

Article

Integrating Phenological Features to Enhance Coastal Salt Marsh Monitoring and Infer Vegetation Succession Mechanisms: A Case Study of Yancheng National Nature Reserve

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Abstract

Rapid changes in coastal salt marsh vegetation highlight the need for accurate monitoring to support sustainable management. This study aims to track annual salt marsh landscape dynamics and discuss vegetation succession mechanisms. A novel approach was proposed to improve the discrimination of different plant species by integrating phenological features derived from NDVI time series, thereby enhancing salt marsh classification. The results showed that the proposed method achieves an overall accuracy of 93.6%, significantly outperforming schemes based solely on spectral indices (81.6%) or combined spectral and textural features (85.5%) ($p < 0.05$). The overall accuracy of annual classification maps for the Yancheng National Nature Reserve wetland from 1994 to 2025 averaged 90.5%, with a minor fluctuation of 2.8%, demonstrating the accuracy and reliability of this method for long-term monitoring of salt marsh landscapes. Annual classification maps revealed that the encroachment of *Spartina alterniflora* and *Phragmites australis* has intensified the fragmentation of *Suaeda salsa*. Notably, eradication efforts targeting *Spartina alterniflora* appear to have contributed to controlling this invasive species (decreasing by 33.22 km²) and restoring native species (increasing by 2.56 km²). This method serves as a reference for advancing salt marsh landscape classification frameworks.

Keywords: coastal salt marsh; classification; phenological features; vegetation succession; Google Earth Engine



Academic Editor: Ana Picado

Received: 9 June 2026

Revised: 25 July 2026

Accepted: 27 July 2026

Published: 31 July 2026

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1. Introduction

Coastal salt marshes, dominated by salt-tolerant vegetation, provide multiple important ecosystem services, including carbon sequestration, wastewater purification, storm surge buffering, and habitat provision for diverse benthic organisms and birds [1]. Vegetation patterns in salt marshes vary along environmental gradients [2], but are vulnerable to impacts from climate change and anthropogenic stressors [3]. Sea-level rise leads to persistent soil waterlogging and increased soil salinity in low marshes, causing vegetation dieback or landward expansion [4]. In the Liao River Delta, approximately 45% of salt marshes have been lost due to conversion into aquaculture ponds, oil fields, or paddy rice fields [5]. Over the past 40 years, China's coastal salt marshes have experienced a 59% loss, with native plant coverage decreasing by 70%, while the invasive *Spartina alterniflora* (*S. alterniflora*) expanded 680-fold [6,7]. These rapid changes in vegetation extent and spatial

distribution highlight the urgent need for accurate monitoring of salt marsh landscapes to support sustainable management.

Traditional field surveys for monitoring salt marsh landscape changes are impractical due to their high cost and time consumption. Remote sensing offers a cost-effective, timely, and repeatable large-scale observation [8]. Advances in remote sensing data and classification methods have further enhanced salt marsh mapping. Widely used data sources include aerial imagery, multispectral optical imagery, synthetic aperture radar (SAR), light detection and ranging (LiDAR), hyperspectral data, unmanned aerial vehicle (UAV) data, and multi-source fusion [9]. Multispectral optical imagery with low cloud cover enables classification based on land cover reflectance differences [10], while SAR and LiDAR penetrate clouds and dense vegetation to capture topographic and structural information [11]. The fusion of LiDAR and SAR with optical data improves classification accuracy beyond that of any single data type [12]. Recently, Sentinel-1/2, LiDAR, and UAV data have become preferred for monitoring small, inaccessible salt marshes due to their fine spatial resolution [12]. Classification algorithms have evolved from empirical threshold segmentation to machine learning techniques such as support vector machines, decision trees, maximum likelihood classification, and random forests. Deep learning approaches, convolutional neural networks and semantic segmentation models, have further advanced salt marsh plant species classification [13].

Despite extensive advances in remote sensing data sources and classification algorithms, research on classification features remains limited. Salt marsh landscape mapping is challenging due to high spatial heterogeneity [14]. Spectral similarity among land cover types makes achieving satisfactory classification difficult, even with extensive manual correction [10,15]. Previous studies have combined spectral indices with features like DEM and texture for classification. For instance, Yeo et al. [16] used a 2 m resolution LiDAR-derived DEM but found decreased accuracy because LiDAR penetration is limited in dense salt marsh vegetation, restricting detection of subtle elevation changes in flat coastal areas [17]. Textural features help distinguish aquaculture ponds with regular boundaries from irregular natural water bodies [18], but their role in differentiating plant species is limited [19]. Recent studies show significant phenology differences, such as the timing of green-up, maturity, and dormancy, between native salt marsh species and the invasive species *S. alterniflora*, enabling potential species discrimination based on phenology [20]. Tukey HSD results confirm significant separability of phenological parameters in coastal salt marsh vegetation [21]. However, phenological features have rarely been incorporated to improve species-level classification and overall accuracy, partly due to inefficiencies in traditional remote sensing data acquisition and processing, especially for long-term time series [22–24]. The Google Earth Engine (GEE) platform, offering extensive datasets, a user-friendly interface, fast computation, and low cost, has been widely applied in land cover classification, hydrology, climate analysis, and image processing [25]. Several studies have used GEE for dynamic monitoring of coastal wetlands, including mangroves, salt marshes, and seagrass beds [26–28].

This study integrates different feature combinations involving spectral indices, textural features, and phenological features into a random forest classifier and evaluates the classification performance of these methods. Annual classification mapping of the Yancheng National Nature Reserve (YNNRC) wetland from 1994 to 2025 was achieved with the optimal feature combination based on the GEE platform. This study addresses the two questions: (1) What is the performance of different classification methods? (2) What are the potential mechanisms of salt marsh vegetation succession in the YNNRC wetland?

2. Materials and Methods

2.1. Study Area

The YNNRC wetland ($120^{\circ}29'16''$ – $120^{\circ}41'38''$ E, $33^{\circ}28'48''$ – $33^{\circ}38'24''$ N) is located on the central coast of Jiangsu, east of the seawall situated between the southern bank of the Xinyang Port River and the northern bank of the Doulong Port River (Figure 1). Sediment deposition from both the ancient Yellow River and the modern Yangtze River drives the coastline's seaward expansion at a rate of $13.34 \text{ km}^2 \text{ a}^{-1}$ [29]. The study area is characterized as a typical muddy tidal flat that exhibits a standard semi-diurnal tide with an average tidal range of 2.5–4.0 m. It receives approximately $502.42 \text{ kJ cm}^{-2}$ of annual solar radiation, with a mean temperature of 18.7°C , and annual precipitation ranging from 900 to 1060 mm [30]. Since the 1990s, the region has seen a gradual decline in annual precipitation and a warming trend in temperature, though no extreme precipitation or temperature events have been recorded. The study area is divided by the Zhonglu Port boundary into two distinct zones: the northern section, heavily influenced by human activity and dominated by artificial structures such as aquaculture ponds, presents a monotonous landscape; in contrast, the southern section remains a natural wetland with minimal human disturbance, preserving the original wetland environment. The YNNRC wetland is dominated by *S. alterniflora*, *Phragmites australis* (*P. australis*), and *Suaeda salsa* (*S. salsa*), which form a belt-like distribution from the sea towards the land [31].

