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A Review of Remote Sensing-Based Approaches for River Morphological Change Analysis using DSAS and Machine Learning Techniques

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Abstract

River morphology is very dynamic, and it continues to adapt to natural processes and human activities, with channel migration, bank erosion and deposition occurring at varying rates; these processes can create major difficulties in sustainable river management. The efficiency in monitoring such morphological changes over large spatial and temporal scales has been made possible due to advances in satellite remote sensing. The Digital Shoreline Analysis System (DSAS) is one of several approaches that have been widely used to measure rates of riverbank changes through statistical calculations, including Net Shoreline Movement (NSM), End Point Rate (EPR), and Linear Regression Rate (LRR). The reliability of DSAS-based analysis, however, is very dependent on the accuracy of the bankline that is extracted from the satellite image. The recent advancement of machine learning techniques, especially those based on random forest (RF) and support vector machine (SVM), has shown better accuracy in land–water classification and feature extraction in challenging riverine environments. The combination of machine learning and DSAS provides increased robustness in the delineation of riverbanks and the evaluation of morphological changes that have occurred. The present paper provides a detailed review of remote sensing–based approaches for morphological assessment of natural streams with a particular emphasis on the simultaneous use of DSAS and machine learning techniques. The study reviews pertinent published sources, discusses their strengths and weaknesses and outlines current trends and gaps in the literature. A conceptual framework is suggested to combine the integration of DSAS, RF and SVM to support future studies in order to enhance the accuracy and applicability of river morphology monitoring in the context of sustainable management of river basins.

Keywords: River morphology; Remote sensing; Digital Shoreline Analysis System (DSAS); Machine learning; Riverbank erosion

Introduction

The river is a dynamic geomorphic system, which constantly changes in reaction to complex interaction of the hydrological regime, sediment transport processes, channel geometry, tectonic controls and anthropogenic effects like dams, embankments, river training works, and land use changes in the catchment (Thieler et al., 2009; Himmelstoss et al., 2018). These mutually related drivers lead to spatial and temporal variations in channel planform, river bank position and floodplain morphology. The changes are evidenced by channel migration, bank erosion, lateral accretion, and the creation or destruction of sandbars and islands, and have important impacts on flood hazards, infrastructure stability, agricultural productivity, and riparian ecosystems, as described in (Chin, 2005; Brown et al., 2020). Over the past decades, the magnitude and occurrence of river morphological changes have increased in many areas, especially with the increasing rate of urbanization, deforestation, climate variability, and flow regulation (Himmelstoss et al., 2018). Uncontrolled riverbank erosion creates a number of socio-economic problems, especially along the floodplains of densely populated areas where agricultural land and settlement have been lost and damage is common. As a result, the quantitative evaluation and monitoring of river morphological changes have been necessary for the sustainable management of river basin and disaster risk reduction strategies (Gregory, 1979). River monitoring techniques such as cross-sectional surveys and ground observations are commonly used to measure river morphology at local scale but are often expensive, have limited spatial coverage and lack temporal continuity (Chin, 2005).

The constraints limit their use for long-term and large-scale monitoring of rivers. Satellite remote sensing, on the contrary, has become a very powerful and low-cost observation tool, providing synoptic, repetitive and multi-temporal observations of river dynamics, on large spatial scales (Jensen & Lulla, 1987; Tucker, 1979). Long-term satellite archive has greatly improved the capacity of researchers to study past and present channel modifications. To delineate riverbanks, map channel migration, and quantify erosion–accretion patterns, there have been many applications of multi-temporal satellite datasets acquired by various sensors, ranging from Landsat MSS, TM, ETM+ to OLI and Sentinel-2 MSI.There are many applications that use multi-temporal satellite datasets acquired by different sensors (Landsat MSS, TM, ETM+, OLI and Sentinel-2 MSI) for delineating riverbanks, mapping channel migration, and quantifying erosion–accretion patterns in various fluvial environments (Tucker, 1979; IEEE Geoscience and Remote Sensing Letters, 2018; Martimort et al., 2007).

