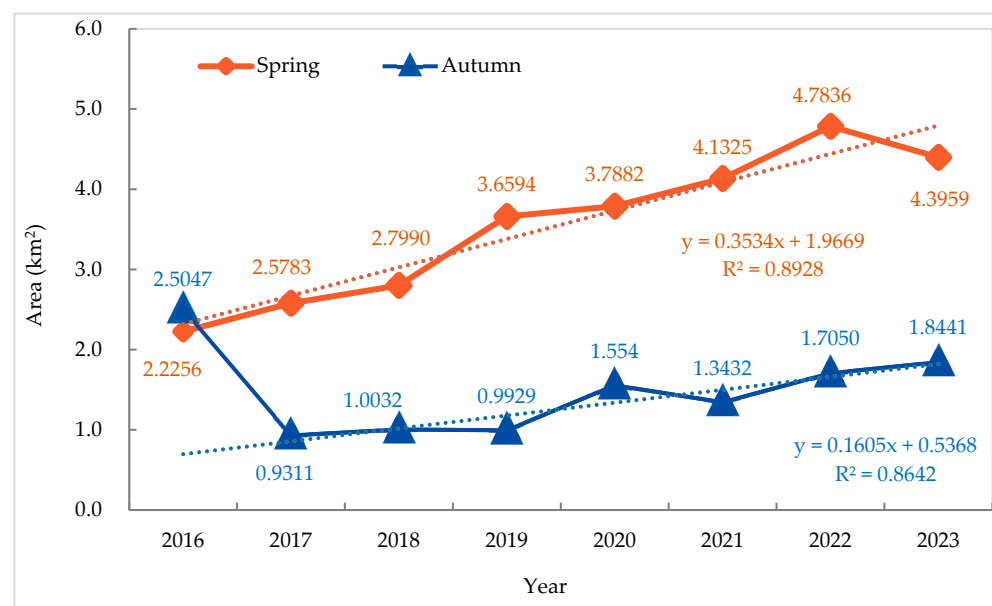


Figure 6. Spatiotemporal dynamics of the mixed ecotone in Chongming Dongtan: expansion trends and seasonal patterns (2016–2023). The dashed lines represent the linear regression trend for spring (2016–2023) and the polynomial regression trend for autumn (2017–2023), respectively.

Linear regression analysis indicated a significant expansion trend ($R^2 = 0.89$, $p < 0.05$) in the spring ecotone area, with an average annual growth rate of 13.93%. The expansion process showed two phases: a rapid expansion phase (2016–2019) with an average annual growth rate of 21.47%, followed by a slower phase (2020–2023) with a rate of 5.35%. The area peaked in 2022, followed by a slight decline in 2023, but remained above the levels recorded at the start of the monitoring period. In contrast, the autumn area showed high variability, which was well described by polynomial regression ($R^2 = 0.86$). A sharp decline of 62.83% occurred in 2017 relative to the 2016 baseline, which was likely linked to vegetation damage from extreme climate events such as intense typhoons or high tides. Following this decline, a gradual recovery occurred at a mean annual rate of 16.34% (2017–2023), although the area did not return to pre-decline (2016) levels by the end of the study period. Inter-annual variability in autumn was more pronounced than in spring, suggesting greater sensitivity of the vegetation to external perturbations during this season.

- Centroid Migration Trajectory and Spatial Expansion Pattern.

Centroid migration analysis shows the spatial evolution of the mixed ecotone, as shown in Figure 7. A general seaward migration of the mixed ecotone was observed in spring (mean azimuth: 112°), indicating a seaward expansion trend. The centroid migrated at a higher rate between 2016 and 2019, averaging 219.20 m per year. This was followed by a deceleration between 2020 and 2023, with the average annual displacement decreasing to 70.70 m and accompanied by periodic oscillations. These patterns suggest possible regulation by hydrological resistance or interspecific competition. The autumn migration trajectory showed greater complexity, with a net displacement of 1068.80 m and a mean orientation of $N17.0^\circ E$. The trajectory progressed through three phases: an initial south-westward retreat (2016–2018), likely reflecting post-disturbance recovery heterogeneity; a northeastward shift in 2019; and sustained northeastward expansion (2020–2023), which showed directional alignment with spring migration patterns.

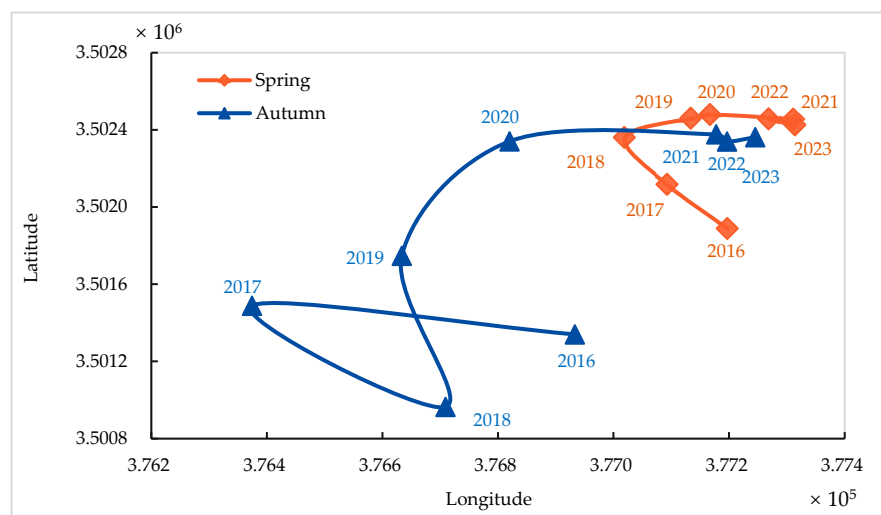


Figure 7. Spatiotemporal dynamics of mixed ecotone centroid migration (2016–2023).

Integrated spatiotemporal analysis indicates a predominant long-term seaward expansion of the mixed ecotone, despite variability in both area fluctuations and centroid trajectories. This dynamic pattern reflects how the competition between *S. alterniflora* and *P. australis* is influenced by multiple environmental drivers. Sediment accretion and climatic warming likely promote seaward progression, whereas episodic disturbances—including typhoons, salt stress, and hydrological fluctuations—contribute to short-term variability and localized retreat. The study elucidates the response of coastal wetland vegetation

to climate change and natural disturbances, providing a spatiotemporal framework for adaptive ecosystem management.

