

Review

A Review of Tidal-Flat Remote Sensing Methods and Applications 2000–2025

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Abstract

Tidal-flats buffer coasts support biodiversity and are changing rapidly, yet reported global declines contrast with local expansions, leaving managers uncertain about the direction and drivers of change. Here we investigate this tension by systematically reviewing how monitoring by remote sensing has been used to observe, extract, validate, and interpret tidal-flat dynamics. We considered the literature from January 2000 to March 2025 and screened 951 records related to 339 research articles, classifying 63% (215/339) predominantly focused on tidal-flat extraction and area change, while 37% (124/339) emphasized the analysis of driving factors. Publications surged after 2019, and three tidal-flat extraction families dominate practice: waterline methods (most widely applied), image classification, and composite/optical–Synthetic Aperture Radar (SAR) fusion. Across studies, the prevailing trend is net decline in tidal-flat extent, attributed to reduced riverine sediment supply, sea level rise, and reclamation; however, robust local counter-examples exist (e.g., ~18% expansion in Germany’s Wadden Sea, 1998–2016), underscoring strong spatial heterogeneity. Although ~31% of global tidal-flats fall within protected areas, effectiveness is uneven under sustained human pressure. We synthesize common failure modes (tide/scale mismatch, validation gaps) and outline standards for multimodal data fusion and benchmarking. This review synthesizes current knowledge on tidal-flat remote sensing methods, identifies key methodological challenges, and outlines priorities for future research to support reliable monitoring.

Keywords: tidal-flats; remote sensing; intertidal; waterline; image segmentation; image classification



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1. Introduction

Tidal-flats are critical interfaces of land–sea interaction, primarily unvegetated bare flats located within the intertidal zone (between the highest and lowest tide lines), including intertidal mudflats, rocks, and sand [1,2]. Tidal-flats possess unique ecological value and resource potential, serving important functions including biodiversity conservation, coastal protection, and salt production [3,4]. About 50% of the world’s population lives within 200 km of the coast, making tidal-flats one of the most heavily impacted coastal ecosystems

by human activities [5]. With climate change and rising sea levels, global tidal-flats are disappearing at 1.4% annually, losing over 28,000 km² in 40 years [1]. This has occurred in tandem with coastal erosion, mangrove decline, leading to international concern [6,7].

In the 20th century, preliminary research on coastal wetlands included tidal-flats as a component [8]. After the 1960s, tidal-flat research evolved from exploring physicochemical properties like sedimentation and organic matter distribution [9,10] to deeper studies of tidal-flat ecological impacts and human influence on tidal-flat organisms [11]. However, research on monitoring and protection of tidal-flats received little attention for a long time. Since the 21st century, climate change, aquaculture, and coastal development have drastically reduced tidal-flats, threatening biodiversity and human safety [7]. However, due to complex coastal environments, storms, and tidal inundation, tidal-flats undergo dynamic frequent changes that make extraction difficult [12]. Thus, early tidal-flat conservation research remained limited in scope and scale [2,13,14].

Rapid developments in remote sensing, management and seamless processing of big data, using such as Google Earth Engine (GEE), has enabled dynamic monitoring of tidal-flats [1,15]. For example, Wu et al. (2022) used Landsat images, tidal inundation frequency and time-series indices to dynamically map changes to Fujian's coastal wetlands from 1994 to 2018 [16]. Lee et al. (2011) used Radarsat-1 SAR backscattering to overcome cloud cover limitations in monitoring changes in tidal-flats on the west coast of Korea [17]. These innovative advances have enabled tidal-flats extraction from multi-source data fusion for dynamic monitoring.

Current challenges include fragmented methodologies, unclear scale effects, and insufficient analysis of cause–effect driving forces [18–20]. Existing methods primarily comprise a variety of shoreline-based classifications methods that lack systematic methodological comparison [21,22]. Global studies mostly rely on single data sources, resulting in limited accuracy in characterizing microtopographic features of the intertidal zone [1]. Further, driving forces and impact mechanisms from natural factors and human activities have not been fully elucidated [23,24]. These knowledge gaps constrain the scientific basis for integrating tidal-flat monitoring within coastal zone management.

Here, we conduct a literature review by integrating 339 publications from the Web of Science Core Collection together with relevant references from other fields. Our review focuses on the three main aims: tidal-flats extraction methods; assessing changes across space–time from remote-sensing monitoring; and exploring the drivers of change. Thus, the analytical framework integrates across the three dimensions of methodological developments, spatiotemporal dynamics, and driving mechanisms. The specific objectives are (1) to elucidate the different methods for tidal-flat delineation, (2) to uncover the spatial–temporal variability of tidal-flat changes at global and local scales, and (3) to evaluate the natural and anthropogenic drivers of these changes. Together, the results of this study provide scientific evidence-based methodological support for adaptive management of coastal ecosystems that considers global tidal-flat conservation initiatives under the Ramsar Convention framework [25].

2. Materials and Methods

Reference data were sourced from the Web of Science (Core Collection) (<https://www.webofscience.com/> accessed on 1 April 2025). We employed a stepwise refinement approach to search and screen relevant publications (Figure 1) by applying sequential filters based on: “Subjects”, “Data”, and “Objectives”. In our search strategy for publications, the following techniques were used to optimize retrieval effectiveness: (1) Quotation marks (“”) were used to enforce exact phrase matching, preventing term dissociation; (2) The Boolean operator (OR) was applied to expand search scope by incorporating synonymous/near-

synonymous terms; and (3) Wildcard asterisk (*) was utilized to capture morphological variations and derivative forms of keywords.

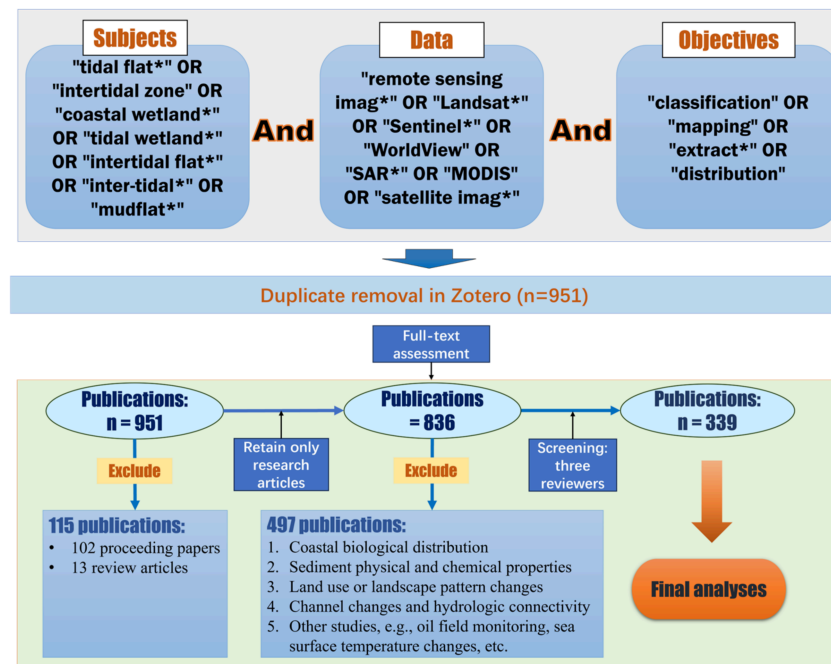


Figure 1. Process of searching and screening relevant publications: * was utilized to capture morphological variations and derivative forms of keywords.

- Search query

TOPIC: ("tidal flat*" OR "intertidal zone" OR "coastal wetland*" OR "tidal wetland*" OR "intertidal flat*" OR "inter-tidal*" OR "mudflat*") AND ("remote sensing imag*" OR "Landsat*" OR "Sentinel*" OR "WorldView" OR "SAR*" OR "MODIS" OR "satellite imag*") AND ("classification" OR "mapping" OR "extract*" OR "distribution*")

- Document types: article
- Publication date: January 2000 to March 2025
- Citation count > 0 (only for publications published before 2023)

The initial search retrieved 951 publications published between 1 January 2000 and 31 March 2025, including 836 research articles, 102 proceeding papers, and 13 review articles. We focused exclusively on research articles and conducted an initial screening of the 836 publications based on their titles and abstracts to efficiently exclude clearly irrelevant records. Two reviewers independently evaluated the titles and abstracts of the 836 publications. For publications where relevance could not be determined from the title and abstract alone, the full text was retrieved and assessed. Disagreements between the two reviewers were resolved through discussion, with a third reviewer consulted when necessary. Following this, 497 articles were excluded as they addressed topics unrelated to tidal-flat extraction and change monitoring, including: (1) Coastal biological distributions, (2) Sediment physical and chemical properties, (3) Land use or landscape pattern changes, (4) Channel changes and hydrologic connectivity, and (5) Other unrelated studies, e.g., oil field monitoring, sea surface temperature changes, etc. The remaining 339 articles were then retrieved and thoroughly reviewed in full text to confirm relevance and extract key information for our systematic analysis. Ultimately, these 339 articles were included in the final synthesis (Supplementary Materials: Table S1).

Additionally, we conducted cross-validation in the Scopus database (<https://www.scopus.com/> accessed on 17 July 2026). Due to Scopus's limitations on the number of

Boolean operators, the search string is adjusted to: (“tidal-flat” OR “mudflat” OR “inter-tidal flat”) AND (“remote sensing”) AND (“classif” OR “extraction” OR “distribut”) NOT (TITLE-ABS-KEY (“mangrove” OR “aquaculture”)), with a time range of 2000–2025. The initial search retrieved 668 research publications, and after manually removing 114 publications published after March 2025, 554 publications remained. Through screening by research domain, title, abstract, and preliminary content review, 477 irrelevant publications were excluded (e.g., coastal biological distribution, sediment physical and chemical properties, land use changes, channel changes and hydrologic connectivity, oil field monitoring, sea surface temperature changes, etc.). The remaining 77 publications were validated against the original 339 Web of Science publications from our review in Zotero (version 9.0). The results showed that 41 publications (53%) were duplicates across both databases. After further evaluation, the 36 unique publications were not included in the final analysis set, primarily for two reasons: (1) the publications published before 2023 had zero citations and had already been excluded during the initial Web of Science screening criteria; and (2) the research content primarily focused on coastline and saltmarsh-related studies, which deviates from the thematic focus of our review on tidal flat extent dynamics monitoring.

3. Bibliometric Analyses

Bibliometric analysis was conducted using VOSviewer (version 1.6.20). For the journal analysis, citation data from the 339 included publications were imported into VOSviewer. Journals with at least two published articles were included in the analysis and were automatically grouped into 14 clusters by VOSviewer’s default clustering algorithm. In Figure 2, node size represents the total number of publications in each journal, and the background heatmap color also reflects journal publication volume, with colors ranging from light to dark indicating increasing numbers of publications.