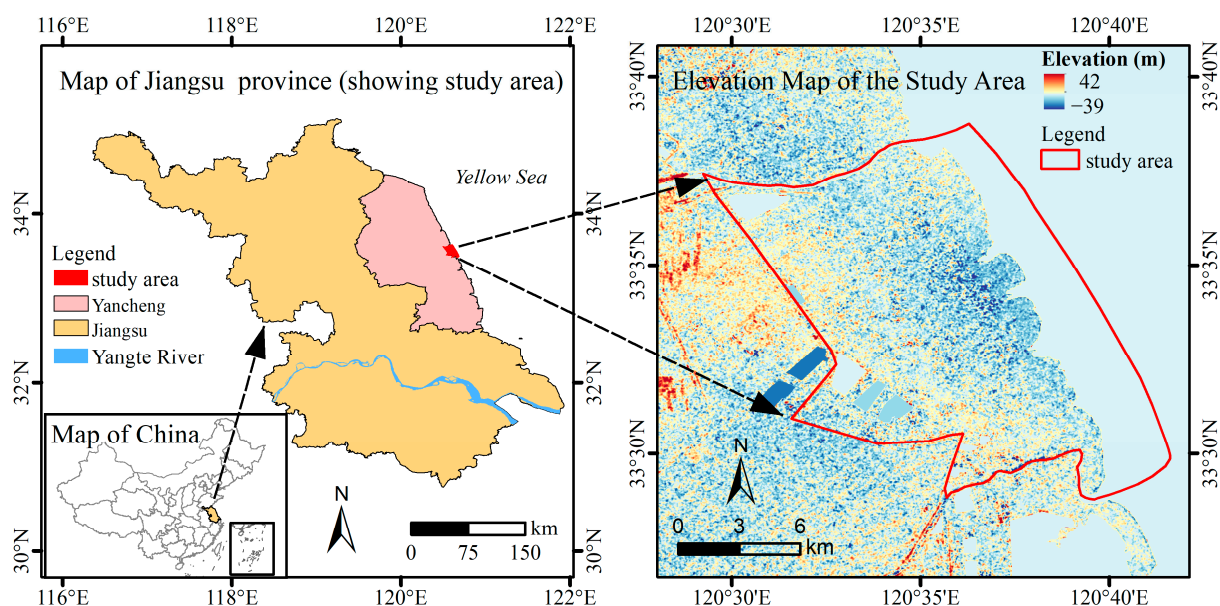


Figure 1. Location of the study area (the datum is WGS_1984, the coordinate system is GCS_WGS_1984, and the DEM data is derived from SRTM with 30 m resolution).

2.2. Data Sources

Landsat surface reflectance images from 1 January 1994, to 1 September 2025 were used to generate classification features. All images, with a spatial resolution of 30 m, were obtained from the “Level 2, Collection 2, Tier 1” product available on the GEE platform. Radiometric calibration and geometric correction were applied to the images. After filtering based on temporal and spatial constraints, a total of 822 images were obtained, including 246 images from 1995 to 2012 for Landsat 5, 363 images from 2000 to 2025 for Landsat 7, and 213 images from 2013 to 2025 for Landsat 8. In addition, high-resolution images from Sentinel-2, GF-1, ZY-1F, and ZY-3 were obtained to support validation sample collection (Table S1).

2.3. Methods

The proposed methods for mapping and monitoring salt marsh landscapes include five main steps (Figure 2): (1) data preprocessing, (2) feature extraction, (3) comparison experiments, (4) sample selection, and (5) classification and assessment.

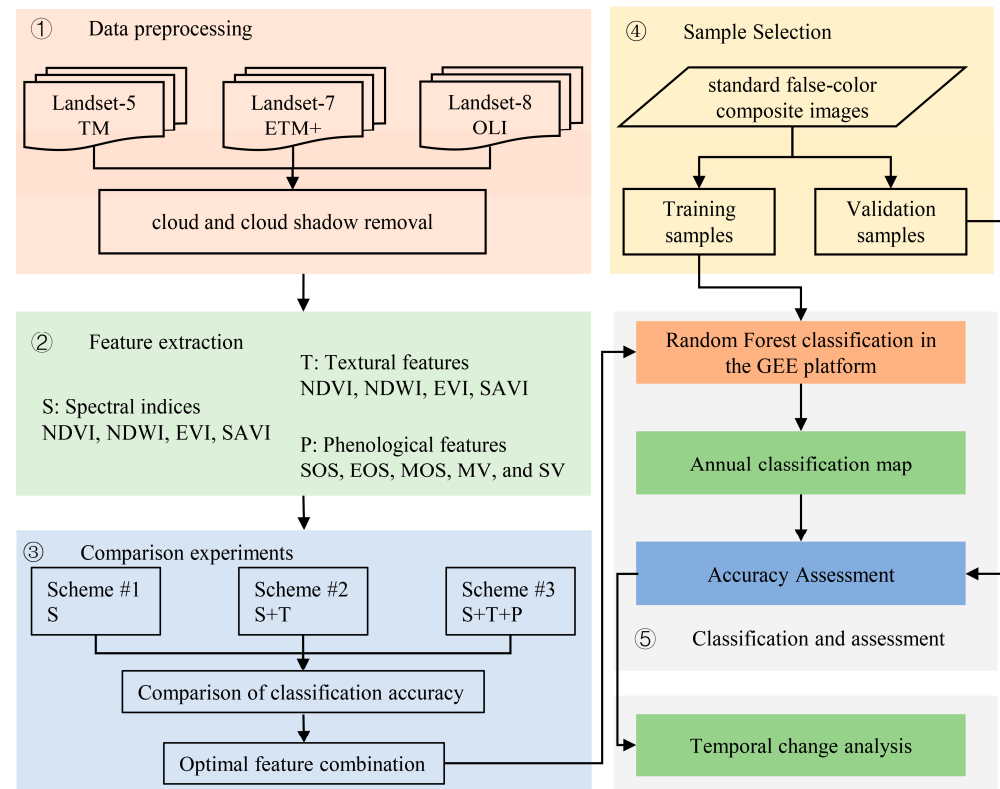


Figure 2. Methodological workflow implemented in Google Earth Engine (GEE).

2.3.1. Data Preprocessing

Landsat 5/7/8 images include a quality assessment (QA) band that contains cloud and cloud shadow information. Cloud and cloud shadow contamination were identified using the CFMask algorithm and recorded in the QA band. Clear-sky pixels were selected based on the QA information. Landsat 7 ETM+ images acquired after 31 May 2003, were used in this study following cloud removal. To satisfy the observation quantity requirements for NDVI reconstruction, Landsat images acquired between 1994 and 2025 with less than 50% cloud and cloud shadow coverage were retained. To ensure spectral consistency across all years, Landsat-8 OLI surface reflectance was converted to Landsat-7 ETM+ (or Landsat-5 TM) equivalent values. This conversion was performed using linear transformations derived from the cross-calibration of overlapping images acquired within one day of each other during both winter and summer seasons (Table S2) [32].

2.3.2. Feature Extraction

1 Spectral indices

Four spectral indices derived from Landsat surface reflectance image bands were utilized for coastal wetland landscape classification. These included three vegetation-related indices, namely the normalized difference vegetation index (NDVI), the enhanced vegetation index (EVI), and the soil-adjusted vegetation index (SAVI), as well as one water-related index, the normalized difference water index (NDWI). NDVI serves as an indicator of vegetation presence and abundance and exhibits high sensitivity to changes in vegetation conditions. Based on NDVI, EVI incorporates a blue band to account for

atmospheric absorption and includes an anti-saturation term for high biomass areas [33]. SAVI introduces a soil adjustment factor L related to vegetation coverage [34]. Adjustment of L facilitates mitigation of soil background interference; however, empirical selection of L values can introduce errors. Therefore, an optimized SAVI (OSAVI) was adopted instead of SAVI. Sensitivity analysis confirmed that setting L to 0.16 maximizes the robustness of OSAVI to soil background effects [35]. NDWI is sensitive to changes in water content. The formulas for calculating each index are as follows:

$$\text{NDVI} = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}}} \quad (1)$$

$$\text{NDWI} = \frac{\rho_{\text{green}} - \rho_{\text{nir}}}{\rho_{\text{green}} + \rho_{\text{nir}}} \quad (2)$$

$$\text{EVI} = 2.5 \times \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + 6 \times \rho_{\text{red}} - 7.5 \times \rho_{\text{blue}+1}} \quad (3)$$

$$\text{SAVI} = \frac{(\rho_{\text{nir}} - \rho_{\text{red}}) \times (1 + L)}{\rho_{\text{nir}} + \rho_{\text{red}} + L} \quad (4)$$

$$\text{OSAVI} = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}} + L} \quad (5)$$

2. Textural features

Eighteen texture feature bands were generated using the Gray-Level Co-occurrence Matrix (GLCM) algorithm on the GEE platform, employing an 8-bit grayscale image, a 3×3 window size, and an average direction [19]. The grayscale image was derived from a weighted linear combination of the Near-Infrared (NIR), *red*, and *green* bands of a Landsat median composite image and was then linearly normalized to an 8-bit (0 to 255) integer range [36]:

$$\text{Gray} = (0.3 \times \text{NIR}) + (0.59 \times \text{red}) + (0.11 \times \text{green}) \quad (6)$$

The abundant texture feature bands may contain redundant texture metrics and reduce computational speed, which in turn impacts classification performance [37]. Based on experience with feature contribution analysis, the optimal features for vegetation were contrast, sum average (savg), and variance (var) [38]. Two other texture variables, peak prominence (prom) and shade prominence (shade), with spatial differences, were also considered (Figure 3).