They provide a long time series of observations, which is ideal for short-term fluctuation analysis and long-term morphological changes. The extraction of riverbank position from satellite imagery is still a difficult task because of the mixed pixels, turbid water conditions, dense riparian vegetation and seasonal changes of water level (Brown et al., 2020; Miller et al., 2024). Digital Shoreline Analysis System (DSAS) is one of the remote sensing–based analytical techniques that has been widely used for quantifying linear rates of riverbank and shoreline changes (Thieler et al., 2009; Hasan et al., 2025). Within the GIS environment, DSAS uses a transect approach to calculate statistically sound metrics, including Net Shoreline Movement (NSM), End Point Rate (EPR), and Linear Regression Rate (LRR).

They are commonly used to evaluate the erosion and accretion along a reach and to detect spatial variations in riverbank changes (Himmelstoss et al., 2018; Brown et al., 2020). However, the precision of input banklines is of vital importance to the accuracy of change rates derived from the DSAS, and reliable bankline extraction is essential to an accurate assessment of change (Brown et al., 2020; Miller et al., 2024). Machine learning (ML) methods have been more and more combined with satellite remote sensing to overcome some of the drawbacks related to index-based and threshold-based classification approaches over the past few years (Tyralis et al., 2021; Lang et al., 2018). Because of their capability to deal with large data dimensionality, nonlinearity, and spectral heterogeneity, supervised algorithms like Random Forest (RF) and Support Vector Machine (SVM) have been proven to be able to discriminate between land and water bodies and to extract geomorphic features from the images (Tyralis et al., 2021; Pal, 2011). Classification using ML has been demonstrated to have a significant impact on the consistency and accuracy of the delineation of riverbanks, and thus on the accuracy of the subsequent DSAS-based morphological change analysis (Brown et al., 2020; Miller et al., 2024). There is a body of literature applying river morphology assessment techniques independently using either DSAS or machine learning, but there is still a lack of consolidation that looks into an integrated application (Chin, 2005; Munasinghe et al., 2021).

Most of the current literature consists of site-specific case analyses, and there is relatively little synthesis of methodological frameworks, comparative performance, limitations, and trends in research (Munasinghe et al., 2021). The gap highlights the need for a structured review, which systematically analyzes the joint application of DSAS and machine learning method in the analysis of river morphological changes. This paper, then, summarizes a broad range of remote sensing-based techniques for examining natural stream morphological change and describes the incorporation of DSAS and machine learning techniques, specifically Random Forest and Support Vector Machine (Tyralis et al., 2021; Brown et al., 2020). The review identifies gaps in the literature and offers suggestions for further research and future directions while examining the strengths and weaknesses of the existing literature. A conceptual framework is provided to connect DSAS and machine learning techniques in order to give a coherent perspective of contemporary approaches for sustainable river morphology monitoring and management (Fig. 1).