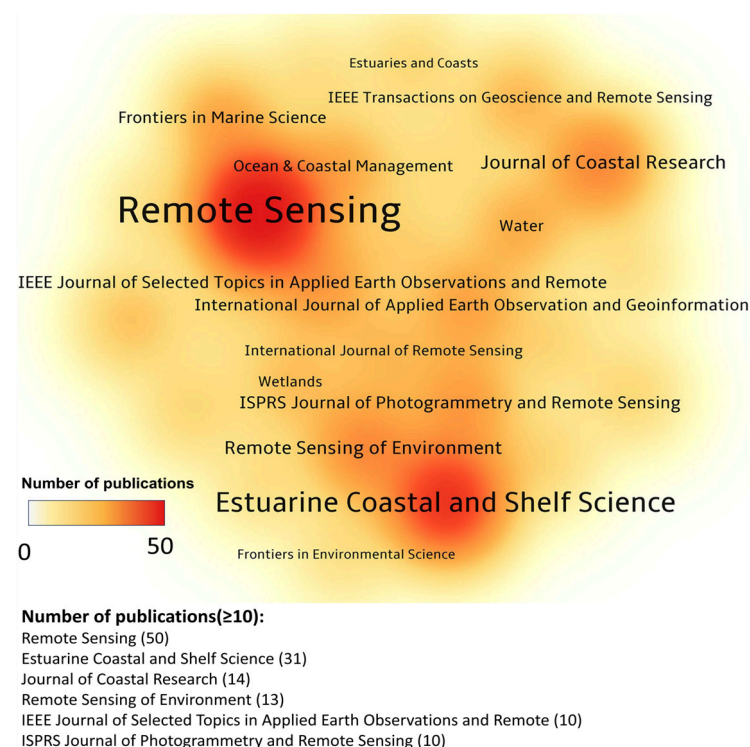


Figure 2. Distribution of journals for publications.

The selected 339 research articles were published in 118 journals, with *Remote Sensing* having the largest number of publications, followed by *Estuarine Coastal and Shelf Science*

(Figure 2). On research content, the 339 publications were classified into two mutually exclusive categories using a method-priority rule. A total of 215 publications discuss methods for tidal-flat extraction, while 124 publications focus on tidal-flat changes and driving factors, including 52 publications that primarily address geomorphological changes in tidal-flats.

Geographically, these 339 research publications originated from 36 countries (Figure 3): 177 from China, 84 from USA, 82 from Europe, 57 from Asia (excluding China and Republic of Korea), 29 from Republic of Korea, 23 from Oceania, 23 from South America, 12 from North America (excluding USA), and 8 from Africa. Among them, the same publication may come from multiple countries. These 36 countries are almost all coastal nations, with mid-latitude countries contributing more publications.

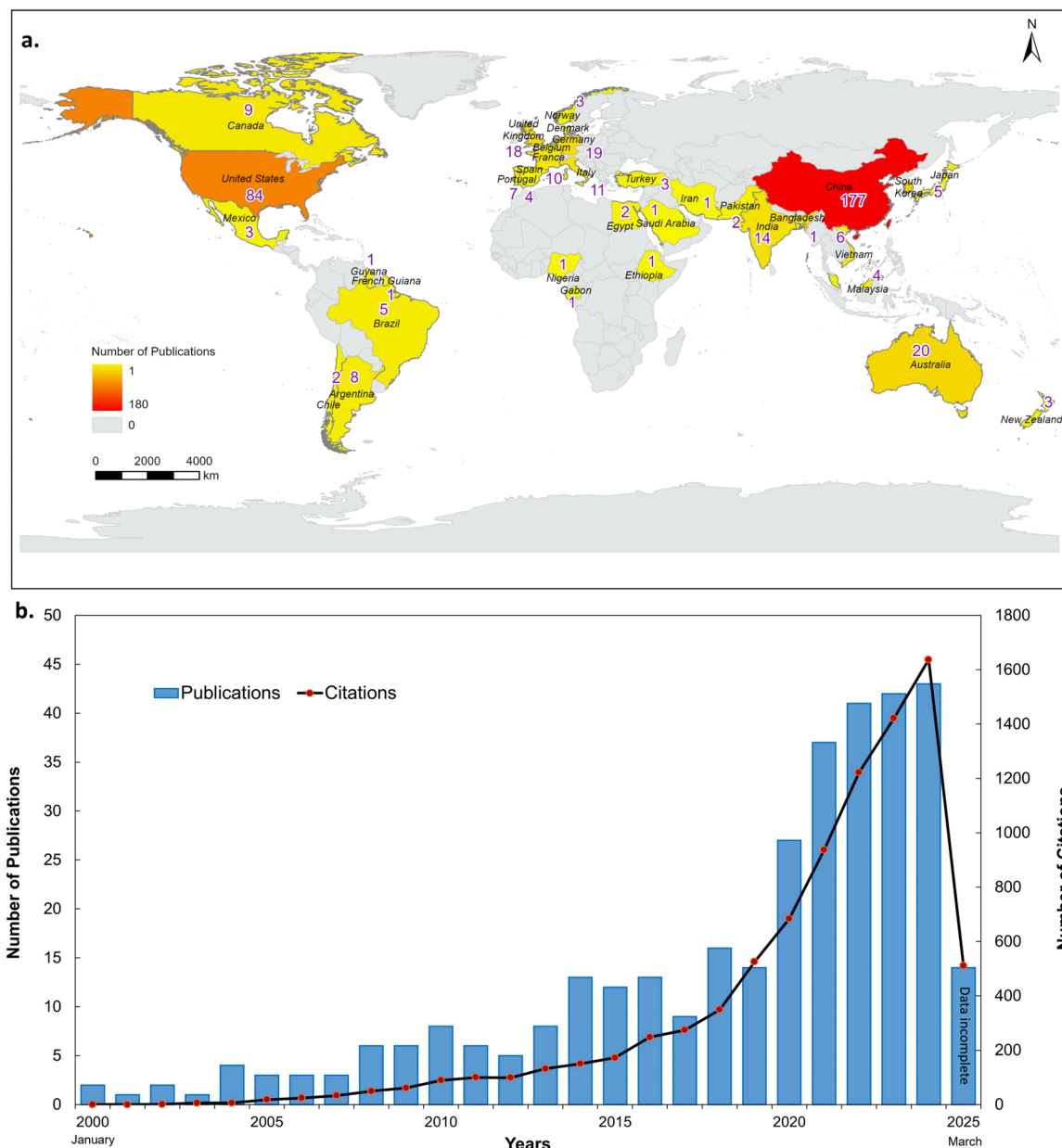


Figure 3. Country distribution and yearly statistics of publications: (a). The 339 publications from 36 countries, with statistics on publication counts for each country. (b). Annual publication and citation statistics for the 339 publications from January 2000 through March 2025.

Trends in publications and citation numbers increased from January 2000 to March 2025, with a sharp upturn occurring after 2019 (Figure 3). In 2019, Murray et al. (2019) published the first global tidal-flats distribution dataset, setting a precedent for large-scale tidal-flats extraction using GEE [1]. This significantly promoted large-scale, long-term time-series research on monitoring tidal-flats changes (Figure 3).

4. Extracting Tidal-Flats from Remote Sensing

Traditional field-based tidal-flat mapping mainly relies on photogrammetric techniques such as LiDAR and stereoscopic measurements which offer higher reliability but are limited by onsite accessibility, weather conditions, and costs [26]. Current extraction of geographical location and environmental characteristics of tidal-flats typically use segmentation and classification. The main methods fall into three categories: waterline extraction, classification-based and composite methods. Among 215 publications on tidal-flats extraction, 122 publications were on waterline extraction methods: 75 publications on threshold segmentation, 23 publications on edge detection, 13 publications on deep learning semantic segmentation, and 11 publications on water frequency methods. Classification-based methods appear in 90 publications: 81 publications used supervised classification, and 9 publications used unsupervised classification. In addition, three publications used composite methods.

4.1. Waterline Extraction

Identifying the highest and lowest tidal land–water boundary is key to extracting tidal-flats [15]. Thus, the core concept of the waterline method is to use remote sensing imagery to extract land–water boundaries during different tidal cycles [27]. The waterline method was first proposed by Mason et al. (2010) [13] and has undergone significant improvements to become one of the most common methods for extracting tidal-flats [28,29]. The main techniques used in this process include edge detection and image segmentation.

4.1.1. Edge Detection Methods

Edge detection uses image gradients or other features of sharp changes to distinguish the land–water boundary [30]. Detection can be divided into visual interpretation, semi-automatic detection, and automatic detection (Table 1) [31,32]. Visual interpretation is mainly used for extracting boundaries in small-scale areas where visual differences are obvious [33]. For example, Liu et al. (2024) used high-resolution imagery to extract revetment dikes as artificial shorelines [34]. For waterlines with low visual contrast in images, semi-automatic or automatic detection methods are commonly used [32,35,36]. Semi-automatic methods include the edge proxy method and shoreline digitization [35,37]. Edge proxy methods generally use other feature boundaries that roughly coincide with the waterline as the water boundary. For example, Martins et al. (2023) used the vegetation edge as a proxy for the coastline to significantly improve the stability of shoreline extraction [37]. But the proxy edge is not the actual waterline. Therefore, its reliability and potential errors still need further validation. Thus, Jin et al. (2022) adopted an automated marsh-edge detection based on Normalized Difference Vegetation Index (NDVI), using Landsat imagery to calculate the NDVI and extracting locations with significant NDVI changes as marsh edges [35]. By quantitatively distinguishing water and land through spectral indices, it avoided subjective judgment and ensured repeatable results. However, the intertidal mixing of land and water can interfere with geomorphic status—tidal residual water bodies may produce false “water” signals, thus affecting extraction accuracy.

Automatic edge detection uses edge detection operators to extract the waterline. Common operators include the Sobel and Canny operators [32,38]. The Sobel operator is a

gradient-based method. It uses convolution to calculate the changes in pixel values in both horizontal and vertical directions, giving the gradient’s magnitude and direction. The Sobel operator typically uses two 3×3 convolution kernels: one for the horizontal gradient, and the other for the vertical gradient [32]. The calculation formulas are as follows:

$$G = G_x^2 + G_y^2$$

(1)

$$\theta = \arctan \frac{G_y}{G_x}$$

(2)

where G and θ are the gradient magnitude and direction respectively. G_x and G_y are the horizontal and vertical gradients, respectively. This method performs well in detecting edges at regions of sharp grayscale variations. Its dependence on small neighborhood information, however, leads to complex small-scale edge variations that fails to represent broad coastline continuity and structures beyond the convolution scale.

The Canny edge detection algorithm achieves more coherent edge extraction through complex multi-stage processing and parameter adjustments that challenge real-time processing [39]. Additionally, the influence of image noise and edge pixels results in discontinuous shoreline definition, indicating a need for improvements [40,41]. Song et al. (2024) improved the Canny edge detection method by enhancing task partitioning, vector memory access, and NDRange optimization [40]. These modifications improved computational efficiency by nearly four times.

