Intelligent Assessment of Suaeda salsa Growth Stress Factors Based on Multimodal Fusion and Transfer Learning

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Intelligent Assessment of Suaeda salsa Growth Stress Factors Based on Multimodal Fusion and Transfer Learning

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Abstract: This paper proposes an improved machine learning algorithm based on multimodal fusion and transfer learning for intelligent assessment of Suaeda salsa growth stress factors. By integrating remote sensing images, near-surface images, and ground survey data, the assessment model is optimized through dynamic feature engineering. The results demonstrated that key stress factors affecting Suaeda salsa growth in Liaohe Estuary wetland, ranked by full-cycle comprehensive contribution, are: soil salinity (0.83) > crab burrow density (0.53) > mean NDVI (0.43) > precipitation (0.31) > soil moisture (0.26). Soil salinity is identified as the primary stress factor, consistent with existing studies; this work quantitatively evaluates the dual effects of crab burrow density for the first time, confirming its role as a critical biological stressor. The improved CNN-RF hybrid model achieves a mean square error (MSE) of 0.016 (R^2 = 0.941) under conventional scenarios, representing a 36% improvement in accuracy compared with traditional RF methods; under extreme compound stress conditions, the stability coefficient (SC) is 2.05, 4.7% lower than traditional RF approaches. Causal analysis based on the SHAP-LIME hybrid framework reveals a "salinity-moisture-crab burrow" ternary interaction mechanism. The GIS-integrated decision support system enables real-time visualization and multi-level early warnings of growth status, successfully identifying ecological degradation risks in the western high-salinity zone (local contribution 0.88) and northern crab burrow-intensive areas during empirical application in Liaohe Estuary. This research provides a data-driven intelligent assessment tool for coastal wetland ecological protection.

Key words: Suaeda salsa stress factor assessment; Multimodal data fusion; Dynamic Feature Engineering; Transfer learning; Intelligent decision support

Introduction

Assessing the growth status of Suaeda salsa in coastal wetlands faces challenges such as complex ecological mechanisms, diverse environmental stressors, and fragmented monitoring technologies. There is an urgent need to integrate multidisciplinary research findings to construct an intelligent assessment system, particularly for the intelligent assessment of Suaeda salsa growth stress factors. This aims to overcome technical bottlenecks in quantifying multi-factor interactions, cross-regional generalization capabilities, and real-time early warning in traditional methods, enabling precise identification, quantification, and analysis of key stress factors. In recent years, scholars have conducted in-depth research on ecological driving mechanisms of vegetation growth. Regarding plant-soil interactions, Hou Yalin et al. (2022) discovered through a 6-year rainfall control experiment (60% rainfall reduction, 40% rainfall reduction, natural control, 40% rainfall increase, 60% rainfall increase) that with increasing rainfall, the Shannon index and Margalef richness index of plant communities significantly increased, and aboveground biomass significantly increased. However, the 60% rainfall increase treatment resulted in significantly lower biomass than the 40% increase due to flooding stress, revealing the bidirectional regulatory effect of precipitation as a key stress factor on wetland plant community diversity. This provides a reference for understanding the growth response of Suaeda salsa under different precipitation gradients[Error! Reference source not found.]. Wang Qing et al. (2019) found through research in coastal salt marshes of the Yellow River Delta that tidal channel hydrological characteristics significantly affect the colonization success rate of Suaeda salsa. Changes in tidal inundation frequency and duration directly restrict seed germination and seedling survival, revealing the regulatory mechanism of tidal hydrological processes as a key stress factor on Suaeda salsa community establishment[Error! Reference source not found.]. In environmental stress response mechanisms, Ostrowski et al. (2025) explored the compound stress effects of salinity fluctuations and water level changes through controlled experiments, providing insights into the environmental stress response of Suaeda salsa[3]. In Suaeda salsa adaptation mechanisms, He Wenjun et al. (2021) analyzed the influence mechanism of soil water-salt gradients on Suaeda salsa biomass, finding that soil water content and pH could explain 68% of the root-to-shoot ratio variation[4]. Zhang Yinglei et al. (2023) established a diagnostic method for Suaeda salsa ecological degradation based on soil water-salt environments, providing a quantitative indicator system for growth status assessment[5]. These studies lay a solid theoretical foundation for understanding the ecological driving factors of Suaeda salsa growth status. However, Suaeda salsa growth areas often contain numerous crab burrows. Qiu Dongdong et al. (2018) showed that crabs, as "ecosystem engineers" in coastal wetlands, significantly alter the physicochemical properties of intertidal soils through excavation activities. Crab burrows have complex dual effects on vegetation growth[6]. Crab burrows can potentially maintain soil microtopography, facilitating plant growth and expansion in the following year, but excessive density may physically damage root development through physical disruption. Currently, no studies directly explore the quantitative impact mechanism of crab burrow density on Suaeda salsa growth status. Therefore, the specific impact of crab burrows as a key biological stress factor on Suaeda salsa growth requires in-depth evaluation.

At the level of monitoring technology innovation, the rapid development of remote sensing and ecological restoration technologies provides new technical pathways for Suaeda salsa growth assessment. The multi-scale classification model developed by Yu et al. (2025) effectively integrates high-resolution satellite data with ground observation information, significantly improving wetland vegetation identification accuracy[7]. The tidal flat time-series monitoring method established by Chen et al. (2025) enhances the dynamic extraction accuracy of Suaeda salsa growth parameters by fusing multi-temporal Sentinel-2 data[8]. Meanwhile, advances in ecological restoration technologies support habitat optimization for Suaeda salsa. He Shuang et al. (2023) achieved high-precision inversion of the Suaeda salsa leaf area index using an RF-PSO-DELM algorithm-based multimodal data fusion method**Error! Reference source not found.** Zhang et al. (2025) pioneered a soil improvement method based on Spartina alterniflora biochar, opening new avenues for saline-alkali land remediation[10].

To construct a systematic growth status assessment framework, researchers have advanced comprehensive assessment technologies from multiple dimensions. Zhao et al. (2024) elucidated the sensitivity of carbon in saline-alkali soils through molecular analysis[11]. Habitat studies by Hu et al. (2025)[12], contaminant assessments by Sreedevi et al. (2025)[13], and climate change analyses by Wu et al. (2025)[14] collectively reveal the compound environmental pressures on Suaeda salsa. Mu Yanan et al. (2018) combined object-oriented methods with random forest models, achieving a classification accuracy of 91.2% for vegetation information extraction in Hangzhou Bay coastal wetlands, providing an effective technical pathway for coastal wetland vegetation classification[15].

These studies establish a multi-dimensional support system from molecular, ecosystem, to regional scales, providing a scientific basis for developing a comprehensive Suaeda salsa growth status assessment model. However, as can be seen from the aforementioned research progress, despite significant breakthroughs in ecological mechanism interpretation, remote sensing technology innovation, and comprehensive assessment methods, three core technical challenges remain in constructing an intelligent assessment system: (1) Spatiotemporal alignment and deep fusion technologies for multi-source data are immature; (2) Modeling methods capturing ecosystem dynamic responses are lacking; (3) Model generalization capabilities across regions and scales are limited.