3.5.2. Intra-Annual Dynamics (Seasonal Variations)

Analysis of the Seasonal Area Ratio (SAR) index (2016–2023; Figure 8) shows a multi-tiered competitive structure in the seasonal dynamics of the *S. alterniflora*–*P. australis* mixed ecotone in Chongming Dongtan. A tipping point in seasonal competition patterns occurred in 2017, corresponding to the autumn ecotone contraction during 2016–2017, which was likely triggered by extreme climate events as analyzed in Section 3.5.1. At the inter-annual scale, spring dominance occurred in seven of the eight monitoring years, forming a “1-year autumn/7-year spring dominance” pattern. The year 2016 was the only period of autumn dominance (SAR = 1.1254), suggesting that *S. alterniflora* maintained a late-season competitive advantage due to its extended growth period. In contrast, SAR values remained below 1 (range: 0.27–0.42) from 2017 to 2023, indicating a spring-dominated regime after the extreme disturbance. During this phase, the earlier phenology of *P. australis* provided a competitive advantage.

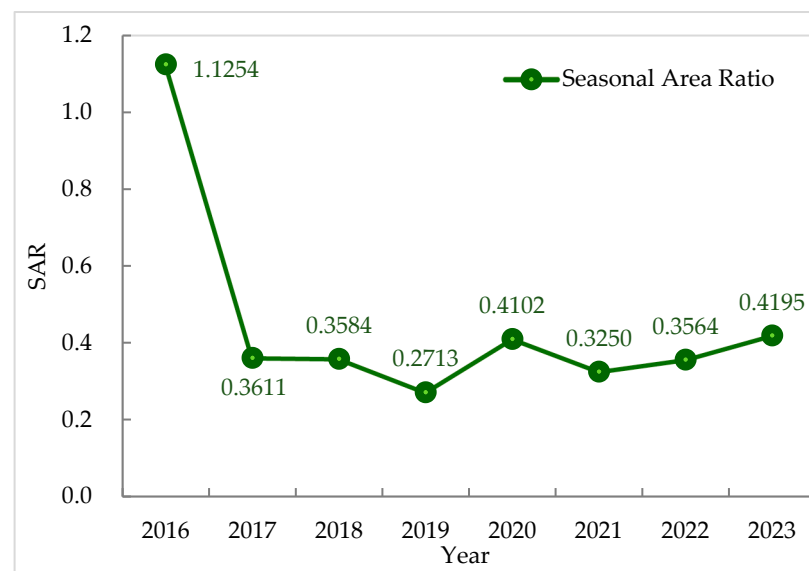


Figure 8. Interannual variability of the Seasonal Area Ratio (SAR) in the mixed ecotone (2016–2023).

During the seven-year spring-dominated phase, the SAR index showed sawtooth fluctuations with alternating low, medium, and high annual values, indicating ongoing dynamics in competitive intensity. Troughs with low SAR values (2019: 0.2713; 2021: 0.3250) represent periods of *P. australis* dominance in spring, resulting from its resource preemption capacity during early phenological stages or favorable hydro-meteorological conditions in those years. Medium SAR values (2017–2018, 2022: ≈ 0.36) indicate an equilibrium phase with a temporary competitive standoff between the two species. Elevated SAR values (2020: 0.4102; 2023: 0.4195) indicate that *S. alterniflora* temporarily regained competitiveness in some years, likely due to niche penetration and phenotypic plasticity, leading to a rebound in its autumn area.

This composite pattern—a regime shift coupled with internal fluctuations—illustrates the competitive dynamics between *P. australis* and *S. alterniflora* in terms of phenological asynchrony and niche differentiation. *P. australis* gains an initial advantage through its phenological lead in spring, while *S. alterniflora* maintains competitive resilience through physiological adaptation and clonal expansion, resulting in an annual seesaw dynamic. The SAR index captured a transition in the vegetation competition pattern and, through

its inter-annual variations, helped quantify and understand long-term dynamics between invasive and native plants in coastal wetlands under changing conditions. This underscores the role of phenological strategies in shaping interspecific competition.

3.6. Method Comparison

To quantitatively evaluate the performance of the proposed integrated method (denoted as Proposed Method: 3D-feature-space-guided seasonal NDVI + Adaptive Otsu), a comparative analysis was conducted using the autumn 2023 Sentinel-2 image as a benchmark. Five alternative approaches, representing common remote sensing classification paradigms, were implemented:

(1) NDVI coupled with Supervised Classification (MaxLik): the NDVI layer was classified using a Maximum Likelihood classifier trained on the same set of 2023 reference points. (2) NDVI combined with Multi-threshold Otsu (Fixed): the multi-threshold Otsu algorithm was applied directly to the NDVI layer, omitting the preceding 3D feature-space diagnostic and seasonal index selection steps. (3) NDVI combined with K-Means Clustering: the NDVI layer was subjected to unsupervised clustering into three classes using the K-Means algorithm. (4) NDVI combined with OBIA (Local Std. Dev.): Object-Based Image Analysis was performed using the multi-resolution segmentation algorithm in eCognition. Mean NDVI and its local standard deviation served as the primary object features for the subsequent classification. (5) NDVI combined with Low-pass Filtering and Otsu: a mean (low-pass) filter was first applied to the NDVI layer to reduce spatial noise, followed by multi-threshold Otsu segmentation.

The classification accuracy of each method was evaluated against an independent validation dataset from 2023. Key accuracy metrics are summarized in Table 6. The spatial distribution of the extracted mixed ecotone from each method is visually compared in Figure 9, focusing on two representative sub-areas with complex boundaries: a naturally fragmented tidal creek zone and an area featuring a sharp, linear anthropogenic structure.

Table 6. Quantitative accuracy assessment of different classification methods for the autumn 2023 dataset.

Method	Overall Accuracy (%)	Kappa Coefficient	Mixed Ecotone	
			Producer's Accuracy (%)	User's Accuracy (%)
Proposed Method	88.7	0.87	85.8	84.5
NDVI + MaxLik	83.2	0.79	78.1	76.4
NDVI + Otsu (Fixed)	85.1	0.81	80.5	79.2
NDVI + K-Means	80.5	0.76	74.3	72.9
NDVI + OBIA	84.6	0.80	81.2	77.8
NDVI + Filter + Otsu	82.9	0.78	76.7	75.1

Note: "Proposed Method" denotes the integrated 3D-feature-space-guided seasonal NDVI with adaptive Otsu segmentation.

The results indicate that the proposed method attained the highest overall accuracy (88.7%) and Kappa coefficient (0.87), and most notably, achieved the highest accuracy for the target mixed ecotone (Producer's accuracy: 85.8%, User's accuracy: 84.5%). Visual inspection of Figure 9 further reveals that: The Proposed Method (Figure 9a) generates ecotone boundaries that are spatially coherent, align well with natural gradients, and accurately resolve fine-scale details along tidal creeks, while also providing a clear delineation of the linear anthropogenic feature. Supervised Classification (MaxLik) (Figure 9b) exhibits pronounced "salt-and-pepper" noise and over-segmentation, particularly within the heterogeneous northwestern sector. Direct Otsu applied to the NDVI layer (Figure 9c), though relatively robust, yields a somewhat more fragmented and less spatially coherent ecotone,

particularly in areas characterized by subtle spectral gradients. The K-Means classification (Figure 9d) exhibits the lowest accuracy, with notably poor separation between vegetation classes and frequent misplacement of the ecotone boundary. The OBIA result (Figure 9e) produces overly smoothed boundaries, where the narrow ecotone is often merged into adjacent, larger patches of pure vegetation. This results in a loss of linear continuity and an underestimation of its spatial complexity. The Filtering + Otsu approach (Figure 9f) results in blurred ecotone edges, causing the boundary to either become indistinct or excessively expand into adjacent pure vegetation stands. This illustrates the loss of high-frequency spatial information that is critical for precise boundary delineation.