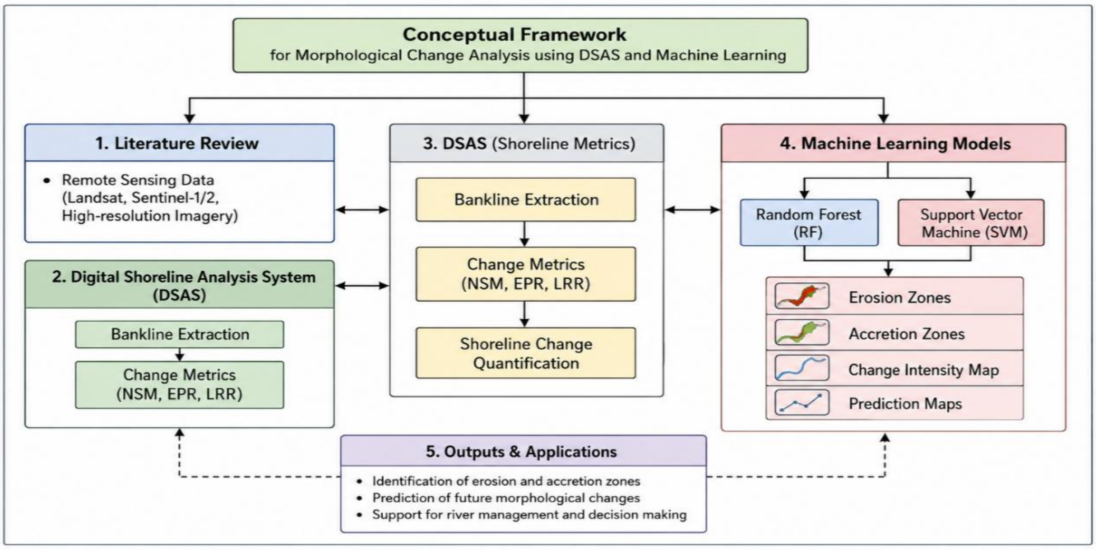

Fig. 1. Conceptual framework for morphological change analysis using DSAS and machine learning (adapted from Thieler et al., 2009; Brown et al., 2020; Tyralis et al., 2021).

Data sources and methodological overview

The availability of multi-temporal satellite data with adequate spatial and temporal resolution is one key prerequisite for the use of remote sensing–based analysis of river morphological changes (Jensen & Lulla, 1987). Satellite missions, which are freely available like Landsat and Sentinel, have been key players in fluvial monitoring studies over the last few decades and have provided repetitive and synoptic observations of river systems (Tucker, 1979; IEEE Geoscience and Remote Sensing Letters, 2018). These datasets have been available for a long time and consistently and are very useful to describe long-term and consistent information on channel migration, riverbank erosion and accretion processes in natural streams on various scales and time dimensions (Chin, 2005; Martimort et al., 2007).

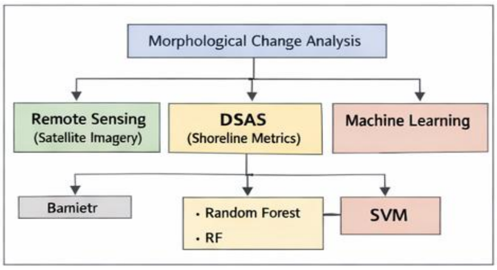

Fig. 2. Classification of techniques used for river morphology analysis (compiled from Chin, 2005; Munasinghe et al., 2021, Hasan et al., 2025).

The fluvial geomorphology studies have been extensively used with the use of landsat missions such as MSS, TM, ETM+ and OLI sensors; these sensors have been able to capture a long time series of data with moderate spatial resolution, which makes these data very suitable for studying the changes that occur in river systems over a decadal time scale (Tucker, 1979; IEEE Geoscience and Remote Sensing Letters, 2018). Sentinel-2 MultiSpectral Instrument (MSI) data, however, have better spatial resolution and shorter revisit cycles, which allow them to better enable detailed land–water discrimination and recent morphological assessments in dynamic riverine environments (Martimort et al., 2007). The details of satellite datasets commonly used for river morphology studies are summarised in Table I (Tucker, 1979; Martimort et al., 2007).

Pre-processing of satellite imagery is one of the important steps to ensure consistency and reliability in the analysis of river morphology using satellite imagery (Jensen & Lulla, 1987). Radiometric and atmospheric correction, geometric correction, image co-registration and cloud masking are common pre-processing operations reported in the literature and are necessary to reduce sensor-induced noise and to ensure accurate spatial alignment of multi-temporal images (Tucker, 1979; IEEE Geoscience and Remote Sensing Letters, 2018). Water and land features are usually separated by pre-processing and then with spectral indices and classification (Chin, 2005; Jensen & Lulla, 1987). Many indices have been developed to improve the visibility of water features and reduce the number of non-water pixels, including the NDWI (Brown et al., 2020) and the Modified NDWI (MNDWI) (Miller et al., 2024). The index-based approaches, however, can be inadequate in complex riverine environments with dense vegetation, water with high sediment load, and significant seasonal fluctuations (Miller et al., 2024; Munasinghe et al., 2021).

Cloud-based platforms like Google Earth Engine (GEE) have also been shown to effectively process vast quantities of satellite data for applications like river monitoring (Martimort et al., 2007).