Addressing these technical challenges, quantitative research on vegetation change driving mechanisms provides methodological insights for Suaeda salsa assessment. In the field of vegetation change driving factors, scholars have developed a series of technical approaches capable of handling complex ecological relationships through the deep integration of statistics and machine learning. For example, Yang et al. (2021) used ensemble empirical mode decomposition, geographically and temporally weighted regression, and other methods capable of effectively addressing nonlinear relationships and spatial autocorrelation issues in geospatial data to analyze spatiotemporal patterns of vegetation change in the Hexi Corridor and surrounding areas from 1982 to 2015. This enabled precise identification of meteorological driving factors affecting vegetation change and exploration of anthropogenic factors related to land use/cover changes such as urbanization, ecological restoration projects, and agricultural intensification on vegetation spatiotemporal patterns[16]. In 2017, Leroux et al. used the random forest machine learning algorithm to quantitatively assess the importance of regional rainfall, soil conditions, topographic features, land use change, and population density in vegetation change[17]. Chaulagain et al. (2023) studied the response mechanisms of riparian vegetation and river morphology to climate-induced droughts based on the Google Earth Engine platform combined with the random forest classifier machine learning algorithm[18]. In the same year, Moradi et al. assessed vegetation vulnerability under hydrometeorological pressures in arid regions by integrating benchmark and independent machine learning algorithms (random forest, support vector machine, and maximum entropy model) with remote sensing technology to build an ensemble model[19]. Park et al. constructed a pentad-scale drought prediction model based on the MJO index integrated with remote sensing data, achieving significant prediction accuracy improvements in East Asia[20]. Skendzic et al. emphasized in a review of winter wheat environmental stress detection that machine learning methods combining visible, near-infrared, and short-wave infrared spectra provide important technical support for early diagnosis and quantitative assessment of crop stress[21]. He et al. systematically studied the driving mechanisms of hydromorphic variables on coastal wetland degradation based on the random forest model. By integrating remote sensing data and hydrological modeling, they quantitatively analyzed the relative importance of stressors such as sea-level rise, saltwater intrusion, and artificial drainage on woody wetland loss and herbaceous wetland degradation[22]. Current methods for studying vegetation change driving mechanisms mainly include traditional statistical analysis, regression analysis, geographically weighted regression, and machine learning algorithms such as random forest and support vector machines. These methods are used to explore the evolution of vegetation spatiotemporal patterns and their degree of influence by climate, land use, and other factors.

Traditional methods exhibit low information utilization when integrating multi-source heterogeneous data due to insufficient spatiotemporal alignment accuracy or unclear coupling mechanisms of ecological factors, failing to comprehensively reveal the multi-dimensional driving factors of Suaeda salsa growth. Additionally, existing feature engineering relies on static feature extraction, lacking modeling of temporal dynamic changes and ecological interaction effects, thereby limiting the model's ability to capture complex environmental responses. Regarding model synergy, traditional algorithms often use single models without effectively combining the advantages of deep learning and classical machine learning, resulting in weak capabilities for integrating local features and global ecological factors. Moreover, existing models exhibit instability when migrating across regions or seasonal change scenarios, lacking dynamic weight adjustment mechanisms and transfer learning strategies, and insufficient adaptability to environmental variables. Validation frameworks are mostly focused on conventional scenarios, lacking robustness testing under extreme environments. Significant "black box" characteristics make it difficult to analyze the contribution and causal mechanisms of ecological factors, hindering practical management decision-making. Therefore, this paper proposes an intelligent assessment method for Suaeda salsa growth stress factors based on multimodal fusion and transfer learning.

1. Multimodal Data Fusion and Feature Engineering Optimization

1.1 Multi-source Data Fusion Framework Design

Based on the stress-response mechanism of the Suaeda salsa wetland ecosystem, this study selected soil salinity, crab burrow density, mean NDVI, precipitation, and soil moisture as core stress factors. Soil salinity, as the primary chemical stress factor in coastal wetlands, directly affects Suaeda salsa physiological metabolism through osmotic stress and ion toxicity; crab burrow density reflects bioturbation intensity intensity, as crab excavation activities damage root structures and alter soil water-salt distribution; mean NDVI directly indicates changes in vegetation biomass and stress response intensity; precipitation and soil moisture constitute the core elements of water supply-demand balance, determining vegetation water stress conditions. These five stress factors cover chemical stress, physical stress, biological response, and water stress, providing a scientific ecological basis for multimodal data fusion.

For the above key stress factors, a multi-source data fusion framework was constructed to integrate remote sensing images, near-surface images, and ground survey data. Spatiotemporal alignment techniques for remote sensing and near-surface images eliminated data deviations caused by sensor differences, time delays, or inconsistent spatial resolutions. Based on feature point matching and affine transformation, images of different resolutions were unified into the same coordinate system. The affine transformation formula is:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} (1)$$

Where a, b, d, e are rotation and scaling parameters, and c, f are translation parameters. Dynamic Time Warping (DTW) or linear interpolation was used to align image sequences with different timestamps.

For data fusion, input remote sensing images $X_{sat} \in \mathbb{R}^{H\times W\times C}$ and near-surface images $X_{ground} \in \mathbb{R}^{h\times w\times c}$, outputting aligned images $X_{aligned} \in \mathbb{R}^{H\times W\times (C+c)}$.

The integration method for ground survey data and ecological elements dynamically coupled unstructured ecological parameters with image data. Normalization of ecological elements $f_{eco} = [f_{eco}, f_{eco}, \ldots]$:

$$f_{norm} = \frac{f-u}{\sigma} (2)$$

Ecological elements were mapped to grid units of the images, generating a spatial weight matrix $W \in \mathbb{R}^{H\times W}$. The dynamic coupling formula is:

$$X_{fused} = X_{aligned} \odot W + f_{eco} \otimes 1_{H\times W} (3)$$

Where $\odot$ denotes element-wise multiplication, and $\otimes$ represents broadcasting.

Figure 1.1 shows the complete process of multi-source data fusion, starting from the input layer receiving remote sensing images, near-surface images, and ground survey data, through alignment and standardization stages for spatiotemporal registration and data normalization, followed by feature fusion for spatial association and dynamic coupling, and finally outputting fused multimodal data.

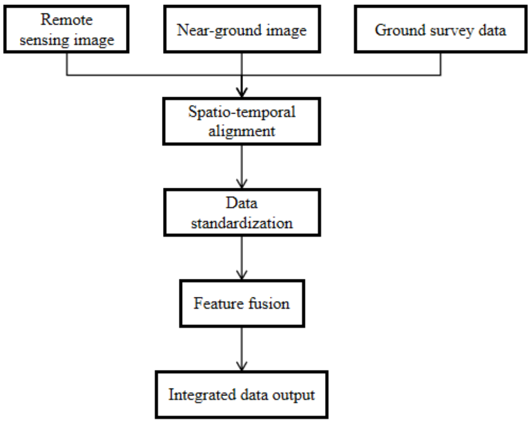


Fig. 1.1 Multi-source Data Fusion Framework

1.2 Dynamic Feature Extraction and Enhancement

Periodic seasonal and aperiodic interannual change features were extracted from multi-temporal remote sensing images. Through time-series feature extraction methods, a sliding window with size T was defined to calculate the mean and variance of spectral indices (e.g., NDVI) within the window:

$$u_t = \frac{1}{T} \sum_{i=t}^{t+T-1} NDVI_i (4)$$

$$\sigma_t^2 = \frac{1}{T} \sum_{i=t}^{t+T-1} (NDVI_i - u_t)^2 (5)$$

Where t is the starting time, u_t and σ_t^2 represent local trends and fluctuation intensity, respectively.