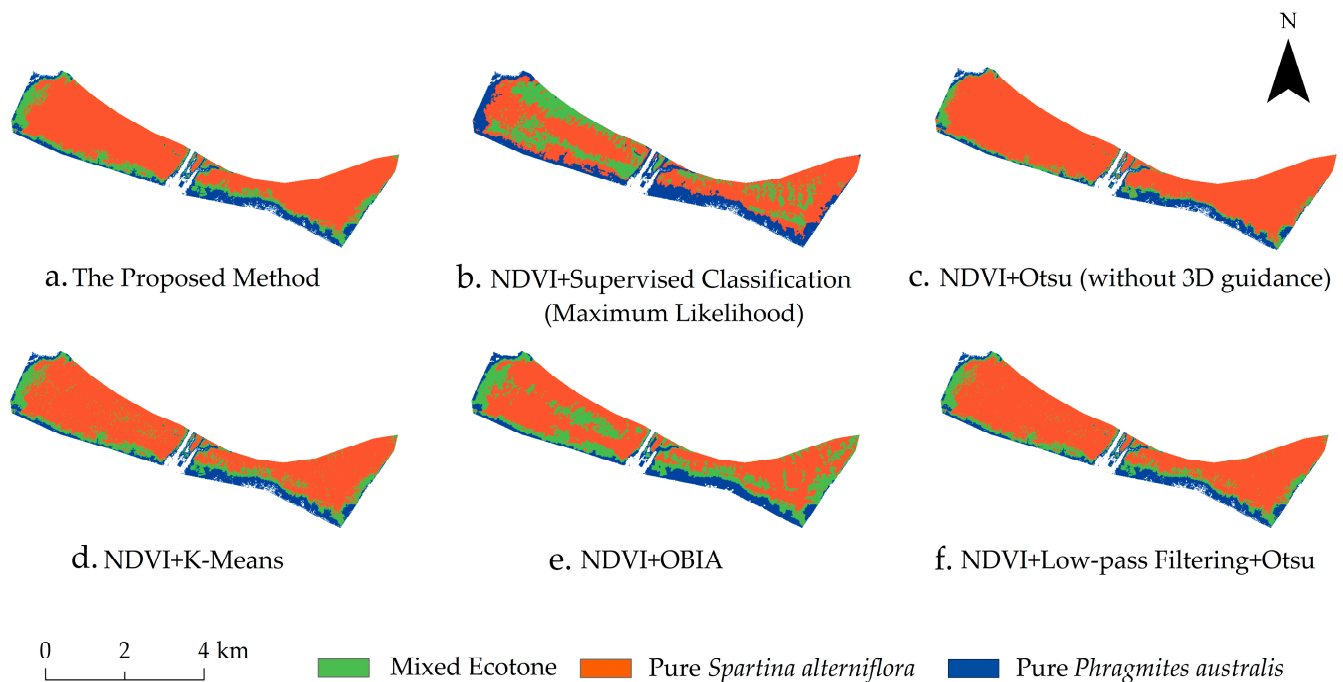


Figure 9. Visual comparison of the mixed ecotone extracted by six different classification methods for autumn 2023: (a) Proposed Method, (b) NDVI with MaxLik, (c) NDVI with Fixed Otsu, (d) NDVI with K-Means, (e) NDVI with OBIA, and (f) NDVI with Filtering and Otsu.

This empirical comparison indicates that the integrated framework—which combines spatial-spectral diagnostics for optimal feature selection with adaptive, scene-specific thresholding—provides improved performance for accurately delineating narrow, dynamic ecotones in complex intertidal environments.

4. Discussion

4.1. Methodological Innovations and Comparative Analysis

This study presents an integrated remote sensing framework that combines a 3D geographic feature space with multi-threshold Otsu segmentation. Its advancement over conventional 2D methods lies in the transition from a purely spectral feature space to a spatio-spectral one. Unlike approaches that treat spectral signatures independently of geographic context, the proposed method constructs three-dimensional scatter plots that incorporate pixel geographic coordinates (X, Y) and spectral features (Z). This design accounts for spatial autocorrelation and environmental gradients—such as elevation and distance from tidal creeks—which are important drivers of wetland vegetation distribution [13–15]. Consequently, the framework can distinguish pixels that are spectrally similar but ecologically distinct due to differing spatial positions, thereby addressing a source of error in intertidal zone classification. Building upon the seasonal spectral index method

of Yao et al. [10], which leveraged phenological differences, the present approach extends the methodology by incorporating a spatial constraint layer. While the former focused on temporal discrimination, the integrated “3D feature space and Otsu” framework handles spatial heterogeneity (through coordinate embedding) and temporal spectral variability (via seasonal index selection and Otsu’s adaptability). This design contributes to the high overall accuracy (87.3%) achieved in delineating narrow and dynamic mixed ecotones.

The insightful question of why geographic coordinates (X, Y) were not directly used as classification features—despite their utility in the diagnostic 3D feature space—deserves clarification. While integrating spatial coordinates as additional feature dimensions (e.g., in a combined [X, Y, Spectral Index] vector) is a feasible approach in contextual classification and has shown value in other studies [50,51], the design to use coordinates only for diagnostic visualization and optimal index selection was intentional, based on the specific objectives and challenges of this study. First, the central complexity in intertidal monitoring arises from spectral mixing caused by tidal inundation and micro-topography. The strategy addresses this by first using spatial coordinates to visually diagnose and identify the single spectral index (e.g., NIR in spring) that shows the least confounding spatial gradient and the greatest inter-class separability. This step effectively “purifies” the spectral signal before classification, allowing the algorithm to focus on the most discriminative one-dimensional feature rather than directly modeling spatial heterogeneity. Second, the multi-threshold Otsu algorithm operates efficiently and clearly on a univariate histogram; the resulting thresholds (T_1 , T_2) retain straightforward biophysical interpretability. Introducing coordinates would transform the segmentation into a multivariate thresholding problem, increasing computational complexity and obscuring the direct ecological meaning of the thresholds. Third, merging geographic coordinates—which span several kilometers—into normalized spectral indices (0–1) would require careful scaling or normalization. This nontrivial step could inadvertently weight one dimension over another, potentially distorting the classification of narrow transitional zones. Finally, for long-term time-series analysis, the per-image adaptive Otsu thresholding already accounts for inter-annual spectral variations. Including static geographic coordinates as features would likely contribute little additional explanatory power for year-to-year changes, while complicating the model. The consistently high accuracy achieved across the eight-year series (overall accuracy $87.3 \pm 1.4\%$) supports the conclusion that the “spatially informed spectral index selection + adaptive univariate thresholding” framework is both robust and fit-for-purpose in monitoring fine-scale, dynamic ecotones.

