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Review

A Review of Open Remote Sensing Data with GIS, AI, and UAV Support for Shoreline Detection and Coastal Erosion Monitoring

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Abstract: This review discusses the evolution and integration of open-access remote sensing technology in shoreline detection and coastal erosion monitoring through the use of Geographic Information Systems (GIS), Artificial Intelligence (AI), Unmanned Aerial Vehicles (UAVs), and Ground Truth Data (GTD). The Sentinel-2 and Landsat 8/9 missions are highlighted as the primary core datasets due to their open-access policy, worldwide coverage, and demonstrated applicability in long-term coastal monitoring. Landsat data have allowed the detection of multi-decadal trends in erosion since 1972, and Sentinel-2 has provided enhanced spatial and temporal resolutions since 2015. Through integration with GIS programs such as the Digital Shoreline Analysis System (DSAS), AI-based processes such as sophisticated models including WaterNet, U-Net, and Convolutional Neural Networks (CNNs) are highly accurate in shoreline segmentation. UAVs supply complementary high-resolution data for localized validation, and ground truthing based on GNSS increases the precision of the produced map results. The fusion of UAV imagery, satellite data, and machine learning aids a multi-resolution approach to real-time shoreline monitoring and early warnings. Despite the developments seen with these tools, issues relating to atmosphere such as cloud cover, data fusion, and model generalizability in different coastal environments continue to require resolutions to be addressed by future studies in terms of enhanced sensors and adaptive learning approaches with the rise of AI technology the recent years.

Keywords: sentinel-2; sentinel-1; Landsat; coastal erosion; shoreline; remote sensing; shoreline detection; open access; satellite data; AI; UAV; machine learning

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1. Introduction

Coastal erosion is highlighted as an urgent, pressing global issue affecting approximately 80% of shorelines worldwide with erosion effects from 1 centimeter to 30 m/year, calling for shoreline monitoring and sustainable coastal zone management with early warning frameworks and forthcoming predictions for stakeholder decisions [1]. The main factors contributing to and enhancing this phenomenon are natural forces such as waves, storms, and tides, as well as human activities such as urbanization of the coastal front and the construction of water-retaining dams. Sea level rise and extreme weather events drive significant changes in shoreline dynamics, increasing the risk of erosion, inundation, and habitat loss along the coastlines. Even moderate sea level rise is directly linked to the degradation of natural defense lines like dunes and mangroves, accelerating landward shoreline retreat, particularly in low-lying deltaic settings where land subsidence impacts the problem caused by shoreline retreat even more [2,3]. Severe occurrences such as storm surges and hurricanes are directly correlated with increased sea levels, increasing wave energy and sediment transport. This interaction rapidly shapes the morphology of the coastline [4,5]. Urbanized coastlines are particularly vulnerable due to a lack of natural defense lines and buffers, which increases the likelihood of storm-induced erosion [6,7]. These phenomena cause socio-economic instability, damaging infrastructure, reducing the biodiversity in wetlands and estuaries, and harming tourism and livelihoods [8,9].

Remote sensing, in addition to predictive models and other AI software like WaterNet, has the potential to address these issues and enhance the monitoring and forecasting of shoreline changes under climate change. Proactive and adaptive approaches—such as nature-based solutions and resilient infrastructure—require access to accurate, high-resolution spatial and temporal data, especially in areas exposed to accelerated erosion and development pressures [10,11].

Traditional shoreline monitoring methods—like ground surveys and aerial photography—serve as foundational tools but often fall short in frequency, coverage, and timeliness, especially in fast-changing or remote environments [5,6,12]. These techniques are also labor-intensive, expensive, and frequently impacted by weather or terrain constraints. In contrast, satellite-based remote sensing has revolutionized coastal monitoring by enabling regular, cost-effective observations of extensive areas under open-access policies. These platforms allow the frequent acquisition of high-resolution imagery critical for detecting shoreline changes [13].

Among the available resource datasets, open-access satellite missions like Sentinel and Landsat stand out as vital resources due to the open-access data policy. The Sentinel program, launched by the European Space Agency (ESA), includes Sentinel-1 and Sentinel-2, which provide radar and optical imagery, respectively [14]. Sentinel-2 offers high-resolution optical images with frequent revisits, while Sentinel-1's synthetic aperture radar (SAR) capabilities enable data collection regardless of weather or lighting conditions. These features make Sentinel missions especially effective in capturing rapid coastal changes under dynamic environmental conditions. The Landsat program, operated jointly by USGS and NASA since 1972, provides the most extended continuous global archive of multispectral imagery [15], which is critical and informative for understanding decadal trends in shoreline dynamics and environmental change [16].

The Sentinel-2 and Landsat missions offer complementary capabilities for shoreline detection and coastal erosion analysis. Sentinel-2 contributes by providing high-spatial-resolution imagery (10 m for visible and near-infrared bands), a wide swath width (290 km), and a frequent revisit time of 5 days with both satellites (Sentinel-2A and 2B) [14]. On the other hand, Landsat missions, especially Landsat 8 and 9, offer a moderate spatial resolution (30 m) while providing unmatched temporal depth, with an archive extending back to 1972 and a revisit time of 16 days. The long historical continuity of Landsat data is essential for analyzing multi-decadal shoreline change, while Sentinel-2 enhances spatial detail and short-term variability. Various methods have been employed to fuse the datasets, including pixel-level stacking, temporal harmonization, and machine learning-based fusion. The synergetic action results in surpassing cloudy periods, filling gaps, cross-validating the results, and enhancing spatiotemporal resolutions, as studies have shown, for instance, the improvement of shoreline delineation accuracy and tracing seasonal trends in short-term and long-term monitoring periods [17]. The open-access data policy that facilitates both missions is cost-effective and scalable, and their datasets offer replicable shoreline monitoring across diverse and harsh coastal environments [18].

The need for further improvement in coastal monitoring has been progressed and enhanced by integrating satellite data as core technologies with Geographic Information Systems (GIS), Unmanned Aerial Vehicles (UAVs), and Artificial Intelligence (AI). GIS is a powerful means of carrying out advanced spatial analysis. It allows researchers to combine satellite images with many environmental and human aspects. In this way, they can obtain a detailed, three-dimensional vision of essential problems such as shoreline variability, sediment movements, and erosive pattern dynamics [14]. Tools such as the Digital Shoreline Analysis System (DSAS)—developed by the USGS—extend GIS functionality to quantify shoreline change over time [19]. DSAS provides essential shoreline change metrics like EPR (End Point Rate), NSM (Net Shoreline Movement), and LRR (Linear Regression Rate) and can be integrated with machine learning algorithms to process large volumes of satellite data efficiently.

AI has been posited to be a powerful tool in coastal monitoring, aiding shoreline segmentation, water delineation, erosion prediction modeling, and pattern recognition. Techniques such as Machine Learning (ML) and Deep Learning (DL) are increasingly applied in coastal erosion studies for prediction models and data analysis [20,21]. For example, WaterNet, an advanced deep-learning model, has achieved over 99% accuracy in shoreline segmentation using satellite imagery [20]. UAVs complement satellite-based monitoring by capturing high-resolution multispectral imagery and generating 3D models of areas inaccessible by conventional means [22]. These UAV datasets are essential for the in situ validation of satellite results and to produce detailed Digital Elevation Models (DEMs), which improve erosion impact terrain assessments. Combined, these technologies form a multi-scale, integrated framework for dynamic shoreline monitoring [23].

Given the persistent effects of climate change and escalating human activity on coastlines, there is a pressing necessity to implement adaptive coastal management strategies based on resilience and technology integration. In changing coastal environments with rapid transformation rates, conventional approaches are not enough. Satellite-based monitoring coupled with UAVs, AI, and GIS is a feasible and scalable approach to simultaneous high-frequency and high-accuracy shoreline monitoring. This review discusses the effectiveness of missions on Sentinel and Landsat and their integration with state-of-the-art tools in support of multi-scale coastal erosion tracking and resilience planning.

This review carefully examines literature from 2021 onward to highlight recent advancements in Artificial Intelligence (AI), Unmanned Aerial Vehicles (UAV), and high-frequency satellite observations enabled by Sentinel-2 and Landsat 8/9. Although it is not all-encompassing, this focus ensures relevance to the emerging tools and methodologies utilized in shoreline monitoring. The primary objectives of the current review are to (i) identify and categorize shoreline detection and coastal erosion monitoring with open-access satellite applications, (ii) outline integrated workflows involving AI, UAV, GIS, and Ground Truth validation, and (iii) evaluate operational constraints and potential for the development of adaptive coastal monitoring systems based on open access satellite data.

2. Review Methodology

The literature review workflow was conducted using the Web of Science database, with the search date appointed as 2 April 2024. The Web of Science (WoS) database was chosen as the database source for identifying relevant journal articles [24–26]. This decision was based on WoS's comprehensive indexing of high-quality, peer-reviewed journals across disciplines, its advanced search capabilities, and its inclusion of citation metrics, which are critical for evaluating the impact of research.

We identified papers researching coastal erosion and shoreline analysis using satellite images from the Sentinel mission and Landsat over the past three years (1 January 2021–1 March 2024). The list of chosen keywords was suggested to ensure all-round coverage and included "Coastal Erosion", "Shoreline", "Satellite", "Remote Sensing", "Earth Observation", "Copernicus", "Landsat", and "Sentinel". We chose the "Title" option in the search table to identify journals' titles containing the keywords "Coastal Erosion" OR "Shoreline" and utilized the "AND" Topic feature to limit the study to the specific subject of interest by including the keywords "satellite OR remote sensing OR earth observation". Also, keywords such as "Copernicus OR Sentinel OR Landsat" expanded the search scope of the subject.

Applying the "Publication Date" option, we tuned the search to include only the past three years: "1 January 2021–1 March 2024". The timeframe was chosen mainly due to the Sentinel mission, first deployed in 2015, considering that it has established a research background over the past decade, with significant advancements revealed in research methods in the last three years as we intended to preserve it as a core technology in the review [27].

The search process followed the proposed flow chart of Figure 1, which identified 103 journal articles. We reviewed the articles' keywords, DOIs, topic relevance, titles, and language (English). The screening results were analyzed using Microsoft Excel® (Microsoft, Redmond, Washington, DC, USA), sorting the thematic sections using filtering options and classifying the citations from highest to lowest in each thematic section.

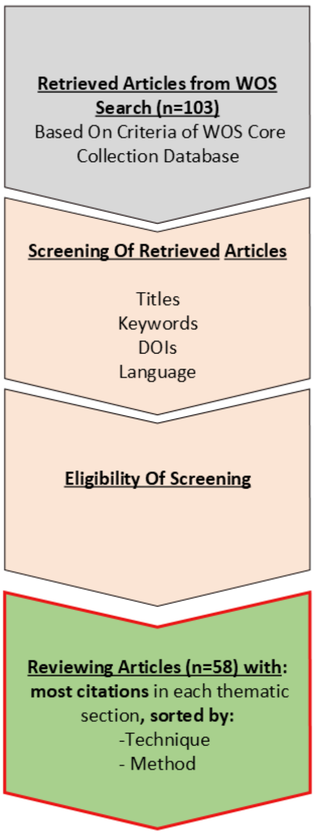

Figure 1. Flow diagram showing the systematic process reviewing WOS articles: 103 retrieved, screened by titles, keywords, DOIs, and language, yielding 58 eligible articles. The most-cited (at least 3 at the time the literature review was conducted) articles were reviewed by thematic section, technique, and method.

The chosen period (2021–2024) captures a time of fast development in the domain of remote sensing, facilitated by the confluence of AI and high-resolution satellite technology. Zhang and Zhang (2022) [28] exemplified how AI has transformed the work structure of geospatial analysis by maximizing classification accuracy and streamlining processing. Equally, Ulhaq and Gomes (2022) [29] showed how the blending of UAV data and big data brought novel paradigms of analysis, allowing for greater insight into coastal monitoring. This is a move toward more sophisticated, AI-capable data processing methods that underpin a number of the studies under review.

We only considered the eligibility of articles concerning the scope of our research, with a preference for those with the highest citations [30]. Articles that had been cited a minimum of at least three times during the period of our study, spanning the three-year timeframe of the review, were shortlisted for further consideration. Out of the 103 research papers, only 58 were studied more closely, incorporating remote sensing along different dimensions such as the methodology and the employment of tools and equipment.

This approach aims to prioritize highly relevant and impactful articles, always during the timeframe of the research. Articles were selected based on the following eligibility criteria:

- Minimum of 3 citations (as of April 2024).
- Alignment with the study's scope (shoreline detection and coastal erosion).
- Use of open remote sensing data (Sentinel and/or Landsat).
- Application of key methodologies (AI, GIS, UAV, or GNSS validation).
- Thematic and methodological relevance.

Articles below the citation barrier, or not aligned with the theme or methodologically sound, were not considered. This might preclude a few potentially useful but extremely new studies, but it does guarantee a close examination of highly influential research. We recognize that some articles published in late March 2024 could be too new for citations and thus are underrepresented in this overview. These would be considered in future reviews.

To facilitate a holistic, multi-disciplinary overview, the 58 articles were allocated into seven theme-based sections, each highlighting a unique technical or methodological feature of remote sensing in coastal monitoring. The sections vary from specialized methods (e.g., DSAS, NDWI) through integrated approaches (e.g., UAV-satellite fusion, AI models) to encompass both traditional and new techniques.

Several sections reflect cross-disciplinary interfaces, e.g., between machine learning and GIS platforms.

The screening of articles was made possible through thematic keyword filters within article titles and metadata. Remarkably, articles were not excluded during this stage based merely on geographic area or area of application—guaranteeing methodological diversity.