3. Phenological features

The distribution of NDVI observations was fitted using phenological curves, from which phenological features were extracted. The accuracy of phenological information depends on the quality of the reconstructed NDVI time series. In coastal regions, frequent cloudy weather and tidal fluctuations often result in unavailable or poor-quality remote sensing observation data [39]. Furthermore, Landsat-7 images have suffered from striping interference since 2003, further reducing data availability (Figure S1). Insufficient observations, especially during the growing season, may lead to false phenological curves and reduce vegetation classification accuracy (Figure S2) [21]. Thus, this study adopted the method proposed by Sun et al. [21], which simulates intra-annual time series by fusing neighboring half-yearly observation data to avoid biases in NDVI fitting. Specifically, this method uses observation data not only from the corresponding year but also from the second half of the previous year and the first half of the following year. This method avoids obscuring rapid ecological transitions through two mechanisms: (1) for unchanged pixels, increased observation density reduces the uncertainty caused by the lack of available data;

(2) for changed pixels, three-quarters of the observations (those from the current year and the first half of the following year) reflect the post-change state.

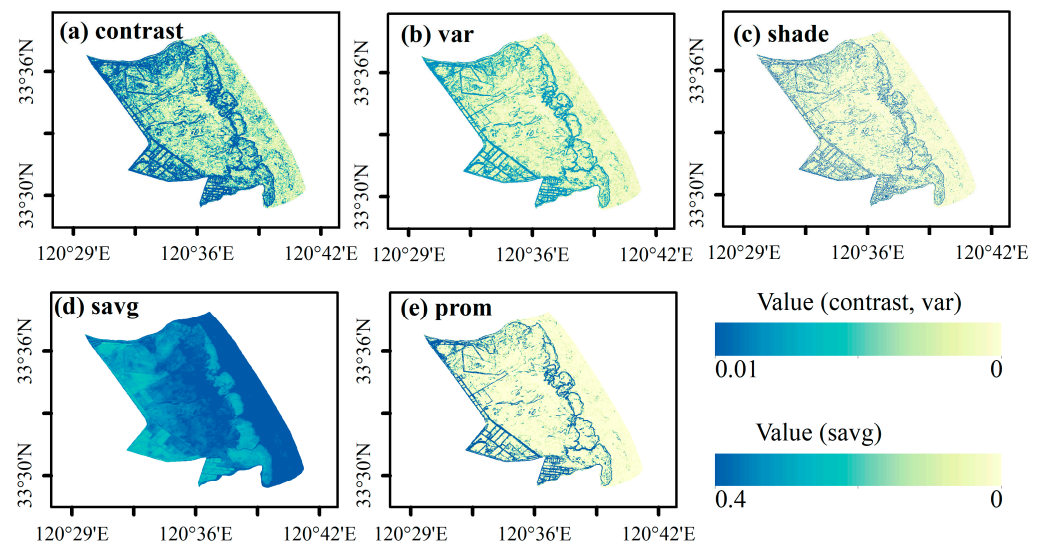


Figure 3. Textural features based on GLCM method in this study: (a) contrast, (b) var, (c) shade, (d) savg, and (e) prom.

Harmonic functions were employed to derive optimal phenological curves through iterative fitting procedures. The parameter settings for harmonic functions proposed by Zhou et al. [40] were adopted: the number of harmonic coefficients was set to 1 to ensure periodic unimodal variation, which prevents overfitting to extreme weather noise; a minimum of three valid observations per pixel per year was required to ensure model stability; the iteration process was terminated when the maximum deviation between the original observations and the reconstructed results fell below 0.05; and since NDVI values contaminated by clouds or tides were lower, outliers below the fitted model were rejected by default. NDVI often saturates in dense canopies, which may lead to overlapping phenological curves among vegetation types. Nevertheless, different plant species typically exhibit unique seasonal dynamics. To enhance species separability, we extracted six phenological parameters from the reconstructed NDVI time series using the dynamic threshold method [41]. These included four time-related parameters: start of season (SOS), end of season (EOS), length of season (LOS), and maximum of season (MOS), as well as two value-related parameters: maximum value (MV) and start value (SV) (Figure 4a). SOS and EOS are defined as the days of the year when the curve reaches 50% of the difference between the maximum and minimum values during the ascending and descending phases, respectively; LOS represents the time interval between SOS and EOS; MOS is the date when the curve reaches its maximum value.

Spatial distribution maps of phenological parameters were generated through per-pixel fitting, revealing heterogeneous spatial patterns. For the time-related parameters (SOS, MOS, EOS), areas dominated by *S. alterniflora* exhibited later occurrences, while *S. salsa* regions showed relatively earlier life cycles (Figure 4(b1–b3)). For the value-related parameters (SV, MV), *P. australis* and *S. alterniflora* areas displayed higher values compared to *S. salsa* (Figure 4(b4,b5)). Due to low NDVI in sparse *S. salsa* communities, the end of season (EOS) precedes the start of season (SOS), causing LOS values [42]. Therefore, LOS was excluded from the parameter set.

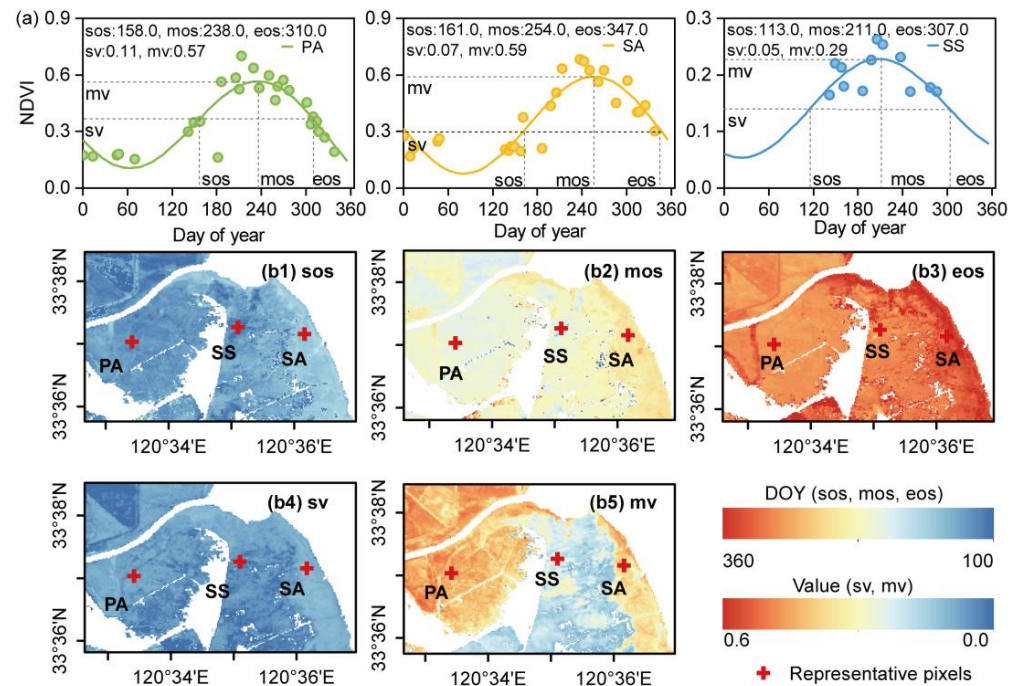


Figure 4. Phenological curves and extracted phenological parameters based on NDVI time series fitting (Yancheng coastal wetlands as a case study). **(a)** Phenological curves for *P. australis* (PA), *S. alterniflora* (SA), and *S. salsa* (SS) and five phenological parameters: maximum value (mv), minimum value (sv), start of the growing season (sos), end of the growing season (eos), and mid-growing season (mos); **(b1–b5)** Spatial distribution of the five phenological parameters.