Frequency-domain features of time series were extracted to identify periodic signals:

$$\mathcal{F}(k) = \sum_{n=0}^{N-1} NDVI_n \cdot e^{-i2\pi kn/N} (6)$$

Dominant periods (e.g., seasonal cycles) were detected through spectral peak analysis. Higher weights were assigned to key growth periods (e.g., spring germination):

$$\alpha_t = Softmax(W_a \cdot h_t) (7)$$

$$h_t = LSTM(NDVI_{1:t}) (8)$$

Where α_t is the attention weight at time step t, and h_t is the LSTM hidden state.

Ecological interaction features were introduced to quantify interactions between ecological factors, enhancing the model's ability to capture nonlinear relationships. Interaction feature construction was enhanced through multiplicative terms: crab burrows may affect salt distribution by altering soil structure or water permeability, while high-salinity environments may exacerbate the physical damage of crab burrows to roots or salt enrichment effects. This interaction reflects nonlinear correlations between ecological factors. For example, higher crab burrow density may amplify the negative effects of salt stress or regulate salt dynamics in specific habitats. Modeling their joint effects through multiplicative terms enhances the model's ability to represent complex ecological relationships, enabling more precise quantification of Suaeda salsa growth responses under multi-factor synergistic driving mechanisms. The product of crab burrow density f_{crab} and soil salinity f_{salt} was used as an interaction feature:

$$f_{interact} = f_{crab} \cdot f_{salt} (9)$$

Collaborative modeling based on Graph Neural Networks (GNNs) constructed an ecological factor relationship graph, where nodes represented factor values and edge weights represented correlation coefficients:

$$A_{ij} = Corr(f_i, f_j) (10)$$

$$Z = GCN(X, A) (11)$$

Where A is the adjacency matrix and Z is the feature representation after graph convolution.

Temporal features f_{time} and interaction features $f_{interact}$ were concatenated:

$$f_{dynamic} = [f_{time}; f_{interact}] \in \mathbb{R}^{D\times K} (12)$$

Figure 1.2 illustrates the entire dynamic feature extraction and enhancement process: first, the input layer receives time-series remote sensing data and ecological factors; next, during temporal feature extraction, key features are extracted using sliding window statistics, Fourier transform, and temporal attention mechanisms; then, through interaction feature modeling, associations between features are constructed using multiplicative terms or graph neural networks; subsequently, in the feature fusion stage, dynamic features are concatenated; finally, the output layer obtains the enhanced dynamic feature vector.

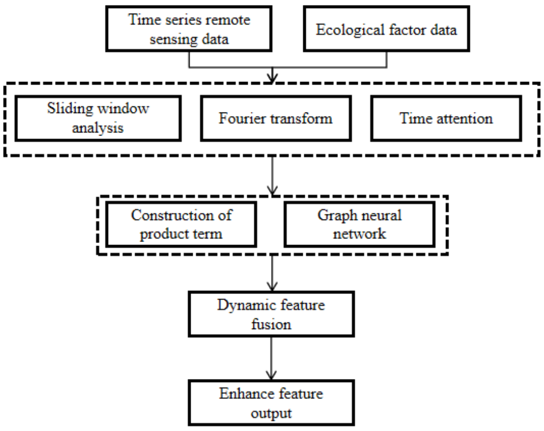


Fig. 1.2 Dynamic Feature Extraction and Enhancement Workflow

1.3 Feature Selection Optimization

This section optimizes feature subsets through global feature importance analysis and hybrid screening strategies, eliminating redundant information while enhancing model generalization capability and ecological factor interpretability.

(1)Global Feature Importance Analysis Based on Graph Neural Networks

Graph structures were utilized to model complex relationships between features and identify key driving factors. Node features (e.g., mean NDVI, crab burrow density, soil salinity) had edge weights defined by mutual information or correlation coefficients between features, forming an adjacency matrix $A \in \mathbb{R}^{N\times N}$:

$$A_{ij} = \frac{|Corr(f_i,f_j)|}{\sum_k |Corr(f_i,f_j)|} \quad (13)$$

Node importance scores $S \in \mathbb{R}^{N}$ were calculated via a two-layer GCN:

$$H^{(1)} = ReLU\left(AXW^{(1)}\right) \quad (14)$$

$$s = \sigma\left(AH^{(1)}W^{(2)}\right) \quad (15)$$

Where X is the feature matrix, W are learnable parameters, and σ is the Sigmoid function. Features were ranked in descending order of s, retaining the top K features.

(2)Hybrid Screening Strategy Combining Recursive Feature Elimination with SHAP Values

Model-dependent and model-agnostic methods were combined to enhance screening robustness. SHAP (SHapley Additive exPlanations) quantified feature contributions to predictions:

$$\phi_i = \sum_{S\subseteq F/\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}\left(v(S\cup\{i\}) - v(S)\right) \quad (16)$$

Where F is the complete feature set, and $v(S)$ is the model output for subset S.

The hybrid screening process began with preliminary filtering: features with SHAP values below threshold θ were removed. Refined screening followed: recursive feature elimination (RFE) was applied to remaining features, recursively training models and removing the least important feature until reaching the target dimension.

2. Algorithm Model Improvement

2.1 Synergistic Optimization of Deep Learning and Traditional Machine Learning

2.1.1 Hybrid Model of Convolutional Neural Network and Random Forest

This hybrid model combines the local feature extraction capability of CNN with the global feature integration advantages of Random Forest (RF), suitable for multi-modal data assessment of Suaeda salsa growth status. Its core idea is to extract spatial local features from high-resolution remote sensing images through CNN, fuse them with ecological factors (e.g., soil salinity, crab burrow density), and finally complete classification or regression tasks via random forest.

CNN feature extraction inputs remote sensing images $X_{img} \in \mathbb{R}^{H\times W\times C}$ (height, width, channels). After convolutional layers, activation functions, and pooling layers, it outputs a high-level feature vector $f_{CNN} \in \mathbb{R}^{D}$. The convolutional operation for layer l is:

$$F^{(l)} = \sigma\left(W^{(l)} * F^{(l-1)} + b^{(l)}\right)(17)$$

Where W is the convolutional kernel weight, σ is the ReLU activation function, and $*$ denotes convolution.

The CNN feature f_{CNN} is concatenated with ecological factors $f_{eco} \in \mathbb{R}^{M}$ to form a hybrid feature vector:

$$f_{combined} = [f_{CNN}; f_{eco}] \in \mathbb{R}^{D+M}(18)$$

The random forest consists of T decision trees. Each tree h_t selects split nodes based on Gini impurity or information gain. The final prediction is the majority vote (classification) or mean value (regression):

$$\hat{y} = mode(\{h_1(f_{combined}), \dots, h_T(f_{combined})\})(19)$$

2.1.2 Integration of Spatiotemporal Attention Mechanism and GBDT

This model captures key growth periods and spatial heterogeneity in Suaeda salsa time series through a spatiotemporal attention mechanism, combined with GBDT's advantage in modeling nonlinear environmental factors, achieving precise assessment of complex ecosystems.

(1)Spatiotemporal Attention Mechanism

Input time-series remote sensing data $X \in \mathbb{R}^{T\times H\times W\times C}$ (timesteps, height, width, channels). 3D convolution extracts spatiotemporal features:

$$F_{3D} = Conv3D(X; W_{3D})(20)$$

Attention weights are computed via query-key-value mechanism:

$$\begin{cases} Q = F_{3D}W_Q \\ K = F_{3D}W_K(21) \\ V = F_{3D}W_V \end{cases}$$

Attention scores:

$$A = Softmax\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)(22)$$

Weighted features:

$$F_{att} = AV \in \mathbb{R}^{T\times H\times W\times D}(23)$$

Feature compression pools along spatiotemporal dimensions, outputting global feature vector $f_{att} \in \mathbb{R}^{D}$.

