

Review

Remote Sensing of Coastal Saline-Alkali Land in China: Progress in Identification, Ecological Restoration, and Sustainable Management

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Highlights

What are the main findings?

- Remote sensing methods for coastal saline-alkali land identification have evolved from spectral indices and conventional statistical models to machine learning (e.g., Random Forest and XGBoost/LightGBM) and deep learning approaches (e.g., CNNs, U-Net, and Transformers), substantially improving mapping accuracy. However, model transferability across different coastal regions remains limited because of variations in soil parent material, salt composition, soil moisture, and spatiotemporal vegetation dynamics.
- For ecological restoration and sustainable management, remote sensing has been widely applied to monitor vegetation recovery and landscape connectivity under physical, chemical, and biological restoration measures, while also supporting salinization risk assessment, crop structure optimization, and zone-based management.

What are the implications of the main findings?

- Future research should prioritize the development of physics-informed transfer learning and domain adaptation frameworks, together with open-access remote sensing sample libraries covering different coastal environments, seasons, and land-cover types. These advances will improve the generalization of salinity inversion models and facilitate their operational application across different coastal regions.
- Remote sensing monitoring systems should be more closely integrated with saline-alkali land management platforms. By incorporating artificial intelligence (AI), the Internet of Things (IoT), and digital twin technologies, remote sensing can evolve from passive observation to predictive analysis and from static mapping to dynamic simulation, thereby providing stronger scientific support for the sustainable management of coastal land resources and ecosystems.



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Abstract

Coastal saline-alkali land represents an important reserve land resource and a highly fragile ecosystem in China. Accurate identification, dynamic monitoring, ecological restoration, and sustainable management of these lands have become major research priorities in the field land-resource management, ecological conservation, and environmental governance. Owing to its broad spatial coverage, high temporal resolution, efficient data acquisition, continuous monitoring capability, and non-destructive observation, remote sensing has

become a vital tool for the investigation, monitoring and management of coastal saline-alkali land, providing essential technical support for both scientific research and practical decision-making. This review systematically summarizes recent advances in the application of remote sensing to coastal saline-alkali land in China. First, we examine the development of remote sensing data sources, soil salinity inversion algorithms, and information extraction methods for saline-alkali land identification, with particular emphasis on the contributions of multi-source data fusion, machine learning, and deep learning techniques to improving mapping accuracy and reliability. Second, we review recent applications of remote sensing in ecological restoration, focusing on vegetation recovery monitoring and landscape pattern analysis in restored coastal ecosystems. Third, we summarize the use of remote sensing products in sustainable land management, including regional land-use planning, ecological risk assessment, salinization early warning, and precision management. Finally, we discuss the major challenges that remain, including the limited transferability of salinity inversion models, the insufficient adaptability of remote sensing approaches under complex environmental conditions, and the weak integration of remote sensing technologies with field-scale management practices. Future research should emphasize physics-informed artificial intelligence, multi-source data fusion, and intelligent decision-support systems to enhance the operational application of remote sensing for the sustainable utilization and ecological restoration of coastal saline-alkali land.

Keywords: coastal saline-alkali land; remote sensing; salinity identification; ecological restoration; sustainable management

1. Introduction

Saline-alkali land is a distinct type of land in which the concentration of soluble salts in the surface soil exceeds a critical threshold and soil alkalinity degree is elevated, resulting in degraded physicochemical properties, inhibited crop growth, and impaired ecosystem stability. Despite these constraints, saline-alkali land represents an important global land resource with considerable potential for development and utilization [1,2]. As an important subset of saline-alkali land, coastal saline-alkali land poses substantial environmental and agricultural challenges. It severely restricts agricultural production in coastal regions by reducing crop yields or even causing complete failure, thereby threatening food security [3,4]. In addition, it degrades ecosystem structure and function, reduces biodiversity, and accelerates land degradation and desertification [5,6]. Coastal salinization may also adversely affect groundwater quality, posing potential risks to the drinking water supply of coastal communities [7]. Therefore, effective monitoring, ecological restoration, and sustainable management of coastal saline-alkali land are of strategic importance for ensuring national food security, maintaining ecological integrity, and promoting the sustainable development of coastal regions.

China possesses abundant saline-alkali land resources, covering approximately 3.67×10^5 km² and accounting for about 25.2% of the country's cultivated land resources [8]. These lands have considerable strategic value for enhancing food security, expanding land resource reserves, and maintaining regional ecological balance [8,9]. Coastal saline-alkali land, one of the major types of saline-alkali land in China, is distributed along the eastern coastline in a belt-like pattern. It serves as an important reserve land resource that supports agricultural production, ecological conservation, and wetland protection. Consequently, it plays a vital role in alleviating land-use conflicts in densely populated

coastal regions, strengthening coastal ecological security, and promoting sustainable regional development [10].

With the increasing intensity of land resource utilization and the continued advancement of ecological civilization in China, the development, restoration, protection, and long-term management of coastal saline-alkali land have become major research priorities in the fields of land resources and environmental science [11,12]. Coastal saline-alkali land is characterized by extensive spatial distribution, pronounced spatial heterogeneity, and significant temporal variability. Consequently, large-scale, long-term monitoring, condition assessment, and management planning are essential for its sustainable utilization and conservation. Conventional investigations typically rely on field surveys, fixed-point sampling and laboratory physicochemical analyses. Although these methods provide highly accurate local measurements, they are limited by restricted spatial coverage, labor-intensive data collection, high costs, and long survey circles, making them unsuitable for continuous, large-scale monitoring. These limitations have constrained both scientific research and practical management of coastal saline-alkali land [13,14].

Remote sensing technology has provided new opportunities to overcome these limitations. Its broad spatial coverage, high temporal resolution, efficient data acquisition, continuous monitoring capability, and non-destructive nature make it particularly well suited for large-scale investigations of coastal saline-alkali land. As a result, remote sensing has been widely applied throughout the entire research process, including resource inventory, information extraction, dynamic monitoring, and restoration assessment [15–17]. In recent years, the rapid development of multi-platform and multi-source remote sensing systems, together with continuous advances in image interpretation and quantitative inversion techniques, has greatly expanded the applications of remote sensing in coastal saline-alkali land research and generated substantial scientific and practical achievements.

This review focuses on recent advances in remote sensing applications for China's coastal saline-alkali land. Specifically, it systematically summarizes research progress in three major areas: (1) saline-alkali land identification, (2) ecological restoration monitoring, and (3) sustainable management. By reviewing the technological evolution, major achievements, existing challenges, and future development directions, this paper aims to provide a comprehensive overview of the current state of the field and to offer theoretical and technical references for the efficient utilization, ecological protection, and sustainable management of coastal saline-alkali land resources.

To achieve these objectives, we conducted a systematic literature review of the relevant literature. Publications were primarily retrieved from the Web of Science, Scopus, CNKI, and Google Scholar databases, with the literature search completed in May 2026. The search terms included “coastal saline-alkali land,” “soil salinization,” “remote sensing,” “soil salinity inversion,” “ecological restoration,” “machine learning,” and “deep learning.” To ensure both comprehensiveness and relevance, non-research articles and studies with limited relevance to the topic were excluded during the initial screening process.

The selected literature was subsequently classified according to the principal application areas of remote sensing in coastal saline-alkali land research, including saline-alkali land identification and salinity inversion, ecological restoration monitoring and assessment, and sustainable management. Within each category, the literature was critically analyzed with emphasis on four aspects: (1) the characteristics and advantages of different remote sensing data sources; (2) the development and performance of soil salinity inversion algorithms; (3) remote sensing indicators and evaluation methods for ecological restoration; and (4) the application of remote sensing technologies in land-use planning, ecological risk assessment, and management decision-making. Through a comprehensive synthesis and comparison of these studies, this review identifies the technological development trajectory,

major research achievements, current challenges, and future directions of remote sensing applications for coastal saline-alkali land in China, providing valuable guidance for future research and practical implementation.

2. Distribution and Causes of Coastal Saline-Alkali Land

Coastal saline-alkali land in China is primarily distributed within the land–sea transition zone along the eastern coastline, forming a belt-like pattern whose spatial extent is strongly influenced by coastal geomorphology and topographic conditions [18,19]. According to available statistics, coastal saline-alkali land covers approximately 2.17×10^6 hm², accounting for about 5.9% of the total saline-alkali land area in China [1,9]. Among the various types of saline-alkali land, modern saline soils occupy the largest proportion, representing approximately 45.3% of the national saline-alkali land area. Coastal saline-alkali land, however, is characterized by the greatest spatiotemporal variability and plays a particularly important role in maintaining coastal ecological security [1,20].

Overall, the muddy coastal plains of northern China contain the largest and most continuous areas of coastal saline-alkali land. Extensive saline-alkali soils occur in the low-lying regions surrounding Liaodong Bay, Bohai Bay, Laizhou Bay, and the Yellow River Delta, as well as across the extensive tidal flats along the northern Jiangsu. In contrast, the southern coastal provinces, including Zhejiang and Fujian, are dominated by bedrock-controlled embayed coastlines, where tidal flats are smaller, fragmented, and discontinuously distributed. Consequently, coastal saline-alkali land in these regions generally occurs as isolated patches. Although saline-alkali land is also present in the Pearl River Estuary and the coastal areas of Guangdong, Guangxi, and Hainan, both its spatial extent and degree of salinization are substantially lower than those observed in northern China [20,21].

These regional differences are largely attributable to climatic conditions. Southern coastal regions receive abundant precipitation throughout the year, and frequent rainfall effectively leaches soluble salts from the soil profile through surface runoff and groundwater drainage, thereby alleviating soil salinization [22,23]. In contrast, northern coastal regions experience relatively low precipitation and high evaporation, conditions that inhibit salt leaching and promote salt accumulation within the soil profile [24]. Consequently, soil salinity generally decreases with increasing distance from the coastline, while substantial spatial heterogeneity and pronounced seasonal variations arise from the combined influences of hydrological, climatic, and geomorphological factors (Figure 1) [24].