Hence, the current research undertakes a structured and directed overview of influential methods employed in studies of coastal erosion, in this instance, through open-access Sentinel and Landsat satellite imaging. From Figure 1, 103 initial articles were extracted from the Web of Science Core Collection, from which 58 were kept following title, keyword, DOI, and language-based filtering. These were then divided by thematic relevance as well as citation impact, ensuring a good reflection of both innovation and practical applicability. For a few cases involving article duplication, additional studies of relevance were incorporated to maintain scope based on the same criteria.

In future iterations, we intend to extend the scope of this review to include the Scopus database, which will further enrich the dataset, especially in fields such as coastal engineering, geophysics, and marine infrastructure monitoring.

3. Materials and Methods

The outcomes of this review investigating the chosen screened papers are compiled in Table 1 and indicate the range of applications of various shoreline detection and coastal erosion methodologies, providing information on the central function played by Sentinel-2 and Landsat satellite missions. These are the central necessary technologies, with other methodologies revolving around them, evidencing how significant and central they are in this field. Such a focused methodology allowed us to gather precious information to promote study technologies on coastal erosion. In addition, it emphasized the contribution of satellite data in shoreline monitoring and analysis.

Table 1. Overview of reviewed articles on remote sensing technology used in shoreline detection and coastal erosion monitoring (2021–2024). This table summarizes the presence (✔) of key methods and data sources (e.g., Sentinel-2, Landsat, GIS, UAV, Ground Truth, and AI) across 58 selected studies, supporting thematic classification and methodological comparisons.

Number	Reference	Sentinel-1	Sentinel-2	Landsat	GIS	UAV/Drone	Ground Truth Data	AI/Machine Learning/Neural Network
1	[6]			✔	✔		✔	
2	[31]			✔	✔			
3	[21]		✔	✔	✔			✔
4	[32]			✔	✔			
5	[33]		✔	✔	✔		✔	✔
6	[11]		✔	✔	✔			
7	[20]			✔	✔			✔
8	[15]			✔	✔		✔	
9	[34]		✔	✔			✔	
10	[35]	✔		✔	✔			
11	[12]			✔	✔			
12	[3]		✔	✔	✔		✔	
13	[36]		✔	✔	✔		✔	
14	[37]			✔	✔		✔	
15	[9]			✔	✔		✔	
16	[38]			✔	✔			
17	[8]		✔	✔	✔		✔	
18	[2]			✔	✔			
19	[39]	✔					✔	
20	[40]			✔	✔			
21	[41]			✔	✔		✔	
22	[42]			✔	✔			
23	[43]		✔		✔		✔	
24	[44]		✔		✔	✔	✔	✔
25	[45]			✔	✔		✔	

Table 1. *Cont.*

Number	Reference	Sentinel-1	Sentinel-2	Landsat	GIS	UAV/Drone	Ground Truth Data	AI/Machine Learning/Neural Network
26	[46]			✔	✔		✔	
27	[7]			✔	✔			
28	[47]		✔		✔			
29	[48]		✔	✔	✔			
30	[49]			✔	✔			
31	[50]			✔	✔			✔
32	[51]			✔	✔		✔	
33	[4]			✔	✔		✔	
34	[14]			✔	✔			
35	[52]		✔	✔	✔		✔	
36	[53]			✔				
37	[54]		✔	✔	✔		✔	✔
38	[55]	✔	✔		✔		✔	✔
39	[10]			✔	✔			
40	[56]		✔	✔	✔			
41	[13]		✔	✔			✔	✔
42	[5]			✔	✔			
43	[18]		✔	✔	✔			
44	[57]		✔	✔	✔			✔
45	[1]			✔	✔			
46	[58]			✔	✔			
47	[59]		✔	✔	✔		✔	
48	[60]			✔	✔			
49	[61]			✔	✔			
50	[62]		✔	✔	✔			
51	[63]			✔	✔			
52	[64]		✔		✔			
53	[65]			✔	✔			
54	[66]			✔	✔			
55	[67]			✔	✔			
56	[68]			✔	✔			
57	[69]			✔	✔			
58	[19]			✔	✔			

The technologies listed in Table 1 are further aggregated and classified by dominant methodological themes in Table 2. This thematic breakdown allows for a clearer comparison of the main approaches adopted across the reviewed studies, such as DSAS-based analysis, AI implementation, or UAV-supported validation.

Table 2. Dominant techniques and methods used in reviewed studies on shoreline detection (2021–2024). The table presents a thematic classification of 58 reviewed articles based on the primary technologies applied—such as Sentinel-1/2, Landsat, GIS, UAV, Ground Truth Data (GTD), and AI/ML—highlighting the prevalence of each technique across the dataset.

Category	Sentinel-1	Sentinel-2	Landsat	GIS	UAV/Drone	Ground Truth Data	AI/Machine Learning/Neural Network
No. of Articles (n = 58)	3/58	21/58	53/58	55/58	1/58	21/58	9/58
Percentage (%)	5.17%	36.21%	91.38%	94.83%	1.72%	36.21%	15.52%

3.1. Sentinel and Landsat Sensors

Satellite imagery is the core technology used as a base for conducting this review. Table 3 provides a comparative overview of the main satellite missions, with the core technologies mainly being Sentinel-2, Landsat, and Sentinel-1 across the reviewed literature. These missions form the foundation of coastal remote sensing due to their consistent global availability, spectral variety, and high revisit frequency. Sentinel-2 offers high spatial and temporal resolutions, which makes it ideal for tracking shoreline changes with a higher temporal resolution and short timeframes, while Landsat offers long-term historical continuity [70]. Sentinel-1 provides synthetic aperture radar (SAR) data, enabling cloud-independent monitoring, which is crucial in tropical and storm-prone coastal zones [71]. However, Sentinel-1 was not highlighted in the review as it was not among the studies that fulfilled the criteria selection in the workflow, in comparison with Sentinel-2 and Landsat.

Table 3. Comparison of key characteristics of Sentinel-1, Sentinel-2, and Landsat 8/9 satellite missions commonly used in shoreline detection and coastal erosion studies. The table summarizes each mission's spatial, spectral, and temporal resolution, data type, and key applications relevant to coastal monitoring.

Mission	Sentinel-1	Sentinel-2	Landsat-8/9
Agency	ESA (European Space Agency)	ESA (European Space Agency)	NASA/USGS
First Launch Year	2014 (Sentinel-1A)	2015 (Sentinel-2A)	2013 (Landsat-8), 2021 (Landsat-9)
Revisit Time	6 days (combined 1A & 1B)	5 days (combined 2A & 2B)	16 days each
Spatial Resolution	10 m (SAR)	10 m (VIS/NIR), 20 m (RE/SWIR), 60 m (Atmospheric)	15 m (panchromatic), 30 m (multispectral), 100 m (thermal)
Spectral Bands	C-band SAR	13 spectral bands	11 spectral bands
Swath Width	250 km	290 km	185 km
Temporal Coverage	2014–present	2015–present	2013–present
Primary Applications	All-weather imaging, terrain motion, flood monitoring	Land cover, vegetation, water bodies, coastal zones	Land use/land cover change, agriculture, hydrology

3.2. Remote Sensing Indices and Analytical Tools for Shoreline Monitoring

Remote sensing core technologies, in combination with analytical tools, provide a solid approach to monitoring alterations and shoreline variability [72]. The most common analytical tools employed for addressing the purpose of shoreline analysis include the indices of the Normalized Difference Water Index (NDWI), as stated by Vasanthi et al. [73], and the Digital Shoreline Analysis System (DSAS). While NDVI is not typically used for direct shoreline extraction, it has been included in some studies [67] to monitor vegetation loss adjacent to shorelines, indirectly indicating erosion processes in sensitive coastal zones [9,50]. In shoreline contexts, NDVI is useful for detecting vegetative dune systems or mangrove degradation [74], which serve as early indicators of erosion-prone zones.

Therefore, these specialized indices and methodologies will enable accurate monitoring results and data analysis, which are fundamentally required at the formulation and implementation levels of an effective coastal management strategy [21,41,50]. The selection of those specific remote sensing indices and GIS techniques for shoreline analysis that we refer to is based on the popularity of the reviewed articles.

3.2.1. Spectral Indices for Shoreline Delineation

The Normalized Difference Water Index (NDWI) enhances the presence of water features in remotely sensed imagery. It is calculated using the formula:

$$NDWI = (G - NIR)/(G + NIR), \tag{1}$$

where G is the green spectral band reflectance and NIR is the near-infrared spectral band reflectance. NDWI values close to +1 represent water bodies, whereas values close to 0 or negative are indicative of non-water surfaces. The NDWI is useful for distinguishing between water bodies and land masses, as well as for shoreline change detection. For example, the NDWI has been used to identify land masses versus water bodies in shoreline detection applications [33].

The NDWI (primarily) and NDVI (indirectly) are indices broadly accepted as global standards for measuring vegetation and water body behaviors in coastal areas. However, in comparison with research based on high-resolution commercial satellites like WorldView, there is valuable insight that can be gained. WorldView satellites' ability to capture fine-grained coastal details, such as narrow coastlines, patches of vegetation, and finely grained anthropogenic structures, as seen in McAllister et al., 2022 [21], is unparalleled. Such detail at this level significantly increases effectiveness in detection accuracy and shoreline change analysis, particularly in urban or sediment-rich coastal areas where NDVI and NDWI values derived via lower-resolution satellites such as Sentinel and Landsat are at a disadvantage [5,40]. While NDVI and NDWI are useful in large-scale analysis, effectiveness is lost when high spatial accuracy is required for analysis, where sub-meter resolutions are optimal for detecting subtle changes in vegetation or waterbody boundaries. Integrating high-resolution comparisons emphasizes how commercial satellite systems may complement or outshine open-access systems, particularly coastal monitoring applications [53].

Other spectral indices, apart from the NDWI, have been proposed to enhance water feature recognition in different environments. The Modified Normalized Difference Water Index (MNDWI) developed by Xu (2006) [75] substitutes the use of the NIR band in the NDWI with the Short-Wave Infrared (SWIR) band, allowing for better discrimination of water features, particularly in urban environments, to counteract the interference of built-up features in the water extraction process. Such is the case with the Automated Water Extraction Index (AWEI) by Feyisa et al. (2014) [76], wherein several spectral bands are fused in order to better discriminate water from non-water features, such as shadows and dark targets, thus leading to better water extraction accuracy in complicated environments. The integration of these indices with NDWI can improve shoreline extraction accuracy in a wide range of coastal environments.

3.2.2. Digital Shoreline Analysis System (DSAS) Overview

The Digital Shoreline Analysis System (DSAS, version 6.0.170) is an application software designed by the United States Geological Survey to compute rate-of-change statistics based on several historical shoreline positions. It automates the determination of measurement sites, calculates rates, and delivers related uncertainties [77]. The DSAS accommodates multiple statistical methods, such as the End Point Rate (EPR), which measures the shoreline change rate between the oldest and most up-to-date shoreline positions. The EPR is effective in cases where two shoreline positions exist. LRR constructs all shoreline positions based on a least-squares regression line to obtain a rate of change. LRR is more powerful in the presence of multiple shoreline positions, yielding an overall picture of shoreline development. Other measurements provided by the DSAS are the Shoreline Change Envelope (SCE), measuring the distance between the most landward and most seaward shoreline positions as a function of time.

NSM estimates the distance between the oldest and most up-to-date shoreline positions, quantifying results. The Weighted Linear Regression Rate (WLR) is similar to LRR but it gives weight to shoreline positions based on their uncertainty, providing an improved rate of change. The use of the DSAS for shoreline change analysis has been illustrated in different studies [11,41,78]. For instance, the DSAS has been applied for shoreline changes on the Odisha coast of India based on historical satellite data [4]. In addition, Figure 2 depicts the metrics of EPR, NSM, and SCE in elaborate detail in each of the metrics.

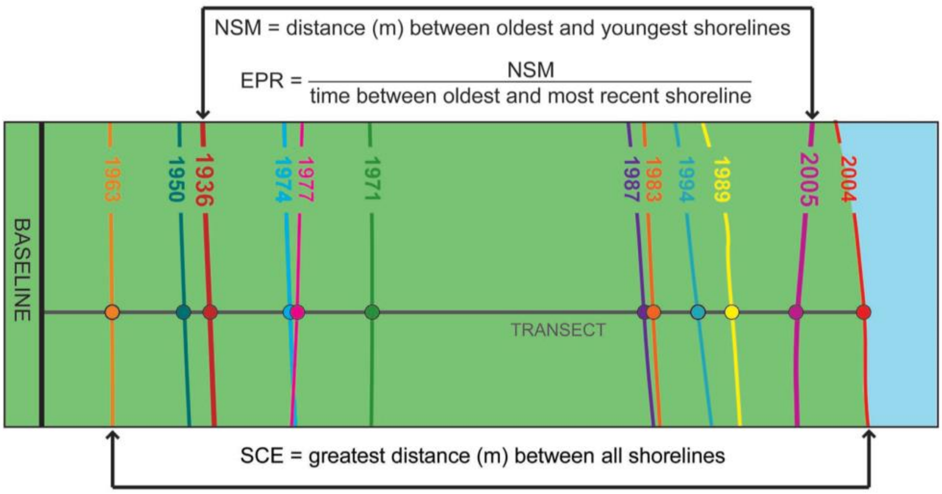

Figure 2. A shoreline dataset including baseline (black), transect (gray), and shoreline and intersect data (multicolor) to illustrate the relationship between shoreline change statistics: Net Shoreline Movement (NSM), End Point Rate (EPR), and Shoreline Change Envelope (SCE). NSM is the distance along the transect in meters (m) between the oldest shoreline (1936, red) and the most recent shoreline (2005, magenta). The EPR is the NSM distance divided by the time between the oldest (1936, red) and most recent (2005, magenta) shorelines (69 years in this example). The SCE is the greatest distance between all the shorelines regardless of date. Note. Adapted from Himmelstoss, E.A., Henderson, R.E., Kratzmann, M.G., and Farris, A.S., 2021, Digital Shoreline Analysis System (DSAS) version 5.1 user guide: U.S. Geological Survey Open-File Report 2021–1091, 104 p., https://doi.org/10.3133/ofr20211091 [79].