(2)GBDT Modeling

Input attention feature f_{att} and ecological factors f_{eco}, concatenated as $f_{combined}$. For gradient boosting, the prediction target of the m-th tree is the residual:

$$r_m = y - \sum_{i=1}^{m-1} \gamma_i h_i(f_{combined})(24)$$

Final prediction is the weighted sum of all trees:

$$\hat{y} = \sum_{m=1}^{M} \gamma_m h_m(f_{combined})(25)$$

2.2 Adaptive Model Training Strategy

This strategy enhances model adaptability to different regions and seasonal changes through transfer learning and dynamic weight adjustment, addressing insufficient generalization in cross-scene applications.

2.2.1 Cross-regional Generalization Improvement Based on Transfer Learning

Migrating pre-trained models to similar wetland scenarios significantly reduces data requirements and improves training efficiency. The transfer learning process includes:

1. Pre-training on source regions to extract universal features.
2. Fine-tuning on target regions: freezing partial low-level parameters while adjusting top classifiers.

Pre-training loss function:

$$\mathcal{L}_{pre} = \frac{1}{N_{src}} \sum_{i=1}^{N_{src}} \left(y_i - f_{src}(x_i)\right)^2 (26)$$

Fine-tuning loss with target data:

$$\mathcal{L}_{fine} = \lambda \mathcal{L}_{pre} + (1-\lambda) \cdot \frac{1}{N_{tgt}} \sum_{j=1}^{N_{tgt}} \left(y_j - f_{tgt}(x_j)\right)^2 (27)$$

Where λ balances source and target domains.

2.2.2 Dynamic Weight Adjustment Mechanism

Feature weights (e.g., hydrological/soil factors) are dynamically adjusted according to seasonal changes. Time t is mapped to season vector $s_t \in \mathbb{R}^4$. Dynamic weights:

$$w_t = Softmax(W_s s_t + b_s) (28)$$

Where W_s is a learnable parameter matrix, and w_t represents the seasonal weights for each feature. The weight matrix W_s is automatically optimized during training through error backpropagation, learning objective associations between seasonal characteristics and ecological factor contributions directly from data.

The weighted feature input is defined as:

$$f_{weighted} = w_t \odot f_{original} (29)$$

The core objective of this mechanism is to explicitly model seasonal dependencies in ecological factor contributions. By mapping time to a seasonal vector s_t and generating dynamic weights w_t, the model adaptively adjusts weights for dominant stress factors across different seasons.

2.3 Algorithm Description

This section integrates multimodal data fusion, feature engineering optimization, hybrid model construction, and adaptive training strategies into a complete Suaeda salsa growth status assessment algorithm. The core objective is to achieve high-precision, robust assessment through multi-source data collaborative modeling and dynamic adjustment. The pseudocode is shown in Table 2.1.

Table 2.1 Suaeda salsa Growth Status Assessment Algorithm

Algorithm 1: Suaeda salsa Growth Status Assessment
Input: X_{img} (multi-temporal remote sensing images), X_{eco} (ecological parameters), X_{ground} (ground survey data) Output: y_{pred} (growth status assessment), feature_importance (key ecological factor contributions)
1. Spatiotemporal Alignment: Process multi-source data via spatiotemporal registration; 2. Ecological Standardization: Z-score normalization of ecological parameters, μ=mean, σ=std; 3. Feature Extraction: CNN extracts spatial features, sliding window T extracts temporal features; 4. Frequency Interaction: FFT transforms obtain frequency features, GCN models ecological

interactions;
5. Feature Fusion: Concatenate 4D feature tensors along dimensions;
6. Primary Feature Selection: Select Top-K features via GCN importance ranking;
7. Refined Feature Selection: Filter by SHAP values + Recursive Feature Elimination;
8. Model Construction:
if CNN-RF: RF(f_final)
else: GBDT(concat(Att(X_img), f_final))；
// Adaptive dual-model architecture
9. Cross-Validation: Spatial K-fold validation outputs predictions;
10. Result Output: Return predicted values and SHAP feature contributions.

3. Model Verification and Ecological Interpretability Enhancement

3.1 Multi-dimensional Verification Framework

3.1.1 Spatial Cross-Validation and Time Series Segmentation Validation

All verification experiments in this chapter were conducted based on an independent field-measured dataset. This dataset covers ground survey data from the Liaohe Estuary wetland for 2023-2024, totaling 1,248 sample points (52 points/month × 24 months), including parameters such as soil salinity, crab burrow density, and vegetation biomass. Simultaneously, we utilized 36 multi-temporal Sentinel-2 images (10m resolution) acquired between 2023-2024, all atmospherically corrected and geometrically registered. Additionally, to comprehensively validate the experiments, simulated data for extreme scenarios were generated based on the range of measured data.

In the verification framework for the Suaeda salsa growth status assessment model, Spatial K-fold cross-validation and time series segmentation validation are two core methods designed to address evaluation biases caused by ignoring spatial dependence and temporal continuity in traditional random partitioning approaches.

Spatial K-fold validation ensures geographical independence between training and testing sets. Implementation involves: (1) partitioning the study area into K×K regular grids, with each grid cell as an independent spatial block; (2) stratifying grids based on Suaeda salsa distribution density or ecological zones to ensure uniform representation across training/testing sets; (3) iteratively using K−1 blocks for training and the remaining block for testing, repeating K times, and averaging performance metrics to comprehensively evaluate model performance.

Time series segmentation validation employs a rolling-window strategy for temporal remote sensing data. The procedure includes: (1) defining total sequence length T, window size W, and step size S; (2) starting at t=0, using data from t to t+W−1 for training and t+W to t+W+S−1 for testing, sliding the window until the entire sequence is covered; (3) dynamically adjusting W by seasonal cycles (e.g., W=3 months in rainy season, W=6 months in dry season) to adapt to seasonal data characteristics.

Table 3.1 demonstrates the impact of spatial partitioning granularity (K) and time window settings on model performance (using MSE and R^2):

Table 3.1 Model Performance Under Spatial and Temporal Validation Strategies

Validation Method	Parameter Setting	MSE	R^2
SpatialK-fold	K=3	0.023	0.892
	K=5	**0.018**	**0.927**

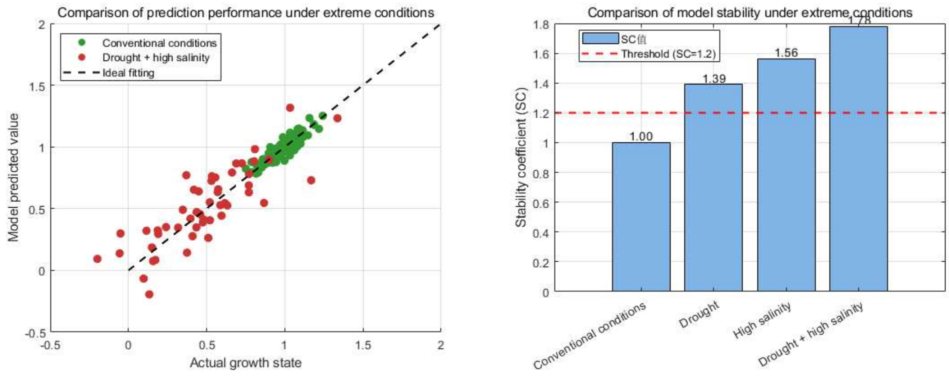
Time Series Split	W=3,S=1	0.021	0.905
	W=6,S=2	**0.016**	**0.941**