The clear separability of phenological parameters indicates significant phenological differences among plant species (Table 1). Tukey HSD test results for time-related parameters showed that *S. alterniflora* exhibited a lagged phenological cycle compared with *S. salsa*, with SOS and MOS delayed by 12.25 days ($p = 0.0005$) and 24.59 days ($p = 0.0000$), respectively, and EOS showing significant variations across all pairs ($p < 0.05$). Significant variations were also found in the value-related parameters. For instance, all species showed significant differences in SV ($p < 0.05$), whereas for MV, significant differences were observed between *S. salsa* and *S. alterniflora* ($p = 0.0000$).

Table 1. Results of pairwise comparison of phenological parameters (SOS, EOS, MOS, MV, SV) among the saltmarsh plant species (SA—*S. alterniflora*, SS—*S. salsa*, and PA—*P. australis*) based on the Tukey HSD test.

Parameters	Species1	Species2	Estimated	Lower	Upper	<i>p</i> Value
SOS	SA	PA	21.192	−2.205	44.588	0.3148
	SS	PA	33.44	9.369	57.511	0.9637
	SS	SA	12.248	0.603	23.894	0.0005
MOS	SA	PA	−5.368	−16.297	5.56	0.1224
	SS	PA	19.223	7.98	30.467	0.1599
	SS	SA	24.592	19.152	30.031	0.0000
EOS	SA	PA	−14.076	−21.402	−6.75	0.0020
	SS	PA	8.536	0.999	16.073	0.0015
	SS	SA	22.611	18.965	26.258	0.0000
SV	SA	PA	0.109	0.034	0.184	0.0083
	SS	PA	0.206	0.13	0.283	0.0000
	SS	SA	0.098	0.06	0.135	0.0003
MV	SA	PA	−0.013	−0.036	0.009	0.3017
	SS	PA	0.023	0	0.046	0.0930
	SS	SA	0.036	0.025	0.048	0.0000

2.3.3. Comparison Experiments

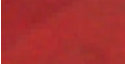
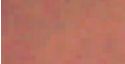
Based on previous findings, the salt marsh was classified into seven distinct land cover types: water, aquaculture ponds, mudflats, *P. australis*, *S. salsa*, and *S. alterniflora* [43,44]. To assess the influence of different classification features on results, three experimental schemes with varying combinations of feature variables were designed. Scheme #1 used spectral indices as a baseline method [45], Scheme #2 added texture features, and Scheme #3 further incorporated phenological features. All schemes employed the Random Forest algorithm for training and prediction, and their classification performances were systematically evaluated.

2.3.4. Sample Selection

Given the significant inter-annual variability of salt marshes, identifying reliable sample points across multiple years is challenging [46]. Fortunately, a priori knowledge of salt marsh landscapes, including color and shape differences derived from standard false-color composite images, is helpful for sampling efforts. Mudflats display a distinctive taupe color, while aquaculture ponds are easily identifiable due to their distinctive rectangular shape. Previous studies have shown that the growth patterns of *P. australis*, *S. salsa*, and *S. alterniflora* do not overlap [46]. Composite images from three periods in 2001 illustrate distinct color changes among these species: (1) from April to June, *P. australis* appears bright red, *S. salsa* appears dark red, and *S. alterniflora* appears reddish brown; (2) from June to October, the color of *S. alterniflora* deepens to a more intense red, surpassing the red intensity of *P. australis* and *S. salsa*; and (3) from October to December, the color of *P. australis* and *S. salsa* lighten, while *S. alterniflora* remains bright red.

Training and validation samples were collected through visual interpretation of the composite images (Table 2). Sampling years were determined based on differences between adjacent images. A total of 2508 training samples were gathered for 1994, 2001, 2006, 2012, and 2018, with 1075 validation samples generated for these years. In addition, samples from three independent years (1998, 2008, and 2025) were introduced for validation. For years before 2008, validation samples were derived from the same imagery as the training data. To prevent optimistic accuracy estimates due to spatial autocorrelation, a spatial buffering strategy (buffer size > 100 m) was implemented to ensure strict spatial separation between training and validation sets. For later years, validation samples were obtained via visual interpretation of high-resolution imagery. The final validation samples for 1994, 1998, 2001, 2006, 2008, 2012, 2018, and 2025 numbered 133, 117, 207, 197, 230, 257, 281, and 266, respectively.

Table 2. Remote sensing interpretation marker for plant species in YNNRC wetland.

Plant Species	From Apr. to Jun.	From Jun. to Oct.	From Oct. to Dec.
<i>S. alterniflora</i>			
<i>P. australis</i>			
<i>S. salsa</i>			

2.3.5. Classification and Assessment

The Random Forest algorithm is an ensemble classifier based on classification and regression trees, using randomly selected subsets of training samples and variables to generate multiple decision trees. Two key parameters are required in the algorithm: the number

of final decision trees and the number of variables per split during tree construction. The final classification decision is determined by averaging the class assignment probabilities calculated across all trees. This classifier performs well when handling high-dimensional data and multicollinearity issues and has been widely employed in wetland remote sensing studies in recent years.

The random forest algorithm was used for salt marsh landscape classification. The number of decision trees was set to 100, and the number of variables per split was set to the square root of the total number of input variables. Spectral indices, texture features, and phenological features served as classification inputs. Training samples from 1994, 2001, 2006, 2012, and 2018 were merged to train the Random Forest model, which was then used to predict annual classification maps from 1994 to 2025. The 1688 validation samples from 1994, 1998, 2001, 2006, 2008, 2012, 2018, and 2025 were employed to assess the classification accuracy through confusion matrices, kappa coefficients, and overall accuracy metrics.

2.4. Statistical Analysis

McNemar's test was used to determine whether the performance differences between the proposed method and alternative schemes are statistically significant [47]. To avoid differences in accuracy due to sampling variability, an identical set of validation samples was applied across all schemes. Based on two error matrices, the test calculates the chi-square (X^2) statistic with L-1 degrees of freedom. The null hypothesis, which assumes no difference in accuracy among the algorithms, is rejected when $p < 0.05$ ($X^2 > 3.8414$).

Piecewise linear regression was conducted on the temporal change curves of different landscape types using the pwlf package in Python 3.11.4 [48]. The model automatically identified optimal breakpoint positions by minimizing the sum of squared residuals. For each segment, the slope (β), coefficient of determination (R^2), and p -value were computed to assess the goodness-of-fit and statistical significance.

3. Results

3.1. Performance Comparison Across Experimental Schemes

The random forest algorithm was employed as a uniform classifier in all experimental schemes, using different combinations of classification features as inputs. The resulting land cover classifications are shown in Figure 5b–d. Overall, all scenarios successfully identified the major land cover types. However, notable differences appeared in classification details (Figure 6). Scheme #1, which relied solely on spectral indices, exhibited considerable classification errors, with mudflats at site S1 misclassified as aquaculture ponds, and open water areas at sites S2 and S3 confused with aquaculture ponds. Scheme #2, which incorporated additional textural features, improved the delineation of salt marsh boundaries and effectively corrected these misclassifications. Scheme #3 substantially reduced confusion among the three dominant vegetation species, namely *P. australis*, *S. salsa*, and the invasive *S. alterniflora*.