1. End Point Rate (EPR) is calculated by dividing the distance between the oldest and most recent shorelines by their time elapsed. It is calculated using the formula:

$$EPR = (D\_new - D\_old)/(T\_new - T\_old) \quad (2)$$

where D_new = distance of the most recent shoreline, D_old = distance of the oldest shoreline, T_new = year of the most recent shoreline, and T_old = year of the oldest shoreline.

2. The Linear Regression Rate (LRR) uses linear regression to find the rate of shoreline movement over time. It is calculated using the formula:

$$LRR = \frac{\sum(y_i - \overline{y})}{\sum(x_i - \overline{x})} \tag{3}$$

where y_i = individual shoreline positions, x_i = corresponding times for each shoreline position, $\overline{y}$ = mean of all shoreline positions, and $\overline{x}$ = mean of all times. Figure 3 illustrates the LRR method for analyzing shoreline change over time.

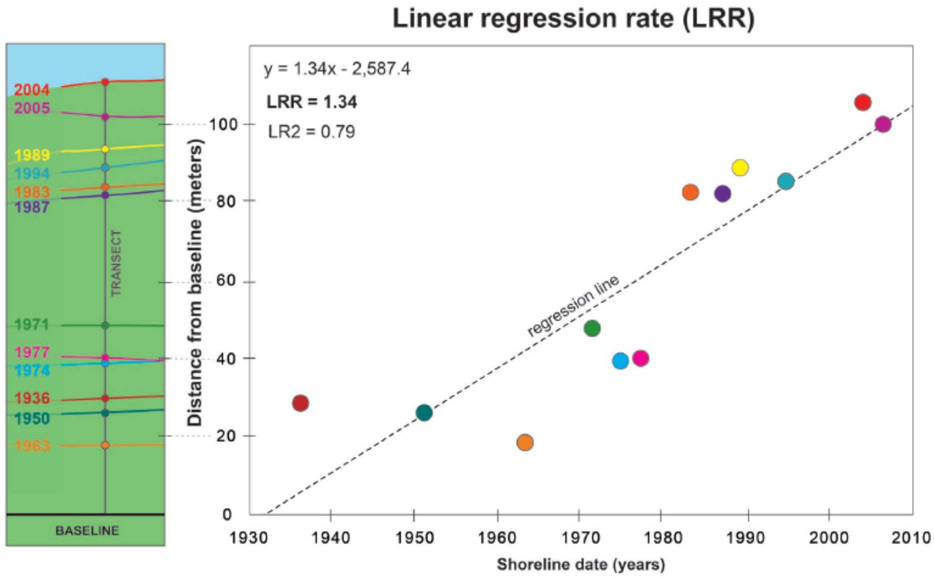

Figure 3. A shoreline dataset (baseline (black), transect (gray), and shorelines and intersects (multicolor)) presented on a map and as a graph of distance from the baseline versus the shoreline date in relation to the LRR regression line. The LRR was determined by plotting the shoreline intersect positions (distance from baseline) with respect to time (years) and calculating the linear regression equation of y = 1.34x − 2587.4. The slope of the equation describing the line is the rate (1.34 m per year). LR2, R-squared of linear regression. Note. Adapted from Himmelstoss, E.A., Henderson, R.E., Kratzmann, M.G., and Farris, A.S., 2021, Digital Shoreline Analysis System (DSAS) version 5.1 user guide: U.S. Geological Survey Open-File Report 2021–1091, 104 p., https://doi.org/10.3133/ofr20211091 [79].

3. The Shoreline Change Envelope (SCE) is the distance between the farthest landward and farthest seaward shorelines over a given time period. It is calculated using the formula:

$$\text{SCE} = |\,\text{D\_seaward} - \text{D\_landward}\,| \tag{4}$$

where D_seaward = farthest seaward shoreline and D_landward = farthest landward shoreline.

4. The Net Shoreline Movement (NSM) is the total distance between the oldest and most recent shorelines, without considering the time interval. It is calculated using the formula:

$$\text{NSM} = |\,\text{D\_new} - \text{D\_old}\,| \tag{5}$$

where D_new = distance of the most recent shoreline and D_old = distance of the oldest shoreline.

5. The Weighted Linear Regression Rate (WLRR) uses linear regression with weights to account for differences in data accuracy or time intervals. It is calculated using the formula:

$$WLRR = \frac{\sum(w_i \cdot (y_i - \overline{y}))}{\sum(w_i \cdot (x_i - \overline{x}))} \quad (6)$$

where w_i = weight for each data point, y_i = individual shoreline positions, x_i = corresponding times, $\overline{y}$ = mean of all shoreline positions, and $\overline{x}$ = mean of all times. Figure 4 illustrates the Weighted Linear Regression (WLR) method for analyzing shoreline change over time, incorporating the concept of shoreline uncertainty.

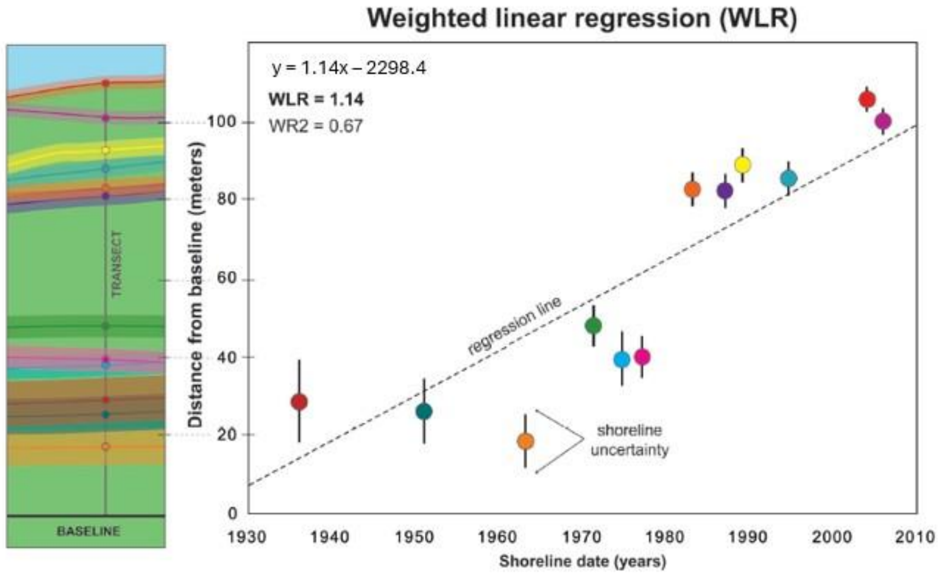

Figure 4. A shoreline dataset (baseline (black), transect (gray), and shorelines and intersects (multicolor), with shoreline position uncertainty) presented on a map and as a graph of distance from the baseline versus the shoreline date in relation to the weighted linear regression (WLR) line. The WLR rate is determined by plotting the shoreline positions with respect to time. Smaller positional uncertainty values (shown as vertical bars around each data point in the graph) have more influence than other values in the regression calculation because of the weighting component in the algorithm. The slope of the regression line is the rate (1.14 m per year). WR2, R-squared of weighted regression. Note. Adapted from Himmelstoss, E.A., Henderson, R.E., Kratzmann, M.G., and Farris, A.S., 2021, Digital Shoreline Analysis System (DSAS) version 5.1 user guide: U.S. Geological Survey Open-File Report 2021–1091, 104 p., https://doi.org/10.3133/ofr20211091 [79].

Vallarino Castillo et al. (2022) [10] revealed on the Pacific coast (Panama) that EPR values indicated the rate of shoreline change over specific periods, with maximum erosion values recorded as −11.29 m/year (1998–2004) and maximum accretion values as 4.14 m/year (1998–2004), offering ease of use in only two shorelines for analysis. However, it neglects intermediate information when more than two shorelines are used. The LRR provided a mean shoreline change rate of 0.45 m/year across the zones, with a maximum rate of 1.75 m/year and a minimum of −0.98 m/year. The NSM provides the distance between the oldest and most recent shoreline, with maximum negative distances recorded as −80.51 m in Zone III, offering a clear measure of shoreline change over time, where it may not account for short-term fluctuations in shoreline position.

In João Pessoa city (Brazil), Santos et al. (2021) [31] used EPR for short-term analysis and indicated significant erosion in all zones from 1985 to 1990, with a mean rate of −3.15 m/year. The highest erosion was recorded in Zone I (−4.51 m/year) and Zone II (−3.55 m/year) where LRR provided a mean shoreline change rate of 0.45 m/year across the zones, with a maximum rate of 1.75 m/year and a minimum of −0.98 m/year. These findings highlight the importance of long-term analysis and providing a more stable estimate of shoreline change, maintaining the drawback that occurs from data point selection and missing short-term fluctuations of importance. Further analysis showed that WLR provided a mean shoreline change of 0.55 m/year, incorporating uncertainty measurements that enhance the accuracy of coastline change estimates, but all of this was achieved by adding more complex calculations and data for the accurate weight of results. Lamptey et al., 2022 [69] conducted research along the coast of Keta (Ghana) using EPR, resulting in a mean erosion rate between 1991 and 2018 of 1.64 m/yr, while the investigation of the mean erosion rate using LRR between 1991 and 2018 resulted in a value of 2.22 m/yr. Murray et al., 2023 [50] investigated the Southwestern Coast (South Africa), indicating that 95% of the study area had received negative NSM over the past 83 years, with an average movement of −38 m. The greatest NSM recorded was −99.29 m along Sixteen Mile Beach, while the least affected area was Yzerfontein Main Beach, with an average of −8.58 m. The SCE showed variability in shoreline movement, with Sixteen Mile Beach experiencing the most significant average change of 52.13 m, while the EPR results indicated that all Pearl Bay Beach transects had negative EPRs, averaging −0.36 myr, while Yzerfontein Main Beach had the smallest average EPR of −0.10 myr. LRR revealed a dominant trend of landward movement along the coastline, with 86% of the study site showing negative rates and an average rate of −0.28 myr. Finally, the WLR provided a more reliable rate of change, showing that Sixteen Mile Beach had a maximum erosion rate of −1.19–0.47 myr. The author acknowledged that the data extracted from Landsat imagery have large uncertainty values (>15 m), which can affect the reliability of the results. This uncertainty necessitates the use of methods like the WLR to provide more reliable rates of change, s only 34% of the study site transects have significantly negative rates of change and none of the positive LRR values are considered statistically significant for any of the beaches, which may limit the robustness of the findings. Conclusively, EPR is best for short-term analyses where simplicity is key, but its lack of intermediate data consideration limits its use in dynamic contexts. LRR and WLR excel in long-term, comprehensive analyses, with WLR offering enhanced accuracy through uncertainty weighting. NSM and SCE are straightforward for spatial trend visualization but lack temporal and rate-based insights.

3.3. Modeling Long-Term Erosion Trends

Long-term erosion patterns along the shoreline are accurately modeled using temporal predictive and regression methods applied to historical shoreline positions based on satellites. Such common methods include the EPR, LRR, and WLR, all of which are encapsulated in the DSAS approach [80]. Santos et al. [31] applied the WLR, for example, to examine 34 years of shoreline changes in Brazil, while for 83 years of Landsat-derived shoreline data in South Africa, Murray et al. [50] utilized these metrics. Vallarino Castillo et al. [10] showed the tolerance of WLR in evaluating shoreline variability along the Pacific coast of Panama. Where temporal gaps or uncertainty in position are problems, WLR is superior in terms of reliability as it can include confidence intervals across shoreline dates. Dynamic predictive models such as the Kalman Filter have, for their part, been applied for the assimilation of historical and future shoreline data, as well as the prediction of future changes. For example, Hossain et al. [2] utilized Kalman-based modeling in projecting shoreline position forward to 2031 and 2041 along India's eastern coast, while Taveneau et al. [34] combined real-time video monitoring data with sediment transport to calibrate future shoreline trajectories in Senegal. These models show that where historical remote-sensing imagery is combined with either dynamic or statistical modeling methodologies, shoreline erosion patterns may be reliably monitored and predicted on decadal timescales, with these predictions being used in proactive coastal management.

4. Advancements in Remote Sensing Technologies for Coastal Monitoring

Recent research breakthroughs have revealed an abundance of new knowledge and methodologies that are transforming the investigation and development of equipment and tools. These new developments significantly sharpen our capacity for monitoring shoreline activity in an efficient and effective manner, on budget and on schedule. Using recently developed methodologies [11,32], scientists can now acquire and interpret data with higher accuracy, gaining enhanced insights into coastal processes and making shoreline environments more sustainably managed.

4.1. Satellite Data for Coastal Monitoring

Both the Sentinel and Landsat missions serve complementary functions in shoreline surveillance, each superior in different temporal and spatial regimes. Sentinel-2 has high resolution (10 m) and 5-day revisits, making it very effective for detecting relatively short-term shoreline changes related to storms, tidal action, or human activities, with near-real-time coastal hazard information [47]. Its shorter temporal record since 2015, however, hinders it in the analysis of long-term trends.

On the other hand, Landsat satellites provide a four-decade record of observation beginning in 1972, which is extremely useful for the analysis of long-term coastal trends like gradual sea level rise or sediment re-allocation [20,51]. Though its 30 m spatial resolution and recurring 16-day visitation may overlook finer-scale events, Landsat is an anchor resource for historical shoreline analysis [19].