Overall, visual interpretation methods are generally suitable for high-precision local studies but are difficult to apply for large-scale monitoring. Semi-automatic detection methods balance automation with manual intervention and can work well for multi-temporal data comparison and large-area intertidal zone extraction, though they require careful pseudo-change filtering and parameter adjustment. Automatic detection methods offer advantages in full automation, consistency, and real-time performance. The Canny operator typically provides refined edge localization but requires high computational resources, whereas the Sobel operator is computationally efficient but may be less robust in complex coastal settings (Table 1). It should be noted, however, that method performance also depends on factors such as image resolution, coastal setting, filtering, and validation.

Table 1. Comparison of edge detection methods.

Type	Name	Description	Advantages	Limitations	
Manual Detection	Visual Interpretation	Direct image observation to determine edge positions based on visual differences	Accurate and reliable	High workload, low efficiency, strong subjectivity	[23,33,42,43]
	Edge Proxy	Uses direct line fitting and other methods to select stable parts in edge transition areas for fitting	Good stability, less interference from single-point noise	Low accuracy due to uncertainty in threshold definition	[37]
Semi-automatic Detection	Coastline Digitization	Combines spectral indices with automatic threshold algorithms to extract water boundaries as coastline sources	High automation, convenient for multi-temporal change comparison	Affected by pseudo-changes (shadows, waves, etc.), high parameter adjustment requirements	[35,44,45]

Table 1. Cont.

Type	Name	Description	Advantages	Limitations	
Automatic Detection	Sobel Operator	Calculates horizontal and vertical gradients of images, detects gradient changes through convolution kernels	Simple calculation, good real-time performance, certain noise resistance	Rough edges, insufficient detail capture	[32,46,47]
	Canny Operator	Calculates gradients after Gaussian filtering preprocessing, then performs non-maximum suppression and dual-threshold detection to extract fine edges	Precise edge localization, good noise suppression	Complex algorithm, high computational load, parameter sensitive	[40,41,48]

4.1.2. Image Segmentation Methods

With the enrichment of spectral band and polarization information in remote sensing imagery, threshold segmentation based on band values and spectral indices has been widely applied in tidal-flat extraction [49–51]. SAR imagery offers advantages of all-weather capability and high revisit frequency, enabling waterline extraction even under cloudy conditions [29]. Lee et al. (2011) extracted waterlines through C-band backscatter variations in SAR imagery [17]. Wan et al. (2021) extracted water bodies based on full polarimetric decomposition of SAR data, compensating for the accuracy limitations of single-polarization methods [52]. However, SAR backscattering signals are directly influenced by tidal water and surface conditions. In particular, speckle noise is inherent to SAR imaging, surface roughness modulates backscatter intensity, and suspended sediments contribute to volume scattering, all of which complicate waterline delineation [15]. Moreover, open-source radar data is limited, and acquisition costs are significantly higher than optical imagery [53]. Therefore, more researchers prefer tidal-flats extraction based on optical imagery [15,54,55].

Ryu et al. (2002) proposed a waterline extraction method based on Landsat single-band reflectance density slicing [27]. It was the first application of threshold segmentation for waterline extraction. Various spectral indices have subsequently been developed to enhance the accuracy and robustness of waterline and tidal-flat extraction [49]. For example, Sagar et al. (2017) used Normalized Difference Water Index (NDWI) to distinguish water from non-water [56]. Tang et al. (2022) proposed an Improved Water Index (IWI) combined with the Otsu algorithm to extract muddy coastlines from Landsat optical imagery [57]. However, seawater erosion and sediment deposition reduce spectral differences between tidal-flats and water, affecting single spectral index performance. Therefore, Wang et al. (2020) first applied the water frequency method to obtain annual tidal-flat maps along China's coast from long-term Landsat imagery [55]. The core principle of the water frequency method is to delineate water and tidal-flat boundaries based on the frequency differences in tidal-flats submersion under different tidal states using long-term remote sensing image series [55]. The main formulas [55] are as follows:

$$\text{water} = \begin{cases} 1 & \text{EVI} < 0.1 \text{ and } (\text{mNDWI} > \text{EVI} \text{ or } \text{mNDWI} > \text{NDVI}) \\ 0 & \text{other values} \end{cases} \quad (3)$$

$$F_{\text{water}} = \frac{\sum N_{\text{water}}}{\sum N_{\text{total}} - \sum N_{\text{bad}}} \quad (4)$$

where water = 1 indicates water pixels and 0 indicates non-water. F_{water} is the frequency of water inundation. N_{water} is the number of times a pixel is identified as water, N_{total} is

the total number of observations, and N_{bad} is the number of poor-quality observations. Water and non-water pixels are determined based on the frequency of water occurrence at pixel locations. The highest and lowest tidal lines are identified through water frequency thresholds.

The water frequency method uses multiple spectral indices and threshold segmentation for different land covers, effectively avoiding misclassification from single spectral indices. It also solved the dependence on tidal data when extracting highest and lowest tidal lines from optical imagery, representing a major advance in optical image-based tidal-flat extraction [58]. However, the water frequency method often requires calculating spectral indices and frequency values for numerous images individually [55]. Additionally, the manual selection of frequency thresholds lacks unified standards, resulting in considerable uncertainty in classification results [16,55]. Subsequently, Jia et al. (2021) proposed the Maximum Spectral Index Composite and Otsu algorithm method (MSIC-OA) based on Sentinel-2 imagery [15]. They generated the first 10 m resolution tidal-flat map of China with 95% overall accuracy through the GEE platform. This method rapidly synthesizes highest and lowest tide images using modified Normalized Difference Water Index (mNDWI) and NDVI spectral indices. It avoided tedious image calculations and manual threshold selection, and enabled efficient acquisition of large-scale tidal-flat distributions [15,26].

Threshold segmentation methods demonstrate high efficiency in large-scale tidal-flat extraction. However, under complex tidal conditions, the extracted waterlines are prone to breaks or scattered noise, and extraction accuracy is sensitive to threshold values.

For ambiguous water–land boundaries in intertidal zones, it is difficult to interpret them through a single threshold. Deep Convolutional Neural Networks (DCNN) significantly improve semantic segmentation accuracy [59]. Many studies now combine semantic segmentation with remote sensing tidal-flats extraction. For instance, Zhang et al. (2022) proposed WENet, a semantic segmentation model for tidal-flats using Sentinel-1 SAR imagery that automatically and accurately extracts tidal-flat waterlines and constructs tidal-flats DEM [60]. Such deep learning models maintain strong generalization capabilities and high recognition accuracy even under complex imaging conditions. However, their powerful feature learning ability requires extensive annotated training data that is both expensive and time-consuming [61]. Additionally, model training and inference demand substantial computational resources, posing constraints for applications with stringent real-time requirements [62–64].

Overall, threshold segmentation has an obvious advantage in quickly obtaining a large range of preliminary results. Deep learning-based semantic segmentation methods provide higher refinement of segmentation results at higher task requirements and complex scenarios (Table 2).

Table 2. Comparison of images segmentation methods.

Type	Name	Description	Advantages	Limitations	
SAR Image Segmentation	Single-Polarization SAR Segmentation	Segmentation based on differences in backscattering intensity of a single polarization	All-weather observation, simple implementation	Limited information, sensitive to noise, difficult to determine threshold	[29,65]
	Full-Polarization SAR Segmentation	Segmentation using multi-polarization decomposition and joint classification algorithms to extract rich scattering features	High accuracy, good robustness, adapts to complex backgrounds	High data acquisition and processing costs, complex algorithms and high computational resource requirements	[52,66,67]

Table 2. Cont.

Type	Name	Description	Advantages	Limitations	
Threshold Segmentation	Single-Band Density Slicing	Grading and color assignment based on single-band grayscale distribution for initial segmentation	Simple implementation, high computational efficiency	Weak adaptability to complex features, susceptible to noise and shadow interference	[27,51,68]
	Spectral Index Threshold Segmentation	Determining the segmentation threshold of spectral indices for extracting water or tidal-flats based on land-cover reflectance	High efficiency and low cost, suitable for large-scale tidal-flat extraction	Low robustness in complex scenes, and susceptible to cloud cover and seawater coverage interference	[69–71]
	Water Frequency Method	Using multi-temporal data to statistically analyze water occurrence frequency to achieve long-term distinction between water and non-water bodies	Captures dynamic tidal-flat characteristics, reduces accidental mis-segmentation	Requires large amounts of data, subjective threshold selection, complex data processing	[16,55,72]
	MSIC-OA	Combining spectral information to synthesize high-quality tidal images and segmenting based on automatic Otsu thresholding	Efficient and stable. Able to extract tidal-flats covered by seawater, obtaining a relatively complete tidal-flat range	Single threshold makes it difficult to accurately separate blurred water–land boundaries, and thresholds are easily disturbed by noise	[15,73,74]
Deep Learning Methods	Deep Convolutional Neural Network Semantic Segmentation	Using multilayer convolutional neural networks to automatically learn multi-scale image features for end-to-end segmentation	Automatic feature extraction, high segmentation accuracy, strong adaptability to complex backgrounds	Requires large amounts of labeled data and high-performance computing hardware, limited transferability	[62,75,76]

4.2. Image Classification Methods

Classification methods use spectral, textural, or polarimetric features to separate tidal-flats from other landscapes [54]. These include both supervised and unsupervised techniques [54,77]. Recently, machine learning has significantly boosted the efficiency and accuracy of tidal-flat mapping through classification-based approaches [1].

4.2.1. Supervised Classification

Supervised classification uses manually selected training samples and classifiers. It automatically classifies tidal-flats and surrounding features based on spectral and textural characteristics [78]. Common supervised classification methods for tidal-flats extraction include statistical classification, decision boundary classification and decision-tree classification [1,50,79].

Statistical-based classification methods were one of the first techniques applied to remote sensing images [80]. It is based on probabilistic statistical models, the most common being maximum-likelihood classification (MLC) [80,81]. MLC assumes Normal distribution for classes and calculates the probability of samples belonging to classes, with assignment to the class with the highest probability [81]. However, the actual probability distribution of feature values directly affects class selection by MLC [80,81]. Targeted improvements are needed in practical applications as intertidal ground features have similar characteristics

and non-normal distributions. Statistical classification typically performs worse than decision boundary and decision-tree classification methods [82].

Decision boundary and decision-tree classification methods do not directly rely on the probability distribution of features [83]. They are more robust to imbalanced samples and noisy data, and widely used in tidal-flats and shoreline extraction [1,83]. Among commonly used decision-based classifiers, both Random Forest (RF) and Support Vector Machine (SVM) have demonstrated strong performance in land-cover classification, with reported average accuracies of 85.81% and 85.19%, respectively [84]. SVM is effective for handling mixed pixels and complex textural features in specific areas [50]. RF uses random sampling and feature subset selection to reduce overfitting and improve classification stability [1]. The accuracy of decision-based methods depends on image quality and feature selection, and they perform well in classifying distinctly different land-cover types [50]. They are suitable for large-scale and multi-type tidal-flat classification combined with tidal data [21]. Moreover, the abundance of multi-source remote sensing imagery, spectral indices, and other feature parameters provides favorable conditions for classification [85]. For example, Murray et al. (2019) calculated the NDWI, Automated Water Extraction Index (AWEI), mNDWI, and NDVI based on Landsat images to enhance the contrast between tidal-flats and water bodies, facilitating subsequent classification [1]. Zhang et al. (2023) captured the complex temporal dynamics and spectral heterogeneity of wetlands by integrating Landsat imagery and Sentinel-1 SAR imagery [86].