Table 3 summarizes the classification accuracy for the three experimental schemes. Accuracy metrics, including overall accuracy (OA), the Kappa coefficient, producer's accuracy (PA), and user's accuracy (UA), were derived from confusion matrices based on independent validation samples. Scheme #1 achieved an OA of 81.6% and a Kappa coefficient of 0.775. Scheme #2 improved these results with an OA of 85.5% and a Kappa coefficient of 0.823. Scheme #3 demonstrated the highest accuracy, with an OA of 93.6% and a Kappa coefficient of 0.922, significantly outperforming Scheme #1 ($X^2 = 16.7$, $p < 0.05$) and Scheme #2 ($X^2 = 9.4$, $p < 0.05$). Notably, the classification accuracy of *S. salsa* in Scheme #1 was very low, with PA and UA values of 61.9% and 54.2%, respectively. In Scheme #2, PA increased by 4.8% and UA by 5.9%, while Scheme #3 further improved PA and UA by 28.6%

and 40.8%, respectively. These comparative results indicate that Scheme #3 offers superior classification performance and accuracy, and it was therefore selected for the annual land cover classification of the YNNRC wetland.

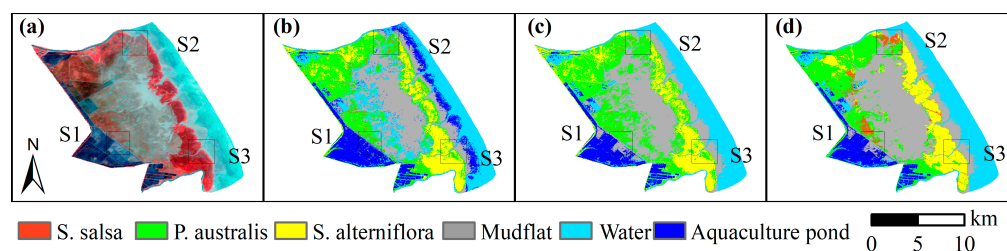


Figure 5. Comparison of classification results for the YNNRC wetland in 2001: (a) standard false-color composite image; (b) classification based on spectral indices; (c) classification derived from the combination of spectral and textural features; (d) classification integrating spectral, textural, and phenological features.

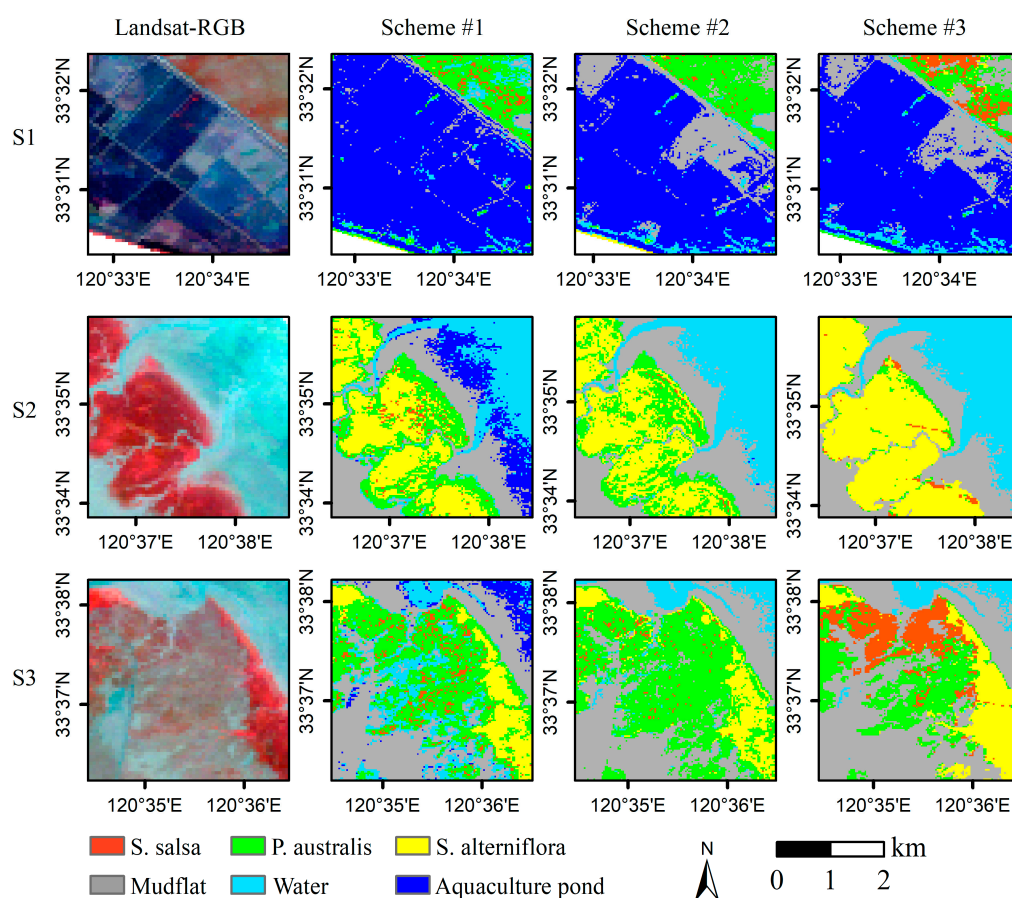


Figure 6. Enlarged classification results corresponding to the sites (S1–S3).

Table 3. Comparative analysis of classification accuracy across different comparison experiment schemes.

Class	Scheme #1		Scheme #2		Scheme #3	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
<i>S. salsa</i>	54.2	61.9	60.1	66.7	95.0	90.5
<i>P. australis</i>	73.3	68.8	80.0	75.0	91.2	96.9
<i>S. alterniflora</i>	82.1	79.3	83.3	86.2	96.6	96.6
Mudflat	85.3	83.0	93.9	89.0	97.0	91.0

Table 3. Cont.

Class	Scheme #1		Scheme #2		Scheme #3	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Water	83.3	88.2	82.5	94.3	86.5	91.4
Aquaculture Pond	94.5	92.9	98.1	92.9	96.2	94.4
OA (%)	81.6		85.5		93.6	
Kappa	0.775		0.823		0.922	

3.2. Assessment of Annual Classification Accuracy

Based on the confusion matrix analysis, the OA of classification maps for years with training samples averaged 92.02%, including 93.9% (1994), 93.6% (2001), 91.8% (2006), 90.3% (2012), and 90.5% (2018) (Figure 7a; Table S3). For the years without training samples, the average OA of the classification maps is 87.56%, comprising 88.0% (1998), 85.6% (2008), and 89.1% (2025). The small difference of 4.46% between these two groups indicates that training samples from the selected five years adequately represent the spatiotemporal changes in salt marsh landscapes over the study period. Although independent validation was not conducted for every year, the eight-year validation supports the robustness of Scheme #3 for annual classification. Furthermore, the overall accuracy across all validated years averaged 90.35%, with a minor fluctuation of 2.8%, demonstrating satisfactory performance for the classification mapping (Figure 7a).