The use of a per-image adaptive Otsu thresholding strategy is an important methodological design for long-term time-series analysis. By allowing classification thresholds to be re-optimized for each seasonal image, the approach accommodates natural inter-annual variability in spectral signatures due to climatic fluctuations and phenological shifts. This reduces the risk of misclassification that could arise from applying a single, static threshold—derived from a reference year—to all subsequent years under differing conditions. The high classification accuracy achieved across the time series, together with the variation in the thresholds, supports the robustness of this adaptive strategy. Consequently, subsequent analyses of ecotone dynamics are based on a consistent classification series, in which changes in area and centroid position can be more reliably attributed to ecological processes rather than methodological inconsistency.

The quantitative and visual comparisons suggest empirical support for the advantages of the integrated approach over several common alternatives. The OBIA method achieved relatively lower performance (Overall Accuracy: 84.6%; Ecotone Producer’s Accuracy: 81.2%), and its characteristically smooth outputs (Figure 9e) indicate a key limitation for ecotone mapping. In heterogeneous environments such as tidal flats, the segmentation

step in OBIA can result in boundary objects that either absorb the narrow ecotone into larger, uniform patches or fragment it unnaturally, thereby compromising the accuracy of spatial delineation. Similarly, the low-pass filtering + Otsu approach (Overall Accuracy: 82.9%; Ecotone Producer's Accuracy: 76.7%) illustrates a known limitation: spatial filtering suppresses the high-frequency spectral variations that are critical for defining sharp ecological boundaries, often leading to systematic underestimation or overestimation (Figure 9f). This result suggests that conventional neighborhood smoothing, while potentially beneficial for noise reduction, can be counterproductive when the target feature is itself a high-spatial-frequency transition.

The higher accuracy of the proposed method compared to the simple NDVI + Otsu (Fixed) baseline—a gain of approximately 3.6% in overall accuracy and 5% in ecotone producer's accuracy—highlights the value added by the 3D feature-space diagnostic phase. This phase guides the selection of a phenologically appropriate spectral index and aims to ensure that the chosen index exhibits strong separability within the specific spatial context of the study area, a refinement step that pure spectral thresholding lacks. Furthermore, the higher accuracy of the proposed method relative to the supervised classifier (MaxLik) underscores the potential benefit of adaptive Otsu thresholding for long-term monitoring. While a supervised classifier can perform well on a single date, its fixed spectral signatures may not generalize optimally across years with varying environmental conditions. In contrast, the per-image adaptive thresholds are designed to inherently account for inter-annual spectral variability, which may help maintain consistent performance throughout a time series.

These empirical comparisons indicate that integrating spatial and spectral dimensions within the proposed framework can offer a distinct advantage. Unlike conventional pixel-wise classifiers that may overlook locational context [52], the diagnostic phase explicitly accounts for spatial autocorrelation and gradients. Compared with OBIA, which can be sensitive to segmentation parameters when delineating linear features [22], the pixel-based approach allows ecotones to be delineated directly from spectral data without prior—and potentially biasing—segmentation. Similarly, while neighborhood-based filtering can dilute fine-scale positional information [23], the proposed method retains and utilizes geographic coordinates to inform feature selection. Thus, this framework does not aim to displace established techniques but rather offers a straightforward, empirically validated strategy for embedding spatial context into a classification workflow—a strategy that appears well-suited to monitoring fine-scale, dynamic ecological boundaries.

4.2. Ecological Implications and Mechanistic Insights

The mixed ecotone showed a “seaward expansion” trend and a composite pattern of “overall regime shift with internal fluctuations.” These dynamics help elucidate mechanisms related to the ecological invasion process of *S. alterniflora*. The ecotone's seaward migration (annual spring rate: 13.93%, azimuth: 112°) can be attributed to physiological and ecological adaptations of the invasive species, such as well-developed aerenchyma, high photosynthetic efficiency, and clonal potential, which provide an advantage in waterlogged, high-salinity environments [53,54].

To examine temporal competition mechanisms underlying the observed spatiotemporal patterns, the Seasonal Area Ratio (SAR)—defined as the ratio of autumn to spring ecotone area—was used. This metric captures shifts in spatial occupancy between the two competing species during key phenological windows. In contrast to broad-spectrum phenological indicators (e.g., start-of-season derived from NDVI time series), which track the growth cycle of a single species or community, SAR quantifies the outcome of phenology-mediated competition for space. Its application showed a multi-tiered competitive structure:

a regime shift in 2017, followed by sawtooth fluctuations within a spring-dominated phase. This pattern (“1-year autumn/7-year spring dominance”) illustrates a “seasonal push–pull” mechanism: *P. australis* gains an early advantage through phenological precedence (sprouting 15–20 days earlier), while *S. alterniflora* maintains resilience and autumn competitiveness through extended growth and niche penetration [55–57]. This form of niche separation, rooted in phenological differentiation, is a mechanism for long-term species coexistence amid ongoing competition [58,59]. Thus, the value of SAR lies in its conceptual appropriateness and practical utility in translating complex interspecific competition into a quantifiable and ecologically interpretable temporal signal.

Beyond these natural drivers, this study also shows anthropogenic influences on vegetation patterning. The geometrically regular linear features in the central study area are consistent with engineering infrastructure, such as embankments and ditches, supporting previous findings on human-induced habitat fragmentation in coastal wetlands [60]. This indicates that human engineering activities, alongside natural factors, influence wetland vegetation patterns, highlighting the need for their integration into future ecological assessments and management strategies.

4.3. Management Implications and Recommendations

Based on the findings of this study, the following management recommendations are suggested:

1. Develop seasonal management strategies based on phenological asynchrony. This involves implementing control measures during *S. alterniflora*'s physiologically vulnerable periods (e.g., green-up and flowering/fruiting stages) [61], and conducting ecological restoration projects during the spring dominance phase of *P. australis*. Implementing these strategies can offer synergistic benefits, enhancing management efficacy with minimal ecological disruption.
2. Adopt spatially differentiated management strategies. This involves accounting for micro-topographic and salinity gradients [62] to implement tailored strategies for the patchy northwestern ecotone. In the central region, which is affected by human activities, ecological engineering assessments and adaptive restoration planning should be undertaken to mitigate the impacts of infrastructure on vegetation patterns.
3. Establish a dynamic monitoring and early-warning system. By integrating multi-source remote sensing data with ground observation networks [63], a model can be developed to capture spatial, phenological, and competitive dynamics, track the expansion of *S. alterniflora*, and issue early risk alerts, thereby providing decision support for coastal wetland conservation.