Table 1. Details of Satellite Data Used in The Study

Sensor	Platform	Spatial Resolution	Temporal Coverage	Use
MSS	Landsat	60 m	1972–1980	Historical channel
TM	Landsat 5	30 m	1984–2011	Bankline mapping
ETM+	Landsat 7	30 m	1999–present	Change detection
OLI	Landsat 8	30 m	2013–present	DSAS analysis
MSI	Sentinel-2	10-20 m	2015-present	ML classification

To address the above challenges, machine learning–based classification techniques have become more popular in recent years (Tyralis et al., 2021; Lang et al., 2018). To enhance the accuracy of land–water classification, various algorithms have been employed, such as Random Forest and Support Vector Machine that combine spectral bands, derived indices and ancillary data (Tyralis et al., 2021; Pal, 2011). These classified outputs can then be used as reliable input to derive the riverbank lines, which are analyzed with the Digital Shoreline Analysis System (DSAS) to calculate riverbank change metrics (Brown et al., 2020; Hasan et al., 2025).
Figure 2 shows the classification of major techniques discussed in this study, and the overall methodological linkage between the remote sensing data, the classification using machine learning technique and the change analysis using DSAS technique can be conceptualized as shown in Fig. 1. This integral approach is the methodological basis for current assessment of river morphology which will be discussed in subsequent sections (Chin, 2005; Munasinghe et al., 2021).

Digital Shoreline Analysis System (DSAS)

The U.S. Geological Survey (USGS) has created the Digital Shoreline Analysis System (DSAS) as a geospatial tool for quantifying linear shoreline and riverbank changes in position over time, which is widely used (Thieler et al., 2009; Hasan et al., 2025). Initially developed for application to coastal environments, in recent years DSAS has been widely modified to account for riverbank migration and channel dynamics in fluvial systems, because of its flexibility and its implementation in a geographic information system (Himmelstoss et al., 2018; Brown et al., 2020). It has been widely used in river morphology studies due to its compatibility with commonly used GIS platforms and its ability to produce statistically robust change metrics (Thieler et al., 2009; Hasan et al., 2025).

The basic concept of DSAS is to cast a series of regularly-spaced transects perpendicular to the river bankline and parallel to a baseline that is oriented parallel to the general bank direction (Thieler et al., 2009). These transects are intersected by multi-temporal riverbank positions derived from satellite imagery, allowing the calculation of erosion and accretion rates in a spatially explicit manner for a reach of a stream (Himmelstoss et al., 2018; Brown et al., 2020). This transect-based method enables one to systematically compare bankline positions over time and to conduct detailed spatial analysis of fluvial morphological variability (Hasan et al., 2025).

The riverbank change quantified by several statistical metrics is most commonly reported in the literature, among which Net Shoreline Movement (NSM), End Point Rate (EPR), and Linear Regression Rate (LRR) are the most widely used ones (Thieler et al., 2009; Himmelstoss et al., 2018; Hasan et al., 2025). NSM is the cumulative horizontal movement of the riverbank over the entire time period of observation, whereas EPR is based on the difference between the earliest and the latest dates of observation and reflects the average annual rate of change (Brown et al., 2020). LRR is calculated using all bankline positions available and linear regression, and it is more robust than the others as it encompasses multiple time steps and reduces short-term variability effects (Hasan et al., 2025). The general statistical parameters used in the riverbank change analysis based on DSAS are listed in Table II (Thieler et al., 2009; Himmelstoss et al., 2018; Hasan et al., 2025). Although effective, the precision in the DSAS-based analysis is highly dependent on the accuracy of extraction of the riverbank from satellite imagery (Himmelstoss et al., 2018; Brown et al., 2020). Mixed pixels, seasonal water-level fluctuations, riparian vegetation cover, and water conditions with sediment can lead to errors in bankline delineation that can propagate to outputs of DSAS and have a significant impact on the estimation of erosion and accretion rates (Brown et al., 2020; Miller et al., 2024). In order to do so, several studies have highlighted the need for upgrading and using more reliable bankline extraction methods before implementing change analysis based on DSAS (Himmelstoss et al., 2018; Hasan et al., 2025).

Table 2. DSAS metrics used for riverbank change analysis

Metric	Description	Unit	Interpretation
NSM	Net shoreline movement	m	Total bank shift
EPR	End point rate	m/year	Annual erosion/accretion
LRR	Linear regression rate	m/year	Long-term trend

These limitations have been addressed in recent literature by incorporating DSAS with more sophisticated classification methods (Tyralis et al., 2021; Lang et al., 2018). The use of machine learning–based land–water classification techniques has been demonstrated to improve the consistency and reliability of banklines extracted, leading to better estimates of erosion and accretion for DSAS (Brown et al., 2020; Miller et al., 2024). Figure 3 shows a typical DSAS output that displays the riverbank change analysis and erosion – accretion pattern associated with a transect as reported in the literature (Thieler et al., 2009; Himmelstoss et al., 2018).