Natural factors provide the fundamental conditions for the formation and evolution of coastal saline-alkali land, with land–sea interactions and regional environmental conditions jointly controlling soil salt accumulation (Figure 2). Seawater constitutes the primary source of soluble salts in coastal soils. Processes such as tidal inundation, seawater intrusion, and wave action continuously transport salts into both the soil profile and shallow groundwater. Among these processes, tidal dynamics are the dominant drivers of coastal water and salt transport. Periodic tidal fluctuations promoted vertical infiltration and drainage of seawater while simultaneously facilitating the horizontal movement of salts from the coastline toward inland areas. During high tide, seawater transports large quantities of dissolved salts into surface soils and deeper soil layers through infiltration and surface flow. During low tide, although some salts are removed with the receding water, substantial amounts remain in the soil because of intense evaporation, resulting in progressive salt accumulation within the surface soil and shallow groundwater. This tidally driven exchange of water and salts exerts a fundamental influence on both the spatial distribution and temporal dynamics of coastal soil salinity [25,26].

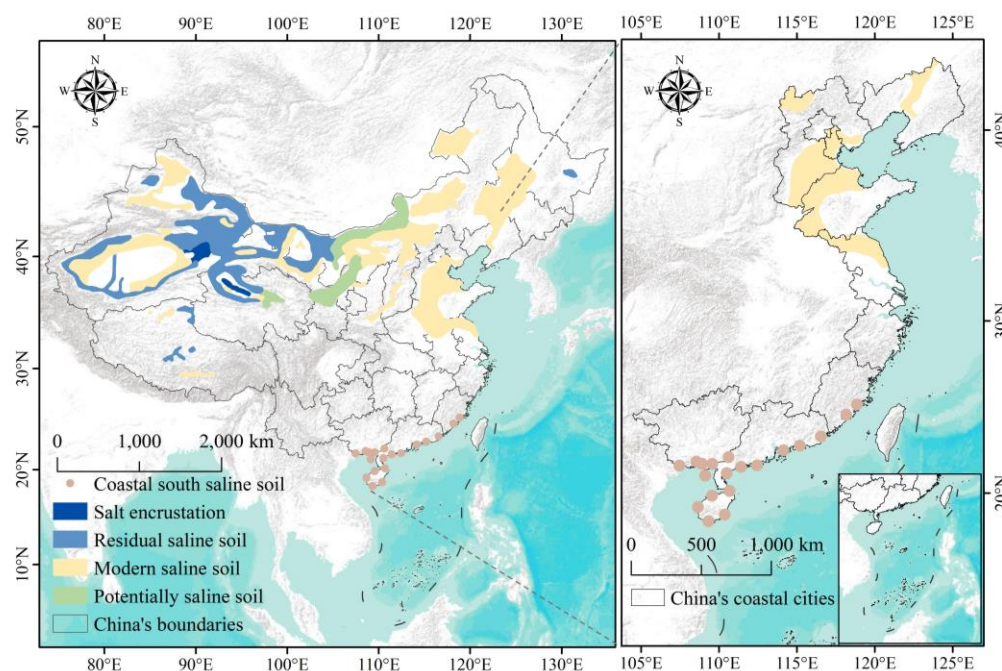


Figure 1. Distribution map of saline-alkali land in China.

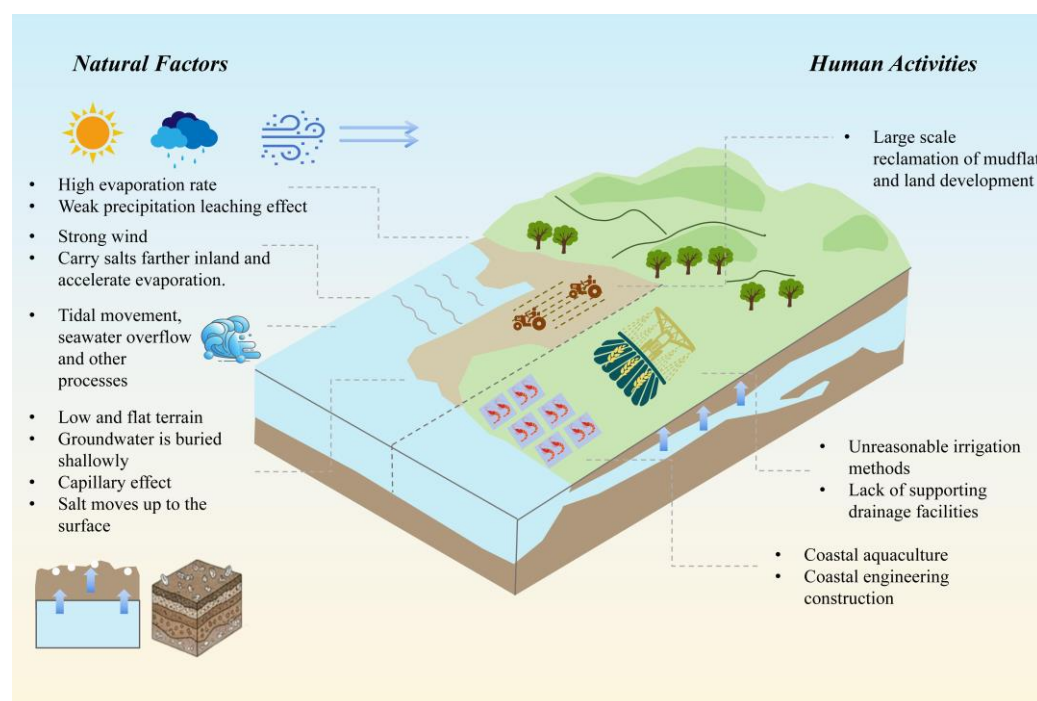


Figure 2. Formation of coastal saline-alkali land.

In addition to tidal processes, coastal regions are typically characterized by low relief, poor surface drainage, and shallow groundwater tables. Under these conditions, capillary rise continuously transports dissolved salts from the groundwater toward the soil surface, further intensifying surface salinization [27,28]. Wind also plays an important role in the development of coastal salinity. Strong winds can increase the inland extent of seawater inundation and intrusion while simultaneously enhancing surface evaporation. Increased evaporation accelerates upward water movement through the soil profile, leaving soluble salts behind as water evaporates and thereby promotes salt accumulation at the soil surface [20,29]. This process is particularly pronounced in northern coastal regions, where

high evaporative demand and relatively weak rainfall leaching create favorable conditions for persistent soil accumulation. Furthermore, coastal sediments deposited in river deltas are generally young, possess relatively high initial salt contents, and often exhibit poor soil structure and limited natural leaching capacity. Together, these characteristics provide the geological and pedological foundation for the long-term development of coastal saline-alkali land [30,31].

Human activities have further accelerated the expansion and intensification of coastal salinization (Figure 2). Large-scale coastal reclamation and land development have disrupted native vegetation and natural hydrological systems, increased surface evaporation, and promoted rapid salt accumulation within the upper soil layers. In agricultural production, inappropriate irrigation practices combined with inadequate drainage systems often raise groundwater levels, leading to secondary salinization. In addition, coastal aquaculture and engineering projects can alter local topography and groundwater flow paths, increasing the likelihood of seawater intrusion and further expanding areas affected by salinization [32,33]. These anthropogenic disturbances have not only intensified salinity in existing saline-alkali lands but also generated extensive areas of secondary salinization, resulting in increasingly complex spatial patterns of soil salinity. Consequently, greater demands have been placed on the accurate identification, quantitative inversion, and dynamic monitoring of coastal saline-alkali land.

In recent years, alongside advances in remote sensing, physically based water–salt transport models have become increasingly important tools for investigating the formation and evolution of coastal saline-alkali land. Models such as HYDRUS and SWAP simulate water flow and solute transport to quantify salt migration and accumulation under different groundwater depths, precipitation regimes, and irrigation practices [34,35]. For example, Qi et al. used HYDRUS-2D to simulate water and salt transport in winter wheat fields established on coastal saline-alkali land and subsequently identified an optimal planting strategy for winter wheat production [36]. More recently, the integration of remote sensing data with physical process models has emerged as a major research direction. By assimilating remotely sensed variables, such as soil moisture and vegetation indices, into process-based models, researchers can dynamically calibrate model parameters and state variables, thereby improving the accuracy of regional-scale simulations of water and salt transport. This integrated approach provides valuable technical support for salinization prediction, ecological restoration, and precision management of coastal saline-alkali land [37].

3. Identification and Salinity Inversion of Coastal Saline-Alkali Land

Coastal saline-alkali land is located within the land–sea transition zone, where the environmental conditions governing remote sensing identification and salinity inversion differ markedly from those of inland saline-alkali land. First, soil salts in coastal areas are dominated by chlorides and sulfates, whereas inland saline soils in northwestern China are primarily sulfate- or chloride-dominated, and those in northeastern China are mainly carbonate (sodic) soils. These differences in salt composition produce distinct spectral absorption characteristics and sensitive wavelength regions. Second, coastal environments are strongly influenced by tidal fluctuations and seawater intrusion, resulting in rapid temporal changes in surface salinity, whereas inland salinity typically changes more gradually in response to seasonal evaporation and precipitation. Consequently, the timing of image acquisition relative to the tidal cycle is a critical consideration for coastal salinity inversion. Third, coastal soils generally have higher and more variable moisture contents than inland arid soils, leading to stronger moisture-induced spectral interference and making pure soil pixels more difficult to identify. Finally, coastal halophytic vegetation

often exhibits high coverage and substantial seasonal phenological variation, resulting in more complex relationships between vegetation and soil salinity than those observed in sparsely vegetated inland environments. Owing to these environmental differences, remote sensing models developed for inland saline-alkali land often perform poorly when directly applied to coastal regions, presenting a major challenge for coastal salinity mapping.

From a methodological perspective, remote sensing approaches for coastal saline-alkali land have evolved from spectral index-based methods to statistical regression models, followed by machine learning, deep learning, and, more recently, multi-source data fusion approaches. Early studies primarily relied on spectral band combinations and empirical regression models, which were computationally efficient and relatively easy to interpret. Subsequently, machine learning algorithms substantially improved the ability to model nonlinear relationships and complex interactions among multiple environmental variables. More recently, the integration of hyperspectral imagery, SAR, UAV observations, ground-based spectroscopy, and cloud computing platforms has shifted salinity inversion from single-image mapping toward multi-source, multi-temporal, multi-scale, and physically informed monitoring frameworks.