4.4. Limitations and Future Research

This study has several limitations. First, the global Otsu thresholding approach may lead to localized misclassification in regions of high spatial heterogeneity. Second, the limited temporal coverage of ground-validation data restricts a comprehensive evaluation of dynamic ecological processes. Third, the interpretation of vegetation competition mechanisms relies on remote sensing inversion [64]. To address these limitations, future work could focus on the following directions:

1. Adopting advanced analytical techniques—such as object-based image analysis or deep learning—to improve the detection of fine-scale boundaries and heterogeneous landscape features.
2. Developing an integrated multi-temporal validation system that combines long-term monitoring plots with UAV-acquired hyperspectral data to improve classification reliability and strengthen the interpretation of ecological processes.

3. Implementing spatially explicit models to quantify the combined impacts of anthropogenic drivers (e.g., engineering infrastructure) and natural factors on ecotone dynamics.
4. Further validation of the transferability and refinement of the analytical framework is needed. Although the workflow—integrating three-dimensional visualization, optimal spectral index selection, and Otsu thresholding—is conceptually generalizable, applying it to new sites requires recalibrating spectral thresholds based on local conditions. Future research should assess the framework’s performance across a range of coastal wetland systems and explore strategies for deriving spectral indices and threshold rules that are regionally adaptive or broadly applicable to support more extensive ecological monitoring.

5. Conclusions

Using spring and autumn Sentinel-2 satellite imagery from 2016 to 2023, this study developed an integrated framework that combines a three-dimensional feature space with multi-threshold Otsu segmentation for high-accuracy extraction and multiscale dynamic monitoring of the mixed *S. alterniflora*–*P. australis* ecotone in Chongming Dongtan. The main findings are as follows:

- A seasonally adaptive spectral index framework, incorporating a three-dimensional feature space, was developed to extract the mixed ecotone. The identification of optimal spectral features—near-infrared reflectance for spring and NDVI for autumn—followed by the use of the multi-threshold Otsu algorithm, enabled accurate vegetation community classification. The validation results showed high accuracy, with an overall accuracy of $87.3 \pm 1.4\%$ and a Kappa coefficient of 0.84 ± 0.02 . The mixed ecotone was delineated with producers’ and users’ accuracies of 85.2% and 83.6%, respectively, which enhances the identification of narrow transition zones.
- This study documented a land-to-sea ecological sequence—pure *P. australis*–mixed ecotone–pure *S. alterniflora*—in the Chongming Dongtan wetland, with the vegetation arranged in an east–west belt. The northwestern sector showed a patchy distribution influenced by tidal creeks and micro-topography, related to salinity gradients and hydrological differentiation caused by elevation heterogeneity. Meanwhile, regular linear features in the central area were associated with engineering infrastructure, indicating spatial heterogeneity shaped by both natural and anthropogenic drivers.
- The mixed ecotone showed seaward expansion from 2016 to 2023. During spring, it showed an average annual growth rate of 13.93%, with the centroid migrating seaward at an azimuth of 112° . The migration rate decreased in later years, with periodic reversals, suggesting possible regulation by hydrological resistance or interspecific competition. Influenced by extreme climate events, the ecotone area showed fluctuations in autumn—most notably a 62.83% decline from 2016 to 2017. The centroid migration path was also complex, following a three-phase sequence of “retreat-leap-expansion.” The spatiotemporal dynamics were influenced by long-term drivers, such as sediment deposition and climate warming, and by short-term factors, including typhoons, salt stress, and hydrological disturbances.
- Analysis of the SAR index showed a tipping point in 2017, when the seasonal competition pattern shifted from one year of autumn dominance to a seven-year phase of spring dominance. During the spring-dominated phase, the SAR values showed a sawtooth-like fluctuation (0.27–0.42) with cyclical low-medium-high shifts, indicating a dynamic equilibrium in which *P. australis* gains dominance through phenological advancement. Meanwhile, *S. alterniflora* maintains competitive resilience through niche penetration. The SAR index served as a metric to quantify phenological competition

dynamics, revealing a mechanism of coexistence through seasonal niche differentiation between the invasive and native species.

The integrated “spatial–spectral–temporal” monitoring framework developed in this study provides a technical foundation for managing invasive species and supporting ecological restoration in coastal wetlands. This study contributes to advancing UN Sustainable Development Goal (SDG) 15.1 on wetland conservation and informs China’s national strategy for “integrated protection of mountains, waters, forests, farmlands, lakes, grasslands, and deserts.”

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Data Availability Statement: The data supporting the findings of this study are available from the following sources. The primary remote sensing data comprise Sentinel-2A/2B imagery obtained from the Copernicus Data Space Ecosystem (<https://dataspace.copernicus.eu/>). For ground validation, 127 field points were collected along the mixed ecotone boundaries in April and November 2023 using GPS RTK and UAV aerial photography (Figure 1). These points were interpreted from high-resolution UAV orthophotos to establish a comprehensive validation dataset encompassing all three vegetation types. All datasets generated and analyzed in this study will be made publicly available via a persistent repository upon publication.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SAR	Seasonal Area Ratio
JM	Jeffries-Matusita
3D	Three-Dimensional
2D	Two-dimensional
<i>S. alterniflora</i>	<i>Spartina alterniflora</i>
<i>P. australis</i>	<i>Phragmites australis</i>
<i>B. mariqueter</i>	<i>Bolboschoenoplectus mariqueter</i>
NIR	Near-Infrared Reflectance
NDVI	Normalized Difference Vegetation Index
GIS	Geographic Information System
NLSD	National Land Survey Data
CLCD	China Land Cover Dataset
OBIA	Object-Based Image Analysis
GF-1	Gaofen-1satellite
UAV	Unmanned Aerial Vehicle
MSI	Multispectral Instrument
GPS	Global Positioning System
RTK	Real-Time Kinematic

MaxLik	Maximum Likelihood
Local Std. Dev.	Local Standard Deviation
UN	United Nations
SDG	Sustainable Development Goal