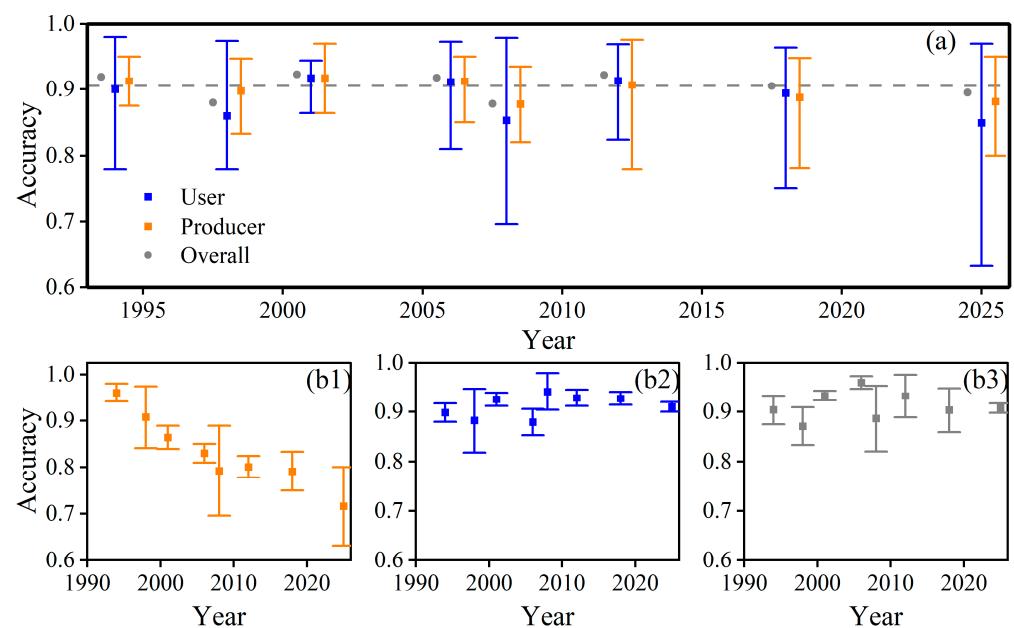


Figure 7. Accuracy assessment of the classification mapping. (a) Overall accuracy and the distribution of users' and producers' accuracies for the classification maps for 1994, 1998, 2001, 2006, 2008, 2012, 2018, and 2025. (b1–b3) Distribution of users' and producers' accuracies for *S. alterniflora* (SA), *P. australis* (PA), and *S. salsa* (SS). The dashed line represents the multi-year average of overall accuracy.

UA (63.2%) and PA (80.0%) for *S. salsa* in 2025 were low (Figure 7(b1), Table S3), largely due to the confusion between *S. salsa* and *P. australis*. Accuracy fluctuations over time were smaller for *S. alterniflora* and *P. australis* but more pronounced for *S. salsa* (Figure 7(b1–b3)). This is likely attributable to the gradual decline in the spatial extent of *S. salsa* within the YNNRC wetland, which resulted in a limited number of validation samples and thus increased sensitivity of accuracy estimates to classification errors.

3.3. Spatiotemporal Characteristics of Changes in the YNNRC Wetland

The spatial–temporal distribution patterns of the YNNRC wetland from 1994 to 2025 were obtained using the GEE platform (Figure 8).

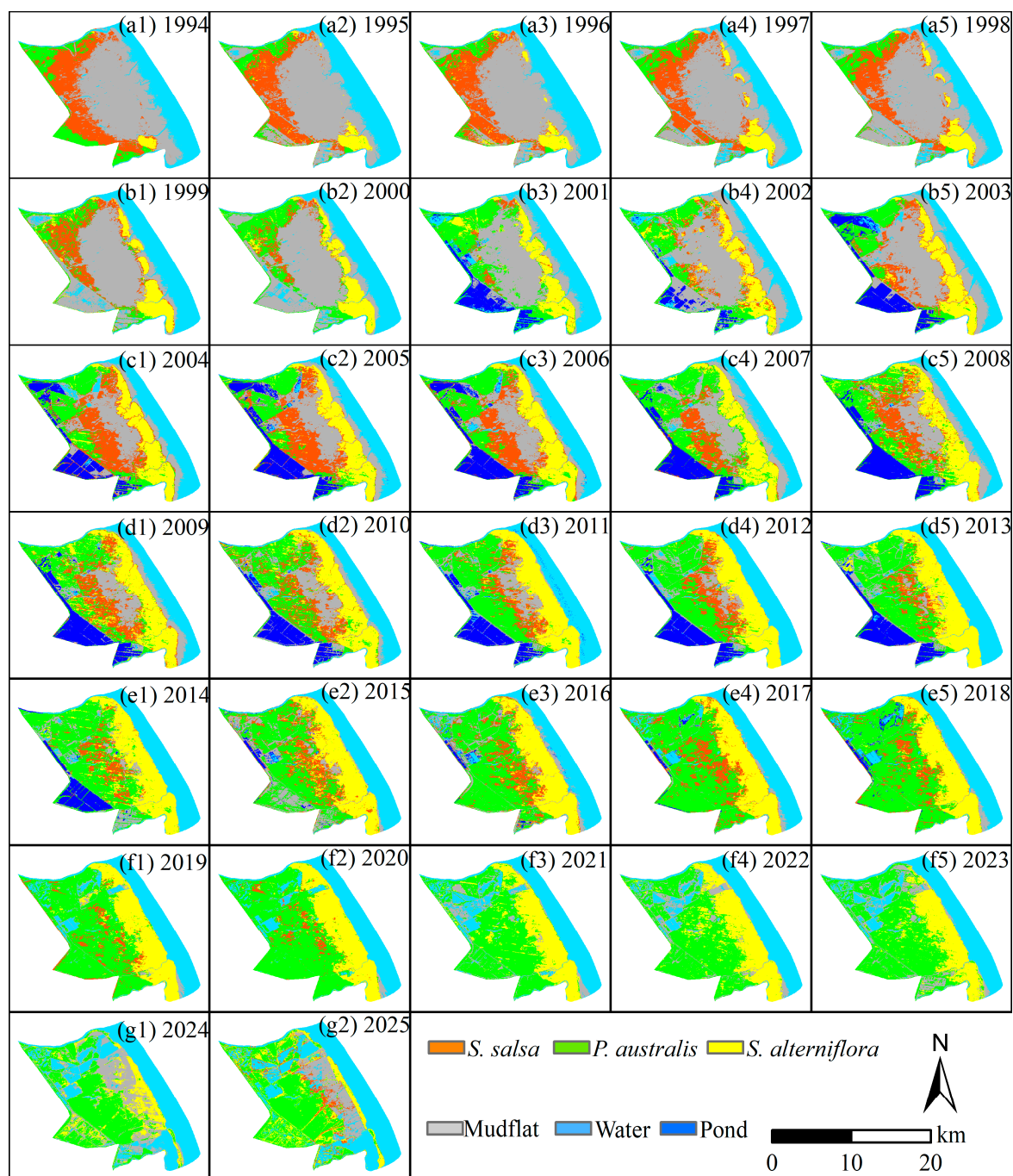


Figure 8. Spatial–temporal distribution of the YNNRC wetland from 1994 to 2025: (a1–a5) year 1994–1998; (b1–b5) 1999–2003; (c1–c5) 2004–2008; (d1–d5) 2009–2013; (e1–e5) 2014–2018; (f1–f5) 2019–2023; (g1,g2) 2024–2025.

Given the significant changes in *P. australis* area, two breakpoints were detected in its time series using the Python package pwlf, dividing the temporal dynamics of salt marsh vegetation over the past 30 years into three distinct stages (Figure 9a). During the first stage (1994–2010, *S. alterniflora* expansion stage), the area of *S. alterniflora* increased 19-fold, with an average growth rate of $2.95 \text{ km}^2 \text{ a}^{-1}$. In the second stage (2010–2020, *P. australis*

expansion stage), the area of *S. alterniflora* stabilized, while *P. australis* expanded by 54.14%. A statistically significant but weak negative correlation was observed between the annual areas of *S. salsa* and *P. australis* during the first two stages ($R^2 = 0.371$, $p < 0.01$). The third stage (2020–2025, ecological recovery stage) was characterized by rapid declines in both *P. australis* (−16%) and *S. alterniflora* (−21%) areas.