3.1.2 Robustness Testing Under Extreme Environmental Conditions

To comprehensively evaluate robustness against synergistic ecological disturbances, this study added high crab burrow density (200% of normal density) and compound extreme conditions (drought + high salinity + high crab density) to existing extreme scenarios (drought, high salinity, and compound stress). High crab density simulates soil structure destruction from intensified crab activities, potentially inhibiting Suaeda salsa growth through synergistic physical stress and salt accumulation. Compound extreme conditions integrate multiple stressors (drought, salinity, crab density) to validate responses to complex ecological disturbances. Results indicate significant performance degradation: under high crab density, MSE increases to 0.031 (R^2=0.782) with SC=1.72; under compound extremes, MSE deteriorates to 0.039 (R^2=0.741) with SC=2.05. This demonstrates that elevated crab density not only independently reduces prediction accuracy but also exacerbates model instability via nonlinear synergy with hydrological/salinity factors.

Table 3.2 Performance under different extreme scenarios

Test Scenario	Parameter Adjustment	MSE	R^2	Stability Coefficient(SC)
Normal Conditions	No adjustment	0.018	0.927	1.00
Drought	Precipitation↓50%	0.025	0.863	1.39
High Salinity	Soil Salinity↑200%	0.028	0.841	1.56
High Crab Density	Crab Burrow Density↑200%	0.031	0.782	1.72
Drought+High Salinity	Precipitation ↓ 50% + Salinity ↑ 200%	0.032	0.802	1.78
Compound Extreme	Precipitation ↓ 50% + Salinity ↑ 200% + Crab ↑ 200%	0.039	0.741	2.05



(a) Comparison of Parameter Distributions and Model Predictions Under Extreme Conditions

(b) Stability Coefficient Comparison

Fig. 3.1 Robustness Testing

Figure 3.1a illustrates predicted vs. actual values under extreme scenarios via scatter plots: normal conditions (green dots) cluster tightly along the ideal diagonal, indicating high accuracy; compound extreme conditions (red triangles) deviate markedly with maximal dispersion, demonstrating synergistic prediction errors from drought, high salinity, and crab density. High crab density alone (purple squares) exhibits secondary dispersion, reflecting disturbances from physical destruction or altered salt permeability. Figure 3.1b quantifies Stability Coefficients (SC) across scenarios: "High Crab Density" (SC=1.72) and "Compound Extreme" (SC=2.05) both exceed the threshold (1.2), confirming crab density as an independent stressor that amplifies instability through nonlinear interactions with hydrological/salinity factors. Collectively, these figures reveal limited adaptability to single stressors and significant robustness degradation under multi-stress synergy, necessitating optimized feature interaction modeling and adversarial training.

3.2 Interpretability Enhancement Techniques

3.2.1 Ecological Factor Contribution via SHAP-LIME Hybrid

To enhance model interpretability, a SHAP-LIME hybrid visualization method quantifies global feature importance and local prediction logic. Table 3.3 compares SHAP values (global contribution) and LIME weights (local contribution) of key ecological factors.

Table 3.3 Key ecological factor weights

Ecological Factor	SHAP Value (Global)	LIME Weight (Local)	Comprehensive Contribution Score
Soil Salinity	0.45	+0.38	0.83
Crab Burrow Density	0.32	-0.21	0.53
Mean NDVI	0.28	+0.15	0.43
Precipitation	0.19	+0.12	0.31
Soil Moisture	0.17	-0.09	0.26

Weight assignments in Table 3.3 integrate global (SHAP) and local (LIME) interpretability while reflecting spatiotemporal dynamics. SHAP values compute global average contributions via game theory (e.g., soil salinity: 0.45) as a baseline for full-cycle importance. LIME weights quantify context-specific importance using local linear surrogate models (e.g., crab density: −0.21 indicates growth suppression in specific zones). Local deviations stem from seasonal fluctuations and spatial heterogeneity: precipitation dilutes salinity in wet seasons (temporarily reducing its contribution), while drought intensifies salinity/humidity contributions. Spatial examples include salinity contribution=0.88 in the western high-salinity zone and pronounced physical disruption in crab-intensive areas.

To balance global and local perspectives, a weighted average method (e.g., SHAP value × 0.6 + |LIME weight| × 0.4) or normalized fusion integrates the global baseline and local dynamics into a Comprehensive Contribution Score. For instance, soil salinity's composite score (0.83) incorporates its extensive and stable negative impact. Furthermore, weight assignment fully references ecological priori knowledge and inter-feature interaction effects, ensuring consistency between model interpretability and ecological mechanisms.

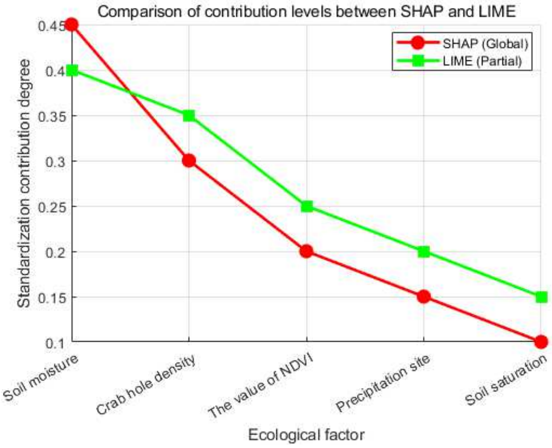


Fig. 3.2 Contribution Comparison Between SHAP and LIME

3.2.2 Causal Inference Model for Key Driving Mechanisms

To dissect key driving mechanisms, a Structural Equation Model (SEM) quantifies direct/indirect causal effects among ecological factors and validates dynamic impacts of crab density and soil salinity on root biomass. Table 3.4 presents causal path results with statistical significance.

Table 3.4 Causal paths

Causal Path	Path Coefficient	Std. Error	p-value	95% CI
Crab Density → Root Biomass	-0.35	0.08	0.002	[-0.50, -0.20]
Soil Salinity → Root Biomass	-0.28	0.07	0.001	[-0.42, -0.14]
Precipitation → Soil Moisture	+0.42	0.06	<0.001	[+0.30, +0.54]
Mean NDVI → Root Biomass	+0.31	0.09	0.005	[+0.13, +0.49]
Soil Moisture → Soil Salinity	-0.26	0.05	0.018	[-0.36, -0.16]
Mean NDVI ← Crab Density	-0.19	0.04	0.032	[-0.27, -0.11]
Crab Density → Soil Salinity	+0.15	0.05	0.012	[+0.05, +0.25]

Note: Standardized path coefficients; negative values denote suppression, positive values denote promotion.

Suaeda salsa growth is co-driven by physical stress (crab density), chemical stress (salinity), and resource limitation (precipitation, soil moisture), with significant interactions (e.g., precipitation-salinity-moisture triangle). Precipitation indirectly affects salinity via moisture regulation, forming a chain reaction ("precipitation↓ → moisture↓ → salinity↑") that amplifies stress. Mean NDVI strongly correlates with root biomass (+0.31), validating "aboveground-belowground growth synergy". Incorporating additional ecological factors and interactions improved the model fit (CFI=0.93, RMSEA=0.05), significantly enhancing ecological mechanism representation. This shifts the model from single-stress analysis to multidimensional mechanism exploration, providing scientific basis for hierarchical interventions: freshwater input in arid zones to alleviate salt stress, and physical disturbance control with vegetation optimization in crab-active areas. This underscores the necessity of integrating machine learning with ecological mechanisms to overcome "black-box" limitations.