Overall, different supervised classification methods show varying applicability in tidal-flat extraction. Traditional statistical methods exhibit reduced effectiveness when dealing with highly heterogeneous and noisy remote sensing data. In contrast, SVM and RF can compensate for the shortcomings of traditional methods by constructing more nuanced decision boundaries and ensemble models. However, parameter optimization and data preprocessing tailored to specific problems are required in practical applications (Table 3).

Table 3. Comparison of supervised classification methods.

Type	Description	Advantages	Limitations
Statistical Method	Based on the assumption that each class follows a normal distribution in multidimensional spectral space, calculates probability values for each pixel and assigns it to the class with highest probability	Solid theoretical foundation; high classification accuracy for normally distributed data	Sensitive to data distribution; obvious mixed pixel issues; reduced classification accuracy for non-normal distributions [80,81,87]
Decision Boundary Classification	Constructs optimal hyperplanes to maximize inter-class margins, uses kernel functions for nonlinear mapping to handle high-dimensional data	Effectively handles nonlinear and high-dimensional data; suitable for complex textures and mixed pixel areas	Requires extensive parameter tuning and computational resources; sensitive to noisy data; complex kernel function selection [52,88,89]
Decision-Tree Classification	Based on decision tree ensemble, constructs numerous decision trees through random sampling of data and features, determines final class using voting mechanism	Simple parameter tuning, easy implementation; strong robustness against redundant features and noise; can evaluate feature importance	Poor interpretability; may exhibit bias toward majority classes when training samples are severely imbalanced [1,83,90]

4.2.2. Unsupervised Classification

Unsupervised classification automatically groups image data without training sample data. Commonly used methods include clustering algorithms and dimensionality reduction methods [91,92]. Traditional clustering algorithms, such as K-Means and ISODATA, perform preliminary segmentation of images and automatically classify different feature classes based on similarity within classes and dissimilarity across classes [91,93]. However, the spectral similarity between tidal-flats and turbid water bodies limits the effectiveness of this algorithm. Kang et al. (2007) found that ISODATA clustering had difficulty distinguishing tidal-flats from adjacent water bodies in Landsat imagery, with extraction accuracy lower than that of land and ocean [93]. Chen et al. (2023) extracted tidal-flats of Chongming Dongtan based on K-means clustering, integrated unmanned aerial surveys, and satellite images [94]. They found that spectral similarity between intertidal features and complex radar backscattering made it challenging to accurately delineate instantaneous waterlines with very high sediment concentrations. These findings show that traditional clustering algorithms are suitable for highly heterogeneous features.

Fuzzy C-Means (FCM) uses fuzzy clustering theory to assign data points to multiple cluster centers with different weights. This fuzzy assignment makes FCM more robust to noise and outliers than clustering algorithm such as K-means. Chen et al. (2015) used FCM with fuzzy factors to improve wetland classification accuracy based on SAR imagery [67]. However, intertidal spectral features are highly similar and have fuzzy boundaries, requiring the use of ancillary data to enhance feature comparison, such as topographic parameters [95].

Dimensionality reduction methods such as Principal Component Analysis (PCA) compress high-dimensional spectral data into low-dimensional space, reducing computational effort and highlighting heterogeneity to provide a clearer feature space for tidal-flat classification. Kwon et al. (2016) used a two-step PCA transformation to extract heterogeneous conditions from saturated conditions and highlight inter-class differences [96].

Deep neural networks have automatic unsupervised feature extraction capability. Huang et al. (2023) proposed a spatiotemporal-spectral weighted adversarial domain adaptation (SSWADA) network for cross-scene wetland mapping using hyperspectral images (HSI) [53]. Compared with the best deep-subdomain adaptation networks, this approach improved wetland classification accuracy by 5.7%. However, deep neural networks require high-performance computing devices and have limitations such as long computation times and complex parameter tuning [53].

In summary, traditional clustering and FCM are easy to implement but struggle with complex or non-spherical data. PCA reduces dimensionality well but is limited with nonlinear patterns. Deep neural networks extract features automatically but require significant resources and lack interpretability (Table 4).

Table 4. Comparison of unsupervised classification methods.

Type	Description	Advantages	Limitations
Traditional Clustering	Hard clustering based on Euclidean distance, assigning data points clearly to designated clusters (e.g., K-means, ISODATA)	Simple and efficient algorithms, suitable for large-scale data	Sensitive to noise and outliers; struggles with complex or non-spherical data

[77,91,93]

Table 4. Cont.

Type	Description	Advantages	Limitations	
FCM Fuzzy Clustering	Distributes data points among multiple clusters using fuzzy membership, iteratively updates by minimizing an objective function	Handles fuzzy boundaries; reveals intrinsic data structure; more robust to noise	Strongly affected by initial center selection; higher computational complexity	[67,95]
Principal Component Analysis (PCA)	Maps high-dimensional data to a lower-dimensional space using covariance matrix and eigen decomposition, retaining main information	Eliminates redundancy, speeds up subsequent computation, intuitively shows main data variability	Only suitable for linear structures; sensitive to outliers	[92,96,97]
Deep Neural Networks	Extracts complex features using multilayer nonlinear transformations, autoencoders, GANs, etc.	Strong feature representation, adapts to various domains, high classification accuracy	Time-consuming training, high computational resources required, complex hyperparameter tuning, poor interpretability	[53]

4.2.3. Composite Methods

The waterline method using edge detection and segmentation captures land–water boundaries well but struggles to separate complex features within the intertidal zone. Classification methods differentiate land-cover types using spectral and terrain features but may misclassify mixed boundary pixels. Composite methods have recently emerged as an effective strategy because they integrate the geometric strength of waterline-based methods with the thematic discrimination capability of classification algorithms. In general, these approaches can be divided into two main types. The first is boundary-constrained classification, in which waterline extraction or water-frequency segmentation is used to define the intertidal zone before classification is performed within this extent. It improves boundary accuracy and reduces misclassification outside the intertidal zone. For example, Yan et al. (2021) combined a waterline method with RF in Jiaozhou Bay and achieved an overall accuracy of 96.7%, higher than that of RF alone (94.8%) and the waterline method alone (91.7%) [98].

Hydroperiod-assisted classification represents another major category of hybrid approaches. It incorporates temporal inundation metrics derived from multi-date imagery into the classification process, so that tidal dynamics can be used alongside spectral information to improve class discrimination. This is particularly valuable for separating land-cover types with similar spectral signatures but different inundation regimes. For instance, Liu et al. (2022) integrated hydroperiod- and water-frequency-related metrics from Sentinel-2 time series into an RF classifier to map tidal-flats and other coastal wetlands in Vietnam, achieving an overall accuracy of 82.07% [99]. The complementary strengths of the waterline and classification methods offer a new approach for accurate tidal-flat extraction.

Overall, composite methods may be particularly effective in complex coastal settings, such as estuaries and bays with fragmented tidal-flats, complex creek networks, or aquaculture ponds. By combining improved boundary delineation with within-zone class discrimination, they may provide a more robust and adaptable framework for tidal-flat mapping than either method used alone.

5. Tidal-Flats Change Monitoring

5.1. Tidal-Flats Change Trends on Different Scales

Studies at global and regional scales have revealed different trends of change in tidal-flat distribution along coastlines worldwide. Murray et al. (2019) found that global tidal-flats cover at least 127,921 km², mainly in the Northern Hemisphere, with about 44% in Asia [1]. However, the global area of tidal-flats continues to decline despite formal protection. Hill et al. (2021) pointed out that 31% of global tidal-flats are within protected areas, a proportion much higher than that of oceans (6%) and land (13%) [100]. However, protected tidal-flats are still subject to various pressures and their ecosystems remain threatened. Especially in some regions of Asia, individual protected areas have seen net tidal-flats losses of up to 86.4 km², and most tidal-flats face moderate to very high levels of human disturbance [100]. This indicates that although the extent of protection has increased, it is still insufficient to effectively prevent ecological degradation.

At the national level, China holds the world's second-largest tidal-flat area and has the highest loss rate, decreasing by about 2.6% per year [55]. From 1984 to 2016, tidal-flats in South Korea decreased by 30% to 40% due to coastal development and land reclamation [77]. At the local scale, tidal-flat changes show significant regional differences. For example, although Shanghai has a relatively large tidal-flat area, the rate of tidal-flat loss is much lower than that in Jiangsu [101]. In contrast to the global trend of tidal-flat loss, Wachler et al. (2020) found that Wadden Sea tidal-flats in Germany expanded by 18% between 1998 and 2016 [102]. Similarly, increases in tidal-flat elevation have been observed along the coasts of the Netherlands and France, causing localized "steepening" of regional topography. However, the expansion and contraction of tidal-flats in these areas show clear cyclical patterns [103,104]. The tidal-flats area in the Beibu Gulf decreased by 29% from 1897 to 2021, and fragmentation of the tidal-flats has continued to intensify [26]. In addition, the water area and tidal-flat area of Zhoushan Island, China, decreased by 6% and 10% from 1985 to 2017 [105]. The tidal-flats of Gomso and Hampyeong Bay in South Korea show significant seasonal fluctuations in sedimentation and erosion [33]. The rates of sedimentation and retreat vary considerably due to differences in tides, hydrodynamic conditions, and local sediment supply [33].

Local changes combine to drive large-scale tidal-flats changes. Thus, the evolution of tidal-flat area and shape involves multiple factors at both global and local scales.

5.2. Mechanisms Driving Change

5.2.1. Natural Factors

For most terrigenous-dominated tidal-flat systems, sediment supply is key to maintaining tidal-flats as river sediment input defines their formation and evolution. Globally, 66% of tidal-flat loss is linked to indirect drivers such as sediment supply and wave erosion [106,107]. For example, the Yangtze River's sediment flow to the sea has dropped by about 90% over the past fifty years, reducing sediment replenishment [108]. Sedimentation processes vary by region; Shanghai's tidal-flats are relatively stable, while Jiangsu's are disappearing faster due to different sediment environments. Biological factors also influence tidal-flat sedimentation. Intertidal vegetation can trap sediment with their roots, increasing deposition, especially in areas with faster water flow or coarser sediment [109]. Periodic and discontinuous sedimentation leads to a dynamic adjustment in tidal-flat evolution. Grandjean et al. (2024) shows tidal-flat stability is closely related to turbidity levels [110].

Sea level rise is a global environmental driver that affects tidal dynamics and sediment processes across all spatial scales of coastal zones. Wachler et al. (2020) found that sea level rise significantly increased flow velocities in tidal channels, resulting in enhanced tidal asymmetry [102]. This finding is consistent with the study of [110]. Currently, about 25%

of estuarine tidal-flats globally are experiencing elevation loss or area reduction due to sea level rise, particularly in regions like the western European coast, the Yellow Sea, and the Yalu River estuary [110,111].