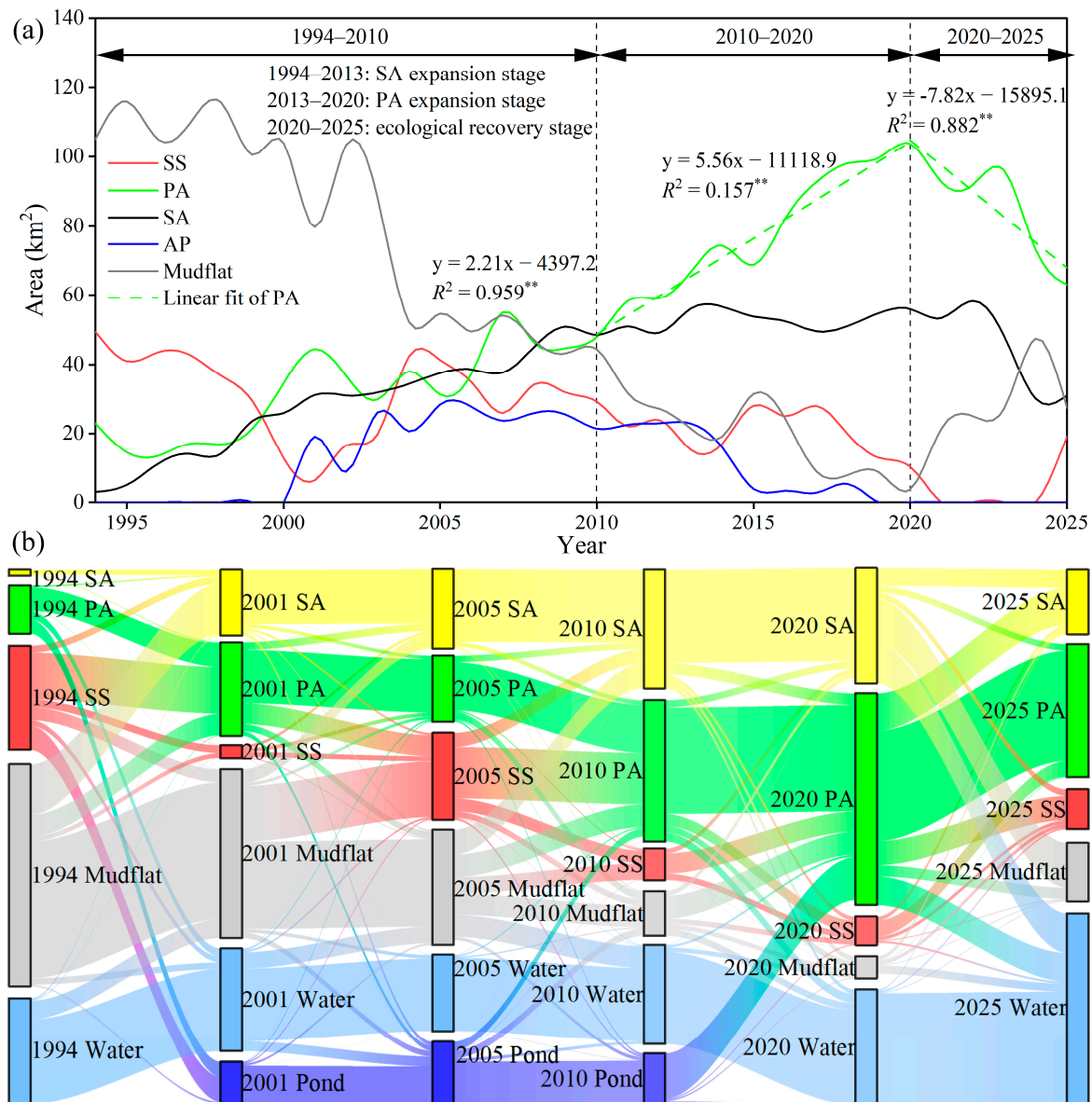


Figure 9. Three stages of YNNRC wetland landscape evolution from 1994 to 2025; (a) Temporal change curves and piecewise linear fitting lines for different landscape types from 1994 to 2025; (b) Sankey diagrams of landscape type transitions at six key time nodes (1994, 2001, 2005, 2010, 2020, 2025). The trend in *P. australis* area was fitted using piecewise linear regression, and all trends were significant ($** p < 0.01$). SS, PA, SA, and AP are *S. salsa*, *P. australis*, *S. alterniflora*, and aquaculture pond, respectively.

To clarify transitions among different land cover types, two temporal nodes (2001 and 2005) were introduced, allowing an overall assessment of the area transition matrix across these time nodes (Figure 9b). Notably, classification uncertainties may amplify the magnitude of certain shifts shown in the Sankey diagram. Therefore, these transition estimates should be interpreted as indicative of broad ecological trends rather than precise quantitative measures. Four key findings were derived: (1) the development of aquaculture

ponds and the expansion of *S. alterniflora* led to increased transfer flows and higher flow network density; (2) in the first stage, the area of *P. australis* (26.05 km²) was smaller than that of *S. salsa* (34.21 km²) in 2005, with aquaculture ponds development since 2000 encroaching on 1.84 km² of *P. australis* habitats, while extensive mudflats (21.93 km²) were converted to *S. salsa*; (3) in the second stage, aquaculture ponds (19.06 km²) were converted into *P. australis* wetlands, and *P. australis* further encroached upon areas of *S. salsa* (12.46 km²) and mudflats (17.64 km²); (4) during the third stage, ecological restoration efforts, such as enhanced waterway connectivity and *S. alterniflora* removal, resulted in 33.22 km² of *Spartina* marshes and 15.71 km² of reed marshes reverting to mudflats and water bodies, alongside the re-establishment of 2.56 km² of *S. salsa*.

4. Discussion

4.1. Advantages of the Proposed Method

This study proposes an enhanced method for monitoring salt marsh landscapes by integrating phenological features to improve plant species classification. This approach offers notable advantages in terms of dataset availability, classification methods, and classification performance.

The feature variables used were derived from steadily available observational datasets, enabling long-term and large-scale monitoring that can be extended to other regions. Lidar-derived DEM, hyperspectral data, and SAR data were excluded [11,49].

The random forest algorithm was selected for land cover classification in the YNNRC wetland due to its lack of constraints from prior data distribution assumptions and its robust tolerance of outliers, such as texture feature data with non-normal distributions or visually interpreted samples [9]. In addition, random forest requires fewer parameter settings and trains faster than other algorithms [50].

Accuracy assessment from comparative experiments demonstrated that the proposed method, which integrates spectral indices, textural features, and phenological characteristics, outperforms approaches relying on a single feature. Prior studies have shown that leveraging multiple texture feature bands can enhance land cover classification accuracy by up to 40% [51]. This improvement stems from texture features accounting for spatial neighborhood information of pixels, providing richer insights than spectral data from individual pixels alone [52]. Application of the Shapley Additive Explanations model in detecting *S. alterniflora* at Chongming East Beach identified the image texture feature component GLCM Variance as having a stronger influence on land cover discrimination than other spectral bands or indices [44]. Furthermore, feature contribution analyses of wetland classification in Yancheng indicated that phenological parameters, including MV and SOS, have a more significant impact on plant species classification than NDVI and NIR [43]. This is because vegetation exhibits similar green characteristics during growing seasons, while MV and SOS show greater separability among plant species, particularly in high-latitude regions [21].

4.2. Limitations and Future Work

First, this study collected plant samples based on color variations observed in standard false-color composite images, which may introduce uncertainty into salt marsh plant species classification. *P. australis* and *S. salsa* exhibit similar colors throughout the growing season, making differentiation challenging in transitional zones. Consistent with prior studies, high classification accuracy was maintained despite potential errors in prior knowledge, achieving an average OA of 90.35% [53–55]. This robustness is likely attributable to the use of the Random Forest classifier, which is relatively insensitive to systematic labeling errors; its overall Kappa value decreases modestly from 78.3% without mislabeling to 70.1%

with 25% mislabeling per class, while classifier uncertainty declines more rapidly [56]. The higher uncertainty in *S. salsa* supports that training samples collected using color-based prior knowledge increased classification uncertainty (Table S4). Future studies employing random forest should incorporate additional samples from different sources, such as field surveys, UAV imagery, and high-resolution satellite imagery, to improve classification accuracy and reduce uncertainty.

Second, phenological differences between species correlate with latitude, with SOS typically advancing at lower latitudes [21]. *S. alterniflora* demonstrates greater sensitivity to SOS than *P. australis*, resulting in a reduced SOS difference between these species with decreasing latitude [21]. These findings indicate that using SOS to differentiate native from invasive species may be less effective in regions south of Jiangsu Province. It is important to consider whether all native species exhibit distinct MV. For instance, the MV of *Tamarix chinensis* is similar to that of *S. salsa* along the coastal Shandong, China [57].