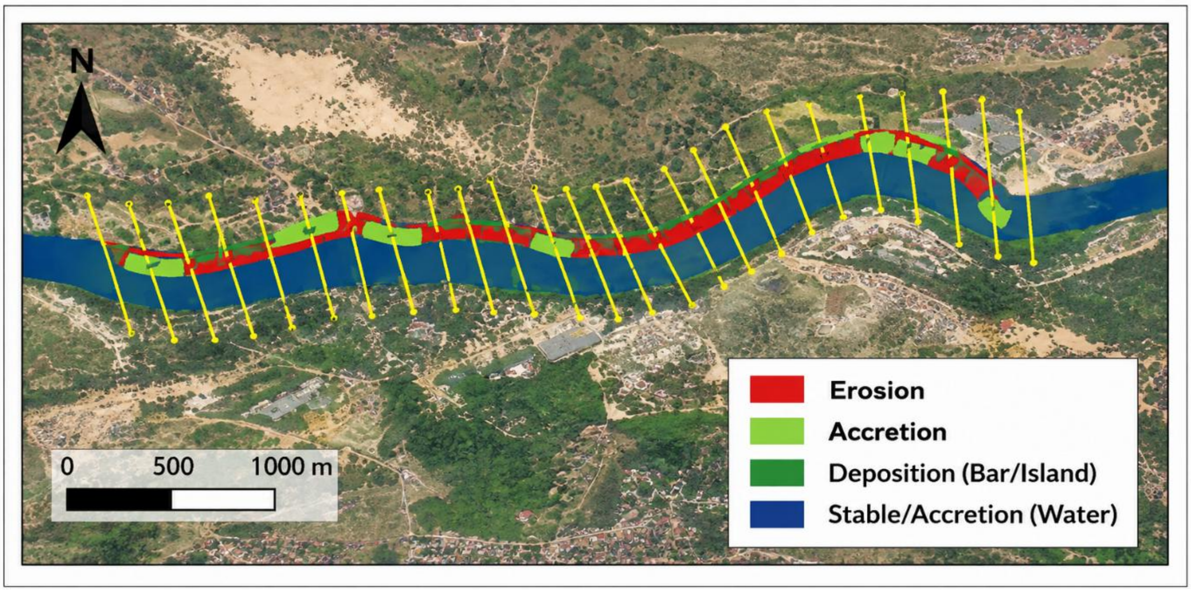

Fig. 3. Representative DSAS output illustrating riverbank change metrics (Thieler et al., 2009; Himmelstoss et al., 2018).

In general, DSAS is an effective and versatile tool for assessing riverbank changes, especially when used in conjunction with sound pre-processing and classification methods. The combination of its machine learning approach is a key methodology in modern river morphology research and a powerful basis for long-term monitoring and river sustainable management.

Machine learning techniques for river morphology analysis

Algorithms based on machine learning (ML) have proven to be effective for identifying geomorphic features from satellite imagery data, especially for the complex riverine environment, where a threshold-based or index-driven approach is often inadequate (Tyralis et al., 2021; Lang et al., 2018). For river morphology studies, ML techniques are mainly used to enhance the land–water classification, identification of sandbars and delineation of riverbanks, which are key inputs to the subsequent change detection and morphological analysis performed by DSAS (Brown et al., 2020; Miller et al., 2024). Machine learning techniques are also effective in dealing with high dimensional datasets, nonlinear class boundaries, and mixed spectral responses often found in fluvial environments, unlike the traditional classification techniques (Tyralis et al., 2021; Pal, 2011). The ML-based classifiers combine water related spectral bands, indices of water, vegetation and exposed sediment surfaces with texture features, which improves the discrimination of water, vegetation and exposed sediment surfaces

(Lang et al., 2018; Brown et al., 2020). Consequently, these methods have come in vogue for using them in river morphology studies to ensure a more consistent and accurate extraction of riverbanks in multi-temporal satellite time series (Miller et al., 2024; Munasinghe et al., 2021). In Table III (Tyralis et al., 2021; Brown et al., 2020; Pal, 2011; Konecny, 1985) are listed commonly used inputs for machine learning based riverbank classification.