3.1. Spectral Index-Based Identification and Salinity Inversion of Coastal Saline-Alkali Land

The physical basis of salinity inversion lies in the spectral responses associated with different salt minerals and their concentrations. Different salt types exhibit distinct diagnostic spectral characteristics. Chloride minerals, such as NaCl, have no prominent diagnostic absorption features in the visible and near-infrared regions, influencing spectral reflectance primarily through indirect effects on soil brightness, surface moisture, and salt crust formation. In contrast, sulfate minerals, including gypsum and mirabilite, exhibit characteristic absorption features associated with water of crystallization and sulfate groups near 1.4, 1.9, and 2.2 μm in the shortwave infrared region, providing more direct indicators of salinity identification [38]. Because coastal saline salts are predominantly chloride-rich, their spectral signatures depend largely on indirect indicators such as soil moisture, surface salt crusts, and vegetation stress, making salinity inversion generally more challenging than in sulfate-dominated inland saline soils. In addition, soil moisture, organic matter, surface roughness, and vegetation cover can alter or obscure the spectral characteristics of salts, which largely explains the reduced accuracy of spectral methods under the moist conditions and dense vegetation cover commonly found in coastal environments [39,40].

Spectral indices remain the most fundamental and widely used approach for identifying coastal saline-alkali land and quantitatively estimating soil salinity. Their underlying principle is to enhance spectral information related to soil salts, vegetation, and moisture through combinations of visible, near-infrared, and shortwave infrared bands while maintaining interference from soil organic matter, surface roughness, and sensor noise [40]. Existing spectral indices can generally be classified into three categories: salinity indices, vegetation indices, and composite indices. Salinity indices directly characterize surface salinity by exploiting the sensitivity of blue, red, and near-infrared bands to salt crusts and bare-soil reflectance [41]. Vegetation indices, such as the NDVI and the EVI, indirectly indicate salinity through their effects on vegetation cover, chlorophyll content, and photosynthetic activity. Composite indices integrate salinity indices with vegetation indices, moisture indices, and land surface temperature to characterize the coupled relationships among soil salinity, moisture, and vegetation conditions.

Numerous studies have applied spectral indices to long-term salinity monitoring using MODIS, Landsat, and similar satellite imagery, demonstrating that medium- and low-resolution remote sensing data are well suited for regional-scale assessments of salinization dynamics [42,43]. For example, Chen Hongyan et al. incorporated shortwave infrared

bands from Landsat 8 OLI imagery into conventional vegetation indices to improve the quantitative inversion of soil salinity in the Yellow River Delta [44]. Similarly, Fan Yanguo, Bian Lingling, and their colleagues investigated the relationships between soil salinity and land surface parameters in the Yellow River Delta using vegetation index–salinity index feature-space methods and composite spectral models [45,46].

In addition to spectral information, environmental covariates have become increasingly important in coastal salinity inversion. Commonly used auxiliary variables include DEMs, slope, distance from the coastline, distance to tidal creeks, groundwater depth, land use and land cover, soil texture, evapotranspiration, precipitation, wind speed, land surface temperature, and vegetation phenological metrics [47,48]. Although these variables do not directly represent soil salinity, they describe the environmental processes governing salt sources, transport pathways, and accumulation patterns. For example, distance from the coastline and tidal creek density are closely associated with seawater-derived salt inputs; DEM and microtopography influence tidal inundation, drainage, and water retention; land surface temperature and evapotranspiration regulate evaporative salt accumulation; and vegetation indices and phenological characteristics reflect ecological responses to salinity stress [49–51]. Incorporating these environmental covariates into salinity inversion models enhances predictive performance while providing greater process-based interpretability than models based solely on spectral information.

The performance of spectral index methods depends strongly on surface conditions. These approaches generally achieve the highest accuracy over bare soil, sparsely vegetated areas, and muddy tidal flats where salt crusts are well developed and readily detectable. In contrast, their performance deteriorates in densely vegetated salt marshes, cultivated farmland, and recently inundated tidal flats, where spectral signals from soil salinity are obscured by vegetation canopies, high soil moisture, and sediment backgrounds. Moreover, the frequent cloud cover and abundant rainfall characteristics of southern coastal regions substantially reduce the availability of cloud-free optical imagery, thereby limiting the temporal continuity and operational applicability of optical remote sensing for long-term salinity monitoring.

3.2. Multi-Source Remote Sensing Data and Multi-Scale Observations

The remote sensing data used for coastal saline-alkali land inversion have evolved from single-source multispectral satellite imagery to a diverse range of data types, including hyperspectral imagery, SAR, UAV observations, ground spectroscopy, and cloud-based geospatial platforms. These data sources differ in their imaging mechanisms, spatiotemporal resolution, coverage, and information content, resulting in varying levels of suitability for coastal environments (Table 1).

Table 1. Comparison of remote sensing data sources for soil salinity inversion in coastal saline-alkali land.

Data Source	Main Advantages	Applicable Coastal Scenarios	Main Interference Factors	Recommended Applications
Medium-resolution multispectral (Landsat, MODIS, etc.)	Long historical record, wide coverage, easy access	Regional-scale salinization trends, long-term dynamic monitoring	Clouds and rain, mixed pixels, vegetation cover	Macroscopic mapping and change analysis
Higher-resolution optical (Sentinel-2, GF-1/2/6, etc.)	Good spatial detail, capable of constructing multiple spectral indices	Farmland, reclamation areas, tidal-flat boundaries, salt patch identification	Clouds and rain, tidal phase differences, vegetation occlusion	Field-scale inversion and land-cover classification

Table 1. Cont.

Data Source	Main Advantages	Applicable Coastal Scenarios	Main Interference Factors	Recommended Applications
Spaceborne hyperspectral (GF-5, EnMAP, PRISMA, etc.)	Continuous bands, capable of identifying spectral differences of salt minerals	Bare-soil salt-affected areas, salt spectral mechanism studies	High-dimensional noise, atmospheric correction, scale mismatches	Salt-sensitive band selection and multispectral calibration
SAR (Sentinel-1, GF-3, etc.)	All-weather, day-and-night capability, sensitive to dielectric properties of wet saline soil	Cloudy/rainy coastal zones, wet tidal flats, salt marshes	Coupling of roughness, moisture content, and vegetation structure	Complementary observations in optically constrained areas and multi-source integration
UAV multispectral/hyperspectral	High spatial resolution, flexible acquisition timing	Experimental fields, engineering sites, early salt stress diagnosis	Limited coverage, scale transformation difficulties	Fine-scale mapping, satellite inversion calibration
Ground spectroscopy and soil samples	Accurate spectral measurement, provides true validation	Standard spectral library construction, physically constrained modeling	High sampling cost, limited spatial representativeness	Model training benchmarks and accuracy validation

Multispectral remote sensing is currently the most widely used data source for coastal saline-alkali land inversion. The Landsat series (30 m spatial resolution) and MODIS (250–1000 m resolution) offer long-term image archives and broad spatial coverage, making them well suited for regional-scale salinization mapping and long-term dynamic monitoring. Sentinel-2 (10–20 m resolution) and China’s Gaofen satellites (e.g., GF-1, GF-2, and GF-6) provide higher spatial resolution, enabling more detailed identification of tidal-flat boundaries, tidal creek networks, and saline patches in agricultural fields. These datasets are therefore particularly suitable for field-scale salinity inversion and engineering-scale monitoring applications [52]. Their optical bands span the visible, near-infrared, and shortwave infrared regions, allowing the construction of salinity, vegetation, and moisture indices. However, optical remote sensing is highly susceptible to cloud cover and precipitation, which substantially reduces data availability in southern coastal areas. Moreover, salinity signals over moist tidal flats immediately after tidal recession and in densely vegetated areas are often obscured by high soil moisture and vegetation cover.

Hyperspectral remote sensing provides hundreds of narrow spectral bands with spectral resolutions typically better than 10 nm, enabling continuous measurement of surface reflectance and the detection of diagnostic absorption features associated with different salt minerals and their concentrations [53]. Consequently, hyperspectral imagery is an important tool for investigating the spectral characteristics of soil salinity and serves as the basis for developing and optimizing multispectral salinity indices [54]. From the perspective of observation platforms, spaceborne hyperspectral sensors such as GF-5, EnMAP, PRISMA, and DESIS have been widely applied to regional salinity mapping and salinization risk assessment [55,56]. UAV-mounted hyperspectral sensors and ground-based spectrometers are more suitable for high-resolution field investigations, where they can be used to establish spectral libraries of saline soils, detect early salt stress in crops, and provide calibration data for satellite-based inversion models [57,58]. Nevertheless, hyperspectral data still face several practical challenges. The large number of spectral bands introduces substantial redundancy, requiring feature selection and dimensionality reduction techniques. In addition, atmospheric correction and scale inconsistencies between satellite and ground observations remain major obstacle scales to their operational application over large areas.

Synthetic Aperture Radar (SAR) offers unique complementary information for coastal saline-alkali land studies. As an active microwave remote sensing technology, SAR operates independently of solar illumination and is largely unaffected by cloud cover or rainfall, enabling all-weather, day-and-night observations. The dielectric properties of

saline soils are significantly influenced by soil moisture, salt concentration, and ionic composition. Consequently, SAR backscatter is sensitive to surface moisture, roughness, and vegetation structure, providing valuable information under wet surface conditions and in regions where optical imagery is frequently unavailable due to persistent cloud cover [59]. Wang et al. used multi-temporal Sentinel-1A SAR imagery to estimate soil salinity in the humid coastal region of Jiangsu Province, demonstrating the practical value of radar data for salinity monitoring in cloudy and rainy environments [60]. Similarly, Hu et al. produced large-scale maps of coastal salt marshes in China using time-series Sentinel-1 data and the GEE platform, showing the strong regional applicability of SAR for coastal wetland monitoring [61]. However, SAR backscatter is simultaneously affected by soil moisture, surface roughness, vegetation structure, and tidal inundation, causing the salinity signal to be strongly coupled with other environmental factors. As a result, SAR alone cannot reliably distinguish soil salinity and is most effective when integrated with multispectral or hyperspectral imagery and environmental covariates within multi-source remote sensing frameworks.