Furthermore, the Synthetic Aperture Radar (SAR) mission, Sentinel-1, provides monitoring in environments where optical sensors are inadequate such as under cloud cover, during night-time imaging, or in sediment-charged waters [55,69]. SAR can monitor changes in surface roughness, suitable for identifying land–water interfaces even in adverse environments [81]. Though it has poorer spatial resolution and less ability to discriminate close surfaces such as wet sand and shallow water, Sentinel-1 is especially useful in monsoon-hit or tropical environments [82,83].

Studies like those of Arjasakusuma et al. (2021), Spinosa et al. (2021), and Zollini et al. (2023) [35,39,55] indicate the efficiency of Sentinel-1 SAR, either used individually or combined with optical data, in providing improved accuracy in shoreline mapping. These studies verify the efficacy of the combination of SAR and optical data in compensating for inherent weaknesses in either dataset to provide consistent monitoring regardless of different environmental scenarios. Table 4 compared major studies using Sentinel-1 SAR for shoreline detection and change detection based on the review content of the selected studies.

Table 4. Sentinel-1 SAR data for enhanced shoreline detection, providing insights into the key findings of each research and unique features.

Reference	Geographical and Temporal Scope	Sentinel-1	Satellite Data	Shoreline Change Metrics	Key Findings	Unique Features
[35]	East Java Province, Indonesia (2000–2019)	Used for shoreline monitoring	Landsat-7, Landsat-8, ALOS Palsar, Sentinel-1	EPR, WLR	Coastal accretion was more significant than erosion, with an average accretion of +4.12 m/year	Multi-sensor approach using random forest and Google Earth Engine for improved shoreline mapping

Table 4. *Cont.*

Reference	Geographical and Temporal Scope	Sentinel-1	Satellite Data	Shoreline Change Metrics	Key Findings	Unique Features
[39]	Apulia Region, Italy	Used for SAR data in shoreline extraction	Sentinel-1 SAR, video monitoring systems	Edge detection, segmentation	Automated shoreline detection method achieved high accuracy, with an error of less than 3.5 pixels	Integrated Sentinel-1 SAR with video monitoring for high accuracy and validation
[55]	Mediterranean Beaches, Spain (Catalunya)	Used for shoreline extraction	Sentinel-1 SAR, Sentinel-2	J-Net Dynamic algorithm for shoreline extraction	Achieved high accuracy with GNSS-RTK validation, SAR performed better on natural beaches compared to man-made areas	Developed a robust methodology (J-Net Dynamic) for shoreline extraction from both SAR and optical data

Sentinel–Landsat Synergy in Shoreline Monitoring

A synergistic combination of both missions, for the monitoring of short-term processes with Sentinel and long-term trends with Landsat, presents the most authoritative coverage for coastal research.

The fusion of Sentinel-2 and Landsat imagery has emerged as a powerful strategy for monitoring coastal dynamics by combining the high spatial and temporal resolution of Sentinel-2 with the long historical archive of Landsat, as our review identified in the selected studies [43,47,69,84].

This synergy enables improved shoreline detection and change analysis across both short- and long-term timeframes. Image enhancement [46] and temporal harmonization enhanced with AI learning-powered super-resolution methods have been utilized to combine the merits of the two datasets [85]. Such methods enable more uniform shoreline extraction in areas of poor coverage due to frequent cloud coverage or seasonality, where optical imagery is inadequate on its own, such as temporal gap-filling with Landsat data, which has effectively assisted in increasing scene continuity in scenarios where Sentinel-2 imagery is partially hindered. Deep learning models, especially those that are dependent on Convolutional Neural Networks (CNNs), have better classification accuracy and maintain the spectral integrity of the fused products [20,21,86].

The effectiveness of this combined approach emerged through recent research. Quang et al. [11] used the DSAS on stacked Sentinel–Landsat data to virtually monitor 30 years of shoreline evolution along the Da Nang coast in Vietnam. Their fusion analysis allowed for an improvement in temporal resolution, as well as the clear detection of erosion and accretion trends. In the same vein, Hossen and Sultana [41] carried out research on Sandwip Island, India, using Landsat (1988–2022) combined with Sentinel-2 imagery within the framework of DSAS-GIS. Their findings permitted the quantification of decadal shoreline changes while also estimating the mean rates of change, showing the capability of the fusion for effective long-term monitoring in dynamic delta settings.

Machine learning is also at the forefront of extending the benefits of fused data. McAllister et al. [21] applied Sentinel-2 imagery fused with supervised classifiers for shoreline proxy delineation in several coastal settings. Their approach showed high accuracy in classification, affirming spectral fusion's use in facilitating automated shoreline extraction. Also, Zollini et al. [55] suggested semi-automatic shoreline extraction with the fusion of Sentinel-1 SAR with optical data for Sentinel-2. The use of the J-Net Dynamic algorithm considerably enhanced detection performance in the presence of artificial features, as well as varying shoreline complexity, especially where optical-only methods could not perform as expected.

At broader scales, Taveneau et al. [34] combined Sentinel-2 and Landsat imagery in order to observe coastal erosion on Senegal's Langue de Barbarie. Combining historical and modern-day satellite imagery made it possible to map significant shoreline displacement due to anthropogenic disturbances and sea-level rise. Similarly, Arjasakusuma et al. [35] combined Landsat, Sentinel-2, and ancillary data in order to map long-term shoreline retreat due to coastal degradation and subsidence on the northern coast of Java in Indonesia.

Together, these studies highlight the efficacy of Sentinel–Landsat synergy in facilitating coastal monitoring activities [18]. The combined datasets enhance the spatial resolution without compromising historical depth for vigorous trend analysis. Not only is this union instrumental in increasing the accuracy of shoreline detection under varying environmental circumstances, but it is also an adaptable and open-access solution for coastal area management. As illustrated in the literature surveyed, multi-sensor fusion is useful for both retrospective analysis and near-real-time applications, making it invaluable for climate adaptation, spatial planning, and evidence-based decision-making for vulnerable coastal areas. Complementing each other, Sentinel's temporal frequency and Landsat's temporal extent ensure an excellent foundation for shoreline monitoring [51].

4.2. GIS for Shoreline Change Analysis and Coastal Monitoring

The Geographic Information System (GIS) has become an indispensable tool in contemporary shoreline monitoring, facilitating the precise spatial analysis and visualization of coastal change [67]. Coupled with tools such as the Digital Shoreline Analysis System (DSAS), the GIS can facilitate the processing of historical positions of the shoreline, compute erosion and accretion rates, and visualize long-term coastal evolution. This facilitates large-scale geospatial data management, predictive modeling, and decision-making in coastal management.

Recent studies have utilized GIS to efficiently analyze shoreline dynamics and long-term coastal changes. With the aid of the Digital Shoreline Analysis System (DSAS) [59], used as an add-on tool in ArcGIS, researchers could undertake the extraction, quantification, and prediction of shoreline changes with high accuracy. GIS plays a critical role in understanding erosion and accretion patterns and the impacts of natural and human activities on coastal environments. It enables the creation of better and more knowledgeable coastal management and protection policies. Table 2 (GIS-based approaches to shoreline change detection) reveals concentrated information highlighting the main findings with the core technologies Sentinel-2 and Landsat aided by GIS.

Quang et al. [11] investigated the long-term shoreline evolution in Quang Nam Province, Vietnam, with a temporal resolution of 1990 to 2019. Employing the DSAS, he analyzed satellite imagery erosion and accretion patterns, indicating significant coastal changes caused by natural processes and human activities. The methodology attempted to extract historical coastline positions from all available data scenes of Sentinel-2 and Landsat satellite series, i.e., Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETMP), and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS), over the period of 1990–2019. Satellite images with a percentage below 20% land cloud cover were used for the analysis. Then, all available data were collected and utilized to detect the coastline dynamic. The estimated change rate in Quang Nam province, employing the modified Normalized Difference Water Index (mNDWI) for shoreline detection, was used to classify water and land regions on satellite images with stable performances compared to the NDWI, which contains built-up land noises. The results from the changes using the ArcGIS add-in toolkit DSAS showed that the EPR and LRR indices had a strong correlation (R^2 = 0.96). The results identified 401 erosional and 414 accretional transects in a coastline length of 81.5 km, emphasizing the dynamic nature of the coastline, with significant erosion observed in the north of the Cua Dai estuary and notable accretion in its southern segment.

Santos et al. [31] conducted research on the changes in the shoreline variability of João Pessoa City (Brazil) over the last 34 years (1985–2019), using multitemporal remote sensing data from Landsat 5-TM and 8-OLI satellites as a dataset, which were downloaded from the Google Earth Engine (GEE). Statistical techniques were performed, such as EPR for short-term analysis and LRR and Weighted Linear Regression (WLR) for long-term analysis provided by the DSAS. The technique was used to analyze 351 transects across 4 distinct zones, involving a detailed examination of the factors influencing the shoreline changes, including data such as the sea level, tidal range, wave height, beach morphology, and ocean currents. The statistical methods used included Standard Deviation (SD) and the Coefficient of Variance (CV), which are capable of interpreting the spatiotemporal changes along coastline transects. In one case for Zone 1 during the period of 2014–2019, the CV (2064.2) and SD (3.89) had high values, which implied inconsistency among the data, validating the need to use statistical methods for correct data interpretation. The study identified cyclical patterns of erosion and accretion within specific periods, indicating that various environmental and human activities and factors influence the coastal area's dynamics, highlighting that the GIS plays a significant role in environmental monitoring and demonstrates the importance of coastal changes.

Görmüş et al. [38] used 96 Landsat images to carry out a long-term shoreline change analysis for the black sea coastline. The coastline was divided into 28 subsections with 78,943 transects. Landsat (MSS, TM, ETMP, and OLI) images from 1972–2018 were used, with a total of 96 images. The spatial resolution of Landsat 1,3,5 (MSS) is a 60 m resolution, and for Landsat 5 (ETM),7,8, the spatial resolution is 30 m. For the large area of the 5000 km coastline covered by the research, the spatial resolution was appropriate. Once again, the NDWI method was employed to acquire the base image for shoreline delineation. The author indicated that stable performance is provided by the NDWI method. In any case, the validation of the study results via the georeferencing and digitization of aerial photos or in situ measures was unavailable. The images were referenced with WGS84, and digitization was limited by converting automated extraction into a semi-automated process. The shoreline change was computed using the DSAS, which applied the EPR and LRR approaches. LRR indicated a $-0.17/\mathrm{m}$ shoreline change, which is considered logical according to a large-scale basin's erosion and accretion balance. The research detailed other countries and coastline sections, indicating local hotspots. Transects in the methodology matched similar investigations, leading us to conclude the validation of this method.

Matin et al. [32] analyzed the dynamic shoreline of Bangladesh over the last thirty years (1989–2019) with a five-year interval using the dataset of multi-temporal Landsat images with a 30 m resolution and a comparison of tidal conditions collected from 1989–2019. Manual digitization of shorelines was performed. The DSAS was used to analyze the transects. There were 12,000 transects cast with 50 m intervals, resulting in shoreline retreat. Supplementary analysis of polygonal was carried out in ArcGIS, where the net area for shoreline extraction was determined for the entire study period. The LRR method for the shoreline movement NSM was analyzed. Thus, net erosion and accretion for the whole area were carried out, tracing the spatial changes in the area.

Mishra et al. [12] analyzed the short-term and long-term changes in the shoreline of Ganjam district, Odisha, India, between 1990 and 2019. Multiresolution and temporal datasets of Landsat sensor, Thematic Mapper (TM), Enhanced Thematic Mapper (ETM), and Operational Land Imager (OLI) datasets were used for the shoreline change analysis. The DSAS was used in the GIS. Land and water discrimination methods, such as the NDWI, mNDWI, EWI (Enhanced Water Index), and WRI (Water Ratio Index), were employed to extract the shoreline. The authors continued with projections of the coastline's future line for the 2030–2040 period and the potential impact on the area. The analysis used the EPR, WLR, and trigonometric functions to examine shoreline changes from 1990 to 2019 and predict future conditions for 2030 and 2040. The short- to long-term shoreline assessments identified erosion.

GIS-based techniques, enabled through the DSAS, have been found to be invaluable for the analysis of long-term shoreline changes in varied coastal environments. Using Landsat and Sentinel-2 imagery, erosion and accretion patterns have been mapped successfully, with parameters such as the NDWI, mNDWI, and WLR improving shoreline extraction accuracy. The main findings and geospatial methodologies utilized in the studies under review are presented in Table 5, showing how the DSAS allows for effective multi-temporal analysis of shoreline changes. Commonly, studies involving the DSAS utilize EPR, LRR, and WLR metrics on Landsat or Sentinel-2 imagery, demonstrating different spatial patterns of change and supporting the versatility of GIS monitoring tools in different coastal environments.

4.3. Ground Truth Data for Enhanced Coastal Monitoring

Ground Truth Data (GTD) are instrumental in refining the accuracy and reliability of shoreline change detection inferred using satellite-based methodologies. High-precision field measurements like GNSS-RTK or GNSS-RTN surveys, Ground Control Points (GCPs) based on robotic total stations, terrestrial laser scanners (TLS), and RTK-corrected UAV-based photogrammetry are usually included in GTD [34,67,87]. These in situ measurements act as verification references for the corroboration of shoreline positions derived from remote sensing indicators like the NDWI and mNDWI and are frequently overlayed in the GIS space for the evaluation of spatial discrepancies using indices like RMSE or regression R^2 [9,53,57]. For instance, Matin et al. [32] digitized 12,000 shoreline transects in order to calibrate extractions based on Landsat, whereas Taveneau et al. [34] combined GTD with sediment transport modeling and real-time high-resolution video monitoring. In predictive modeling activities like those using the Kalman Filter, GTD are the key input necessary for affirming shoreline forecast reliability in dynamic settings [2,15]. As tabulated in Table 6, GTD allow for the strong validation of outputs inferred from satellites, enhance the accuracy of indicators like EPR, LRR, and WLR, and indirectly support the reproducibility and credibility of coastal monitoring derived outcomes [56,70].