5.2.2. Human Factors

Coastal development disrupts the structure of intertidal-flats and alters sediment conditions. For example, construction of artificial ports caused erosion rates at Freeport, Texas, to exceed 15 m/yr [112]. In eastern China, modern radiating sandbars have lost up to 992 km² of intertidal-flats due to high-intensity reclamation and infrastructure construction [113]. A range of human-driven mechanisms for intertidal-flat changes exhibits significant heterogeneity in both temporal and spatial scales but generally trends toward disrupting the balance between natural deposition and erosion.

Moreover, human activities contribute to the degradation of intertidal-flat areas and functions while increasing coastal ecological risks. Liu et al. (2018) indicated that from 2000 to 2017, the ecological risks of intertidal-flats in Jiangsu's coastal regions significantly increased due to large-scale reclamation, aquaculture, and port construction [114]. It resulted in the gradual disappearance of low-risk areas and the rapid spread of medium to high-risk areas, which now account for as much as 71.75% [114].

6. Discussion

6.1. Limitations of Current Research

6.1.1. Data Acquisition and Quality Limitations

Optical and radar imagery serve as important foundations for tidal-flat monitoring [1,115]. Optical imagery has abundant data sources but is sensitive to cloud cover and phenological changes. Cloud coverage in tidal-flat areas is prominent, making high-quality image acquisition difficult. Although filtering cloudy images based on cloud coverage thresholds ensures final data clarity, it simultaneously reduces available data quantity [52]. For regions with year-round cloud coverage, cloud removal processing leads to data gaps, creating significant uncertainty [15]. For example, Indonesia with the largest area of tidal-flats experiences persistent cloudiness and rain, and Landsat imagery shows some areas with more than 90% annual cloud coverage [1,85]. Additionally, tidal-flats frequently experience seawater scouring and coverage, and satellite revisit cycles make capturing tidal-flat states under different tidal conditions challenging.

Radar imaging operates unaffected by weather and lighting conditions, enabling all-weather, round-the-clock tidal-flat information acquisition [115]. However, open-source data is limited, and data acquisition and processing costs are relatively high [55]. Furthermore, a major inherent defect of SAR imagery is speckle noise [26]. Although traditional filtering algorithms such as Lee and Frost filtering can reduce noise to some extent, they simultaneously eliminate relevant details [116], which affects accurate tidal-flat boundary extraction.

6.1.2. Uncertainty Impacts

We described and analyzed various methods in Section 4 on impacts of uncertainties including data sources, spatial scales, and result validation. Data source uncertainty is mainly reflected in image quality (Section 6.1.1) and spatiotemporal resolution [15]. The exposure and submersion of tidal-flats are controlled by tidal cycles [55]. The specific tidal phase during image acquisition directly affects the representation of tidal-flats in that scene. Insufficient temporal resolution may result in critical tidal phases being missed, causing systematic bias in tidal-flat area estimation. High temporal resolution data can provide more comprehensive tidal coverage and significantly improve estimation accuracy [15].

Multi-temporal imagery has obvious advantages over single-temporal imagery, effectively reducing uncertainties caused by tidal changes and environmental disturbances [117].

Spatial resolution precision directly affects the ability to identify tidal-flat boundaries and handle mixed pixels. Medium-to-low resolution imagery often experience boundary blurring and mixed pixel problems in complex tidal-flat areas [105]. High spatial resolution imagery can more clearly distinguish fine geomorphological structures and reduce tidal-flat boundary blurring and feature confusion [79]. However, high-resolution imagery typically involves large data volumes, requiring trade-offs between data acquisition timeliness, processing efficiency, and monitoring requirements [61].

Spatial scale is a key factor affecting result reliability. Large-scale regional studies often require coarser spatial resolution data to meet computational and storage demands, potentially increasing uncertainty in boundary identification [1]. Additionally, spatial heterogeneity in tidal cycles, geomorphological features, and environmental conditions within large study areas makes it difficult for unified extraction methods to maintain consistent accuracy across all regions [1]. In contrast, small-scale studies are able to use higher-resolution data and employ targeted methods, but their representativeness and generalizability are relatively limited [38]. Uncertainties are further amplified through error propagation mechanisms as local findings are aggregated to larger spatial scales.

Validation uncertainty mainly stems from data acquisition difficulties and quality differences. Due to the dynamic nature of tidal-flats, field validation data must be temporally synchronized with remote sensing imagery, but time discrepancies often occur in practice [15]. Visual interpretation of high-resolution imagery, a common validation method, is affected by interpreter experience and subjective judgment [1]. Additionally, systematic differences between validation methods lead to inconsistent accuracy assessments [29].

In addition, the primary analytical sample was derived from Web of Science and that Scopus was used only for sensitivity analysis or cross-validation.

6.2. Future Prospects

To improve, future monitoring should focus on integrating multi-source data (optical, SAR, LiDAR, UAV) and using features like spectrum, texture, and elevation for greater robustness. Developing more efficient and intelligent data fusion algorithms is crucial. For example, using multimodal fusion networks to automatically learn feature correlations and complementary information between different data sources [118] achieves more precise tidal-flat boundary extraction and change monitoring. Meanwhile, dynamic data fusion algorithms are needed to adjust fusion strategies in real time according to data source quality and availability, matching tidal-flat monitoring needs across scenarios.

Methodological coupling is currently an important approach for improving tidal-flat extraction and change monitoring. For example, using threshold segmentation to quickly screen potential tidal-flats, then employing machine learning models for accurate classification [119]. Future research should enhance algorithm adaptability, and facilitate design of reinforcement-learning-based dynamic threshold adjustment algorithms that automatically optimize segmentation parameters according to seasonal changes. To tackle resource-intensive training, there is a need for lightweight models for parallel computing for efficient large-scale data processing. Additionally, Artificial Intelligence (AI) and large vision models have significant potential to better handle spatial continuity and complex geometric shapes of boundaries.

In summary, multi-source fusion, geographic intelligence, and big data support will become important tools for future tidal-flat research in coastal zone resource protection and management.

7. Conclusions

In synthesizing 339 studies (2000–2025), this review finds that tidal-flat monitoring has rapidly matured, with a clear inflection in 2019 following release of the global 30 m intertidal-flat dataset. Research has expanded from site-specific case studies to regional and truly global analyses, led principally by teams in China, USA, Republic of Korea, and European coastal nations.

Methodologically, practice has diversified and become more effective. Waterline extraction remains the researcher's workhorse for its robustness and simplicity (122 studies), while classification-based approaches are frequently employed when fine delineation is essential (90 studies). Composite methods, though fewer in number, show promise in complex settings by combining the strengths of multiple techniques. Together, these trends signal a shift from ad hoc mapping toward more standardized, scalable, and operational monitoring.

The substantive outcome is unambiguous: despite local exceptions, the total global intertidal-flats are contracting, with concentrated risk zones emerging under combined natural and anthropogenic pressures. Yet today's monitoring still underutilizes multi-sensor data, lacks seamless method integration, and rarely achieves near-real-time performance.

We conclude that the highest-impact next steps are: (1) routine fusion of optical, SAR, and LiDAR to ensure all-weather, all-tide coverage; (2) dynamic, quality-aware fusion that adapts in real time to data gaps and noise; (3) modern learning pipelines (including transfer and weak supervision) to generalize across coasts and epochs; and (4) open benchmarks, code, and repeatable workflows to accelerate translation from research to operations. Prioritizing these directions will convert the current momentum into durable, global capability for timely assessment and stewardship of tidal-flat ecosystems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse14151368/s1>, Table S1: List of the 339 publications included in the review.

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References

1. Murray, N.J.; Phinn, S.R.; DeWitt, M.; Ferrari, R.; Johnston, R.; Lyons, M.B.; Clinton, N.; Thau, D.; Fuller, R.A. The Global Distribution and Trajectory of Tidal Flats. *Nature* **2019**, *565*, 222–225. [[CrossRef](#)] [[PubMed](#)]
2. Dyer, K.R.; Christie, M.C.; Wright, E.W. The Classification of Intertidal Mudflats. *Cont. Shelf Res.* **2000**, *20*, 1039–1060. [[CrossRef](#)]
3. Ghosh, S.; Mishra, D.R.; Gitelson, A.A. Long-Term Monitoring of Biophysical Characteristics of Tidal Wetlands in the Northern Gulf of Mexico—A Methodological Approach Using MODIS. *Remote Sens. Environ.* **2016**, *173*, 39–58. [[CrossRef](#)]
4. Murray, N.J.; Clemens, R.S.; Phinn, S.R.; Possingham, H.P.; Fuller, R.A. Tracking the Rapid Loss of Tidal Wetlands in the Yellow Sea. *Front. Ecol. Environ.* **2014**, *12*, 267–272. [[CrossRef](#)]
5. Bao, J.; Gao, S.; Ge, J. Dynamic Land Use and Its Policy in Response to Environmental and Social-Economic Changes in China: A Case Study of the Jiangsu Coast (1750–2015). *Land Use Policy* **2019**, *82*, 169–180. [[CrossRef](#)]
6. Lu, W.; Xiao, J.; Lei, W.; Du, J.; Li, Z.; Cong, P.; Hou, W.; Zhang, J.; Chen, L.; Zhang, Y.; et al. Human Activities Accelerated the Degradation of Saline Seepweed Red Beaches by Amplifying Top-down and Bottom-up Forces. *Ecosphere* **2018**, *9*, e02352. [[CrossRef](#)]