3.3. Identification and Salinity Inversion of Saline-Alkali Land Based on Statistical Models and Machine Learning Methods

3.3.1. Traditional Statistical Regression Models

Early studies, both in China and internationally, primarily employed multiple linear regression (MLR) and partial least squares regression (PLSR) for soil salinity estimation [62–64]. MLR estimates model parameters using the least squares method, offering a simple model structure and high computational efficiency. However, it is highly sensitive to multicollinearity among spectral bands, and the complex interactions among soil moisture, vegetation cover, and salinity in coastal environments often cause the spectral-salinity relationship to deviate from the model's linear assumptions [65,66]. In contrast, PLSR effectively alleviates multicollinearity by extracting latent variables that maximize the covariance between predictor and response variables. Owing to its robustness, PLSR has been widely applied in hyperspectral salinity inversion and remains a commonly used benchmark model for evaluating more advanced approaches [67–70].

PLSR has also demonstrated good adaptability in studies of China's coastal saline-alkali land. For example, Li et al. compared regression models using Sentinel-1, Sentinel-2, and DEM data and found that PLSR achieved the best overall predictive performance [71]. Similarly, An et al. developed a soil salinity estimation model based on stepwise multiple linear regression for Kenli County in the Yellow River Delta. Their model exhibited high stability and good transferability to Landsat imagery [72]. Nevertheless, the predictive capability of these traditional linear models becomes limited when applied to the highly nonlinear relationships that characterize coastal environments. This limitation has driven the widespread adoption of machine learning methods for salinity inversion [48,73].

3.3.2. Machine Learning and Ensemble Learning

Among classical machine learning algorithms, support vector regression (SVR) offers distinct advantages for nonlinear modeling with relatively small-sample sizes. By using kernel functions to project the original feature space into a higher-dimensional space, SVR effectively captures complex nonlinear relationships [74]. Wang et al. developed an SVR model using multi-temporal Sentinel-1A SAR data along the Jiangsu coast, demonstrating the effectiveness of combining SVR with radar imagery for soil salinity estimation under cloudy and rainy coastal conditions [60].

Random forest (RF) is a nonparametric ensemble learning algorithm based on decision trees. It generates multiple decision trees through bootstrap resampling of the training data and random selection of feature subsets, with the final prediction obtained by aggregating

the outputs of individual trees [75]. RF is highly robust to noise and outliers, can automatically evaluate feature importance, and is relatively resistant to overfitting. Consequently, it has become one of the most widely used machine learning methods for coastal soil salinity inversion [58,76–78]. In a study of China's coastal saline-alkali land, Li et al. integrated GF-2 high-resolution imagery with multiple environmental variables, including salinity indices, vegetation characteristics, and tidal creek information, to predict soil salinity in muddy tidal flats using RF and MLR models. Their results showed that RF outperformed MLR, with distance to the coastline and vegetation type identified as the most influential variables [79]. Similarly, Chi et al. developed an improved environmental factor system and applied multivariate quantile regression and PLSR to model seasonal soil salinity in the Yellow River Delta, concluding that salinity inversion was most accurate during the winter bare-soil period [80].

In recent years, advanced ensemble learning algorithms, including Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost), have further improved the accuracy of soil salinity prediction [55,81]. Through gradient-boosting strategies and optimized tree structures, these algorithms exhibit superior performance when handling high-dimensional dataset features and integrating multi-source remote sensing information [81,82]. For example, Zhang et al. incorporated vegetation phenological features derived from multi-temporal Sentinel-1 and Sentinel-2 imagery into a LightGBM model for soil salinity inversion in the Yellow River Delta [81]. The resulting model achieved an R^2 of 0.77, approximately 13% higher than models based solely on single-date spectral features, demonstrating that vegetation phenology can effectively reduce the influence of crop cover on salinity-related spectral signals [81]. Li et al. also applied machine learning approaches to investigate the environmental factors controlling soil salinization, further illustrating the strong potential of machine learning techniques for salinity assessment in coastal environments [83].

3.4. Identification and Salinity Inversion of Saline-Alkali Land Based on Deep Learning Methods

3.4.1. Convolutional Neural Networks and Pixel-Level Salinity Inversion

Traditional machine learning methods for soil salinity estimation primarily rely on single-pixel spectral information and have limited ability to exploit the spatial relationships among neighboring pixels, which restrict their capability performance in fine-scale salinity inversion. In contrast, deep learning algorithms can automatically learn hierarchical spectral and spatial features, providing a new approach for mapping the spatial distribution of soil salinity (Figure 3).

Convolutional neural networks (CNNs) were among the first deep learning architectures applied to soil salinity inversion. Their principal advantage lies in the extraction of joint spectral-spatial features from pixels and their surrounding neighborhoods through convolution kernels. International research studies have demonstrated the effectiveness of CNNs for salinity estimation. For example, Garajeh et al. developed a multi-layer CNN model that integrated multispectral imagery with auxiliary variables, including the NDVI and land surface temperature [84,85]. Their results showed that the CNN consistently achieved high accuracy in mapping the spatial distribution of soil salinity while effectively capturing the long-term expansion of salinized areas in term time-series analysis [84,85].

Research in China began relatively later but has progressed rapidly by incorporating the specific characteristics of coastal environments. In the Yellow River Delta, researchers developed a multi-depth soil salinity prediction framework based on Sentinel-2 imagery and systematically evaluated the contributions of thermal, moisture, salinity, vegetation, and spatial variables to salinity estimation at different soil depths. Cross-validation against backpropagation (BP) neural networks, support vector machines, and random forests

confirmed the feasibility of multi-depth salinity inversion [86]. In the tidal flats of Yancheng, Jiangsu Province, an improved CIWOABP neural network model incorporating chaotic mapping and an adaptive whale optimization algorithm enhanced the model's ability to represent complex nonlinear relationships, resulting in highly accurate soil salinity inversion and fine-scale classification of tidal-flat salinity [87].

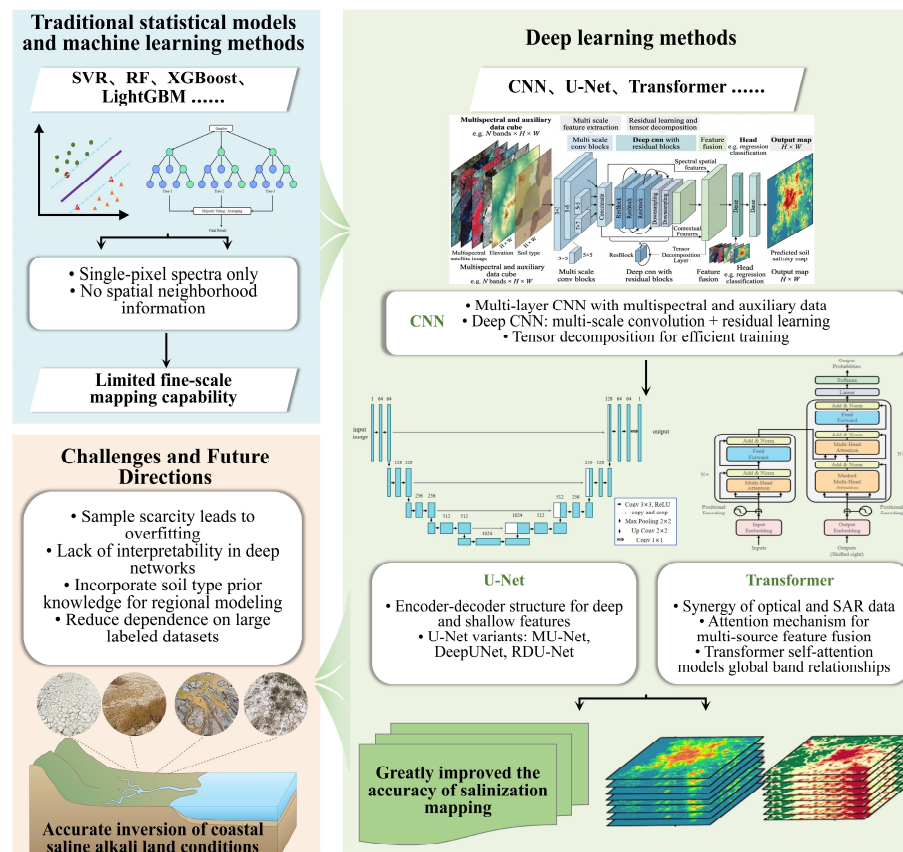


Figure 3. Application of machine learning and deep learning methods in soil salinity inversion.

3.4.2. Semantic Segmentation Models and Transformer-Based Methods

As research has shifted from pixel-level salinity estimation to the delineation of salinized land parcels and patch boundaries, semantic segmentation models based on encoder–decoder architectures have emerged as an important methodological direction. Unlike conventional pixel-wise prediction methods, these models perform end-to-end pixel-level classification across entire images, generating spatially continuous maps of soil salinity. Among them, the U-Net architecture is particularly influential. Through skip connections between the encoder and decoder, U-Net effectively combines high-level features with fine spatial details, making it well suited for identifying salinity boundaries, salt marshes, and transition zones between bare tidal flats and vegetated areas.

International studies have demonstrated the effectiveness of semantic segmentation for salinity mapping. Akca and Gungor applied U-Net to semantic segmentation of salinized land in the Harran Plain, Türkiye, achieving significantly higher classification accuracy than traditional support vector machine methods [88]. El-Rawy et al. proposed the MU-Net architecture, which incorporates residual U-blocks into the original U-Net framework to enhance feature representation and improve long-term salinity monitoring performance [89]. Other variants, such as DeepU-Net and RDU-Net, were developed primarily for pixel-level segmentation of remote sensing imagery and improve the delineation of complex feature boundaries through optimized network structures and computational efficiency.

Their architectural designs also provide valuable references for salinity mapping in coastal environments [90,91].