Table 5. Summary of GIS-based approaches for shoreline change detection, highlighting key findings, core geospatial techniques (e.g., DSAS, NDWI, and mNDWI), and unique features of each reviewed study.

References	Geographical and Temporal Scope	GIS Usage	Satellite Data	Shoreline Change Metrics	Accuracy/Error	Key Findings	Unique Features
[11]	Quang Nam Province, Vietnam, 1990–2019	DSAS in ArcGIS for shoreline extraction and visualization	Sentinel-2 and Landsat (TM, ETMP, OLI/TIRS)	EPR, LRR, mNDWI for shoreline detection, correlation analysis (R^2~0.9)	Shoreline position uncertainty < 1 m; DSAS regression R^2~0.9; ±0.02 m/yr rate error	401 erosional and 414 accretional transects identified. Strong correlation between EPR and LRR (R^2 = 0.96).	Focus on human and natural processes in a tropical region, robust mNDWI application.
[31]	João Pessoa City, Brazil, 1985–2019	DSAS in ArcGIS, statistical tools (CV, SD) for transect analysis	Landsat 5-TM and 8-OLI from Google Earth Engine	EPR, LRR, WLR for long-term change, cyclical erosion-accretion patterns	Digitizing error ± 15 m (TM), ±7.5 m (OLI); shoreline position uncertainty up to ±0.68 m/year; WLR regression with weights based on error; SD and CV reported for all shoreline intervals and zones	351 transects showed cyclical patterns of erosion and accretion, high variability in some zones.	Added depth through CV and SD metrics, which enhanced spatiotemporal interpretation.
[38]	Black Sea Coastline, 1972–2018	DSAS in ArcGIS, NDWI method for shoreline delineation	Landsat (MSS, TM, ETMP, OLI) from 96 images	EPR, LRR, shoreline change rate at −0.17 m/year	88% of 78,943 transects statistically significant (95% CI); EPR–LRR R^2 = 0.97	−0.17 m/year shoreline change over 78,943 transects, hotspots of erosion and accretion identified.	Extensive dataset covering 5000 km of Black Sea coastline using stable NDWI method.
[32]	Bangladesh, 1989–2019	DSAS in ArcGIS, manual shoreline digitization, and area change analysis	Landsat images from 1989–2019 at 5-year intervals	EPR, LRR, manual shoreline retreat analysis via 12,000 transects	SD of shoreline change rates by zone: Western = ±13.66 m/yr, Central = ±61.66 m/yr, Eastern = ±21.85 m/yr; no RMSE reported	12,000 transects indicated shoreline retreat, supplementary polygonal analysis highlighted spatial changes.	Manual digitization and polygonal analysis for net area changes over time.

Table 5. *Cont.*

References	Geographical and Temporal Scope	GIS Usage	Satellite Data	Shoreline Change Metrics	Accuracy/Error	Key Findings	Unique Features
[12]	Ganjam district, Odisha, India, 1990–2019	DSAS in ArcGIS for future projections (2030–2040), shoreline extraction with NDWI	Landsat sensors (TM, ETM, OLI)	EPR, WLR, NDWI, mNDWI, future shoreline predictions for 2030–2040	Shoreline rate uncertainty estimated at ±0.25 m/year using propagated positional and digitizing errors; image-specific positional error ranged from ±7.52 m to ±15.03 m; WLR method used with weights based on error variance	Short-term and long-term shoreline changes identified, projections show continued erosion by 2040.	Projections for future shoreline changes emphasized potential socio-ecological impacts by 2040.

Table 6. Integration of Ground Truth Data for enhanced shoreline change detection, providing insights into the key findings of each research study and unique features.

References	Geographical and Temporal Scope	Ground Truth Data	Satellite Data	Shoreline Change Metrics	Key Findings	Unique Features	GCP Measurement Method
[2]	Purba Medinipur to Balasore coast (90 km stretch), India (1990–2020)	GPS-based validation data	Landsat TM, ETM+, OLI (30 m)	EPR, Kalman Filter for predictions	Erosion rate of −8.80 m/year observed across 90 km coastline; future shoreline positions for 2031 and 2041 predicted using Kalman Filter and validated with GPS transects.	Forecasting with Kalman Filter validated by GPS	GPS (no RTK/RTN or GNSS specified); used for validation of Kalman model
[3]	Nijhum Dwip, Bangladesh (1998–2018)	~1000 GPS points for supervised classification	Landsat (1998, 2008, 2018)	EPR, NDVI; change classification	Land cover change analysis showed mangrove loss and agricultural decline; shoreline accretion trends detected with 90.78% classification accuracy using 1000 GPS points.	Large-scale land cover classification with high-accuracy validation	Single-frequency GPS for supervised classification; no GNSS mentioned

Table 6. *Cont.*

References	Geographical and Temporal Scope	Ground Truth Data	Satellite Data	Shoreline Change Metrics	Key Findings	Unique Features	GCP Measurement Method
[15]	Large-scale coastal regions (global, Australia)	Ground Control Points (GCPs)	Landsat 5,7,8	EPR, LRR	Validated long-term shoreline trends using DEA-backed high-tide shoreline composites; improved shoreline consistency over multi-decadal and continental scales.	GCP-supported global shoreline product; policy-oriented framework	GCPs used; instrument/method not specified in the paper
[34]	Langue de Barbarie, Senegal (2003–2020)	GCPs collected during field visits	Landsat + Sentinel-2	EPR, Kalman Filter	Severe erosion observed along the Langue de Barbarie sand spit; integration of Kalman Filter and GCPs produced highly accurate shoreline evolution forecasts.	Integration of GCPs for future erosion prediction in a dynamic sand spit	GCPs collected; instrument not specified
[6]	Indian Sundarbans (1975–2017)	Field observations (no GPS/GCPs mentioned)	Landsat series + field data	DSAS (shoreline), NDVI (vegetation)	Widespread shoreline retreat and concurrent mangrove degradation identified; NDVI used to assess vegetation health alongside DSAS-derived shoreline change metrics.	Links shoreline retreat with mangrove health using dual RS indices	Field observations only; no GCPs or instruments described

Hossain et al. [2] analyzed remote sensing data and statistical methods to study decadal shoreline dynamics along India's Purba Medinipur-Balasore coastal stretch. The results of his study indicated a continuous erosion pattern from 1990 to 2020, with some portions showing accretion due to land reclamation. The Kalman Filter projection of the probable positions of the shoreline in 2031 and 2041 indicates urgent management needs along the coasts to protect against erosion impact and damage to communities that will be exposed. Islam et al. [3] investigated Nijhum Dwip, Bangladesh, where land cover and shoreline changes are associated with a 20-year data timeline. The researchers observed that the primary changes in mangrove loss are driven by rapid settlement expansion due to population pressure and economic development. Shoreline accretion outpaced erosion, adding about 1153 hectares of land. This study underlines how rising sea levels coupled with anthropogenic activities require a well-managed strategy so that development can occur alongside the protection of the environment.

Mao et al. [15] presented an effective way of quantifying decadal shoreline changes on a large scale using remote sensing and geospatial analysis. The authors also hint at the possibility of urgent automated coastline monitoring, thus reducing the need to involve human labor. This is a very effective methodology that investigates long-term shoreline variations, which are of essence for making informed decisions in the management of the coastal zone.

Taveneau et al. [34] explored coastal erosion in Langue de Barbarie, Senegal, through predictive models based on environmental factors like wave action and sediment transport. Real-time observations combined with predictive modeling provided valuable insights into the various shoreline movements likely to happen in the future. This work also helps underline the value of these tools for improving coastal risk management strategies.

Thakur et al. [6] examined shoreline changes and their impacts on mangrove ecosystems using the NDVI index in the Sundarbans, India. Through remote sensing, they documented rising sea levels and human activities resulting in unprecedented mangrove loss and shoreline retreat. The study emphasized the urgent need for sustainable shoreline protection, mainly to protect the biodiversity of this region and the people depending on it.

Regarding the validation process, GTD play a very relevant role in enhancing the effectiveness of shoreline change detection since these are real-world, precise points used for the calibration and validation of remote sensing methodologies. For example, Daud et al. [40] showed how ground truth data from RTK-GPS measurements increased shoreline position precision derived from Sentinel-2 imagery. In fact, by aligning outputs from satellite-based methods with ground-based observations, the study achieved a value of less than 5 m for RMSE using GTD corrections instead of more than 15. Similarly, Halder et al. [9] discussed the potential of using GTD to reduce noise due to cover from clouds and water turbidity as opposed to what was seen on Landsat imagery to achieve consistent temporal datasets for shoreline position accuracies. The integration of GTD should be especially effective in such an environment where tidal effects are complex. Wang et al. [57] used GTD acquired during high- and low-tide periods to correct the tidal effects in satellite-derived shorelines, reducing misclassifications by 25% in a coastal area like Chongming Island. Ayalke et al. [67] further reiterated this using GTD to separate the natural shoreline from the anthropogenic features in the urbanized area. This approach resulted in a higher-than-15% increase in the delineation accuracy of shorelines. In sediment-rich environments, such as those studied by Da Silva et al. [70]. GTD have been key in calibrating shoreline models to consider sediment plumes. This calibration, in turn, improved the delineation of shorelines under adverse optical conditions, hence reducing errors in areas difficult to analyze earlier. GTD have also proved to be of immense help in the historical analysis of shorelines. Da Silva et al. [70] applied GTD to georeference legacy datasets such as aerial photography, which enabled valid long-term shoreline change studies over decades. In seasonal monitoring, Yiğit et al. [56] integrated GTD to calibrate NDWI-based indices in Antalya's coastal zones for a more accurate shoreline position with an increase in accuracy of up to 18%, and this provided important information on how to manage the areas under tourism pressure. In vegetation-dense areas, Zhang et al. [53] integrated GTD to enhance the subpixel shoreline detection methods and achieved an RMSE of less than 6 m, while models without integrating GTD had an RMSE of 20 m.

The above-mentioned applications and reviewed studies have shown the crucial role of GTD in the monitoring of coastlines: from calibration in tidal areas to noise reduction in sediment-laden areas and georeferencing during historical analysis, GTD enhance reliability and precision for methodologies involving remote sensing, forming the fundamental basis for achieving high accuracy with respect to coastal monitoring and management.

4.4. UAV Technology for Precise Coastal Erosion Monitoring

Modern developments in remote sensing technologies have made shorelines observable by satellite-based observations and Unmanned Aerial Vehicles (UAVs). UAVs provide an ultra-high spatial resolution at a centimeter scale, which is well-suited for collecting small-scale features such as beach cusps, berms, and micro-topography [23]. UAVs equipped with LiDAR or RTK-GPS photogrammetry have demonstrated shoreline mapping precision within 0.1 m [88]. In contrast, satellite imagery, such as Sentinel-2 (10 m), Landsat (30 m), or even PlanetScope (3 m), covers a wider area at a lower resolution, with positional errors generally ranging from 5 to 10 m in favorable situations according to their resolution [54,89]. Satellites generalize the shoreline edge through pixel averaging, whereas UAVs are able to capture small changes, which are useful for local investigations like post-storm beach erosion or dune recession. The temporal consistency of monitoring is also what separates the two methods. Satellites are on repeatable revisit intervals—5 days for Sentinel-2 and 16 days for Landsat—due to which they are particularly useful in building long-term shoreline change records over a span of decades [90].

In comparison to satellite images, UAVs provide centimeter-level spatial resolution, with much finer orders of magnitude compared to Sentinel-2 (10 m) or Landsat (30 m). UAVs are well-suited for identifying fine-scale changes in shorelines like dune crest movement, micro-erosion, or loss of plant cover. Nevertheless, in comparison to the larger spatial extent and less weather dependency, their restricted spatial scope makes them better for local-scale assessments. When used together, satellite data provide an extensive temporal and spatial scope, whilst UAVs provide detailed snapshots for in situ validation and calibration. Previous studies have illustrated this multi-resolution complementarity well, like that of Angnuureng et al. [44] in Ghana where, in addition to satellite observation of a rapidly eroding beach, UAV photogrammetry was used [23]. The work of Angnuureng et al. [44] focused on the application of UAVs in coastal erosion monitoring in connection with other techniques, such as satellite imagery and VCS (video camera systems), using the case of Elmina Bay in Ghana. For this purpose, UAVs were deployed to ensure high-resolution month-to-month beach monitoring, offering detailed information about erosion and deposition along the shoreline. The results showed that UAVs could observe localized event-driven shoreline changes more accurately and frequently than satellite imagery, which does not have the necessary temporal resolution to capture such changes effectively. Complemented by a VCS, UAV data correspond reliably [91] as a value for near real-time monitoring, indicating serious erosion was happening in extensive parts of the beach not covered in the front by jetties. UAV imagery helped emphasize how complicated the engineering solutions of sea defenses were in affecting sediment distribution and, therefore, contributing to downdrift erosion [44]. The conclusion of this study underlined the effectiveness of drones in operation with other remote-sensing platforms for coastal management; thus, UAVs have become very critical for high-resolution monitoring, particularly for event-based changes that satellite data cannot capture.