7. Zhang, L.; Wu, B.; Yin, K.; Li, X.; Kia, K.; Zhu, L. Impacts of Human Activities on the Evolution of Estuarine Wetland in the Yangtze Delta from 2000 to 2010. *Environ. Earth Sci.* **2015**, *73*, 435–447. [\[CrossRef\]](#)
8. Yapp, R.H.; Johns, D.; Jones, O.T. The Salt Marshes of the Dovey Estuary. *J. Ecol.* **1917**, *5*, 65–103. [\[CrossRef\]](#)
9. George, J.D. Organic Matter Available to the Polychaete *Cirriiformia tentaculata* (Montagu) Living in an Intertidal Mud Flat. *Limnol. Oceanogr.* **1964**, *9*, 453–455. [\[CrossRef\]](#)
10. Hawkes, D.D. Erosion of Tidal Flats Near Georgetown, British Guiana. *Nature* **1962**, *196*, 128–130. [\[CrossRef\]](#)
11. Amiard, J.; Amiardtriquet, C. Health and Ecological Aspects of Co-60 Transfer in Seawater Food-Chain Typical of an Intertidal Mud-Flat. *Int. J. Environ. Stud.* **1977**, *10*, 113–118.
12. Wang, X.; Xiao, X.; Zou, Z.; Hou, L.; Qin, Y.; Dong, J.; Doughty, R.; Chen, B.; Zhang, X.; Cheng, Y.; et al. Mapping Coastal Wetlands of China Using Time Series Landsat Images in 2018 and Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* **2020**, *163*, 312–326. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Mason, D.; Scott, T.; Dance, S. Remote Sensing of Intertidal Morphological Change in Morecambe Bay, UK, Between 1991 and 2007. *Estuar. Coast. Shelf Sci.* **2010**, *87*, 487–496. [\[CrossRef\]](#)
14. Gade, M.; Alpers, W.; Melsheimer, C.; Tanck, G. Classification of Sediments on Exposed Tidal Flats in the German Bight Using Multi-Frequency Radar Data. *Remote Sens. Environ.* **2008**, *112*, 1603–1613. [\[CrossRef\]](#)
15. Jia, M.; Wang, Z.; Mao, D.; Ren, C.; Wang, C.; Wang, Y. Rapid, Robust, and Automated Mapping of Tidal Flats in China Using Time Series Sentinel-2 Images and Google Earth Engine. *Remote Sens. Environ.* **2021**, *255*, 112285. [\[CrossRef\]](#)
16. Wu, W.; Zhi, C.; Gao, Y.; Chen, C.; Chen, Z.; Su, H.; Lu, W.; Tian, B. Increasing Fragmentation and Squeezing of Coastal Wetlands: Status, Drivers, and Sustainable Protection from the Perspective of Remote Sensing. *Sci. Total Environ.* **2022**, *811*, 152339. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Lee, H.; Chae, H.; Cho, S. Radar Backscattering of Intertidal Mudflats Observed by Radarsat-1 SAR Images and Ground-Based Scatterometer Experiments. *IEEE Trans. Geosci. Remote Sens.* **2011**, *49*, 1701–1711. [\[CrossRef\]](#)
18. Wang, W.; Gade, M.; Stelzer, K.; Kohlus, J.; Zhao, X.; Fu, K. A Classification Scheme for Sediments and Habitats on Exposed Intertidal Flats with Multi-Frequency Polarimetric SAR. *Remote Sens.* **2021**, *13*, 360. [\[CrossRef\]](#)
19. Zhang, L.; Fan, Y.; Yan, R.; Shao, Y.; Wang, G.; Wu, J. Fine-Grained Tidal Flat Waterbody Extraction Method (FYOLOv3) for High-Resolution Remote Sensing Images. *Remote Sens.* **2021**, *13*, 2594. [\[CrossRef\]](#)
20. Tong, S.; Derooin, J.; Pham, T. An Optimal Waterline Approach for Studying Tidal Flat Morphological Changes Using Remote Sensing Data: A Case of the Northern Coast of Vietnam. *Estuar. Coast. Shelf Sci.* **2020**, *236*, 106613. [\[CrossRef\]](#)
21. Wen, K.; Liao, P.; Jiang, A. Integrating Time Series Sentinel-2 Images and Tide Height to Mapping Tidal Flats in the Chinese Mainland. *J. Hydrol.* **2024**, *645*, 132264. [\[CrossRef\]](#)
22. Bishop-Taylor, R.; Sagar, S.; Lymburner, L.; Alam, I.; Sixsmith, J. Sub-Pixel Waterline Extraction: Characterising Accuracy and Sensitivity to Indices and Spectra. *Remote Sens.* **2019**, *11*, 2984. [\[CrossRef\]](#)
23. Raabe, E.; Stumpf, R. Expansion of Tidal Marsh in Response to Sea-Level Rise: Gulf Coast of Florida, USA. *Estuaries Coasts* **2016**, *39*, 145–157. [\[CrossRef\]](#)
24. Ramsey, E.; Ragoonwala, A.; Chi, Z.; Jones, C.; Bannister, T. Marsh Dieback, Loss, and Recovery Mapped with Satellite Optical, Airborne Polarimetric Radar, and Field Data. *Remote Sens. Environ.* **2014**, *152*, 364–374. [\[CrossRef\]](#)
25. Munguía, S.M.; Heinen, J.T. Piloting the Rapid R-MEET Framework at a Coastal Ramsar Site. *Mar. Freshw. Res.* **2023**, *74*, 941–955. [\[CrossRef\]](#)
26. Gao, E.; Zhou, G.; Li, S.; Fu, B.; Xiao, Y.; Lan, Y.; Wang, F.; Xu, J.; Zhu, Q.; Bai, Y. Spatio-Temporal Evolution Monitoring and Analysis of Tidal Flats in Beibu Gulf from 1987 to 2021 Using Multisource Remote Sensing. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2024**, *17*, 6099–6114. [\[CrossRef\]](#)
27. Ryu, J.; Won, J.; Min, K. Waterline Extraction from Landsat TM Data in a Tidal Flat—A Case Study in Gomso Bay, Korea. *Remote Sens. Environ.* **2002**, *83*, 442–456. [\[CrossRef\]](#)
28. Yang, H.; Chen, M.; Xi, X.; Wang, Y. A Novel Approach for Instantaneous Waterline Extraction for Tidal Flats. *Remote Sens.* **2024**, *16*, 413. [\[CrossRef\]](#)
29. Ding, X.; Nunziata, F.; Li, X.; Migliaccio, M. Performance Analysis and Validation of Waterline Extraction Approaches Using Single- and Dual-Polarimetric SAR Data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 1019–1027. [\[CrossRef\]](#)
30. Wang, Y.; Liu, Y.; Jin, S.; Sun, C.; Wei, X. Evolution of the Topography of Tidal Flats and Sandbanks Along the Jiangsu Coast from 1973 to 2016 Observed from Satellites. *ISPRS J. Photogramm. Remote Sens.* **2019**, *150*, 27–43. [\[CrossRef\]](#)
31. Li, L.; Shen, F.; Xia, Y.; Shi, H.; Wang, N.; He, Z.; Gao, K. Geomorphological Evolution in the Tidal Flat of a Macro-Tidal Muddy Estuary, Hangzhou Bay, China, over the Past 30 Years. *Remote Sens.* **2024**, *16*, 1702. [\[CrossRef\]](#)
32. Zhou, Y.; Zhang, D.; Cutler, M.; Xu, N.; Wang, X.; Sha, H.; Shen, Y. Estimating Muddy Intertidal Flat Slopes Under Varied Coastal Morphology Using Sequential Satellite Data and Spatial Analysis. *Estuar. Coast. Shelf Sci.* **2021**, *251*, 107183. [\[CrossRef\]](#)
33. Xu, Z.; Kim, D.; Kim, S.; Cho, Y.; Lee, S. Estimation of Seasonal Topographic Variation in Tidal Flats Using Waterline Method: A Case Study in Gomso and Hampyeong Bay, South Korea. *Estuar. Coast. Shelf Sci.* **2016**, *183*, 213–220. [\[CrossRef\]](#)

34. Liu, Y.; Xia, X.; Cai, T.; Wang, X.; Zheng, J. Effects of Coastal Reclamation on the Topographic Changes of an Open Estuary: A Case Study in Taizhou Bay, East China. *J. Mar. Sci. Eng.* **2024**, *12*, 1744. [\[CrossRef\]](#)
35. Jin, C.; Gong, Z.; Shi, L.; Zhao, K.; Tinoco, R.; San Juan, J.; Geng, L.; Coco, G. Medium-Term Observations of Salt Marsh Morphodynamics. *Front. Mar. Sci.* **2022**, *9*, 988240. [\[CrossRef\]](#)
36. Xu, N.; Wang, Y.; Huang, C.; Jiang, S.; Jia, M.; Ma, Y. Monitoring Coastal Reclamation Changes Across Jiangsu Province During 1984–2019 Using Landsat Data. *Mar. Policy* **2022**, *136*, 104887. [\[CrossRef\]](#)
37. Martins, D.; da Silva, A.; Duarte, J.; Canário, J.; Vieira, G. Changes in Vessel Traffic Disrupt Tidal Flats and Saltmarshes in the Tagus Estuary, Portugal. *Estuaries Coasts* **2023**, *46*, 1141–1156. [\[CrossRef\]](#)
38. Salameh, E.; Frappart, F.; Turki, I.; Laignel, B. Intertidal Topography Mapping Using the Waterline Method from Sentinel-1 & 2 Images: The Examples of Arcachon and Veys Bays in France. *ISPRS J. Photogramm. Remote Sens.* **2020**, *163*, 98–120. [\[CrossRef\]](#)
39. Mallat, S.; Zhong, S. Characterization of Signals from Multiscale Edges. *IEEE Trans. Pattern Anal. Mach. Intell.* **1992**, *14*, 710–732. [\[CrossRef\]](#)
40. Song, Y.; Li, C.; Xiao, S.; Zhou, Q.; Xiao, H. A Parallel Canny Edge Detection Algorithm Based on Opencl Acceleration. *PLoS ONE* **2024**, *19*, e0292345. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Chen, C.; Liang, J.; Xie, F.; Hu, Z.; Sun, W.; Yang, G.; Yu, J.; Chen, L.; Wang, L.; Wang, L.; et al. Temporal and Spatial Variation of Coastline Using Remote Sensing Images for Zhoushan Archipelago, China. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *107*, 102711. [\[CrossRef\]](#)
42. Ding, X.; Shan, X.; Chen, Y.; Jin, X.; Muhammed, F. Dynamics of Shoreline and Land Reclamation from 1985 to 2015 in the Bohai Sea, China. *J. Geogr. Sci.* **2019**, *29*, 2031–2046. [\[CrossRef\]](#)
43. Ma, Y.; Li, G. Evolution History and Trend of the Modern Huanghe River Delta. *Acta Oceanol. Sin.* **2010**, *29*, 40–52. [\[CrossRef\]](#)
44. Li, Z.; Heygster, G.; Notholt, J. Intertidal Topographic Maps and Morphological Changes in the German Wadden Sea Between 1996–1999 and 2006–2009 from the Waterline Method and SAR Images. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 3210–3224. [\[CrossRef\]](#)
45. Heygster, G.; Dannenberg, J.; Notholt, J. Topographic Mapping of the German Tidal Flats Analyzing SAR Images with the Waterline Method. *IEEE Trans. Geosci. Remote Sens.* **2010**, *48*, 1019–1030. [\[CrossRef\]](#)
46. Yasir, M.; Sheng, H.; Fan, H.; Nazir, S.; Niang, A.J.; Salaududin, M.; Khan, S. Automatic Coastline Extraction and Changes Analysis Using Remote Sensing and GIS Technology. *IEEE Access* **2020**, *8*, 180156–180170. [\[CrossRef\]](#)
47. Buono, A.; Nunziata, F.; Mascolo, L.; Migliaccio, M. A Multipolarization Analysis of Coastline Extraction Using X-Band COSMO-SkyMed SAR Data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 2811–2820. [\[CrossRef\]](#)
48. Tsujii, T.; Yoshida, H.; Iiguni, Y. Automatic Draft Reading Based on Image Processing. *Opt. Eng.* **2016**, *55*, 104104. [\[CrossRef\]](#)
49. Tang, P.; Guo, S.; Zhang, P.; Qie, L.; Pan, X.; Chanussot, J.; Du, P. A Highly Efficient Index for Robust Mapping of Tidal Flats from Sentinel-2 Images Directly. *ISPRS J. Photogramm. Remote Sens.* **2024**, *218*, 742–760. [\[CrossRef\]](#)
50. Dai, S.; Xia, Q.; Zhang, H.; He, T.; Zheng, Q.; Xing, X.; Li, C. Constructing of Tidal Flat Extraction Index in Coastal Zones Using Sentinel-2 Multispectral Images. *Spectrosc. Spectr. Anal.* **2023**, *43*, 1888–1894.
51. Murray, N.J.; Phinn, S.R.; Clemens, R.S.; Roelfsema, C.M.; Fuller, R.A. Continental Scale Mapping of Tidal Flats across East Asia Using the Landsat Archive. *Remote Sens.* **2012**, *4*, 3417–3426. [\[CrossRef\]](#)
52. Wan, J.; Wang, J.; Zhu, M. Water Extraction from Fully Polarized SAR Based on Combined Polarization and Texture Features. *Water* **2021**, *13*, 3332. [\[CrossRef\]](#)
53. Huang, Y.; Peng, J.; Chen, N.; Sun, W.; Du, Q.; Ren, K.; Huang, K. Cross-Scene Wetland Mapping on Hyperspectral Remote Sensing Images Using Adversarial Domain Adaptation Network. *ISPRS J. Photogramm. Remote Sens.* **2023**, *203*, 37–54. [\[CrossRef\]](#)
54. Murray, N.J.; Phinn, S.P.; Fuller, R.A.; DeWitt, M.; Ferrari, R.; Johnston, R.; Clinton, N.; Lyons, M.B. High-Resolution Global Maps of Tidal Flat Ecosystems from 1984 to 2019. *Sci. Data* **2022**, *9*, 542. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Wang, X.; Xiao, X.; Zou, Z.; Chen, B.; Ma, J.; Dong, J.; Doughty, R.; Zhong, Q.; Qin, Y.; Dai, S.; et al. Tracking Annual Changes of Coastal Tidal Flats in China During 1986–2016 Through Analyses of Landsat Images with Google Earth Engine. *Remote Sens. Environ.* **2020**, *238*, 110987. [\[CrossRef\]](#) [\[PubMed\]](#)
56. Sagar, S.; Roberts, D.; Bala, B.; Lymburner, L. Extracting the Intertidal Extent and Topography of the Australian Coastline from a 28 Year Time Series of Landsat Observations. *Remote Sens. Environ.* **2017**, *195*, 153–169. [\[CrossRef\]](#)
57. Tang, W.; Zhao, C.; Lin, J.; Jiao, C.; Zheng, G.; Zhu, J.; Pan, X.; Han, X. Improved Spectral Water Index Combined with Otsu Algorithm to Extract Muddy Coastline Data. *Water* **2022**, *14*, 855. [\[CrossRef\]](#)
58. He, T.; Xia, Q.; Zhang, H.; Zheng, Q.; Zhu, H.; Deng, X.; Zhang, Y. Development of a Tidal Flat Recognition Index Based on Multispectral Images for Mapping Tidal Flats. *Ecol. Indic.* **2023**, *157*, 111218. [\[CrossRef\]](#)
59. Jamali, A.; Mahdianpari, M. Swin Transformer and Deep Convolutional Neural Networks for Coastal Wetland Classification Using Sentinel-1, Sentinel-2, and LiDAR Data. *Remote Sens.* **2022**, *14*, 359. [\[CrossRef\]](#)
60. Zhang, S.; Xu, Q.; Wang, H.; Kang, Y.; Li, X. Automatic Waterline Extraction and Topographic Mapping of Tidal Flats from SAR Images Based on Deep Learning. *Geophys. Res. Lett.* **2022**, *49*, e2021GL096007. [\[CrossRef\]](#)