In China, Xiang et al. developed an MSA-U-Net model based on the fusion of RADARSAT-2 and Landsat-8 optical imagery, significantly improving the classification accuracy of soils with different salinity levels [92]. Although these enhanced network architectures provide useful methodological references, their application to coastal saline-alkali land requires two important modifications. First, the classification scheme must be adapted to coastal environments. Inland studies typically classify saline soils according to salinity severity (e.g., slight, moderate, and severe salinization), where land cover is relatively homogeneous. In contrast, coastal regions contain diverse land-cover types—including bare tidal flats, salt marshes, reed wetlands, aquaculture ponds, and cropland—with considerable spectral overlap, making classification substantially more challenging [93,94]. Second, the input variables should be expanded. While inland studies generally use multi-spectral reflectance and salinity indices as the primary inputs, coastal applications should also incorporate spatial variables related to water and salt transport, such as tidal creek density and distance to the coastline. Direct application of inland classification frameworks without these adjustments often leads to significant reductions in classification accuracy because coastal-specific land-cover types cannot be adequately distinguished [95,96].

At the national scale, Hu et al. used time-series Sentinel-1 SAR imagery to produce high-resolution maps of China's coastal salt marshes using annual composite features and a zonal decision tree classifier [61]. Compared with optical imagery, SAR observations are unaffected by cloud cover and precipitation, making them particularly suitable for monitoring coastal salt marshes in the frequently cloudy and rainy regions of southern China. This advantage is especially important given the predominance of optical remote sensing in current saline-alkali land studies.

Compared with the conventional CNNs, which have limited capability for modeling long-range spectral dependencies, attention-based deep learning methods can capture relationships among spectral bands over broader spatial and spectral ranges. In particular, the self-attention mechanism of transformer architectures provides new opportunities for high-dimensional spectral feature extraction and modeling [97]. Dong et al. developed a multi-scale, multi-branch convolutional neural network for root-zone soil salinity inversion and demonstrated that multi-scale feature extraction substantially improved salinity estimation capability under complex land-surface conditions [98]. Dey et al. proposed the DeepSalt framework, which integrates laboratory and satellite spectral data through domain adaptation and knowledge distillation, thereby improving the capability of large-scale soil salinity estimation [99].

A comparison of the major salinity inversion methods indicates substantial differences in computational requirements, regional transferability, and applicability to coastal environments (Table 2). Spectral index methods are computationally efficient and well suited for rapid salinity identification in bare tidal flats and sparsely vegetated areas. However, their thresholds are highly sensitive to regional differences in surface conditions, resulting in limited transferability. Traditional statistical models, such as MLR and PLSR, have low computational requirements and perform well in relatively homogeneous environments with limited field samples. Nevertheless, they are generally unable to capture the complex nonlinear interactions among soil moisture, salinity, and vegetation that characterize coastal ecosystems.

Table 2. Comparison of major salinity inversion methods for coastal saline-alkali land.

Method Category	Representative Methods	Computational Cost	Cross-Regional Generalizability	Applicable Coastal Scenarios
Spectral indices	SI, NDVI, composite indices	Low	Weak; thresholds require recalibration	Bare tidal flats, low-vegetation areas, rapid identification
Traditional statistical models	MLR, PLSR	Low	Relatively weak	Tidal flats with homogeneous surface and limited field samples
Classical machine learning	SVR, RF	Medium	Moderate; depends on sample representativeness	Multi-source feature fusion, regional-scale mapping
Ensemble learning	XGBoost, LightGBM, CatBoost	Medium-high	Moderate	Multi-temporal and phenological feature-based inversion
Deep learning	CNN, U-Net, Transformer	High; requires GPU and large sample size	Strong when samples are sufficient; prone to overfitting with small samples	High-precision salt patch mapping at parcel scale, large-area complex land surface inversion

Machine learning algorithms, such as RF, can integrate multiple environmental variables—including topography, vegetation, and soil moisture—to achieve substantially higher prediction accuracy than traditional statistical approaches. However, their performance remains highly dependent on the representativeness of the training samples. Gradient boosting models, including XGBoost and LightGBM, further improve prediction accuracy by exploiting phenological information derived from multi-temporal imagery, thereby reducing the masking effects of vegetation and surface water on salinity-related spectral signals, although at the expense of increased computational complexity. Deep learning architectures, including CNNs and U-Net, can simultaneously extract spectral and spatial features, making them particularly suitable for high-resolution salinity mapping when sufficient training data are available. However, these models require considerable computational resources and large annotated datasets and may exhibit reduced generalization capability in small-sample applications.

Overall, no single inversion method is universally applicable across the diverse geomorphological settings of China's coastal regions. Consequently, current research increasingly emphasizes the integration of multi-source remote sensing data with hybrid modeling approaches, enabling the selection of the most appropriate algorithms according to local environmental conditions while balancing computational efficiency and inversion accuracy [95,100,101].

3.5. Model Generalization, Transfer Learning, and Physical Constraints

Current soil salinity inversion models are primarily developed using field samples collected at individual study areas and often experience substantial declines in accuracy when applied to different regions [102,103]. The hydrogeochemical characteristics of China's coastal zones vary considerably between the northern and southern regions. Northern coastal tidal flats typically experience seasonal exposure of bare soil, resulting in relatively distinct spectral signatures of surface salts. In contrast, southern coastal areas are characterized by frequent cloud cover and precipitation, persistent salt marsh vegetation, and regular tidal inundation, all of which maintain high surface moisture and readily obscure salinity-related spectral signals. Consequently, models developed for one region often perform poorly when directly transferred to another, leading to significant prediction errors [95].

The limited transferability of existing models largely stems from their reliance on purely data-driven statistical relationships between spectral features and measured salinity.

Such models do not explicitly account for the physical processes governing salt transport, including seawater intrusion, evaporative salt accumulation, groundwater movement, and tidal flushing. As a result, when environmental conditions such as topography, groundwater depth, or hydrological regimes differ from those of the training area, the learned relationships are no longer valid, reducing model reliability and generalizability [95,104].

Transfer learning offers a promising solution for improving model portability while reducing the effort required to develop models for new study areas. By leveraging well-trained models from source regions, transferable spectral and environmental features can be identified, and only a limited number of local samples are required to fine-tune model parameters for the target region. This approach substantially reduces the need for extensive field sampling, which is often difficult and costly in coastal environments. However, when substantial differences exist in geomorphology, soil parent material, or salt composition between the source and target regions, direct model transfer may still result in considerable performance degradation. In such cases, regional calibration based on hydrological and water–salt transport processes remains essential [105,106].

Another important limitation of purely observation-based models is the lack of physical constraints derived from soil hydrological processes. Without incorporating the mechanisms governing water and salt transport, model predictions may produce unrealistic salinity patterns that are inconsistent with regional hydrological conditions. Previous studies in coastal wetlands have demonstrated that integrating hydrological connectivity, topographic variables, and remote sensing observations can substantially improve both the accuracy and process interpretability of salinity inversion results [95].

Physical constrained modeling addresses this limitation by incorporating hydrogeological variables, such as topographic drainage capacity, groundwater depth, and regional evapotranspiration, into the modeling framework. These variables constrain model predictions through both input features and physically meaningful boundary conditions, thereby reducing unrealistic estimation results and improving model robustness [107]. Coupling remote sensing observations with physically based water–salt transport processes enables large-scale, continuous monitoring while simultaneously providing mechanistic interpretations of the spatial distribution of soil salinity.

At present, most physically constrained salinity inversion models rely on simplified steady-state water–salt balance equations, which cannot adequately represent dynamic coastal processes such as tidal fluctuations, seasonal groundwater variation, and transient salt transport. Future research should focus on integrating remote sensing observations with physically based water–salt transport models that incorporate dynamic boundary conditions. Such approaches are expected to enhance both the mechanistic realism and the cross-regional applicability of soil salinity inversion models for coastal saline-alkali land [108,109].

4. Coastal Saline-Alkali Land Ecological Restoration Engineering and Remote Sensing Monitoring

4.1. Ecological Restoration Measures and Remote Sensing Monitoring

The ecological restoration of coastal saline-alkali land aims to reduce soil salinity, improve soil physicochemical properties, and restore vegetation cover. Restoration strategies generally include three categories of measures: physical, chemical, and biological approaches, as well as various integrated combinations of these methods. In recent years, extensive research has been conducted both in China and internationally to investigate the response mechanisms, spatiotemporal effects, and integrated application of different restoration measures (Table 3, Figure 4). Physical leaching and salt drainage are considered the fundamental approaches for salinity control. Chemical amendments can

rapidly regulate soil salinity and alkalinity, whereas biological restoration promotes long-term and sustainable soil improvement through the establishment of halophytes and beneficial microorganisms.

Table 3. Typical remediation measures and their major outcomes for saline-alkali land.