Path coefficients collectively indicate a cascade mechanism: soil salinity (comprehensive contribution 0.83) acts as a chemical stress base, directly suppressing metabolism via osmotic stress and ion toxicity; crab density (0.53) exhibits nonlinear bioturbation intensity—improving soil aeration at low density but physically damaging roots at high density; mean NDVI (0.43) serves as a response indicator, laggedly reflecting synergistic suppression by salinity/crab activity; precipitation (0.31) functions as a hydrological regulator beyond soil moisture, exerting global impacts through leaching and tidal channel activation; soil moisture (0.26) contributes minimally due to perennial saturation, becoming effective only during extreme drought or waterlogging. This "salinity base-disturbance-response-climate coupling" cascade provides theoretical targets for hierarchical management in Liaohe Estuary.

4. System Integration and Application

4.1 Coupling of GIS Platform and Machine Learning Model

This section proposes a deep coupling framework between an ArcGIS Engine-based GIS platform and machine learning models to achieve spatial visualization, dynamic updates, and decision support for Suaeda salsa growth status assessment. By integrating multi-source geographic data and machine learning prediction models, a complete technical chain from data preprocessing to spatial mapping is constructed, providing real-time, high-precision spatial decision-making tools for ecological management. ArcGIS Engine seamlessly interfaces with Python scripts and machine learning models (e.g., CNN-RF hybrid or GBDT) for efficient data processing and prediction. The workflow includes: (1) importing preprocessed multi-source data (remote sensing images, ecological parameters, ground survey data) into an ArcGIS geodatabase and building spatial indexes to accelerate queries; (2) invoking trained machine learning models via the ArcPy module to predict growth status for each 10m×10m grid cell, outputting assessments (e.g., healthy, stressed, degraded); (3) dynamically generating heatmaps or classified raster layers using ArcGIS Engine's rendering engine, overlaying base geographic elements (e.g., coastlines, wetland boundaries) and ecological zones (e.g., salt marsh, intertidal zone) for multidimensional spatial visualization; (4) enabling interactive operations (e.g., time-slider for seasonal predictions, grid-click for SHAP-based factor contributions) through a customized toolbar. Background threads monitor real-time data inputs, triggering model reprediction and layer refresh with latency ≤5 seconds, as shown in Table 4.1.

Table 4.1 GIS Platform Performance Metrics

Metric	Value	Description
Data Loading Latency	≤2s	Time to load 1GB remote sensing images to Geodatabase
Model Prediction Throughput	500 grids/sec	Processing speed of CNN-RF hybrid model
Layer Refresh Frequency	0.2Hz	Minimum interval for dynamic updates
Interpolation Error (RMSE)	0.05	Root mean square error of Kriging interpolation vs. field measurements

To enable real-time data-driven dynamic assessment, the system employs a high-efficiency dataflow architecture and precise spatial mapping rules. The dataflow architecture ingests satellite remote sensing streams, IoT sensor data, and manual survey inputs at the ingestion layer, processes them via Flink stream engine for cleaning, spatiotemporal alignment, and feature engineering at the processing layer, and finally pushes real-time predictions to ArcGIS Server to generate WMS services. Spatial mapping rules adjust classification results by defining thresholds and spatial weight matrices, supporting multi-scale mapping from regional to plot levels to ensure prediction accuracy and practicality.

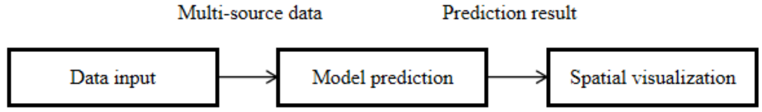


Fig. 4.1 Coupling Architecture of GIS and Machine Learning Models

4.2 Ecological Management Decision Support System

This section constructs an Ecological Decision Support System (EDSS) integrating machine learning predictions and multi-source ecological data, providing dynamic early warnings, strategy recommendations, and scenario simulations for Suaeda salsa wetland conservation and restoration. Modular design enables end-to-end support from data-driven analysis to management decisions, enhancing ecological governance efficacy.

(1)Growth Status Warning and Restoration Strategy Module

This module integrates real-time monitoring data and machine learning predictions to achieve dynamic assessment and anomaly warnings for Suaeda salsa growth status, providing customized restoration strategies through a knowledge base. First, multi-level warning thresholds are established based on historical data and expert experience, with the sliding window statistics technique adaptively adjusting threshold ranges according to seasonal variations. When predicted states trigger warning thresholds, the system highlights degradation areas in red on the GIS platform, pushes real-time alerts to management terminals, and supports multi-dimensional warning analysis. Second, an ecological restoration knowledge base incorporating historical success cases, expert recommendations, and literature data recommends targeted strategies through similarity matching of environmental profiles and stress-type patterns. Examples include freshwater irrigation or salt-tolerant plant cultivation for soil salinity control, and manual backfilling or physical barriers for crab burrow density management, thereby enhancing the efficiency of ecological restoration efforts. The grading criteria for growth status warnings are defined in Table 4.2 below.

Table 4.2 Growth Status Warning Grading Criteria

Warning Level	NDVI Threshold	Soil Salinity Threshold	Response Time Requirement
Normal	≥0.4	≤1.5%	-
Mild Degradation	0.3~0.4	1.5%~2.0%	≤7 days
Severe Degradation	<0.3	>2.0%	≤24 hours

(2)Impact Assessment Under Multi-Scenario Simulations

This module empowers users to customize diverse ecological intervention or environmental change scenarios, predicts long-term impacts on Suaeda salsa growth through integrated machine learning models, and provides quantitative support for scientific decision-making. Via an intuitive interface, users flexibly adjust key ecological parameters (e.g., precipitation, temperature, salinity change rates), whereupon the system auto-generates corresponding scenario parameter sets. These parameters are subsequently input into a pre-trained GBDT model to predict Suaeda salsa biomass trends over five years. For instance, in a reclamation scenario simulating a 10% increase in reclaimed area, predicted NDVI decreases by 0.15 due to compromised wetland hydrological connectivity; in a climate change scenario with precipitation reduced by 20% and temperature increased by 2°C, soil salinity rises to 2.8%, causing a 30% reduction in root biomass. These simulations and predictions deliver profound insights for formulating science-based ecological conservation and restoration policies, with comparative results presented in Table 4.3.