61. Dang, K.; Nguyen, M.; Nguyen, D.; Phan, T.; Giang, T.; Pham, H.; Nguyen, T.; Tran, T.; Bui, D. Coastal Wetland Classification with Deep U-Net Convolutional Networks and Sentinel-2 Imagery: A Case Study at the Tien Yen Estuary of Vietnam. *Remote Sens.* **2020**, *12*, 3270. [[CrossRef](#)]
62. Yu, D.; Ren, L.; Chen, C.; Kong, X.; Zhou, M.; Yang, L.; Han, Z.; Pan, S. An AttSDNet Model for Multi-Scale Feature Perception Enhanced Remote Sensing Classification of Coastal Salt-Marsh Wetlands. *Mar. Environ. Res.* **2025**, *204*, 106899. [[CrossRef](#)] [[PubMed](#)]
63. Tong, Q.; Wu, J.; Zhu, Z.; Zhang, M.; Xing, H. STIRUnet: SwinTransformer and Inverted Residual Convolution Embedding in Unet for Sea-Land Segmentation. *J. Environ. Manag.* **2024**, *357*, 120773. [[CrossRef](#)] [[PubMed](#)]
64. Zhou, N.; Xu, M.; Shen, B.; Hou, K.; Liu, S.; Sheng, H.; Liu, Y.; Wan, J. ViT-UNet: A Vision Transformer Based UNet Model for Coastal Wetland Classification Based on High Spatial Resolution Imagery. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2024**, *17*, 19575–19587. [[CrossRef](#)]
65. Zhu, Y.; Li, Z.; Zhao, Z.; Lu, L.; Yang, S.; Wang, Z. Spatio-Temporal Changes of Coastline in Jiaozhou Bay from 1987 to 2022 Based on Optical and SAR Data. *Front. Mar. Sci.* **2023**, *10*, 1233410. [[CrossRef](#)]
66. Wang, W.; Yang, X.; Li, X.; Chen, K.; Liu, G.; Li, Z.; Gade, M. A Fully Polarimetric SAR Imagery Classification Scheme for Mud and Sand Flats in Intertidal Zones. *IEEE Trans. Geosci. Remote Sens.* **2017**, *55*, 1734–1742. [[CrossRef](#)]
67. Chen, Y.; He, X.; Wang, J. Classification of Coastal Wetlands in Eastern China Using Polarimetric SAR Data. *Arab. J. Geosci.* **2015**, *8*, 10203–10211. [[CrossRef](#)]
68. Ryu, J.; Kim, C.; Lee, Y.; Won, J.; Chun, S.; Lee, S. Detecting the Intertidal Morphologic Change Using Satellite Data. *Estuar. Coast. Shelf Sci.* **2008**, *78*, 623–632. [[CrossRef](#)]
69. Tang, W.; Zhao, C.; Lin, J.; Jiao, C.; Zheng, G.; Zhu, J.; Pan, X.; Han, X. Inversion of Intertidal Zone Topography Based on Optimized Random Forest Regression Characteristic Parameters. *Geocarto Int.* **2023**, *38*, 2213196. [[CrossRef](#)]
70. Lathrop, R.; Merchant, D.; Niles, L.; Paludo, D.; Santos, C.; Larrain, C.; Feigin, S.; Smith, J.; Dey, A. Multi-Sensor Remote Sensing of Intertidal Flat Habitats for Migratory Shorebird Conservation. *Remote Sens.* **2022**, *14*, 5016. [[CrossRef](#)]
71. Yang, W.; Sha, J.; Bao, Z.; Dong, J.; Li, X.; Shifaw, E.; Tan, J.; Sodango, T. Monitoring Tidal Flats Boundaries Through Combining Sentinel-1 and Sentinel-2 Imagery. *Environ. Technol. Innov.* **2021**, *22*, 101401. [[CrossRef](#)]
72. Zheng, X.; Zhou, B.; Lei, H.; Jin, Y.; Su, Q. Mapping Tidal Flat Topography Using Time-Series Sentinel-2 Images and ICESat-2 Data: A Case Study in Cixi City. *Ocean Coast. Manag.* **2024**, *256*, 107278. [[CrossRef](#)]
73. Sun, J.; Tang, C.; Mu, K.; Li, Y.; Zheng, X.; Zou, T. Tidal Flat Extraction and Analysis in China Based on Multi-Source Remote Sensing Image Collection and MSIC-OA Algorithm. *Remote Sens.* **2024**, *16*, 3607. [[CrossRef](#)]
74. Chang, M.; Li, P.; Li, Z.; Wang, H. Mapping Tidal Flats of the Bohai and Yellow Seas Using Time Series Sentinel-2 Images and Google Earth Engine. *Remote Sens.* **2022**, *14*, 1789. [[CrossRef](#)]
75. Li, C.; Cui, H.; Tian, X. A Novel CA-RegNet Model for Macau Wetlands Auto Segmentation Based on GF-2 Remote Sensing Images. *Appl. Sci.* **2023**, *13*, 12178. [[CrossRef](#)]
76. Shi, T.; Zou, Z.; Shi, Z.; Chu, J.; Zhao, J.; Gao, N.; Zhang, N.; Zhu, X. Mudflat Aquaculture Labeling for Infrared Remote Sensing Images via a Scanning Convolutional Network. *Infrared Phys. Technol.* **2018**, *94*, 16–22. [[CrossRef](#)]
77. Kim, K.; Jung, H.; Choi, J.; Ryu, J. Statistical Analysis for Tidal Flat Classification and Topography Using Multitemporal SAR Backscattering Coefficients. *Remote Sens.* **2021**, *13*, 5169. [[CrossRef](#)]
78. Zuo, P.; Li, Y.; Liu, C.; Zhao, S.; Guan, D. Coastal Wetlands of China: Changes from the 1970s to 2007 Based on a New Wetland Classification System. *Estuaries Coasts* **2013**, *36*, 390–400. [[CrossRef](#)]
79. Sun, N.; Zhu, W.; Cheng, Q. GF-1 and Landsat Observed a 40-Year Wetland Spatiotemporal Variation and Its Coupled Environmental Factors in Yangtze River Estuary. *Estuar. Coast. Shelf Sci.* **2018**, *207*, 30–39. [[CrossRef](#)]
80. Dang, A.; Kumar, L.; Reid, M.; Nguyen, H. Remote Sensing Approach for Monitoring Coastal Wetland in the Mekong Delta, Vietnam: Change Trends and Their Driving Forces. *Remote Sens.* **2021**, *13*, 3359. [[CrossRef](#)]
81. Laghari, Y.; Bai, S.; Leghari, S.; Wei, W.; Laghari, A. Coastal Wetlands of Indus River Delta Are Under Risk Due to Reclamation: A Spatiotemporal Analysis During the Past 50 Years from 1972 to 2022. *Land Degrad. Dev.* **2025**, *36*, 832–852. [[CrossRef](#)]
82. Yin, H.; Hu, Y.; Liu, M.; Li, C.; Chang, Y. Evolutions of 30-Year Spatio-Temporal Distribution and Influencing Factors of Suaeda Salsa in Bohai Bay, China. *Remote Sens.* **2022**, *14*, 138. [[CrossRef](#)]
83. Chen, W.; Chang, A.; Lin, C.; Lin, R.; Lin, D.; Lee, P. Losing Tidal Flats at the Midpoint of the East Asian-Australasian Flyway over the Past 100 Years. *Wetlands* **2024**, *44*, 59. [[CrossRef](#)]
84. Ma, L.; Li, M.; Ma, X.; Cheng, L.; Du, P.; Liu, Y. A Review of Supervised Object-Based Land-Cover Image Classification. *ISPRS J. Photogramm. Remote Sens.* **2017**, *130*, 277–293. [[CrossRef](#)]
85. Zhang, J.; Yan, F.; Lyne, V.; Wang, X.; Su, F.; Cao, Q.; He, B. Monitoring of Ecological Security Patterns Based on Long-Term Land Use Changes in Langsa Bay, Indonesia. *Int. J. Digit. Earth* **2025**, *18*, 2495740. [[CrossRef](#)]