Table 3. Input features used for machine learning classification

Feature Type	Parameters
Spectral bands	Blue, Green, Red, NIR
Water indices	NDWI, MNDWI
Vegetation index	NDVI
Texture	Mean, Variance
DSAS inputs	NSM, EPR, LRR

Random Forest (RF)

Random Forest (RF) is an ensemble learning based Supervised Classifier that creates multiple decision trees based on a random selection of input features and training data, and the final output classification is voted on by the individual trees (Tyralis et al., 2021; Pal, 2011). This ensemble approach greatly decreases overfitting and improves the generalization ability. The attributes of RF make it an attractive method for remote sensing–based river morphology studies, as it is robust, efficient in computation and has the capability to estimate the importance of features (Lang et al., 2018; Brown et al., 2020). Random Forest has shown good results for land–water and floodplain classification, especially in morphologically heterogeneous and highly seasonally variable environments (Brown et al., 2020; Miller et al., 2024) when analyzing river morphologies. It is noise-tolerant and not very sensitive to the tuning of parameters, which is suitable for large area and multiple time-scale analyses (Tyralis et al., 2021). There is also some evidence that RF achieves better classification accuracy than traditional classifiers, particularly when additional spectral indices and ancillary variables are included as features in the input (Pal, 2011; Konecny, 1985).

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a margin-based supervised learning algorithm that finds an optimum hyperplane in the higher dimensional feature space for class separation (Lang et al., 2018). Due to its ability to learn nonlinear relationships between input features and target classes through the use of kernel functions, SVM has been shown to be effective in complex patterns for classification problems such as land-cover classification in remote sensing imagery (Tyralis et al., 2021; Pal, 2011).

SVM has been widely adopted for river morphology studies for correctly discriminating land and water, particularly in situatons where training samples are limited (Lang et al., 2018; Miller et al., 2024). It has been established that this has a good theoretical basis and high classification accuracy under a variety of fluvial conditions (Pal, 2011). But, the performance of SVM is kernel and parameter dependent, and the optimization time may increase when dealing with large datasets as mentioned in several studies (Tyralis et al., 2021; Konecny, 1985).

Integration of Machine Learning with DSAS

In recent years, more and more literature has been published regarding the application of machine learning–based classification together with DSAS to improve riverbank change analysis (Brown et al., 2020; Miller et al., 2024). Within this integrated approach, the derived land–water maps and extracted riverbank position from multi-temporal satellite images are used as reliable inputs to compute erosion and accretion metrics like Net Shoreline Movement (NSM), End Point Rate (EPR), and Linear Regression Rate (LRR) (Thieler et al., 2009; Himmelstoss et al., 2018; Hasan et al., 2025).

Figure 4 shows a typical example of classification of land–water using RF and SVM techniques. ML-derived banklines have been found to complement DSAS to enhance spatial accuracy and reduce the uncertainty from mixed pixels and seasonal changes in river environments (Brown et al., 2020; Miller et al., 2024). This integrated approach of DSAS and machine learning has been established as a promising approach in the monitoring and long-term mapping of river morphologies (Munasinghe et al., 2021).

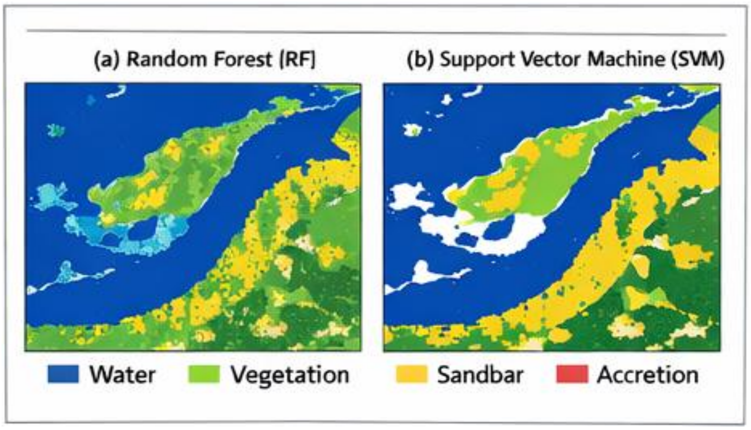

Fig. 4. Illustration of land–water classification using Random Forest and Support Vector Machine (based on Tyralis et al., 2021; Lang et al., 2018; Pal, 2011).