Category of Measures	Specific Measures	Total	References
Physical/Engineering Improvements	Leaching salt removal	Rapid desalination, reducing surface salt content by 20–30%	[110–112]
	Subsurface drainage	Effective control of groundwater depth and promotion of salt leaching	
	Mulching for salt suppression	Reduce evaporation and salt return, improve root-zone microenvironment	
Chemical Improvements	Biochar	Adjusting pH, improving aggregate structure, enhancing CEC, and promoting soil carbon sequestration	[113–115]
	Desulfurized gypsum + Fly ash	Reduce soil pH and exchangeable sodium percentage (ESP) to promote salt leaching	
	Organic amendments	Regulating microbial community structure, enhancing soil organic matter activity and multifunctionality	
Biological Improvement	Halophyte planting	Absorb salt, increase the proportion of macroaggregates, and promote soil organic carbon (SOC) storage	[116–118]
	PGPR	Enhancing plant salt tolerance through plant hormone regulation, osmotic regulation, and antioxidant defense	
	Biochar + PGPR combination	Collaborative transformation of rhizosphere microbiota to increase maize yield by 52.5%	
Comprehensive Improvement	Subsurface drainage + Organic fertilizer	Salt content decreased from 21.6 g/kg to 0.49 g/kg, resulting in an increase in bacterial and functional diversity	[111,119]
	Regional comprehensive governance	The optimal strategy for coastal humid areas is organic improvement + ecological restoration	

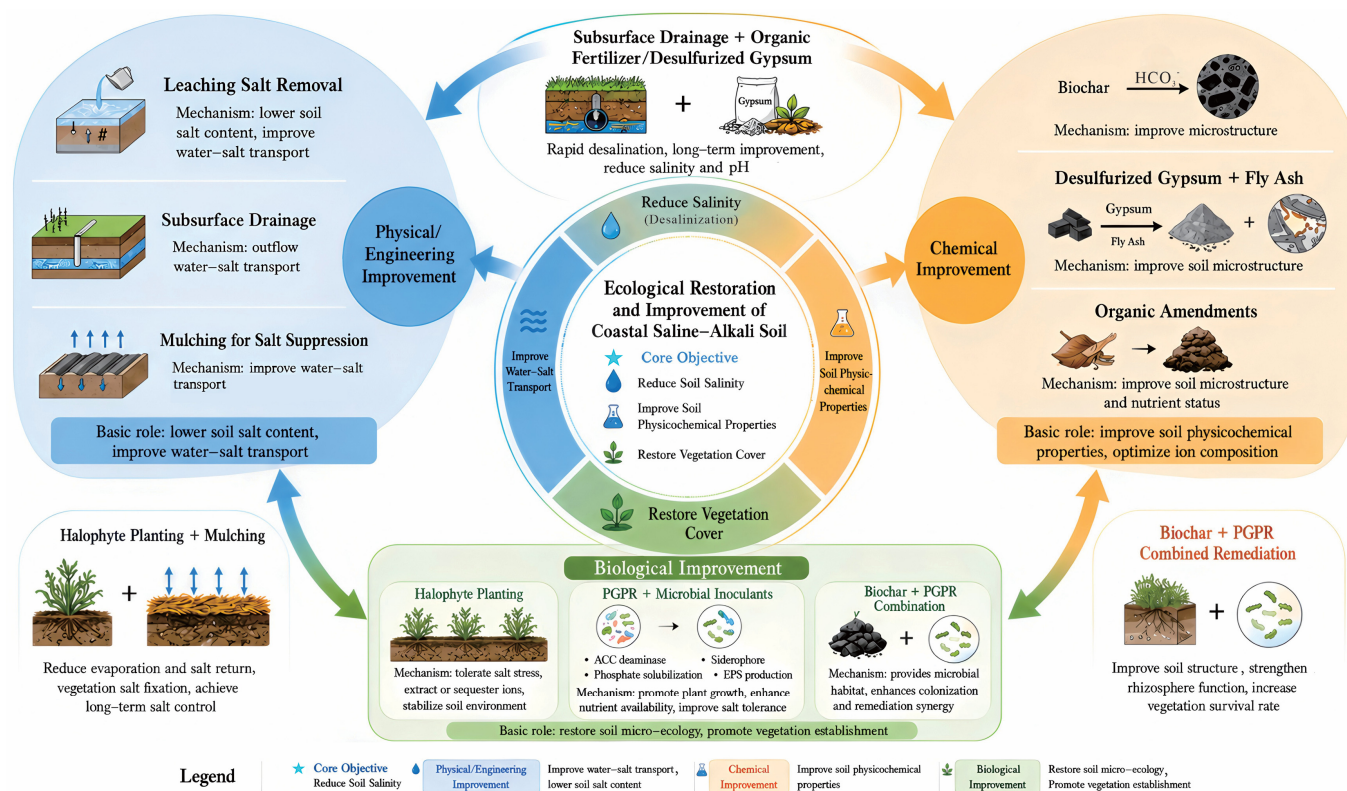


Figure 4. Typical measures for the remediation of saline-alkali land.

4.1.1. Chemical Amelioration Measures and Remote Sensing Monitoring

Chemical amendments, particularly when combined with organic materials, can effectively improve the physicochemical properties and fertility of coastal saline-alkaline soils. Consequently, both their practical applications and underlying mechanisms have attracted considerable research attention. Among the available materials, biochar, organic fertilizers, flue gas desulfurization gypsum, and composite amendments have been the most extensively investigated [120].

Biochar is one of the most important organic amendments because of its multiple beneficial effects on soil properties. In a soybean–wheat rotation system in coastal Shandong, Yu et al. reported that the combined application of biochar and dicyandiamide improved soil aggregate stability, enhanced nitrogen availability, and significantly increased crop yield [121]. Similarly, in coastal saline-alkali soils of Jiangsu Province, Zhang et al. found that the combined application of biochar and fulvic acid significantly increased catalase and alkaline phosphatase activities, improved soil pore structure and ionic conditions, and enhanced overall soil multifunctionality, with synergistic effects exceeding those of individual amendments [122]. Biochar alleviates crop salt stress through several mechanisms, including increasing cation exchange capacity, improving soil structure, and enhancing nutrient retention, and stimulating microbial activity, demonstrating considerable potential for the rehabilitation of coastal saline-alkali land in China [123]. Furthermore, organic amendments promote the development of healthier microbial communities, with increased soil organic matter activity serving as the primary driver of improved microbial health and restoration efficiency [124]. From a remote sensing perspective, the effects of biochar application can be indirectly monitored through changes in land surface temperature, while vegetation indices such as NDVI can be used to evaluate improvements in vegetation growth resulting from biochar application [125].

Because individual amendments often cannot simultaneously satisfy multiple restoration objectives, the combined application of organic and inorganic amendments has received increasing attention [121]. For example, field experiments conducted by Hou et al. in the Bohai Bay region demonstrated that the combined application of flue gas desulfurization gypsum and fly ash reduced soil pH to nearly and decreased the electrical conductivity of the 0–20 cm soil layer by approximately 6.7% [114]. Similar experiments in the Yellow River Delta showed that the combined application of superabsorbent carbon-based material and flue gas desulfurization gypsum significantly enhanced Na^+ leaching. During the rapid desalination stage, Na^+ leaching concentrations increased by approximately 90% compared with the control, resulting in significant reductions in total soluble salt content and soil electrical conductivity [126]. The effectiveness of these chemical amendments can be evaluated using remote sensing by monitoring temporal changes in soil salinity indices, such as the SI and the NDSI.

4.1.2. Bioremediation Measures and Remote Sensing Monitoring

Bioremediation is an environmentally friendly and sustainable approach that has been widely adopted for the ecological restoration of coastal saline-alkali land. Current research primarily focuses on two complementary strategies: halophyte-based remediation and the application of beneficial microorganisms.

Halophytes play a dual role in the restoration of coastal saline-alkali land. They reduce salinity stress by absorbing and immobilizing soil salts while simultaneously providing economic benefits as sources of food, forage, oil crops, biofuel feedstocks, and medicinal materials [127]. In a five-year field experiment along the Yellow Sea coast, Chen et al. demonstrated that planting *Tamarix chinensis* and *Suaeda glauca* enhanced soil organic carbon sequestration by increasing the soil carbon-to-nitrogen ratio and the proportion of

macroaggregates, thereby improving the physicochemical properties of saline soils [116]. Remote sensing has become an important tool for monitoring halophyte restoration. Vegetation indices such as NDVI and EVI can be used to assess vegetation growth, coverage, and biomass, thereby indirectly indicating the improvements in soil salinity conditions [128].

In studies of plant–microbe combined remediation, the synergistic application of plant growth-promoting rhizobacteria (PGPR) and biochar has attracted increasing attention. Field experiments conducted in coastal saline-alkali land in northern China showed that the combined application of nutrient-loaded biochar and PGPR (MNBC treatment) increased maize yield by 52.5%, reduced soil pH by 0.30 units, and significantly increased soil organic matter, total nitrogen, and available phosphorus contents [118]. These benefits arise because PGPR enhance plant salt tolerance through multiple physiological mechanisms, including phytohormone regulation, osmotic adjustment, antioxidant defense, and improved nutrient availability [129].

More recently, bioremediation research has expanded toward integrated and precision remediation technologies. Salt-tolerant microorganisms alleviate salinity stress through extracellular polysaccharide secretion, sodium ion chelation, and phytohormone regulation. These approaches are increasingly being integrated with advanced technologies such as CRISPR-Cas9 gene editing, synthetic biology, multi-omics analysis, microbial volatile compound regulation, nanomaterials, and machine learning, providing promising strategies for precision restoration of saline-alkali soils [130]. Upadhyay et al. further reported that PGPR and beneficial fungi alleviate plant salt stress by regulating osmotic balance, maintaining ion homeostasis, and strengthening antioxidant defense systems, while nanomaterials can improve microbial survival and root colonization efficiency [131]. For example, oxalic acid-modified biochar loaded with salt-tolerant PGPR was applied in pot experiments using coastal saline-alkali soils in eastern China. The results demonstrated that modified biochar served as an effective carrier for functional microorganisms, improving their survival and colonization in the soil. The synergistic interaction between biochar and PGPR promoted wheat growth, increased soil organic matter content, and enriched beneficial bacterial genera such as *Bacillus* [132].

Hyperspectral remote sensing further enhances restoration monitoring by enabling more accurate identification of different halophyte species and facilitating the estimation of physiological and biochemical parameters, including chlorophyll and moisture contents. These indicators provide valuable information for evaluating plant salt tolerance and restoration effectiveness [133]. Likewise, improvements in vegetation growth resulting from the combined application of microbial inoculants and biochar can be indirectly assessed through temporal changes in vegetation indices derived from remote sensing observations [134].

4.1.3. Comprehensive Amelioration

Single amelioration measures often fail to achieve satisfactory results in coastal environments characterized by land–sea interactions and highly dynamic salinity conditions. Consequently, integrated strategies that combine multiple technologies have become the predominant approach for coastal saline-alkali land restoration. Guo et al. systematically evaluated the regional suitability of saline-alkali land remediation technologies across China and classified saline-alkali regions from inland arid areas, the Hetao Irrigation District, and coastal humid regions [119]. They concluded that the combination of organic amendments and ecological restoration is the most effective strategy for coastal humid areas and proposed a region-specific, differentiated management framework. In these regions, leaching-based desalination combined with improvements in soil physicochemi-

cal properties represents the most widely adopted remediation strategy, while biological restoration plays an essential role in maintaining long-term ecosystem functions [119].