86. Zhang, X.; Liu, L.; Zhao, T.; Chen, X.; Lin, S.; Wang, J.; Mi, J.; Liu, W. GWL_FCS30: A Global 30 M Wetland Map with a Fine Classification System Using Multi-Sourced and Time-Series Remote Sensing Imagery in 2020. *Earth Syst. Sci. Data* **2023**, *15*, 265–293. [[CrossRef](#)]
87. Mustapha, M.A.; Lihan, T.; Khalid, L.I. Coral Reef and Associated Habitat Mapping Using ALOS Satellite Imagery. *Sains Malays.* **2014**, *43*, 1363–1371.
88. Zhao, Y.; Zhang, D.; Deng, H.; Cutler, M. Mudflat Surface Sediment Type Mapping by Remote Sensing Considering the Effect of the Chlorophyll-a Content. *Estuar. Coast. Shelf Sci.* **2023**, *284*, 108276. [[CrossRef](#)]
89. Han, X.; Pan, J.; Devlin, A. Remote Sensing Study of Wetlands in the Pearl River Delta During 1995–2015 with the Support Vector Machine Method. *Front. Earth Sci.* **2018**, *12*, 521–531. [[CrossRef](#)]
90. Zhang, K.; Dong, X.; Liu, Z.; Gao, W.; Hu, Z.; Wu, G. Mapping Tidal Flats with Landsat 8 Images and Google Earth Engine: A Case Study of the China's Eastern Coastal Zone Circa 2015. *Remote Sens.* **2019**, *11*, 924. [[CrossRef](#)]
91. Kearney, M.; Riter, J.; Turner, R. Freshwater River Diversions for Marsh Restoration in Louisiana: Twenty-Six Years of Changing Vegetative Cover and Marsh Area. *Geophys. Res. Lett.* **2011**, *38*, L16405. [[CrossRef](#)]
92. Ryu, J.; Na, Y.; Won, J.; Doerffer, R. A Critical Grain Size for Landsat Etm+ Investigations into Intertidal Sediments: A Case Study of the Gomso Tidal Flats, Korea. *Estuar. Coast. Shelf Sci.* **2004**, *60*, 491–502. [[CrossRef](#)]
93. Kang, M.; Im, S.; Jang, T.; Park, S.; Kim, S. Detecting Areal Changes in Tidal Flats After Sea Dike Construction Using Landsat-TM Images. *J. Earth Syst. Sci.* **2007**, *116*, 561–573. [[CrossRef](#)]
94. Chen, C.; Tian, B.; Wu, W.; Duan, Y.; Zhou, Y.; Zhang, C. UAV Photogrammetry in Intertidal Mudflats: Accuracy, Efficiency, and Potential for Integration with Satellite Imagery. *Remote Sens.* **2023**, *15*, 1814. [[CrossRef](#)]
95. Abdullah, A.Y.M.; Masrur, A.; Adnan, M.S.G.; Baky, M.A.A.; Hassan, Q.K.; Dewan, A. Spatio-Temporal Patterns of Land Use/Land Cover Change in the Heterogeneous Coastal Region of Bangladesh Between 1990 and 2017. *Remote Sens.* **2019**, *11*, 790. [[CrossRef](#)]
96. Kwon, D.; Park, W.; Won, J. Classification of Intertidal Sediment Using a Two-Step Principal Component Analysis (PCA) of Optical Reflectance: A Case Study in Ganghwa Tidal Flats. *J. Mar. Sci. Technol.-Taiwan* **2016**, *24*, 1136–1145. [[CrossRef](#)]
97. Tsai, Y.-L.S.; Tseng, K.-H. Monitoring Multidecadal Coastline Change and Reconstructing Tidal Flat Topography. *Int. J. Appl. Earth Obs. Geoinf.* **2023**, *118*, 103260. [[CrossRef](#)]
98. Yan, J.; Zhao, S.; Su, F.; Du, J.; Feng, P.; Zhang, S. Tidal Flat Extraction and Change Analysis Based on the RF-W Model: A Case Study of Jiaozhou Bay, East China. *Remote Sens.* **2021**, *13*, 1436. [[CrossRef](#)]
99. Liu, Y.; Zhang, H.; Zhang, M.; Cui, Z.; Lei, K.; Zhang, J.; Yang, T.; Ji, P. Vietnam Wetland Cover Map: Using Hydro-Periods Sentinel-2 Images and Google Earth Engine to Explore the Mapping Method of Tropical Wetland. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *115*, 103122. [[CrossRef](#)]
100. Hill, N.K.; Woodworth, B.K.; Phinn, S.R.; Murray, N.J.; Fuller, R.A. Global Protected-Area Coverage and Human Pressure on Tidal Flats. *Conserv. Biol.* **2021**, *35*, 933–943. [[CrossRef](#)] [[PubMed](#)]
101. Yuan, R.; Zhang, H.; Qiu, C.; Wang, Y.; Guo, X.; Wang, Y.; Chen, S. Mapping Morphodynamic Variabilities of a Meso-Tidal Flat in Shanghai Based on Satellite-Derived Data. *Remote Sens.* **2022**, *14*, 4123. [[CrossRef](#)]
102. Wachler, B.; Seiffert, R.; Rasquin, C.; Kösters, F. Tidal Response to Sea Level Rise and Bathymetric Changes in the German Wadden Sea. *Ocean Dyn.* **2020**, *70*, 1033–1052. [[CrossRef](#)]
103. de Vet, P.L.M.; van Prooijen, B.C.; Wang, Z.B. The Differences in Morphological Development Between the Intertidal Flats of the Eastern and Western Scheldt. *Geomorphology* **2017**, *281*, 31–42. [[CrossRef](#)]
104. Elias, E.; van der Spek, A.; Wang, Z.; de Ronde, J. Morphodynamic Development and Sediment Budget of the Dutch Wadden Sea over the Last Century. *Neth. J. Geosci.* **2012**, *91*, 293–310. [[CrossRef](#)]
105. Cao, W.; Zhou, Y.; Li, R.; Li, X. Mapping Changes in Coastlines and Tidal Flats in Developing Islands Using the Full Time Series of Landsat Images. *Remote Sens. Environ.* **2020**, *239*, 111665. [[CrossRef](#)]
106. Dethier, E.N.; Renshaw, C.E.; Magilligan, F.J. Rapid Changes to Global River Suspended Sediment Flux by Humans. *Science* **2022**, *376*, 1447–1452. [[CrossRef](#)] [[PubMed](#)]
107. Murray, N.J.; Worthington, T.A.; Bunting, P.; Duce, S.; Hagger, V.; Lovelock, C.E.; Lucas, R.; Saunders, M.I.; Sheaves, M.; Spalding, M.; et al. High-Resolution Mapping of Losses and Gains of Earth's Tidal Wetlands. *Science* **2022**, *376*, 744–749. [[CrossRef](#)] [[PubMed](#)]
108. Chen, Y.; Dong, J.; Xiao, X.; Zhang, M.; Tian, B.; Zhou, Y.; Li, B.; Ma, Z. Land Claim and Loss of Tidal Flats in the Yangtze Estuary. *Sci. Rep.* **2016**, *6*, 24018. [[CrossRef](#)] [[PubMed](#)]
109. Donatelli, C.; Ganju, N.K.; Zhang, X.; Fagherazzi, S.; Leonardi, N. Salt Marsh Loss Affects Tides and the Sediment Budget in Shallow Bays. *J. Geophys. Res. Earth Surf.* **2018**, *123*, 2647–2662. [[CrossRef](#)]
110. Grandjean, T.; Weenink, R.; van der Wal, D.; Addink, E.; Hu, Z.; Liu, S.; Wang, Z.; Lin, Y.; Bouma, T. Critical Turbidity Thresholds for Maintenance of Estuarine Tidal Flats Worldwide. *Nat. Geosci.* **2024**, *17*, 539–544. [[CrossRef](#)]

111. Leuven, J.R.F.W.; Pierik, H.J.; van der Vegt, M.; Bouma, T.J.; Kleinhans, M.G. Sea-Level-Rise-Induced Threats Depend on the Size of Tide-Influenced Estuaries Worldwide. *Nat. Clim. Change* **2019**, *9*, 986–992. [[CrossRef](#)]
112. Luijendijk, A.; Hagenaars, G.; Ranasinghe, R.; Baart, F.; Donchyts, G.; Aarninkhof, S. Author Correction: The State of the World's Beaches. *Sci. Rep.* **2018**, *8*, 11381. [[CrossRef](#)] [[PubMed](#)]
113. Zhao, Y.; Liu, Q.; Huang, R.; Pan, H.; Xu, M. Recent Evolution of Coastal Tidal Flats and the Impacts of Intensified Human Activities in the Modern Radial Sand Ridges, East China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3191. [[CrossRef](#)] [[PubMed](#)]
114. Liu, Y.; Liu, Y.; Li, J.; Lu, W.; Wei, X.; Sun, C. Evolution of Landscape Ecological Risk at the Optimal Scale: A Case Study of the Open Coastal Wetlands in Jiangsu, China. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1691. [[CrossRef](#)] [[PubMed](#)]
115. Omari, K.; Chenier, R.; Touzi, R.; Sagram, M. Investigation of C-Band SAR Polarimetry for Mapping a High-Tidal Coastal Environment in Northern Canada. *Remote Sens.* **2020**, *12*, 1941. [[CrossRef](#)]
116. Liu, G.; Liu, B.; Zheng, G.; Li, X. Environment Monitoring of Shanghai Nanhui Intertidal Zone with Dual-Polarimetric SAR Data Based on Deep Learning. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 4208918. [[CrossRef](#)]
117. Luo, J.; Cao, W.; Li, X.; Zhou, Y.; He, S.; Zhang, Z.; Li, D.; Zhang, H. Mapping Annual Tidal Flat Loss and Gain in the Micro-Tidal Area Integrating Dual Full-Time Series Spectral Indices. *Remote Sens.* **2024**, *16*, 1402. [[CrossRef](#)]
118. Bayoudh, K.; Knani, R.; Hamdaoui, F.; Mtibaa, A. A Survey on Deep Multimodal Learning for Computer Vision: Advances, Trends, Applications, and Datasets. *Vis. Comput.* **2022**, *38*, 2939–2970. [[CrossRef](#)] [[PubMed](#)]
119. Wang, Z.; Gao, Z. Analysis of the Evolution, Losses and Gains of Tidal Wetlands in the Bohai Rim Based on Image Data Cube. *Ocean Coast. Manag.* **2024**, *255*, 107264. [[CrossRef](#)]

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