Results and discussion

This section presents a review and synthesis of the results published in the literature of river morphological change analysis using DSAS and machine learning methods, and highlights their critical discussions. The conference paper is a review paper to focus on the methodological performance, comparative findings, and noticeable research trends observed (Chin, 2005; Munasinghe et al., 2021).

Performance of DSAS-Based Change Analysis

Literature review studies consistently show that the Digital Shoreline Analysis System (DSAS) is an effective tool for quantifying patterns and rates of riverbank erosion and accretion on multi-temporal scales (Thieler et al., 2009; Himmelstoss et al., 2018; Hasan et al., 2025). Various indices have been used to measure the short-term and long-term morphological changes within fluvial systems, including Net Shoreline Movement (NSM), End Point Rate (EPR), and Linear Regression Rate (LRR) (Himmelstoss et al., 2018; Brown et al., 2020). From amongst these measures, LRR is often the preferred in long-term trend analysis because it can include several temporal observations, and therefore lessen the impact of unusual or short-term bankline positions (Thieler et al., 2009; Hasan et al., 2025).

But some studies have reported that the change rates derived from DSAS are very sensitive to accuracy of the input banklines (Himmelstoss et al., 2018; Brown et al., 2020). Uncertainties in delineating the bankline can result in over- or under-estimation of erosion and accretion rates in river systems that have braided channels, dense riparian vegetation and high sediment loads (Brown et al., 2020; Miller et al., 2024). This is a known limitation of the DSAS approach to river morphology assessments and highlights the importance of developing better methods for extracting river banks (Hasan et al., 2025). Erosion-accretion patterns similar to the one obtained from DSAS have been reported for major rivers of India, including the Ganga and the Brahmaputra (Parra, 2022).

Impact of Machine Learning on Bankline Extraction

Today, the challenges of machine learning in bankline extraction are discussed. The effect of machine learning on bankline extraction is discussed today. Random Forest (RF) and Support Vector Machine (SVM) are two of the machine learning techniques that have been reported to significantly enhance the accuracy of land–water classification in complex riverine environments (Tyralis et al., 2021; Lang et al., 2018; Pal, 2011). ML classifiers have been shown to have superior performance in mixed pixels, shadow problems and seasonal changes in water extent compared to index-based methods like NDWI and MNDWI (Brown et al., 2020; Miller et al., 2024). Random Forest is often claimed to deliver stable and reliable classification performance across a variety of datasets, because of its ensemble structure and immunity to overfitting (Tyralis et al., 2021; Brown et al., 2020). However, in situations where the training samples are well-defined Support Vector Machine can sometimes yield slightly better classification accuracy, but with higher sensitivity to the kernel choice and parameter tuning (Lang et al., 2018; Pal, 2011). Table IV (Tyralis et al., 2021; Lang et al., 2018; Miller et al., 2024; Pal, 2011) compares the performance of Random Forest with that of Support Vector Machine.

This table is representative comparison of the Random Forest and Support Vector Machine based land–water classification techniques is shown in Figure 4, which shows that both techniques perform well for complex fluvial environments in accurately representing the geometry of the riverbank (Tyralis et al., 2021; Lang et al., 2018; Pal, 2011). There have been reports of direct improvement in the reliability of subsequent change metrics derived from the DSAS model as a result of improved accuracy in the banklines derived from machine learning (Brown et al., 2020; Miller et al., 2024). The Random Forest and Support Vector Machine have also been found to be effective in land–water classification in complex fluvial environment recently in Indian river systems (Du et al., 2012; Huang, 2018).