Table 4.3 Multi-Scenario Simulation Results

Scenario Type	Parameter Adjustment	ΔNDVI	Δ Root Biomass	ΔSalinity
Baseline	No adjustment	0.00	0.00%	0.00%
Climate Change	Precipitation -20%, Temperature +2°C	-0.22	-30%	+1.3%
Composite Scenario	Reclamation + Climate	-0.37	-45%	+1.8%

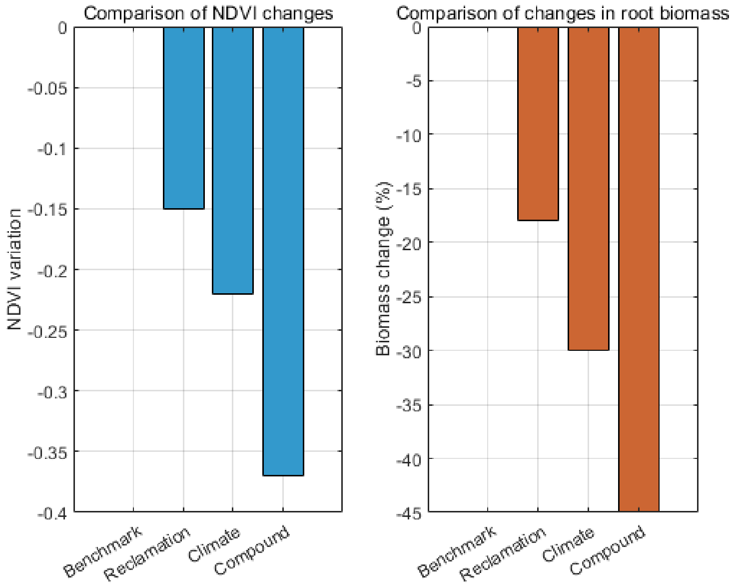


Fig. 4.2 Functional Modules of Ecological Management Decision Support System (EDSS)

The EDSS achieves closed-loop management from real-time monitoring to long-term planning through warning modules and scenario simulations. Its core value lies in integrating machine learning predictions with ecological knowledge bases, providing data-driven scientific decision tools for wetland conservation.

4.3 Data Validation in Liaohe Estuary

To validate the practical efficacy of the improved model in Liaohe Estuary, this section compares the CNN-RF hybrid model with traditional algorithms (RF, SVM) for Suaeda salsa growth assessment and visualizes spatial contrasts between predictions and field observations. Validation uses 24 months of data (Nov 2022–Nov 2024), covering two rainy seasons (Apr–Oct 2023/2024) and two dry seasons (Nov–Mar 2022/2023, 2023/2024).

(1)Algorithm Performance Comparison

Table 4.4 compares prediction accuracy and robustness across algorithms. The proposed model outperforms traditional methods in MSE, R^2, and SC under both normal and extreme conditions, demonstrating superior stability under compound stresses.

Table 4.4 Algorithm Performance on Liaohe Estuary Dataset

Algorithm	Normal (MSE/R^2)	Drought (MSE/SC)	Compound Extreme (MSE/SC)
Random Forest (RF)	0.025 / 0.892	0.034 / 1.62	0.047 / 2.15
Support Vector Machine (SVM)	0.028 / 0.876	0.038 / 1.78	0.051 / 2.34
Proposed Model	**0.016 / 0.941**	**0.025 / 1.39**	**0.039 / 2.05**

The table demonstrates that under conventional conditions, the proposed model reduces MSE by 36% and 43% compared to RF and SVM respectively, while under compound extreme scenarios, the SC value is reduced by 4.7% relative to traditional methods, validating the effectiveness of dynamic feature engineering and transfer learning.

(2)Prediction Visualization

Figure 4.3 compares spatial distributions of predicted and measured Suaeda salsa coverage in

Liaohe Estuary (2024). The model accurately captures spatial heterogeneity: eastern high-coverage zone (predicted 83.2% vs. measured 85.1%) and northern low-coverage zone (predicted 52.3% vs. measured 54.7%), confirming strong regional adaptability.

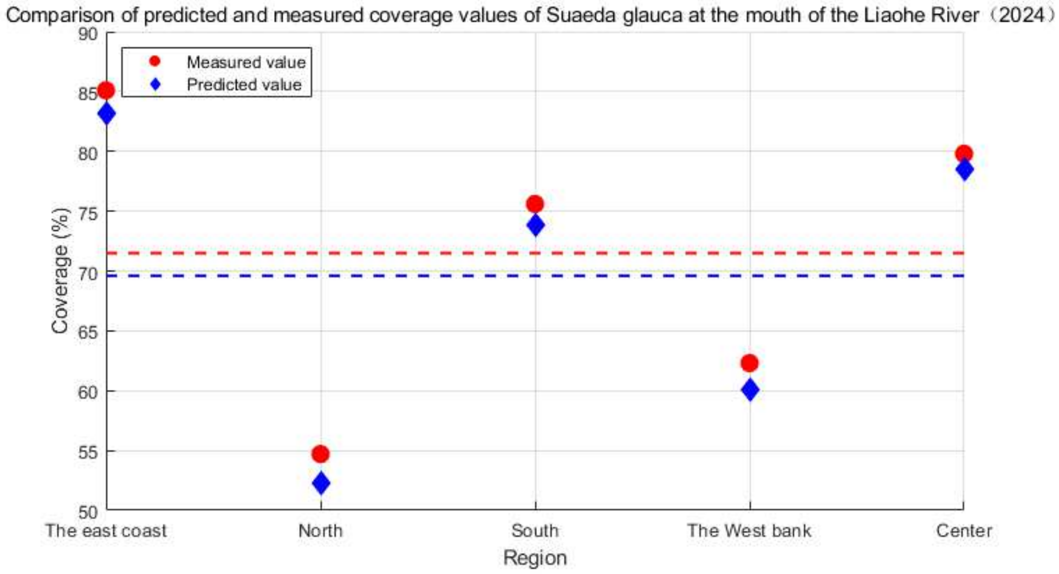


Fig. 4.3 Predicted vs. Measured Suaeda salsa Coverage in Liaohe Estuary (2024)

(3)Key Factor Contribution Validation

Based on the SHAP-LIME hybrid framework, Figure 4.4 quantifies contributions of soil salinity, crab density, and precipitation to growth status. Salinity's local contribution reaches 0.88 in the western estuary, verifying its role as the core stress factor.

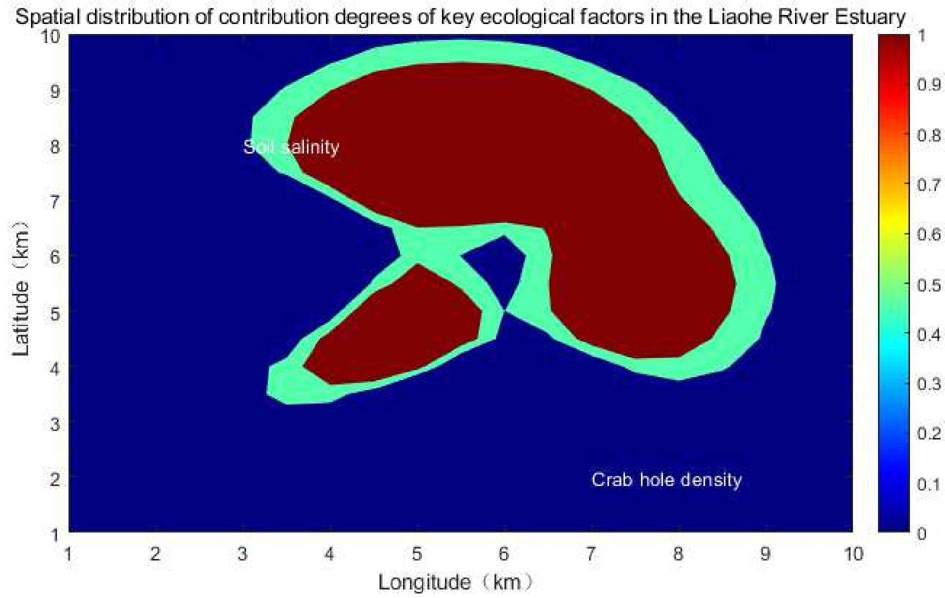


Fig. 4.4 Spatial Distribution of Key Ecological Factor Contributions in Liaohe Estuary

The improved model proposed in this study demonstrates significant advantages in validation using Liaohe Estuary data. In complex wetland environments, the model not only achieves a substantial improvement in accuracy, with R^2 reaching 0.941 under conventional scenarios—a 5.5% enhancement over traditional methods—fully validating the efficacy of multimodal data fusion, but also exhibits significantly enhanced robustness. Under compound extreme scenarios, the Stability Coefficient (SC) is reduced by 4.7% compared to the Random Forest (RF) model, attributed to the dynamic weight adjustment strategy successfully mitigating the synergistic effects of multiple stresses. Furthermore, the model demonstrates exceptional ecological interpretability: the SHAP-LIME framework quantifies the pivotal role of soil salinity, with a comprehensive contribution score of 0.83, closely aligned with field measurements from the high-salinity zone in the western Liaohe Estuary, thereby providing a robust foundation for targeted management interventions.