References

1. Zhu, W.Q.; Ren, G.B.; Wang, J.P.; Wang, J.B.; Hu, Y.B.; Lin, Z.Y.; Li, W.; Zhao, Y.J.; Li, S.B.; Wang, N. Monitoring the Invasive Plant *Spartina alterniflora* in Jiangsu Coastal Wetland Using MRCNN and Long-Time Series Landsat Data. *Remote Sens.* **2022**, *14*, 2630.
2. Zhang, G.L.; Bai, J.H.; Tebbe, C.C.; Huang, L.B.; Jia, J.; Wang, W.; Wang, X.; Yu, L.; Zhao, Q.Q. *Spartina alterniflora* invasions reduce soil fungal diversity and simplify co-occurrence networks in a salt marsh ecosystem. *Sci. Total Environ.* **2021**, *758*, 143667. [\[CrossRef\]](#)
3. Huang, Y.Y.; Huang, Y.Y.; Du, X.L.; Li, Y.M.; Tian, J.T.; Chen, Q.; Huang, Y.H.; Lv, W.W.; Yang, Y.; Liu, Z.Q.; et al. Assessment of macrobenthic community function and ecological quality after reclamation in the Changjiang (Yangtze) River Estuary wetland. *Acta Oceanol. Sin.* **2022**, *41*, 96–107. [\[CrossRef\]](#)
4. Syed, S.; Xu, M.; Wang, Z.F.; Yu, C.F.; Lian, B. Invasive *Spartina alterniflora* in controlled cultivation: Environmental implications of converging future technologies. *Ecol. Indic.* **2021**, *130*, 108027. [\[CrossRef\]](#)
5. Chen, W.J.; Shi, C. Fine-scale mapping of *Spartina alterniflora*-invaded mangrove forests with multi-temporal WorldView-Sentinel-2 data fusion. *Remote Sens. Environ.* **2023**, *295*, 113690. [\[CrossRef\]](#)
6. Chang, D.; Wang, Z.Y.; Ning, X.G.; Li, Z.J.; Zhang, L.; Liu, X.T. Vegetation changes in Yellow River Delta wetlands from 2018 to 2020 using PIE-Engine and short time series Sentinel-2 images. *Front. Mar. Sci.* **2022**, *9*, 977050. [\[CrossRef\]](#)
7. Döweler, F.; Fransson, J.E.S.; Bader, M.K.F. Linking High-Resolution UAV-Based Remote Sensing Data to Long-Term Vegetation Sampling—A Novel Workflow to Study Slow Ecotone Dynamics. *Remote Sens.* **2024**, *16*, 840.
8. Zhou, H.; Tang, M.D.; Huang, J.; Mei, X.X.; Zhao, H.J. Driving mechanisms and multi-scenario simulation of land use change based on National Land Survey Data: A case in Jiangnan Plain, China. *Front. Environ. Sci.* **2024**, *12*, 1422987. [\[CrossRef\]](#)
9. Shi, Z.Y.; Pu, W.P.; Dong, J.H. Spatiotemporal Changes of Land Use and Their Impacts on Ecosystem Service Value in the Agro-pastoral Ecotone of Northern China. *Environ. Sci.* **2025**, *46*, 2373–2384.
10. Yao, H.Y.; Liu, P.D.; Shi, R.H.; Zhang, C. Extracting the transitional zone of *Spartina alterniflora* and *Phragmites australis* in the wetland using high-resolution remotely sensed images. *J. Geo Inf. Sci.* **2017**, *19*, 1375–1381.
11. Dong, D.; Huang, H.M.; Gao, Q.; Zhang, S.P.; Li, K.; Wei, Z.; Sun, Y.C. Combining satellite and UAV remote sensing to monitor a mangrove-saltmarsh ecotone: A case study from Dandou Sea in Guangxi. *J. Appl. Oceanogr.* **2025**, *44*, 167–176.
12. Li, C.W.; Fang, S.B.; Geng, X.L.; Yuan, Y.; Zheng, X.W.; Zhang, D.; Li, R.X.; Sun, W.; Wang, X.R. Coastal ecosystem service in response to past and future land use and land cover change dynamics in the Yangtze river estuary. *J. Clean. Prod.* **2023**, *385*, 135601. [\[CrossRef\]](#)
13. Alam, S.M.R.; Hossain, M.S. Using a water index approach to mapping periodically inundated saltmarsh land-cover vegetation and eco-zonation using multi-temporal Landsat 8 imagery. *J. Coast. Conserv.* **2024**, *28*, 19. [\[CrossRef\]](#)
14. Wittstruck, L.; Jarmer, T.; Waske, B. Multi-Stage Feature Fusion of Multispectral and SAR Satellite Images for Seasonal Crop-Type Mapping at Regional Scale Using an Adapted 3D U-Net Model. *Remote Sens.* **2024**, *16*, 3115. [\[CrossRef\]](#)
15. Zhou, N.; Zhou, M.T.; Sui, H.G. DepthCD: Depth prompting in 2D remote sensing imagery change detection. *ISPRS J. Photogramm. Remote Sens.* **2025**, *227*, 145–169. [\[CrossRef\]](#)
16. Liu, P.D.; Shi, R.H.; Meng, F.; Liu, J.T.; Yao, G.B.; Fu, P.J. Combining Multi-Indices by Neural Network Model for Estimating Canopy Chlorophyll Content: A Case Study of Interspecies Competition between *Spartina alterniflora* and *Phragmites australis*. *Pol. J. Environ. Stud.* **2022**, *31*, 199–217.
17. Najjar Khodabakhsh, Z.; Moradi, H.; Rahimzadeh-Bajgiran, P.; Pourmanafi, S.; Ahmadi, M. A 30-year phenological study of mangrove forests at the species level as a function of climatic drivers using multispectral remote sensing satellites. *Ecol. Indic.* **2025**, *178*, 114038. [\[CrossRef\]](#)
18. Klehr, D.; Stoffels, J.; Hill, A.; Pham, V.D.; van der Linden, S.; Frantz, D. Mapping tree species fractions in temperate mixed forests using Sentinel-2 time series and synthetically mixed training data. *Remote Sens. Environ.* **2025**, *323*, 114740. [\[CrossRef\]](#)
19. Lomeo, D.; Simis, S.G.H.; Selmes, N.; Jungblut, A.D.; Tebbs, E.J. Colour-informed ecoregion analysis highlights a satellite capability gap for spatially and temporally consistent freshwater cyanobacteria monitoring. *ISPRS J. Photogramm. Remote Sens.* **2025**, *228*, 323–339. [\[CrossRef\]](#)
20. Kumbier, K.; Hughes, M.G.; Rogers, K.; Woodroffe, C.D. Inundation characteristics of mangrove and saltmarsh in micro-tidal estuaries. *Estuar. Coast. Shelf Sci.* **2021**, *261*, 107553. [\[CrossRef\]](#)