While fixed satellite scheduling and cloud cover restrict satellite use during peak storm or tidal windows or generally rapidly occurring events, UAVs are able to overcome these by enabling on-demand deployment and exact timing control (i.e., flying at low tide or shortly after the event occurred). Although UAV campaigns are logistically complex and spatially limited—numerically only a few kilometers per flight—truly timely, focused information is provided. An example is the research by Lei et al. [88], which mapped erosion and beach recovery prior to and subsequent to typhoon events with centimeter-scale accuracy, a challenging task to achieve with satellites alone.

A comparative framework (Table 7) is presented below, outlining the strengths and limitations of UAV-based and satellite-based shoreline monitoring methods in terms of resolution, accuracy, revisit rate, and integration potential based on the content of this research study.

Table 7. Comparative evaluation of UAV-based and satellite-based shoreline monitoring methods across key technical and operational parameters. The table summarizes differences in spatial resolution, positional accuracy, revisit frequency, and integration potential, supported by peer-reviewed studies published between 2021 and 2024 as our research indicated.

Aspect	UAV-Based Monitoring	Satellite-Based Monitoring	References
Spatial Resolution	Ultra-high (cm-level) resolution imagery and terrain models. Can detect fine features like beach cusps, berms, dune lines.	Moderate to high (meter-level) resolution (e.g., 10 m Sentinel-2, 30 m Landsat). Small features are often generalized.	[44,88,89]
Positional Accuracy	Centimeter to decimeter accuracy with RTK/PPK GNSS or GCPs. Enables sub-meter shoreline mapping.	Typically ~5–10 m horizontal uncertainty. Subpixel methods improve precision, but less accurate than UAVs.	[54,88,89]
Revisit Frequency	On-demand deployment. Enables site-specific, timely mapping before/after events (e.g., typhoons). Limited by weather/logistics.	Scheduled orbits: Sentinel-2 (5 days), Landsat (16 days). Enables consistent long-term data but may miss rapid changes or specific tidal events.	[89–91]
Coverage Scale	Best for local to sub-regional sites (a few km^2 per flight). Requires multiple missions for broader areas.	Large-scale coverage (100 s of km^2 per image). Suitable for regional or global comparisons.	[44,89,90]
Cost	Equipment, personnel, and post-processing make it costly at scale. Efficient for small area studies.	Low per-area cost due to free sources like Sentinel and Landsat. Commercial data also cost-effective at large scale.	[88,90]
Integration Potential	Ideal for in-situ calibration and validation (e.g., DEMs, GCPs). High flexibility complements satellite gaps.	Sets regional context. Satellite data guides UAV deployment. Enables fused multi-scale shoreline monitoring frameworks.	[6,31,38,44]

4.5. Applications of Machine Learning and Artificial Intelligence in Coastal Monitoring

Recent developments in Machine learning (ML) and Deep Learning (DL) techniques have further reiterated the role of ML and DL in the monitoring and analysis of different environments, especially coastal ones, for shoreline change detection and management. Integrating different Artificial Intelligence (AI) techniques enables the proper mapping of shorelines efficiently and precisely to allow erosion prediction and long-term coastal monitoring, with less human intervention and increased accuracy [20]. Table 8 (application of AI methods for automated shoreline change detection and coastal monitoring) illustrates the research on AI methods applied to automated shoreline change detection and coastal monitoring. Some of the outstanding studies in our review criteria are highlighted, in which AI-based models have been applied to improve shoreline monitoring activities using different methods.

Erdem et al. [20] developed a new model technique, WaterNet, which is an ensemble deep learning model designed to automatically extract shorelines from satellite images. The Intersection over Union (IoU) and F1 scores are crucial metrics for evaluating the accuracy of segmentation models, particularly in shoreline extraction, where they measure the model's ability to differentiate between land and water in satellite images. The IoU assesses the overlap between the predicted and actual shorelines, with a high score of 99.59% indicating exceptional model accuracy. The F1 score, a harmonic mean of precision and recall, balances these two metrics, with a remarkable score of 99.79% highlighting the model's precision and comprehensiveness in identifying shorelines. These impressive results were achieved using the WaterNet model, an ensemble deep learning approach designed for automatic shoreline segmentation from Landsat 8 OLI images specifically from Landsat 8 OLI data. WaterNet integrates five different architectures: Standard U-Net, Dilated U-Net, Fractal U-Net, FC-DenseNet, and Pix2Pix. Each method has its own unique strengths and is applied differently: U-Net is effective for biomedical image segmentation, Dilated U-Net eliminates pooling layers to preserve resolution, Fractal U-Net enhances accuracy by combining different visual feature levels, FC-DenseNet takes dense blocks in advance to increase feature sharing, and Pix2Pix utilizes generative adversarial networks (GANs) for pixel-to-pixel image translation. WaterNet employs a majority voting algorithm, where each model "votes" and decides on the classification of each pixel, enhancing robustness, accuracy, and reliability. The ensemble approach results in high precision, with Intersection over Union (IoU) and F1 scores surpassing 99%, making it highly reliable for real-time coastal monitoring and resource management.

McAllister et al. [21] provided an overview of shoreline extraction techniques, particularly in Multispectral Imaging (MSI) and ML applications. The article's discussion ranged from the more traditional approach, water indexing, to an advanced ML and image segmentation technique. One of the key points this work showed is the difficulty of elaborating a method that can be universally applied to monitoring shorelines regardless of type and location on Earth. This is because of the variation of coastlines, such as sandy beaches, cliffs, and dunes, for which individual extraction needs are expected. In this paper, applying Convolutional Neural Network (CNN)-based machine learning methods will improve shoreline detection accuracy with large-scale monitoring. On the other hand, this review focuses on certain points of attention in current approaches concerning the need for automation and scaling up of methods, with particular attention to shoreline extraction at a global scale. Conclusively, the overall suggestion of this paper is that integrating MSI with machine learning can ensure more sustainable and efficient shore monitoring. However, the further refinement of methods will be necessary for broader application. This is in agreement with, for instance, Erdem et al. [20], whereby these ensemble learning techniques, including WaterNet, were applied to automate shoreline extraction from satellite images by merging multiple deep learning models to improve the models' precision and reliability. In comparison to other reviews on coastal monitoring technologies, this paper aims to emphasize the incorporation of advanced methodologies, particularly AI and UAVs. However, integrating insights from studies like McAllister et al., 2022, could enhance the discussion by offering a global perspective on shoreline detection through the use of multispectral imaging and AI. McAllister et al., 2022, offered a comprehensive analysis of Convolutional Neural Networks (CNNs) for shoreline mapping, emphasizing their adaptability across diverse geographic and environmental contexts. For instance, their work detailed how traditional CNN-based models perform well in processing multispectral datasets from Sentinel-2 and Landsat but may struggle in environments with complex geomorphology, such as sediment-heavy coasts or vegetated shorelines [21]. Referencing McAllister et al. allows a direct benchmark comparison for WaterNet. While WaterNet emphasizes high classification accuracy and reduced error margins, McAllister et al., 2022, provided insights into the computational efficiency and scalability of CNN-based models for large-scale shoreline monitoring. A comparison of this nature would enhance the discourse by placing WaterNet within the larger framework of AI-driven coastal monitoring technologies, thereby highlighting its advantages in relation to conventional methodologies [21].

Furthermore, Almeida et al. [33] stated that AI will play a more competitive role in automated coastal analysis systems. Their research integrated space imagery with machine learning to create a Coastal Analyst, which can automatically process large volumes of remote sensing data with minimum human intervention. While specific architectures were not profoundly explored, the paper underlined the role of AI in enhancing efficiency in data processing by several orders of magnitude and, hence, supporting better decision-making in coastal management by providing quasi-real-time insights into environmental risks such as erosion and urban expansion.

Angnuureng et al. [44] applied AI to multi-platform data by integrating satellite, drone, and video camera platforms to monitor coastal dynamics. ML algorithms played a central role in integrating these data sources, allowing for high-resolution and accurate monitoring of shoreline variations. Moreover, the multi-platform methodologies proposed represent higher spatial and temporal resolutions, complementing the gaps left by traditional single-platform monitoring approaches. ML applied AI to multi-platform data by integrating satellite, drone, and video camera platforms to monitor coastal dynamics. Also, the multi-platform methodologies proposed represent higher spatial and temporal resolutions, complementing the gaps left by traditional single-platform monitoring approaches. The machine learning techniques automatically analyzed and fused heterogeneous data, thus contributing to better overall coastal monitoring and management.

Finally, Murray et al. [50] applied neural networks to process satellite photography to map changes in the shoreline of southwestern Australia. Deep learning models, trained on millions of satellite images, showed higher accuracy in detecting shoreline change and shedding light on long-term trends in coastal erosion. This application of AI (deep learning specifically) will be very important for timely and accurate environmental monitoring, understanding, and mitigation measures for coastal erosion, which are key to preserving coasts, ecosystems, and infrastructural-related results. These studies epitomize the transformational role of machine learning and deep learning in coastal monitoring. AI techniques, primarily ensemble and deep neural networks, have emerged as powerful tools for analyzing large-scale and complex datasets that provide accurate and timely information on shoreline dynamics, erosion patterns, and environmental changes. Their merger through AI and remote sensing technologies offers scalable and automated solutions for coastal management, enabling proactive responses to environmental risks and ensuring sustainability in managing coastal resources.

Table 8. Application of AI methods for automated shoreline change detection and coastal monitoring, providing insights into the key findings of each research study and the unique features.

References	Geographical and Temporal Scope	Neural Networks, AI, or Automatic Processing	Satellite Data	Shoreline Change Metrics	Key Findings	Unique Features
[20]	Global (Shoreline segmentation)	Ensemble deep learning model (WaterNet) using U-Net variants	Landsat 8 OLI	IoU: 99.59%, F1: 99.79% accuracy in shoreline extraction	Achieved very high precision in shoreline extraction using ensemble deep-learning models	Combines multiple U-Net architectures for improved segmentation accuracy
[21]	Various regions (Coastal erosion monitoring)	Supervised machine learning for erosion pattern detection	Multispectral satellite imagery	Predictive models, erosion hotspot identification	Developed scalable models to monitor long-term erosion patterns and identify hotspots	Used historical shoreline data to create predictive models for long-term erosion monitoring
[33]	Global coastal areas (Earth Observation monitoring)	AI-powered Coastal Analyst System (CASSIE) for automated processing	Landsat, Sentinel-2	Shoreline trends, Coastal Vulnerability Indices	Automated real-time analysis of global shoreline changes with high precision	Reduced human intervention in large-scale shoreline monitoring using AI-driven automation
[44]	Elmina Bay, Ghana (Coastal erosion monitoring)	Machine learning for shoreline position extraction (sci-kit-learn)	Sentinel-2, drone, video data	Shoreline change rates, shoreline position	High-resolution monitoring of shoreline change, combining satellite and drone data	Integrated multispectral satellite imagery with drone and video data for fine-scale coastal monitoring
[50]	Southwestern Australia (1937–2020)	Neural networks for processing satellite imagery	Multispectral satellite imagery	Long-term coastal erosion patterns	High accuracy in detecting erosion trends over an 83-year period	Combined historical aerial photos with modern satellite data using advanced tools like CoastSat and DSAS

Chatzipavlis et al. [92] presented a new modeling methodology of beach realignment using a neuro-fuzzy neural network optimized using a backtracking search algorithm. This model is a reasonably competent approach to dealing with the nonlinearities in sediment movement caused by time-varying waves, which are beyond the resolving capability of numerical models. First-order fuzzy rules have been used to model the input–output relationship in this network. It was finally observed and concluded in this research that the backtracking search algorithm enhances performance due to the improvement of mutation and crossover operations. Using experimental data from Santorini, Greece, it was displayed that the proposed method prevails over the existing modeling techniques.

AI models, such as WaterNet, significantly outperform traditional methods like the DSAS and NDWI regarding shoreline variability. This improvement is due to the ability of AI to integrate spatial and spectral features, process extensive data efficiently, and adapt to diverse environmental conditions. For instance, WaterNet achieves over 90% classification accuracy in complex environments, whereas the NDWI typically performs at 70–80% due to the misclassification of mixed land–water features [54,55]. Traditional systems, such as the DSAS, rely much more on predefined parameters and thus perform inefficiently under dynamic conditions. WaterNet, trained on various datasets, copes with different tidal levels and sedimentation. Studies have shown that it reduces the sedimentation-rich coast classification error from 25% for the DSAS to below 10% [56,57]. In terms of accuracy metrics, WaterNet achieves a root mean square error (RMSE) of 5 m compared to 15 m for the DSAS and 18 m for the NDWI, particularly in areas with vegetation interference [66]. Precision and recall are also superior, with WaterNet scoring 0.92 and 0.89, respectively, versus 0.81 and 0.78 for the DSAS [37].

While AI and ML models like WaterNet have shown unparalleled advancement in the field of shoreline detection, scalability to diverse geographies and shorelines should be cautiously considered. Such models are developed for different environments, including sediment-heavy deltas, vegetated coasts, and urbanized shorelines, based on multispectral and temporal datasets [4,12]. WaterNet can process high-resolution UAV imagery or medium-resolution Sentinel-2 datasets, making the technology suitable for modeling complicated shorelines and capturing many environments [2,10]. However, the deployment of such technologies in underdeveloped regions faces serious challenges. Among the critical challenges are high-quality training datasets, which are mostly unavailable within less-developed regions because historic shoreline monitoring has not been performed, or inconsistent data collection practices. Indeed, Palomar-Vázquez et al. (2023) [62] and Thakur et al. (2021) [6] presented these findings. In addition, the computational infrastructure necessary for training and deploying AI models, such as access to high-speed internet and cloud computing platforms, is usually lacking in these areas. This creates a bottleneck in processing large datasets and implementing complex algorithms (Quang et al., 2021; Singh et al., 2023) [5,11]. Another important barrier to scalability involves shoreline variability across geographies. Most AI models, like WaterNet, are trained on regional datasets that cannot capture the geomorphological variability of coastlines around the world. For instance, models that have training data derived from sandy beaches have been shown to not generalize well to rocky coasts or mudflats, requiring regional calibration or retraining of the models themselves [3,7]. This is an expensive process and may hinder the deployment of such models in resource- and expertise-scarce underdeveloped regions. Moreover, the absence of GTD in large, underdeveloped areas has implications for the validation and accuracy of the models. Without strong GTD for calibration, the AI models may fail to capture local tidal variations, vegetation interference, or anthropogenic impacts and thus have higher error margins [8,44]. This calls for methods that effectively use limited or low-cost GTD, such as UAV-based data collection or community-led shoreline surveys.