Finally, although this study integrates interannual observational data, where intra-annual observations are usually sufficient, available observational data for regions subject to frequent tidal influences remain severely insufficient, hindering phenological curves from capturing the true critical phenological periods of *S. alterniflora*. For years with insufficient available observations, *S. alterniflora* located very close to the sea was misclassified as *P. australis* or *S. salsa* (Figure 8(c2–d2)). Furthermore, Landsat-7 ETM+ SLC-off data also resulted in occasional gaps, which likely distorted the phenological curve and classification results. For instance, *P. australis* was erroneously classified as *S. salsa* (Figure 8(d2)). The strip-like distribution of classification errors (accounting for 5.8% of the total study area) is powerful evidence. Although images from various Landsat sensors (TM/ETM+/OLI) were utilized, the minimum interval between adjacent observations spans at least eight days, which is too long for NDVI time series related to phenological parameters. Therefore, fusing Sentinel-2 MSI imagery, with a higher temporal resolution of 5 days, is necessary to reduce uncertainty in phenological parameter extraction.

Furthermore, the 30 m spatial resolution of Landsat data inherently limits the characterization of highly fragmented salt marsh patches, particularly *S. salsa*. While phenology-based classification improves class separability, sub-pixel mixing remains a constraint, potentially smoothing fine-scale spatial heterogeneity. Future research could address these limitations by integrating multi-source data with higher spatial resolution (e.g., Sentinel-2) or by applying sub-pixel unmixing techniques.

4.3. Potential Mechanism of Vegetation Succession

Annual classification maps of salt marsh landscapes enable detailed characterization of vegetation succession patterns and the inference of driving mechanisms. The interaction between tides and elevation creates significant gradients in flooding depth, frequency, duration, and salinity from land to sea, with salinity as a key factor influencing vegetation succession [58,59]. In the YNNRC wetland, salinity ranges from 0.34‰ to 1.07‰, decreasing with increasing elevation [60]. Due to differing tolerance to salt stress, salt marsh plants form a typical zonation pattern along stress gradients: mudflats are colonized by the pioneer species *S. salsa*, whereas *P. australis* predominates near embankments (Figure 8(a1–a4)). The introduction of the exotic species *S. alterniflora* has substantially altered both local biodiversity and vegetation spatial distribution. First introduced to Haizhou Bay along the Jiangsu coast in 1982 [31]. *S. alterniflora* was concentrated in the southern YNNRC wetland between 1994 and 1999, expanding slowly in block-like patterns (Figure 8(a1–b1)). By 2000, it spread along the shoreline, forming a continuous vegetation belt capable of effectively attenuating waves and trapping tidal sediments (Figure 8(b2)). *S. alterniflora* expanded both landward and seaward at annual expansion rates of 9.40 m and 67.46 m, respectively.

The terrain in the distribution area of *S. alterniflora* was elevated due to siltation. DEM profile analysis shows mean elevation rose from 1.79 m in 2002 to 2.07 m in 2011 [61]. The *S. alterniflora* belt functioned as a biological dam, hindering tidal flow into the interior of salt marshes and driving the inferred gradual evolution of the upper intertidal zone into the supratidal zone. Since native *P. australis* and *S. salsa* typically colonize the supratidal and upper intertidal zones, the succession from *S. salsa* to *P. australis* and from mudflats to *S. salsa* can be clearly observed (Figure 8(b3–d5)). This process partly explains the increase in the *S. salsa* community area between 2001 and 2005, the significant expansion of the *P. australis* community from 2005 to 2010, and the sharp decline in bare flat area from 2001 to 2010 (Figure 9a). As *S. alterniflora* expanded landward, it competed with *S. salsa* and occupied its ecological niche, due to its advantages in reproductive capacity, photosynthetic efficiency, and growth plasticity [62]. In addition, the canopy-mediated shading effect of *S. alterniflora* is inferred to create an unfavorable ecological niche for competitors at the community level [63]. The encroachment of *S. alterniflora* and *P. australis* from different directions severely restricted *S. salsa*'s survival space, leading to its drastic decline and continuous fragmentation (Figure 8(e1–f3)).

Anthropogenic factors such as tidal reclamation, dike construction, and ecological restoration have modified hydrological conditions and soil properties through local topographic changes, thereby affecting succession processes and vegetation distribution patterns [64]. In the southwestern YNNRC wetland, a sea embankment constructed before 1998 cut off tidal flows, reducing soil salinity and is inferred to have caused extensive degradation of native *S. salsa* communities (Figure 8(a1–a4)). In the northern YNNRC wetland, aquaculture pond construction seaward occupied *P. australis* habitats, leading to substantial loss of *P. australis* communities (Figure 8(b3–c3)). The “Returning Aquaculture Ponds to Wetlands” policy initiated in 2013 promoted the removal of artificial structures in reclaimed areas, facilitating salt marsh vegetation restoration (Figure 8(d5–f1)). Long-term fishery activities and rainfall dilution lowered soil salinity in these areas, conditions unsuitable for typical salt marsh species except *P. australis*, which has since expanded rapidly (Figure 9a). To preserve rare bird habitats, the government issued the “Special Action Plan for Prevention and Control of the *S. alterniflora* (2022–2025),” aiming to effectively control *S. alterniflora* by 2025. After control, the area of *S. alterniflora* decreased by 96.12% [54]. A Google Earth Pro image dated May 29, 2025, reveals that a narrow strip of *S. alterniflora* persists along the salt marsh foreshore. Notably, small patches of the native species pioneer *S. salsa* were detected in open mudflat areas following *S. alterniflora* removal (Figure 8(g2)), consistent with field survey records [65]. Given the relatively lower classification accuracy for *S. salsa*, this warrants cautious interpretation and further field validation to confirm potential species recovery. While physical eradication likely drove these changes [66], natural succession and site-specific conditions may also contribute to observed recovery.

5. Conclusions

Rapid changes in the spatial distribution of salt marsh vegetation highlight the need for accurate monitoring to support sustainable management. The study proposes an enhanced monitoring method for salt marsh landscapes by integrating phenological features. The main conclusions of this work are summarized as follows:

- (1) The accuracy assessment of comparative experiments demonstrated that the proposed method achieves superior classification performance.
- (2) The high overall accuracies and minor fluctuations observed in the annual maps demonstrated satisfactory performance for the classification mapping.
- (3) The eradication measures targeting *S. alterniflora* in the YNNRC wetland have proven effective in controlling this invasive species and restoring native species.

The method's applicability is restricted by available observations and latitude. With the introduction of Sentinel-2 MSI after 2015 and Landsat-9 OLI-2 after 2021, the number of available observations is expected to increase, potentially enhancing the method's applicability. Future research should prioritize evaluating the adaptability of phenology-based classification techniques across diverse geographical latitudes and wetland types, as local climatic variations significantly influence plant growth cycles.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse14151406/s1>, Table S1: Details of the high spatial resolution (HR) images used for validation in this study. Table S2: Linear transformation coefficients for spectral inter-calibration between Landsat-8 OLI and Landsat-5 TM/7 ETM+. Table S3: Confusion matrices for evaluating the classification accuracy of salt marsh landscapes. Table S4: Uncertainty of salt marsh landscape classification at the class scale. Figure S1: Spatial distribution of the number of available observations at the pixel level from 1994 to 2025. Figure S2: Linear relationship between overall accuracies and available observations.

Author Contributions: Conceptualization, Y.T.; methodology, Y.T.; Resources, Y.W., J.X. and Y.Z.; data curation, Y.W., J.X. and Y.Z.; writing—original draft preparation, Y.T.; writing—review and editing, Y.Z.; funding acquisition, Y.W., J.X. and Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Jiangsu Forestry Science and Technology Innovation and Promotion Project, grant number LYKJ[2022]02 and the Postgraduate Research & Practice Innovation Program of Jiangsu Province, grant number KYCX23_1123.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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

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