21. Deijns, A.A.J.; Michéa, D.; Déprez, A.; Malet, J.P.; Kervyn, F.; Thiery, W.; Dewitte, O. A semi-supervised multi-temporal landslide and flash flood event detection methodology for unexplored regions using massive satellite image time series. *ISPRS J. Photogramm. Remote Sens.* **2024**, *215*, 400–418. [\[CrossRef\]](#)
22. Siljander, M.; Männistö, S.; Kuoppamäki, K.; Taka, M.; Ruth, O. Urban green space classification using Object-Based Image Analysis (OBIA) and LiDAR fusion: Accuracy evaluation and landscape metrics assessment. *Urban For. Urban Green.* **2025**, *112*, 128997. [\[CrossRef\]](#)
23. Sharma, R.; Kumar Panigrahi, R. Texture Classification-Based NLM PolSAR Filter. *IEEE Geosci. Remote Sens. Lett.* **2021**, *18*, 1396–1400. [\[CrossRef\]](#)
24. Saeedzadeh, A.; Setoodeh, P.; Alavi, M.; Habibi, S. Information Extraction Using Spectral Analysis of the Chattering of the Smooth Variable Structure Filter. *IEEE Access* **2023**, *11*, 104992–105008. [\[CrossRef\]](#)
25. Lin, Y.X.; Hu, H.W.; Yang, P.; Ye, G.P. *Spartina alterniflora* invasion has a greater impact than non-native species, *Phragmites australis* and *Kandelia obovata*, on the bacterial community assemblages in an estuarine wetland. *Sci. Total Environ.* **2022**, *822*, 153517. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Wu, W.T.; Yang, Z.Q.; Chen, C.P.; Tian, B. Tracking the environmental impacts of ecological engineering on coastal wetlands with numerical modeling and remote sensing. *J. Environ. Manag.* **2022**, *302*, 113957. [\[CrossRef\]](#)
27. Liu, S.; Hu, Z.; Grandjean, T.J.; Bing Wang, Z.; van Zelst, V.T.M.; Qi, L.; Xu, T.P.; Young Seo, J.; Bouma, T.J. Dynamics and drivers of tidal flat morphology in China. *Nat. Commun.* **2025**, *16*, 2153. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Cao, Y.; Dong, B.; Xu, H.F.; Xu, Z.L.; Wei, Z.Z.; Lu, Z.P.; Liu, X. Landscape ecological risk assessment of chongming dongtan wetland in shanghai from 1990 to 2020. *Environ. Res. Commun.* **2023**, *5*, 105016. [\[CrossRef\]](#)
29. Chen, X.H.; Yang, Q.Q.; Chen, Z.Z.; Lei, J.R.; Wu, T.T.; Li, Y.L.; Pan, X.Y. The interaction between temperature and rainfall determines the probability of tropical forest fire occurrence in Hainan Island. *Front. Vet. Sci.* **2025**, *8*, 1495699. [\[CrossRef\]](#)
30. Zhang, Q.; Li, B. Field practice of *Scirpus mariqueter* restoration in the bird habitats of Chongming Dongtan Wetland, China. *Chin. J. Appl. Ecol.* **2023**, *34*, 2663–2671.
31. Suwanprasisit, C.; Shah Nawaz. Mapping burned areas in Thailand using Sentinel-2 imagery and OBIA techniques. *Sci. Rep.* **2024**, *14*, 9609. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Zhang, J.Y.; Ning, Y.L.; Li, J.X.; Shi, Z.L.; Zhang, Q.Z.; Li, L.Q.; Kang, B.Y.; Du, Z.B.; Luo, J.C.; He, M.X.; et al. Invasion stage and competition intensity co-drive reproductive strategies of native and invasive saltmarsh plants: Evidence from field data. *Sci. Total Environ.* **2024**, *954*, 176383. [\[CrossRef\]](#)
33. Sun, C.; Li, J.L.; Liu, Y.X.; Liu, Y.C.; Liu, R.Q. Plant species classification in salt marshes using phenological parameters derived from Sentinel-2 pixel-differential time-series. *Remote Sens. Environ.* **2021**, *256*, 112320. [\[CrossRef\]](#)
34. Zhao, Q.; Qu, Y.H. The Retrieval of Ground NDVI (Normalized Difference Vegetation Index) Data Consistent with Remote-Sensing Observations. *Remote Sens.* **2024**, *16*, 1212. [\[CrossRef\]](#)
35. Zhang, Q.J.; Guo, Z.H.; Liu, L.; Mei, J.C.; Wang, L. Lithological classification using SDGSAT-1 TIS data and three-dimensional spectral feature space model. *Int. J. Digit. Earth* **2025**, *18*, 2467983. [\[CrossRef\]](#)
36. Li, J.; Wu, Z.C.; Hu, Z.W.; Jian, C.L.; Luo, S.J.; Mou, L.C.; Zhu, X.X.; Molinier, M. A Lightweight Deep Learning-Based Cloud Detection Method for Sentinel-2A Imagery Fusing Multiscale Spectral and Spatial Features. *IEEE Trans. Geosci. Remote Sens.* **2021**, *60*, 1–19. [\[CrossRef\]](#)
37. Turker, M.; Rahimzadeganasl, A. Agricultural Field Detection from Satellite Imagery Using the Combined Otsu's Thresholding Algorithm and Marker-Controlled Watershed-Based Transform. *J. Indian Soc. Remote Sens.* **2021**, *49*, 1035–1050. [\[CrossRef\]](#)
38. Kahaer, Y.; Shi, Q.D.; Shi, H.B.; Peng, L.; Abudureyimu, A.; Wan, Y.B.; Li, H.; Zhang, W.Q.; Yang, N.J. What Is the Effect of Quantitative Inversion of Photosynthetic Pigment Content in *Populus euphratica* Oliv. Individual Tree Canopy Based on Multispectral UAV Images? *Forests* **2022**, *13*, 542. [\[CrossRef\]](#)
39. Yang, X.Z.; Hong, L. A New Classification Rule-Set for Mapping Surface Water in Complex Topographical Regions Using Sentinel-2 Imagery. *Water* **2024**, *16*, 943. [\[CrossRef\]](#)
40. Zhao, J.Q.; Wang, Z.X.; Zhang, Q.J.; Niu, Y.F.; Lu, Z.; Zhao, Z. A novel feature selection criterion for wetland mapping using GF-3 and Sentinel-2 Data. *Ecol. Indic.* **2025**, *171*, 113146. [\[CrossRef\]](#)
41. Zhang, X.M.; Lin, X.F.; Fu, D.J.; Wang, Y.; Sun, S.B.; Wang, F.; Wang, C.P.; Xiao, Z.Y.; Shi, Y.Q. Comparison of the Applicability of J-M Distance Feature Selection Methods for Coastal Wetland Classification. *Water* **2023**, *15*, 2212. [\[CrossRef\]](#)
42. Seo, D.M.; Woo, H.J.; Hong, W.H.; Seo, H.; Na, W.J. Optimization of Number of GCPs and Placement Strategy for UAV-Based Orthophoto Production. *Appl. Sci.* **2024**, *14*, 3163. [\[CrossRef\]](#)
43. Xu, Q.; Jin, M.T.; Guo, P. A High-Precision Crop Classification Method Based on Time-Series UAV Images. *Agriculture* **2023**, *13*, 97. [\[CrossRef\]](#)
44. Motiee, H.; Ahrari, S.; Motiee, S.; McBean, E. Assessment of Climate Change with Remote Sensing Data on Snow and Ice Cover in the Rocky Mountains Glaciers. *J. Environ. Inf.* **2025**, *46*, 544. [\[CrossRef\]](#)