Finally, for AI models like WaterNet, scalability needs to consider how well the model fits and whether this can be achieved through partnerships with local stakeholders and open datasets, such as archival results from Landsat. Simplification of the AI models by reducing the required computation and merging them with low-cost data collection may enable greater technology access. Addressing these limitations means that WaterNet and similar models will enable wider global applicability. This ought to yield more robust means for monitoring shorelines and managing environments for underdeveloped countries.

Although there has been high accuracy exhibited by AI models in shoreline segmentation, the challenge lies in their generalizability in diverse coastal morphologies. For instance, WaterNet [26] recorded a segmentation accuracy of >99% using high-quality images, which are unlikely to be obtained in urban or sediment-rich coastal environments without the need for model retraining. Zollini et al. [55] also noted that their model (J-Net Dynamic) worked better on natural beaches compared to artificial constructions. Furthermore, McAllister et al. [21] reported that regional datasets were used to boost machine learning classifications. These observations point to the fact that although AI is a powerful tool, it tends to need regional calibration and is unlikely to be directly transferable across multiplex environmental conditions without fine-tuning or model retraining.

While the focus of this review remains shoreline-specific AI applications, recent progress in deep learning architecture such as MR-DCAE [93] and Cross-Triplet Context Learning [94] demonstrate transferable techniques that could be applied to coastal monitoring tasks. These models emphasize robust feature learning from limited labeled data and context-aware recognition, which are especially useful in scenarios with sparse ground truth or complex spatial features. Their methodological frameworks provide a foundation for future shoreline detection models to operate under unsupervised or semi-supervised conditions.

5. Discussion

5.1. Technology Usage Trends in Reviewed Studies

The key findings of the studies framed in Tables 1 and 2 were derived from 58 papers from the review methodology. It can be observed from our analysis of the screening results that the GIS appeared in the highest frequency of papers, amounting to 94.8% of papers employing this technology. In contrast, Landsat exhibited applications in 91% of the studies. This finding can be characterized as the most underlined basic need for technologies within remote sensing and geographical information systems. While the GIS has been broadly used to manage, process, and visualize data in a spatial format, Landsat delivers consistent, long-term satellite imagery crucial to environmental and land-cover changes over long periods.

Almost one-third of the review papers employed Sentinel-2 (36.21%) and Ground Truth Data (36.21%). This reliance on Ground Truth Data shows that most studies rely on legwork and empirical observations for model validations or adjust satellite-derived data to ensure the accuracy of their remotely sensed outcomes.

Moreover, Sentinel-1, a radar-based satellite, was used at a low rate of 5.17%, which is indicative of more specialized applications. Sentinel-1 is mainly utilized when other optical satellites, such as Sentinel-2 or Landsat, cannot view the Earth, for instance, during overcast conditions or at night. The limited usage of Sentinel-1 reveals that these conditions have not prevailed in this dataset, and optical data from other satellites can serve most of the requirements of different research studies.

The modest percentage of 15.52% reveals the emerging but still developing trend in remote sensing applications using AI/Machine Learning/Neural Networks. The data analysis comprised sophisticated algorithms that were intricate but not pervasive in implementation in the dataset. This indicates a transition phase in which conventional remote sensing methods remain dominant while AI tools are becoming increasingly popular.

However, the least applied was with UAV/Drone technology accounting for less than 2% of the instances, which may be due to the relatively high costs, limited spatial coverage, or logistical challenges in flying drones compared to satellite-based systems that have broader coverage and may provide more reliable data over time.

5.2. Advantages of Sentinel and Landsat Missions in Coastal Monitoring

Satellite remote sensing technologies, specifically those related to Sentinel and Landsat missions, have been highly preferred in advancing knowledge and monitoring regarding coastal erosion and shoreline dynamics [21,95]. With their public open-access data source archive, these major satellite systems overcome traditional limitations by providing large-scale, high-resolution data that enable accurate monitoring of changes along coastlines [13,15]. Sentinel-2, over time, has proven effective due to its high spatial resolution and frequent revisit times that capture detailed information on coastal shifts that are usually quite difficult to identify [39,96]. The Landsat series, particularly Landsat 8, offers a long-term historical record, which is crucial for understanding coastal processes over decades [18,69]. Studies have continuously reiterated that such technologies yield valuable insights into mapping erosion and accretion patterns along coastlines, providing crucial insights into how natural forces and human interventions shape coasts [12,19]. Based on this review, the major technological application lies in the Digital Shoreline Analysis System derived from the GIS process, which caters to the majority of shoreline change calculations. Metrics like EPR and LRR work with long-term shore movement trends and give surprisingly good predictions about future changes. For example, the study by Quang et al. [11] on the coast of Quang Nam Province in Vietnam identified a total of 800 erosional and accretional sections that provide crucial information on how both natural processes and human activities of land reclamation and urbanization drive changes along the coast. Such an analysis is fundamental to informing management practices of coasts and mitigating the impacts brought about by erosion on vulnerable communities.

5.3. AI and Machine Learning in Shoreline Monitoring

Integrating ML and AI methods in coastal monitoring is a quantum leap in effectively processing and analyzing large volumes of data [33]. These technologies can fully automate processes requiring human labor, such as segmenting and detecting shorelines from satellite imagery. For example, the ensemble deep learning model WaterNet has exhibited extremely high accuracy, reaching 99.79% in shoreline segmentation. This high accuracy enables shoreline dynamic analysis almost in real-time, which is vital for quick responses to environmental changes and long-term planning of coasts. Machine learning models predicting the position of shorelines well into the future also help decision-makers prepare and adapt to the oncoming impacts of climate change.

5.4. The Challenge of Real-Time Integration and Multi-Platform Fusion

Yet, with these developments, the most crucial issue remains the adaption and integration of satellite data in real-time across multi-data platforms. This has made real-time data integration the highest priority and will significantly increase the capability of coastal managers' capability to act adequately in the face of sudden environmental changes related to storms, floods, and landslides that may rapidly reshape coastlines. Indeed, different studies, such as Spinosa et al. [39], showed that Sentinel-1 SAR, in combination with optical Sentinel-2 data, does indeed enable the monitoring of shoreline dynamics under adverse weather conditions on occasions when only optical images may not be sufficient. However, one of the pending challenges is to develop a fully automated system providing real-time data across scales and diverse environmental conditions.

Integrating remote sensing, GIS, machine learning, and UAV technologies opens new horizons for comprehensively monitoring coastal environments [32]. These are very fitting considering the growing threat of climate change, which accelerates the rate at which coasts erode and places communities at greater risk [44]. The trends in the scalability and efficiency of these technologies will call for further research in the future that considers timescales of real-time monitoring and data integration in view of effective coastal management and disaster preparedness.

5.5. Technological Complexities and Data Preprocessing

The integration of data from Sentinel, Landsat, and UAVs for shoreline monitoring presents a host of challenges that surpass resolution and revisit times.

For example, there is heterogeneity in the data: Landsat provides multispectral imagery, while UAVs deliver high-resolution orthophotos; these need complex preprocessing to harmonize inputs [54,57]. The complexity further adds to misalignments due to differences in the angles of satellites and flight paths of UAVs, which require advanced techniques of rectification and accurate georeferencing with the help of ground control points [55,65]. Tidal fluctuations complicate shoreline data even more, making accurate tidal models essential for consistent analysis [37,56]. Integrating UAV imagery with long-term Landsat archives generates large datasets, creating significant computational demands [53,66]. Algorithms such as J-Net Dynamic, used for subpixel shoreline detection, introduce additional layers of complexity [54]. Environmental factors, like cloud cover, often impede optical satellite imagery. UAVs, while less reliant on good weather, require manual launching and supervision. Human activities, particularly those involving coastal engineering, result in rapid changes along the shoreline and further complicate monitoring [57,65]. With its essential contribution, validation using GNSS remains resource-intensive and time-consuming [37,55]. Addressing these challenges requires automated data processing pipelines and standardized methods to ensure consistency and reliability in shoreline monitoring [56].

5.6. Scientific Gaps and Limitations in Model Generalization

Identifying and emphasizing scientific gaps indicates that real-time, multi-platform integrated data are crucial, especially as significant advancements have been made in individual remote sensing platforms, such as satellites, UAVs, and ground-based sensors. However, the generally low interoperability between these platforms remains a critical bottleneck for effective coastal monitoring, particularly in addressing rapid environmental changes caused by storms or erosion events [42,67]. The number of data fusion techniques has grown, increasingly merging Sentinel-1 SAR with Sentinel-2 optical data to enhance monitoring, but these are constrained by weather conditions [46]. Most current data fusion techniques seldom incorporate high-resolution UAV data, which could complement satellite data by addressing temporal and spatial resolution gaps [8,19]. Furthermore, machine learning models, such as WaterNet, show promise but perform well only in localized regions; they lack adaptability across diverse coastal landscapes, primarily due to the need for region-specific tuning, limiting their broader applicability [7,45]. Another key focus is addressing the pressing need for enhanced access to open data, as well as the data gap between regions, with specific attention to developing countries, which are usually at the front lines of most climate-related impacts with less advanced monitoring. Machine learning models must be adapted to work in data-poor situations to achieve equity globally in coastal monitoring. Also, creating open-access platforms for data sharing and predictive models could foster further collaboration and perhaps allow coordinated responses to coastal challenges worldwide.

Despite these achievements, predictive modeling for climate-induced shoreline shifts is still in its infancy, with many models lacking robustness in incorporating long-term sea-level rise and extreme weather patterns [19]. These scientific gaps highlight the urgent need for more cohesive, scalable systems that effectively integrate data sources and adapt to diverse coastal settings.

Regarding enhancement in coastal monitoring, the challenges related to scalability and data integration remain. Satellite remote sensing, in conjunction with recent technologies involving machine learning, has greatly enhanced the capability for shoreline change monitoring, but the integration of datasets across platforms is a key challenge. Several studies have highlighted the potential of dataset combinations from sources like Sentinel-1 SAR, Sentinel-2 optical data, UAV imagery, and ground-based sensors. For example, Angnuureng et al., 2022 [44] combined drone and satellite data to enable high-resolution temporal monitoring of coastal dynamics, showcasing the added value of such multiplatform approaches. However, this often remains compromised due to interoperability or standardization aspects between the platforms, thereby complicating seamless integration into most such efforts. Furthermore, methodologies aiming at data fusion are limited by computational demands and the absence of structured globally accepted frameworks. Studies like those by Zollini et al., 2023 [55] and McAllister et al., 2022 [21] highlight that while combining SAR and optical data offers enhanced insights, it requires significant preprocessing, specialized algorithms, and computational resources that are not universally accessible. Additionally, the use of UAV data is still largely unexamined, even though it can potentially address gaps in temporal and spatial resolution. Studies like Susilowati et al., 2022 [58] emphasize that combining UAV imagery with satellite data has the potential to yield a more complete understanding of coastal dynamics; however, these integrations are infrequently seen due to the absence of standardized workflows.

5.7. Inequity in Data Access and Integration Frameworks

Several main factors, such as technological and methodological inconsistency, cause difficulty in completely integrating datasets. Each data source functions with different resolutions, time intervals, and formats, which presents considerable challenges in harmonizing these datasets. Nguyen Hao and Takewaka 2021 [64] considered that achieving alignment between SAR and optical data is notably difficult without comprehensive preprocessing, which may lead to errors and delays. Many studies, including Erdem et al. (2021) [20] and Singh et al. (2023) [5], emphasize that sophisticated integration methods demand significant computational power and specialized knowledge in the field. This restricts their usage in areas where these resources are limited. This problem is further aggravated by the inequality of data availability among regions; for most developing countries, high-resolution data or advanced processing tools are not readily available, making adopting integrated monitoring systems more complex. This has been pointed out by Islam et al. (2021) [3] and Matin et al. (2021) [32]. For instance, studies like that by Taveneau et al. (2021) [34] stress that the absence of integrated data protocols is one of the main reasons for significant inefficiencies in collaboration among researchers toward producing reproducible results. This rapid development of new methods for data collection, like real-time UAV imagery and AI-driven predictive models, has outgrown the integration frameworks; hence, it has created a gap between technological potential and practical application. Despite these technological advancements, full-platform integration remains elusive due to systemic and technical barriers. The prime reason is that integrating datasets of varied resolutions, temporal frequencies, and sensor modalities is inherently complex.

As Karaman (2021) [36] mentioned, even for advanced thresholding techniques that allow the detection of shorelines, consistent results could not be provided when applied across diverse data sources.

Moreover, regional inequalities in data availability and computational resources create a wide gap in the application of integrated systems. For example, high-income countries can apply AI and advanced geospatial tools, while resource-poor regions struggle to access even the fundamental datasets required for monitoring. Another critical factor has been the lack of collaborative frameworks or open-access platforms that would support global sharing and the integration of data. Studies such as that by McAllister et al. (2022) [21] have shown that without shared repositories and standardized workflows, dataset integration across scales and disciplines remains fragmented and resource-intensive.