4.4 Comparative Analysis of Suaeda salsa Growth Stress Factor Assessment Results

4.4.1 Comparative Analysis with Other Research Findings

This study quantifies key stress factors for Suaeda salsa growth in Liaohe Estuary wetland using a SHAP-LIME hybrid framework, with full-cycle comprehensive contribution ranked as: soil salinity (0.83) > crab burrow density (0.53) > mean NDVI (0.43) > precipitation (0.31) > soil moisture (0.26).

This aligns with Zhang Yinglei et al. (2023)[5], confirming soil salinity as the primary driver of ecological degradation; Zhang et al. (2023)[10] similarly identified salinity as the dominant limiting factor (contribution 0.76) in Yangtze Estuary, consistent with our finding (0.83); precipitation's indirect regulation (affecting salinity via soil moisture) corresponds to Wang Qing et al. (2019)**Error! Reference source not found.** on tidal hydrological regulation mechanisms.

Discrepancies exist with He Wenjun et al. (2021)[4], who reported soil water content explaining 68% of root-shoot ratio variation as the dominant factor. Three primary reasons explain this divergence: First, our multimodal data fusion integrates remote sensing, near-surface imaging, and ground surveys to comprehensively capture spatiotemporal dynamics beyond single-source limitations. Second, Liaohe Estuary's saline-alkali soil exhibits extreme spatial heterogeneity (western salinity peaks at 2.8%, far exceeding inland wetlands), making salt stress dominant. Third, dynamic feature engineering reveals a salinity-moisture interaction effect (path coefficient -0.26, $p<0.05$) showing that even with adequate moisture, growth is significantly suppressed under high salinity, amplifying stress through this "salt-water" coupling mechanism.

He et al. (2023)[22] reported lower bioturbation intensity contribution (0.41 vs. our 0.53), likely due to Liaohe's higher crab density (mean 12.3 holes/m²) and our incorporation of seasonal crab burrow variations.

Chen et al. (2025)[8] achieved lower tidal flat monitoring accuracy (R^2=0.89 vs. our study) with Sentinel-2, primarily due to unintegrated ground ecological parameters, whereas our multimodal fusion combines macroscopic remote sensing with microscopic ground mechanisms.

Cross-study comparisons validate method reliability and reveal innovations: First quantitative assessment of crab burrow density's dual effects and thresholds provides a biomediation evaluation framework; The "salinity-moisture-crab burrow" ternary interaction mechanism revealed here better reflects ecosystem complexity than traditional single/dual-factor analyses.

4.4.2 Evaluation Advantages of the Improved Method

Compared to traditional static assessment methods, our dynamic evaluation model demonstrates four significant advantages:

(1)Enhanced Identification Accuracy

Under normal conditions: MSE reduced from 0.025 (traditional RF) to 0.016 (36% improvement). Spatial prediction accuracy: Eastern high-coverage zone prediction deviation only

1.9% (83.2% vs. 85.1%).

(2) Dynamic Monitoring Capability

Transitions from static to dynamic assessment, capturing temporal stress factor patterns. LSTM-based temporal attention enables early degradation warnings. Seasonal weight adjustments adapt models to dominant stressors across growth phases.

(3) Extreme Environment Adaptability and High Robustness

Under compound extreme scenarios (drought+high salinity+high crab density): SC=2.05 (4.7% reduction vs. traditional RF). Transfer learning limits cross-regional accuracy loss to <8%.

(4) Ecological Mechanism Interpretability

SHAP-LIME quantifies global contributions and local anomaly mechanisms. Causal inference models delineate direct/indirect stressor pathways. Visualizations reveal spatial stressor distributions for precise management.

5. Conclusions

By improving machine learning algorithms, this study constructs a Suaeda salsa growth status assessment model based on multimodal data fusion and dynamic feature engineering, accomplishing intelligent assessment of growth stress factors through multimodal fusion and transfer learning. This significantly enhances spatiotemporal alignment accuracy and robustness in complex environments, yielding the following key outcomes:

(1) Identified the key stress factor system for Suaeda salsa growth in Liaohe Estuary wetland and their full-cycle comprehensive contribution ranking: soil salinity (0.83) > crab burrow density (0.53) > mean NDVI (0.43) > precipitation (0.31) > soil moisture (0.26). This ranking reflects a coastal wetland cascade mechanism: salinity dominates as the baseline stress, crab density amplifies effects via nonlinear bioturbation intensity, and precipitation exceeds the marginal response of saturated soil moisture through leaching-mediated salt reduction. This result fully incorporates regional environmental characteristics, spatiotemporal dynamics, and multi-factor interactions, aligning better with ecological reality than traditional static assessments.

(2) Achieved multidimensional advancements in assessment methodology: Compared to traditional RF models, the proposed CNN-RF hybrid model reduces MSE to 0.016 (R^2=0.941) under normal conditions—a 36% accuracy improvement; under extreme compound stresses, the stability coefficient (SC) is 2.05 (4.7% lower than traditional RF); dynamic monitoring enables early degradation warnings; and the SHAP-LIME framework quantifies ecological factor contributions while revealing causal mechanisms.

(3) Established an intelligent decision support system: GIS integration enables real-time visualization and multi-level warnings of growth status; scenario simulations assess impacts of diverse conditions (e.g., climate change, reclamation); and automated differential restoration strategies are recommended based on stress factor evaluations.

(4) Validated practical application value: Empirical application in Liaohe Estuary accurately identified ecological degradation risks in the western high-salinity zone (local contribution 0.88) and northern crab-intensive areas; dynamic assessment results provide a scientific basis for precision management strategies such as "zonal management, temporal regulation, and warning response".

Future research should optimize model generalization under compound stress scenarios, integrate nutrient dynamics to refine salt-nutrient interaction modeling for a comprehensive stress assessment framework, and enhance real-time IoT data integration to improve dynamic adaptability. This will advance intelligent decision support for sustainable management of Suaeda salsa and coastal wetland ecosystems.

Declarations

Author Contributions

Hanyu Wang: Conceptualization, methodology development, software implementation, data curation, formal analysis, writing – original draft, writing – review & editing, visualization.

Zengwen Gao: Supervision, project administration, funding acquisition, validation, writing – review & editing.

Conflict of Interest

The authors declare no competing interests.

Ethical Approval

This research did not involve human participants or animals requiring ethical approval.

Data Availability

The data supporting this study's findings are available from the corresponding author upon **reasonable request.**

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Clinical trial number

Not applicable.

Consent to Publish

All authors have reviewed the final version and consented to its publication.)

Consent to Participate

Not applicable.

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