45. Wong, C.H.; Li, Z.Y.; Yim, S.H.L.; Chang, T.Y.; Man, C.L.; Cheng, C.H.; Kwok, T.C.Y.; Ho, K.F. The comparison between multiple linear regression and random forest model in predicting environmental noise and its frequency components level in Hong Kong using a land-use regression approach. *Env. Res.* **2025**, *286*, 122919. [[CrossRef](#)]
46. Han, Z.M.; Huang, Q.; Huang, S.Z.; Leng, G.Y.; Bai, Q.J.; Liang, H.; Wang, L.; Zhao, J.; Fang, W. Spatial-temporal dynamics of agricultural drought in the Loess Plateau under a changing environment: Characteristics and potential influencing factors. *Agric. Water Manag.* **2021**, *244*, 106540. [[CrossRef](#)]
47. Qiu, T.Z.; Cong, N.; Rong, L.; Qi, G.; Du, L.; Ren, P.; Xiao, J.T. Spatiotemporal dynamics and driving mechanisms of alpine peatland wetlands in the eastern Qinghai–Tibet Plateau based on a Vision Transformer model. *Ecol. Indic.* **2025**, *178*, 114136. [[CrossRef](#)]
48. Yan, S.Y.; Yang, G.H.; Li, Q.Y.; Zhang, B.; Wang, Y.; Zhang, Y.; Wang, C.H. Distance–Intensity Image Strategy for Pulsed LiDAR Based on the Double-Scale Intensity-Weighted Centroid Algorithm. *Remote Sens.* **2021**, *13*, 432. [[CrossRef](#)]
49. Haight, J.D.; Hall, S.J.; Lewis, J.S. Landscape modification and species traits shape seasonal wildlife community dynamics within an arid metropolitan region. *Landsc. Urban Plan.* **2025**, *259*, 105346. [[CrossRef](#)]
50. Wang, W.; Sun, Y.J.; Li, J.; Wang, X. Frequency and spatial based multi-layer context network (FSCNet) for remote sensing scene classification. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *128*, 103781. [[CrossRef](#)]
51. Chen, G.J.; Chen, H.Z.; Cui, T.; Li, H.H. SFMRNet: Specific Feature Fusion and Multibranch Feature Refinement Network for Land Use Classification. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2024**, *17*, 16206–16221. [[CrossRef](#)]
52. Florath, J.; Keller, S.; Abarca-del-Rio, R.; Hinz, S.; Staub, G.; Weinmann, M. Glacier Monitoring Based on Multi-Spectral and Multi-Temporal Satellite Data: A Case Study for Classification with Respect to Different Snow and Ice Types. *Remote Sens.* **2022**, *14*, 845. [[CrossRef](#)]
53. Wang, J.B.; Lin, Z.Y.; Ma, Y.Q.; Ren, G.B.; Xu, Z.J.; Song, X.K.; Ma, Y.; Wang, A.D.; Zhao, Y.J. Distribution and invasion of *Spartina alterniflora* within the Jiaozhou Bay monitored by remote sensing image. *Acta Oceanol. Sin.* **2022**, *41*, 31–40. [[CrossRef](#)]
54. Yu, H.L.; Zhao, X.Y.; Huang, W.D.; Zhan, J.; He, Y.Z. Drought Stress Influences the Growth and Physiological Characteristics of *Solanum rostratum* Dunal Seedlings From Different Geographical Populations in China. *Front. Plant Sci.* **2021**, *12*, 733268. [[CrossRef](#)]
55. Yin, S.; Liang, G.P.; Wang, C.K.; Zhou, Z.H. Asynchronous seasonal patterns of soil microorganisms and plants across biomes: A global synthesis. *Soil Biol. Biochem.* **2022**, *175*, 108859. [[CrossRef](#)]
56. Lisner, A.; Segrestin, J.; Konečná, M.; Blažek, P.; Janíková, E.; Applová, M.; Švancárová, T.; Lepš, J. Why are plant communities stable? Disentangling the role of dominance, asynchrony and averaging effect following realistic species loss scenario. *J. Ecol.* **2024**, *112*, 1832–1841. [[CrossRef](#)]
57. Feng, J.; Grandjean, T.J.; Wu, X.R.; van de Koppel, J.; van der Wal, D. Long-term phenological shifts in coastal saltmarsh vegetation reveal complex responses to climate change. *Ecol. Indic.* **2025**, *179*, 114219. [[CrossRef](#)]
58. Ai, J.Q.; Chen, L.J.; He, H.Q.; Han, X.X. Revealing the long-term impacts of plant invasion and reclamation on native saltmarsh vegetation in the Yangtze River estuary using multi-source time series remote sensing data. *Ecol. Eng.* **2024**, *208*, 107362. [[CrossRef](#)]
59. Bobrowski, M.; Bechtel, B.; Böhner, J.; Oldeland, J.; Weidinger, J.; Schickhoff, U. Application of Thermal and Phenological Land Surface Parameters for Improving Ecological Niche Models of *Betula utilis* in the Himalayan Region. *Remote Sens.* **2018**, *10*, 814. [[CrossRef](#)]
60. Wei, F.; Han, M.; Han, G.X.; Wang, M.; Tian, L.X.; Zhu, J.Q.; Kong, X.L. Reclamation-oriented spatiotemporal evolution of coastal wetland along Bohai Rim, China. *Acta Oceanol. Sin.* **2022**, *41*, 192–204. [[CrossRef](#)]
61. Zhang, C.; Zhang, Q.; Zhang, H.; Zheng, Y.L.; Yuan, L.; Zhong, Q.C. Climate warming increases the invasiveness of the exotic *Spartina alterniflora* in a coastal salt marsh: Implications for invasion management. *J. Environ. Manag.* **2025**, *380*, 124765. [[CrossRef](#)] [[PubMed](#)]
62. Wang, D.W.; Bai, J.H.; Wang, W.; Ma, X.; Guan, Y.N.; Gu, C.H.; Zhang, S.Y.; Lu, F. Micro-Topography Manipulations Facilitate Suaeda Salsa Marsh Restoration along the Lateral Gradient of a Tidal Creek. *Wetlands* **2020**, *40*, 1657–1666. [[CrossRef](#)]
63. Ma, X.S.; Wang, Z.L.; Liu, Y. Ecological risk assessment of a coastal area using multi-source remote sensing images and in-situ sample data. *Ecol. Indic.* **2024**, *158*, 111470. [[CrossRef](#)]
64. Han, Y.L.; Dong, Y.Y.; Zhu, Y.N.; Huang, W.J. Remote Sensing Inversion of Vegetation Parameters With IPROSAIL-Net. *IEEE Trans. Geosci. Remote Sens.* **2023**, *62*, 1–16. [[CrossRef](#)]

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