These gaps indicate the urgent need for unified global initiatives to make integrated coastal monitoring a reality.

5.8. Remaining Limitations of Open Access Satellite Data

Despite the numerous benefits of open-access satellite datasets such as Sentinel and Landsat, several limitations persist. Cloud cover remains a major obstacle for optical sensors, especially in tropical or monsoon-affected zones. Although Sentinel-1 (SAR) can partially overcome this, its spatial resolution and signal noise can limit shoreline discrimination. Additionally, the bandwidth and computing infrastructure required for large-scale image processing often exceeds what is available in developing regions. Limitations also exist in the archives, indicating spatial gaps such as for Landsat in low-income countries. The pre-1984 Landsat archive also lacks consistent data, constraining historical analyses in many parts of the world. Finally, while platforms like Google Earth Engine have improved access, steep learning curves and limited customization still pose barriers for non-expert users.

Satellite data in an open-access form has changed different research areas, such as climate monitoring, environmental studies, and sustainable development. Even so, in addition to its advantages, drawbacks remain, some of which include regional gaps in data, temporal resolution, data quality and precision, and data usability and accessibility. Here, this section introduces an examination of those drawbacks based on previous research studies.

One of its biggest obstacles is the existence of data gaps at the regional level. These gaps are caused due to uneven coverage, often presented in low-income countries and remote areas. Landsat satellite data, for example, while extensive at the global level, frequently struggles to maintain consistent data in specific areas, resulting in incomplete and skewed interpretations of environmental changes [97]. In this regard, another example is the fact that weather station networks in Africa are also inadequate and uneven in distribution, with most of them located in urban centers while rural and remote locations remain poorly served [98,99]. Regional differences also become large due to the scarcity of high-resolution satellite data in some regions. For instance, satellite-based precipitation estimates, although useful, tend to have poor precision at finer spatial and temporal resolutions, in areas of intricate terrain, and even in areas of poor ground data validation [99]. Such limitations in data are hindering climate variables from being monitored and analyzed properly, negatively affecting those areas that have intensive climate-dependent sectors like agriculture and water resource management.

Temporal resolution problems represent another key constraint for open-access satellite data. Time series gaps in satellite data archives can arise due to launching delays, sensor malfunctions, or cessation of data acquisition. Such gaps reduce the reliability of climate data records and can produce incorrect analyses, especially when identifying long-term climate trends [100]. In addition, the temporal resolution of satellite data is not always sufficient for use by end-users. Applications focused on monitoring extreme weather phenomena or crop productivity demand high-temporal-resolution data, which are not always attainable or accessible [101]. In addition, satellite data integration from other data sources, e.g., ground observations, can create inconsistencies, making temporal climate variable analysis difficult [99].

The introduction of quality and accuracy problems also becomes paramount in open-access satellite data. While satellite data provide useful indicators, its precision is susceptible to problems such as sensor flaws, atmospheric interference, and cloud cover or other obstacles [99,100]. For instance, Dinku et al., (2019) [99] addressed satellite-based rainfall estimation errors and bias in remote locations with poor availability of ground validation data. Moreover, satellite data quality can significantly vary in accordance with the sensor and algorithms utilized. For instance, while satellite-based rainfall estimates using TAMSAT can function well in specific locations, they cannot do so in locations with specific climatologic or terrain profiles.

Despite the growing availability of satellite data for free and open use, issues of accessibility and usability remain. These issues tend to stem from data complexity, non-user-friendly interfaces, and limited capabilities for data handling and analysis among end-users [102]. One of the key problems is the non-interoperability of data across different data sources and types. For instance, climate data are frequently saved as different types and projections, resulting in challenges for users in combining and analyzing them in an optimal manner [101]. Moreover, the volume of satellite data can overwhelm ordinary programming in some cases, especially for those who lack technical knowledge or resources [103]. In an effort to overcome such challenges, platforms such as the Marble climate informatics platform and ENACTS have been created to offer interfaces and tools for data access, data discovery, and data analysis in an easy-to-use manner [104]. Such platforms seek to reduce entry barriers among users, especially in developing countries, through the provision of preprocessed data products and interactive visualization interfaces.

6. Conclusions and Future Research Directions

Advanced remote-sensing technologies have increased significantly, integrating GIS, ML, and UAVs to develop the monitoring of coastal erosion and shoreline dynamics. Indeed, new tools offer heightened spatial and temporal resolutions, which are key elements in the effective and efficient tracking of complex shoreline change patterns. These advances [15,21] in monitoring are centered on free-access satellite missions, Sentinel and Landsat in particular, and provide long-term data for understanding coastal dynamics for both short- and long-term time frames. The high-resolution optical data provided by Sentinel-2, together with the historical records provided by the Landsat series, form precious insights into this aspect and are a convenient source that can be used for investigating long-term changes relevant to planning for future coastal management studies [11,39].

However, some challenges need to be considered in the future. For example, data from these different platforms must be integrated as close to real-time as possible as effective coastal monitoring requires the ability to respond to environmental changes influenced by storms and events with sea-level rise within limited time frames. Interoperability among satellites, UAVs, and ground-based sensors for multi-platform data fusion is, however, currently lacking due to the various erroneous effects, thus reducing the precision and flexibility of any monitoring system in real-world situations [44]. The integration of Synthetic Aperture Radar (SAR) data, such as Sentinel-1, still holds great potential when integrated with optical data, but especially for overcoming issues in cloud cover and adverse weather conditions. However, fully automated systems designed for real-time analysis and seamless multi-source data integration are still under construction.

This should, therefore, make the research target improving machine learning models to suit a wide range of coastal scenarios. Models like WaterNet have enjoyed tremendous accuracies, but applicability is invariably narrow in scope and very often requires region-specific tuning for optimal results to be achieved [20]. These adaptations of the ML models to different coastal morphologies can extend their application globally, with a particular focus on areas with limited conventional monitoring. Lastly, it is a priority that increased access to data and the development of open-data-sharing platforms be addressed to achieve equity in management. Such initiatives could allow informed decision-making globally to support adaptation in developed and developing regions due to climate change impacts on coastal areas [3,50].

Future research needs to focus on overcoming the fundamental problems identified above, which pose a challenge to efficient monitoring of coastal zones: the lack of standards and frameworks, inaccessibility, computational complexity of algorithms, and uneven access to advanced technology. The fact that there is no consensus on standard methods for multi-platform data integration, according to Karaman [36] and Spinosa et al. [39], results in serious interoperability limitations hindering large-scale applications. The distribution of high-resolution data and computational resources themselves identified by Ferreira et al. [49] and Nassar et al. [48] are uneven, which limits the scaling up of monitoring efforts in developing regions. Promising machine learning models like WaterNet show high accuracy, but the application of such models is constrained by region-specific tuning and the computational power required, as identified by Vos et al. [54] and Sunny et al. [18]. This will also involve addressing systemic gaps in global collaboration and open-access platforms and developing adaptive algorithms that make monitoring technologies more inclusive, efficient, and responsive to dynamic environmental challenges. This is critical in building equitable solutions and enhancing resilience in communities living o coastlines worldwide. When addressed, these research directions will enable further developments in remote sensing and data integration with models, enabling actionable insights into the sustainable management of coasts and disaster preparedness, which will enhance the resilience of all coastal communities worldwide.

In forthcoming applications, we envision the integration of a wider array of spatial datasets beyond those currently utilized in satellite missions. Reflecting the observations of Balawejder et al. [105], geoportals at the national level in Poland and Finland provide open-access cadastral, orthophotos, and thematic maps that enable land surveyance and coastal management. Likewise, Apollo et al. [106] underscored the growing availability of public and volunteered geographic information (VGI) from OpenStreetMap, GeoTagging Flickr, Wikimapia, and Google Earth, complemented by authoritative data such as the USGS Earth Explorer and the Sentinel Copernicus Open Access Hub, as well as mapping agencies at the national level. These datasets—LiDAR, bathymetry, GNSS networks, InSAR, and UAV-based photogrammetry—can enable high-resolution shoreline extraction and validate AI-based outputs. Integrating them into our existing satellite and ground truth techniques may provide higher-quality spatiotemporal accuracy and promote the democratization of GIS at the level of coastal stakeholders.

Upcoming works must include the incorporation of airborne LiDAR bathymetry (ALB) methods into enhanced coastal monitoring. According to Kogut et al. (2019, 2021) the systems of ALB, particularly full-waveform processing and artificial neural networks, have been shown to be able to map the features of the seafloor with sub-decimeter vertical accuracy, even in highly complex underwater landscapes [107,108]. These techniques are a good complement to satellite- or UAV-based methods, particularly in turbid water or shallow water situations where the use of passive sensors becomes difficult. The accuracy and classification ability of ALB makes it a very good subject for upcoming studies on coastal erosion, buried structure detection, and digital twins.

Recent developments in Artificial Intelligence brought forth state-of-the-art techniques that can extensively support shoreline detection, erosion mapping, and environmental feature identification. For one, Ren et al. introduced a context-aware Self- and Cross-Triplet Clue learning model to facilitate semantic comprehension based on graph-based context modeling [109], while Zheng et al. [93] designed a Manifold Regularization-Based Deep Convolutional Autoencoder (MR-DCAE) that learns low-dimensional feature-rich representations of noisy data based on manifold restrictions. These models, although originally devised for generic object detection and signal category, point to scalable AI methods that can be applied to geospatial shoreline detection, particularly in difficult coastal environments.

Artificial Intelligence has greatly enhanced remote sensing applications, especially through advancing image analysis technologies in specific tasks such as shoreline segmentation and air scene classification. Wang et al., for example, constructed a Triplet-Metric-Guided Multi-Scale Attention network to boost air scene classification [110]. In a similar way, Regan and Khodayar (2023) proposed a graph convolutional model of triplets to enhance image retrieval in satellite databases [111]. Lv et al. also formulated DeepSA-Net, a bespoke Convolutional Neural Network (CNN) for shoreline segmentation. DeepSA-Net utilizes coordinate attention and strip-pooling mechanisms to boost feature extraction, which attains a segmentation level of over 99% mean Intersection over Union (mIoU) [112]. Liu et al. demonstrated that CNNs taught using UAV data can map soil erosion with high levels of accuracy, highlighting the high potential of AI applications in supporting land degradation studies [113]. These models together signify the vanguard of the application of AI in coastal sciences through segmentation and scene analysis to forecast the erosion of soils and model shores. It is possible that these AI advances may be integrated into existing workflows and boost the level of accuracy and the capability of resulting in better management and protection of the coastal environment.

Long-term shoreline change forecasting depends on the extrapolation of historical trends using statistical and mathematical models. These include the Linear Regression Rate (LRR), Weighted LRR, and the application of Kalman Filtering in forecasting. Hossain et al. [2], for example, used Kalman filtering to forecast shoreline positions for 2031 and 2041 in eastern India, highlighting the importance of erosion management.

Equally, Mishra et al., [12] modeled 2030 and 2040 shoreline positions using DSAS and trigonometric extrapolation. These models are aided by long-term Landsat archives, though their performance is limited by positional uncertainty and environmental variability. Climate data inclusion (e.g., sea-level rise projections) is increasingly becoming a requirement for reliable predictions over the longer term.

Future coastal erosion monitoring developments are anticipated to arise through the fusion of new AI-powered sensors, high-resolution CubeSats, and real-time edge computing. Real-time shoreline identification and alert systems will be facilitated by AI-boosted payloads aboard UAVs or microsatellites. Hyperspectral imaging, while presently not widely offered in open access, possesses the potential to sense subtle aspects of geomorphological change and composition of sediments. Developing methods such as explainable AI (XAI) and transfer learning also permit improved interpretability and generalizability of coastal models. These technologies, combined with growing open-data missions by commercial constellations (e.g., PlanetScope), will facilitate a more comprehensive, near-real-time monitoring system for fragile coasts.

This review paper emphasizes that technological innovation combined with equitable access, standardized protocols, and flexible AI models will be key in protecting vulnerable shores in the face of mounting climate stresses and human activities.

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Abbreviations

ACIS	Applied Climate Information System
ADT	Automatic Weather Station Data Tool
AI	Artificial Intelligence
AI/ML	Artificial Intelligence/Machine Learning
ALB	Airborne LiDAR Bathymetry
AMBUR	Analyzing Moving Boundaries Using R
CNN	Convolutional Neural Networks
CV	Coefficient of Variation
DEA	Digital Earth Australia
DEM	Digital Elevation Model
DL	Deep Learning
DSAS	Digital Shoreline Analysis System
DSAS-GIS	Digital Shoreline Analysis System—Geographic Information System
EO	Earth Observation
EPR	End Point Rate

ESA	European Space Agency
ETM	Enhanced Thematic Mapper
ETMP	Enhanced Thematic Mapper Plus
EWI	Enhanced Water Index
EXCELSIOR	ERATOSTHENES: Excellence Research Centre for Earth Surveillance and Space-Based Monitoring of the Environment
FC	Fuzzy Classification
GCP	Ground Control Points
GEE	Google Earth Engine
GIS	Geographic Information Systems
GTD	Ground Truth Data
LRR	Linear Regression Rate
ML	Machine Learning
MSI	Multi Spectral Satellite Images
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NSM	Net Shoreline Movement
OLI/TIRS	Operational Land Imager/Thermal Infrared Sensor
RMSE	Root Mean Square Error
RS	Remote Sensing
RTN	Real-Time Network
SAR	Synthetic Aperture Radar
SCE	Shoreline Change Envelope
SD	Standard Deviation
TLS	Terrestrial Laser Scanner
UAV	Unmanned Aerial Vehicle
USGS	United States Geological Survey
WLR	Weighted Linear Regression
mNDWI	Modified Normalized Difference Water Index

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