The combined application of subsurface drainage and organic amendments has emerged as a representative physical–chemical–biological remediation strategy for coastal saline-alkali land. Field experiments conducted in the Yellow River Delta showed that subsurface drainage combined with biochar application at a rate of 30 t/hm² significantly improved soil physicochemical properties and enhanced both grain quality and yield of sunflower [135]. Furthermore, the combined use of subsurface drainage and organic fertilizer reduced soil salinity from 21.6 g/kg to 0.49 g/kg and increased the bacterial richness index from 6065 to 7257, significantly enhancing both microbial diversity and functional abundance. These findings indicate that integrated remediation not only reduces soil salinity but also restores key ecological functions by promoting beneficial microbial communities. Likewise, the combination of subsurface drainage and biochar has been shown to significantly reduce the electrical conductivity and moisture content of coastal saline soils [136]. At the material level, calcium–iron-modified biochar effectively removes Na⁺, Cl[−], and SO₄^{2−} through ion exchange and coordination mechanisms, reducing soil salinity by more than 50% [137]. Furthermore, diversified cropping systems combined with biochar application, as well as the integrated use of salt-tolerant plants and functional microorganisms, have achieved significant effects in different coastal saline-alkali regions of China. These advances indicate that remediation strategies are evolving from single-treatment approaches toward integrated, high-value, and sustainable land management [138].

Remote sensing plays a key role in monitoring the effectiveness of integrated remediation practices. Soil moisture associated with subsurface drainage systems can be monitored using Synthetic Aperture Radar (SAR) data, while temporal changes in soil salinity can be quantified through remote sensing inversion of salinity indices, such as the Salinity Index (SI), or by estimating soil electrical conductivity (EC) [139,140].

4.2. Vegetation Restoration, Growth, and Ecological Landscape Pattern Evolution

Vegetation restoration is one of the most direct and quantifiable indicators of ecological restoration success in coastal saline-alkali land. Under saline-alkali stress, changes in vegetation cover, growth vigor, biomass accumulation, and seasonal phenology collectively reflect improvements in soil conditions and the gradual recovery of ecosystem functions. At a broader scale, the spatial configuration of vegetation communities and the evolution of ecological landscape patterns determine ecosystem integrity, connectivity, and long-term stability. Owing to its capability for multi-scale, multi-temporal, and large-area observations, remote sensing has become an indispensable tool for monitoring vegetation dynamics and evaluating ecological landscape evolution. Representative studies are summarized in Table 4 [141,142].

Table 4. Remote sensing monitoring dimensions and techniques for vegetation and ecological landscape in coastal saline-alkali land.

Monitoring Dimensions	Main Data and Methods	Related Research Results	References
Spectral characteristics of vegetation	NDVI/EVI/LAI	NDVI monitoring of vegetation succession in the reclamation area of Hengsha Island; EVI analysis of phenological dynamics of salt marshes along the coast of Jiangsu Province; LAI estimation of salt marsh carbon storage in the Yellow River Delta.	[143–145]

Table 4. Cont.

Monitoring Dimensions	Main Data and Methods	Related Research Results	References
Time-series dynamics	Long time-series analysis of Landsat/Sentinel-2	Revealing the stress of the Yangtze River estuary reclamation and the invasion of <i>Spartina alterniflora</i> on native salt marshes (three evolutionary patterns); Tracking vegetation response before and after the removal project of <i>Spartina alterniflora</i> in the Yellow River Delta.	[146–148]
Machine learning and phenological classification	Machine learning	Classification of halophytes along the coast of Jiangsu Province based on phenological parameters; Subpixel coverage inversion of salt marsh vegetation in the Yellow River Delta; Analyzing the coupling mechanism between soil salinity and vegetation growth.	[149–151]
Landscape pattern evolution	Landscape index, high-resolution images	Assess the fragmentation and connectivity of coastal wetland vegetation in the Yellow River Delta; Quantitative restoration effectiveness of ecological integrity index.	[152–154]

4.2.1. Dynamic Monitoring of Coastal Halophytic Vegetation Based on Vegetation Indices

Saline-alkali causes significant physiological changes in coastal halophytic vegetation, which are reflected in its spectral characteristics. Under salt stress, chlorophyll synthesis is inhibited, chlorophyll content decreases, cellular structures are damaged, and water deficits develop. These physiological changes increase spectral reflectance in the visible region while reducing reflectance in the near-infrared region, thereby providing a spectral basis for remote sensing monitoring of vegetation stress [147].

Vegetation growth parameters derived from remote sensing are fundamental indicators for evaluating the condition of coastal halophytic vegetation. The Normalized Difference Vegetation Index (NDVI) is widely used not only in soil salinity inversion when combined with salinity indices but also for assessing vegetation greenness, photosynthetic activity, vegetation cover, and overall health. It has been extensively applied to monitor typical coastal halophytes, including *Suaeda glauca* and *Phragmites australis* [144]. Time-series studies conducted coastally in the Hengsha Island reclamation area of the Yangtze River Estuary showed that NDVI increased steadily from 0.12 ± 0.05 to 0.35 ± 0.09 as reclamation age increased from 3 to 15 years. These results demonstrate that remote sensing indices can effectively characterize the natural recovery of coastal halophytic vegetation as soil conditions gradually improve [143].

To overcome the saturation effects of NDVI in dense vegetation, the Enhanced Vegetation Index (EVI) incorporates the blue spectral band, thereby improving the monitoring of high-biomass coastal vegetation. Studies in the Yellow River Delta have shown that phenological features derived from Sentinel-2 time-series EVI data can accurately distinguish six dominant halophytic species, including *Phragmites australis*, *Suaeda glauca*, and *Tamarix chinensis*, improving classification accuracy by 5.1% compared with single-data imagery [149]. In addition, the Leaf Area Index (LAI), an important indicator of canopy structure, has been widely used to estimate biomass accumulation and ecosystem carbon sequestration. Using Sentinel-2 imagery, researchers in the Yellow River Delta National Nature Reserve successfully retrieved LAI to monitor interannual changes in salt marsh carbon storage from 2017 to 2022. Their results revealed that carbon storage initially increased and then decreased following the control of *Spartina alterniflora*, highlighting the ecological consequences of vegetation management control [145].

In China's coastal saline-alkali land restoration programs, remote sensing is used not only to monitor the natural recovery of vegetation but also to evaluate the effectiveness of active restoration measures, including the establishment of salt-tolerant plant species. Continuous monitoring of vegetation spectral indices enables the assessment of plant growth dynamics and physiological responses to salinity stress, thereby providing an objective basis for evaluating restoration performance and optimizing future management strategies.

4.2.2. Coastal Halophytic Vegetation Information Extraction Based on Multi-Source Remote Sensing Data

Single-temporal remote sensing data are mostly used for static mapping of the spatial distribution of coastal halophytic vegetation but cannot fully capture long-term vegetation dynamics. In contrast, multi-temporal analysis based on long time-series remote sensing datasets enable the extraction of vegetation change information across continuous spatiotemporal dimensions, providing a comprehensive depiction of the restoration process and development trends of coastal halophytic vegetation [155,156].

For typical coastal salt marsh wetlands, numerous studies have applied multi-source time-series remote sensing data to extract information on halophytic vegetation. In a study of native salt marsh vegetation in the Yangtze River Estuary, Ai et al. integrated multi-source remote sensing data collected between 1985 and 2020 [146]. Using image compositing, zone-based stratified classification, and object-based phenological algorithms, they generated interannual vegetation coverage maps and clarified the combined effects of land reclamation and *Spartina alterniflora* invasion on *Phragmites australis* and *Scirpus mariqueter* communities, thereby overcoming the limitations of previous studies in detecting both gradual and abrupt vegetation changes [146]. In the Yellow River Delta, Wang et al. combined object-based and pixel-based approaches to analyze Landsat imagery acquired from 2013 to 2023, comprehensively documenting changes in vegetation communities before and after the *Spartina alterniflora* eradication program [147].

The integration of multi-source remote sensing data with advanced analytical algorithms can further improve the extraction of halophytic vegetation information. Li et al. combined Zhuhai-1 hyperspectral satellite imagery, acquired between 2019 and 2023, with a U-Net model and the Relief-F feature selection algorithm to map the dynamic distribution of *Spartina alterniflora* throughout its invasion and subsequent removal [144]. Similarly, Chen et al. used Sentinel-2 imagery to quantify annual changes in the carbon storage of salt marsh vegetation in the Yellow River Delta between 2017 and 2022 [145]. Furthermore, Landsat and Sentinel imagery processed on the Google Earth Engine cloud platform enables efficient batch processing and long-term trajectory analysis. Yi et al. integrated multi-source remote sensing imagery acquired from 2000 to 2020 with phenological features and the random forest algorithm to classify and monitor the long-term dynamics of coastal salt marsh vegetation in Yancheng [148].

4.2.3. Remote Sensing Analysis of Ecological Landscape Pattern Evolution in Coastal Saline-Alkali Land

In recent years, ecological restoration projects and land improvement measures have substantially altered the landscape patterns of coastal saline-alkali land. Most studies employ high-resolution remote sensing imagery combined with advanced image analysis algorithms to identify key landscape elements, such as ecological corridors and restoration patches, and to quantify changes in spatial structure using landscape metrics. Commonly used indicators include patch density (PD) and edge density (ED) to characterize landscape fragmentation, as well as the integral index of connectivity (IIC) and probability of connectivity (PC) to evaluate functional landscape connectivity [157–160].

These methods have been widely applied to assess restoration effectiveness in coastal saline-alkali regions. Yu et al. evaluated the effectiveness of biodiversity offsets in China's coastal wetlands from a landscape connectivity perspective, highlighting that offset strategies should be systematically assessed with connectivity metrics to avoid underestimating ecological losses [161]. Bi et al. further integrated graph theory and circuit theory to identify 515.36 km² of natural wetlands for priority conservation, 430 km² of reclaimed wetlands for priority restoration, and 674.4 km² of potential ecological corridors [162]. In the coastal wetlands of Yancheng, Zang et al. analyzed remote sensing imagery acquired from 1987 and 2013 and found that patch density was significantly positively correlated with the human disturbance index, indicating that anthropogenic activities intensified vegetation fragmentation [163]. In the Liaohe estuary, Zhang et al. applied an improved remote sensing ecological index and reported an average ecological quality improvement of 23% over a ten-year monitoring period [164]. For the coastal region encompassing Beijing and Tianjin, Zhang et al. analyzed the spatial distribution and driving factors of important wetland patches, identifying soil type and temperature as the principal environmental controls, while population density, GDP, and aquaculture activities were the dominant anthropogenic drivers. Overall, human activities exerted a significantly greater influence on landscape patterns than environmental factors [165].

The increasing availability of long-term remote sensing datasets and the powerful processing capabilities of the Google Earth Engine cloud have greatly enhanced the capacity to monitor the evolution of coastal landscape patterns. Collectively, these studies demonstrate that landscape dynamics in coastal saline-alkali land are driven by the combined effects of ecological restoration projects, invasive species, and human activities, highlighting the importance of systematic monitoring and assessment using multi-source remote sensing data and landscape metrics.

5. Sustainable Management Based on Remote Sensing Technology

5.1. Regional Land Planning and Resource Optimization Allocation Based on Remote Sensing Data

Remote sensing technology enables the rapid acquisition of spatial information on soil salinity, land suitability, and long-term environmental dynamics, providing a scientific basis for optimizing the allocation of agricultural, forestry, pastoral, aquaculture, and ecological land uses in coastal saline-alkali regions [166,167]. Based on an analysis of multi-source remote sensing data from the Yellow River Delta over the past decade, Zhang Shengnan demonstrated a strong interaction between the spatiotemporal evolution of soil salinization and changes in cropping terms. The study further concluded that single-source monitoring is insufficient to capture these complex dynamics, highlighting the necessity of multi-source remote sensing data fusion for land-use planning [168].

At the regional scale, China has adopted a zonal and classification-based management strategy that considers the cause of salinization, salt types, water resource availability, and ecological functions in different regions [169]. Coastal saline-alkali land is strongly influenced by seawater inundation, tidal processes, and shallow groundwater, resulting in high soil salinity and predominantly clay rich soils. In these areas, remote sensing data play an essential role in delineating priority development zones, ecological conservation areas, and ecological buffer zones, thereby minimizing excessive land reclamation and intensive land modification [170]. In contrast, the inland saline-alkali regions of northwestern China are characterized by extensive land areas, high evaporation rates, and limited water resources. There, remote sensing is primarily used to guide water-saving irrigation, salinity control, and groundwater management to reduce ecological degradation associated with caused groundwater overexploitation [171]. Xiao Xinyi and colleagues summarized the principal technical approaches for managing saline-alkali land in northwestern China,

including grass-crop rotation, cultivation of salt-tolerant crops, water-saving irrigation, and improved drainage systems. They emphasized that management strategies should be region-specific and integrated, with remote sensing serving as a fundamental source of spatial information for decision-making [172].

For the soda saline-alkali soils of northeastern China and the secondary salinized land of the Huang–Huai–Hai Plain, remote sensing-based assessments have been widely applied to support the rehabilitation of medium- and low-yield farmland and improve cultivated land quality [173]. The successful application of remote sensing in these land saline-alkali regions has also provided valuable experience for the management of coastal saline-alkali land. For example, in the Yellow River Delta, remote sensing has supported the planning of coastal grassland belts and the development of salt-tolerant forage industries by providing spatial information that helps alleviate competition between forage and grain production while expanding diversified food production systems [174].

5.2. Dynamic Salinization Risk Assessment and Sustainable Management

Developing remote sensing-based early warning systems for salinization is a critical step in shifting management strategies from passive monitoring to proactive prediction and intervention. Such systems typically incorporate indicators including the rate of salt accumulation, trends in vegetation degradation, and coastal erosion intensity. To improve early warning capability, remote sensing observations should be integrated with meteorological and hydrological data to establish multi-level warning thresholds capable of predicting rapid salinity increases and ecosystem degradation [175,176]. For example, Wang Jundong et al. used reflected signals from the CYGNSS satellite constellation to estimate soil salinity and analyze salt accumulation in the Yellow River Delta [177].

Sustainable management requires differentiated control strategies that account for the degree of salinization, the stage of ecological restoration, and regional management objectives. Remote sensing-based classification and assessment provide the foundation for implementing comprehensive, whole-process salinity monitoring and adaptive management [178]. Mei Xurong et al. emphasized that smart monitoring systems should integrate remote sensing data into management decision-making in real time, thereby shortening the interval between problem detection and management intervention [179]. Similarly, Zuo Qiang et al. in their study of coastal saline-alkali land in the Yellow River Delta, concluded that the sustainable utilization of these lands is constrained by both soil and water resources [180]. They highlighted the importance of continuous remote sensing monitoring to evaluate restoration effectiveness and to support timely adjustments in irrigation and drainage practices, cropping patterns, and other land management strategies [180].

6. Challenges and Prospects

Although remote sensing technology has made significant progress in the identification, ecological restoration monitoring, and sustainable management of coastal saline-alkali land in China, several key challenges remain before it can fully meet the requirements of operational applications.

(1) From a methodological perspective, the limited generalizability and transferability of salinity inversion models remain the most significant challenges. As discussed above, traditional statistical models as well as machine learning and deep learning methods often achieve high inversion accuracy within specific study areas. However, their performance frequently declines when applied to other coastal regions. This limitation primarily arises from substantial regional differences in soil parent material, salt composition, climatic conditions, and hydrological processes, all of which alter the spectral characteristics of saline soils. Coastal saline-alkali land along the muddy coasts of northern China differs

markedly from that along the bedrock-embayed coasts of southern China, not only in salt composition and concentration but also in soil moisture dynamics, organic matter content, and surface roughness. Consequently, models trained in one region often fail to capture the spectral-salinity relationships in another. Furthermore, large temporal fluctuations in soil moisture can obscure or modify the spectral response of salinity, while seasonal variations in vegetation cover make it difficult to obtain representative bare-soil pixels. Most existing models rely on locally collected field samples and lack standardized multi-regional, multi-season training datasets and systematic calibration strategies, thereby fundamentally limiting their cross-regional applicability.

(2) From the perspective of monitoring methodology, remote sensing techniques still face considerable challenges in complex and heterogeneous coastal environments. Coastal saline-alkali land comprises a mosaic of land-cover types, including bare tidal flats, salt marshes, reed wetlands, and agricultural land, each exhibiting distinct spectral characteristics influenced by salinity, soil moisture, vegetation cover, and tidal inundation. Most existing methods are designed for specific environmental conditions and therefore have limited adaptability across diverse coastal landscapes. For example, spectral-salinity indices that perform well over bare soil often lose accuracy when vegetation is present. Similarly, optical remote sensing is frequently constrained by persistent cloud cover and precipitation in southern coastal regions. Although SAR can overcome these limitations by providing all-weather base observations, SAR backscatter is also strongly influenced by surface roughness, vegetation structure, and soil moisture, making it difficult to isolate the salinity signal. Furthermore, periodic tidal inundation causes rapid changes in surface conditions over short time scales, while most remote sensing analyses rely on single-date imagery or annual composites that cannot adequately capture these high-frequency dynamics. Although multi-source data fusion has been widely recognized as an effective strategy for improving monitoring performance, substantial challenges remain due to differences in the spatial resolution, temporal resolution, and spectral characteristics of optical, SAR, and hyperspectral datasets.

(3) Despite significant methodological advances, most remote sensing studies remain focused on technical validation or scientific analysis rather than operational land management. Their outputs are typically limited to salinity maps or retrospective assessments and are rarely integrated into the decision-making processes associated with saline-alkali land management. Key questions—including how remote sensing products can be translated into practical management recommendations, integrated with irrigation scheduling or ecological restoration programs, and delivered at temporal frequencies appropriate for management decisions—have yet to be systematically addressed. Although many studies generate highly accurate salinity distribution maps, land managers often lack the technical expertise required to interpret these products, while researchers rarely design monitoring frameworks based on management needs. Moreover, the economic feasibility of operational remote sensing should not be overlooked. High-frequency, high-resolution remote sensing data remain relatively expensive to acquire and process, and developing cost-effective monitoring systems without compromising accuracy remains an important research priority.

Looking forward, future research on remote sensing applications for coastal saline-alkali land should focus on overcoming these challenges through coordinated advances in both methodology and practical implementation. Improving model generalizability will require the development of physics-informed transfer learning and domain adaptation frameworks. By incorporating prior knowledge and physically based constraints, these approaches can improve predictive performance in regions where field observations are limited, thereby reducing the accuracy loss associated with regional differences. Equally

important is the establishment of open-access remote sensing sample libraries that integrate field measurements and remotely sensed data from diverse coastal environments, seasons, and land-cover types. Such databases would provide standardized benchmarks for model development, validation and cross-regional comparison.

To enhance methodological adaptability, greater emphasis should be placed on multi-source data fusion and multi-scale observation strategies. No single remote sensing platform can simultaneously provide the temporal frequency, spatial resolution, and spectral information required for accurate salinity monitoring. Consequently, integrated observation systems combining satellite, UAV, and ground-based sensors are expected to become an important direction for future research, enabling seamless monitoring from regional to field scales. In particular, UAV-based hyperspectral imagery and ground-based spectroscopic measurements can provide high-quality reference data for satellite calibration and support reliable scale transformation in salinity inversion.

Finally, future efforts should strengthen the integration of remote sensing technologies with operational management systems. Remote sensing monitoring platforms should be closely linked with saline-alkali land management information systems, and decision-oriented visualization products should be developed to support land-use planning, project evaluation, and salinization risk assessment. In the longer term, the integration of remote sensing with emerging technologies—including artificial intelligence, the Internet of Things, and digital twin systems—is expected to transform coastal saline-alkali land management from passive observation to predictive decision support and from static mapping to dynamic simulation. Such developments will provide a more stringer scientific and technological foundation for the sustainable utilization of land resources and the protection of coastal ecosystems.

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