Table 4. Comparative performance of Random Forest and SVM

Parameter	Random Forest	Support Vector Machine
Accuracy	High	Very High
Training samples	Large	Small
Noise handling	Excellent	Good
Computation	Moderate	High
Suitability	FloodPlains	Turbid channels

Integrated DSAS–Machine Learning Framework

Recent research has highlighted the benefits of using machine learning–based classification combined with the Digital Shoreline Analysis System (DSAS) to analyse river morphology (Brown et al., 2020) and (Miller et al., 2024). This integrated approach involves using machine learning algorithms to derive riverbank lines from multiple temporal satellite images, and then applying DSAS to assess erosion and accretion patterns (Thieler et al., 2009; Himmelstoss et al., 2018; Hasan et al., 2025). This holistic method has been shown to effectively minimize the uncertainty that most traditional change detection studies use manual digitization and threshold-based classification techniques (Brown et al., 2020), (Munasinghe et al., 2021). The integrated approaches of DSAS–machine learning are most successful in large river systems and data-poor areas where field-based observations are scarce or nonexistent (Chin, 2005; Miller et al., 2024). As shown in Figure 5, there is a significant rise in the use of integrated approaches over the last 10 years for published studies using DSAS and machine learning methods (Munasinghe et al., 2021). So, with the increasing awareness of the value of machine learning as a supporting technology to complement traditional geomorphic analysis approaches and increase the confidence of riverbank change assessments, this trend is expected to continue. These observations are in agreement with the reported morphological changes of large alluvial rivers in India (Giano, 2024; Courtney, 1980).

Research Gaps and Challenges

Although significant methodological progress, some of the issues that can be found in the use of DSAS and machine learning for river morphology analysis remain (Chin, 2005; Munasinghe et al., 2021). Two-dimensional planform changes are the most common focus of the reviewed studies, whereas three-dimensional channel processes, sediment transport dynamics, and hydrodynamic interactions are generally weak components (Himmelstoss et al., 2018; Brown et al., 2020). Moreover, most applications are based on medium-resolution satellite imagery that might not be sufficient to capture the fine-scale morphological features and localized erosion–accretion processes (Tucker, 1979; Martimort et al., 2007).

Additionally, the absence of standardized methodologies for selecting the training data, optimizing the features, and measuring the accuracy of machine learning–based river studies introduce challenges for comparing various studies and reproducing the results (Tyralis et al., 2021; Pal, 2011; Konecny, 1985). The literature reviewed indicates that there are advantages in using the combined application of DSAS and machine learning techniques for river morphological change analysis, especially when compared with the use of any individual technique alone (Brown et al., 2020; Miller et al., 2024). An important avenue of future research is to overcome these current challenges by standardizing methodologies and integrating more detailed and ancillary datasets (Munasinghe et al., 2021). Some of the earlier studies have also identified the constraints in using remote sensing techniques for Indian rivers, such as data resolution, and the seasonal changes (Lu et al., 2015).

Conclusion

The paper offered a wide overview of remote sensing-based methods for the study of natural stream morphology changes, especially the application of the Digital Shoreline Analysis System (DSAS) and machine learning methods. The review emphasizes the role of satellite remote sensing as an indispensable tool for monitoring river dynamics because of its synoptic coverage, long time-series and its cost-effectiveness compared to the traditional in situ approach. A synthesis of reviewed studies shows that DSAS offers a well-established and consistent method for calculating commonly used statistical measures of riverbank erosion and accretion, including Net Shoreline Movement (NSM), End Point Rate (EPR) and Linear Regression Rate (LRR). LRR is one of these measurements which has proved especially effective in the recognition of long-term morphological trends if multi-temporal bankline information is available. The reliability of outputs from DSAS, however, is greatly affected by the accuracy of the riverbank extraction, which is a major source of uncertainty in fluvial environments. The review also shows that machine learning methods, such as Random Forest and Support Vector Machine, can greatly improve land–water classification and the delineation of riverbanks from multi-spectral satellite data. Random Forest has been generally preferred for large-area and heterogeneous dataset, as it is robust and is very efficient to compute, while Support Vector Machine can be used for limited but well-defined training samples to attain high classification accuracy. These machine learning methods integrated into DSAS have been proven to enhance the uniformity and reliability of riverbank change analysis, and thus boost the overall riverbank morphological dynamics assessment. However, there are a number of problems in current research. Most studies are mostly concerned with two-dimensional platform change, with three-dimensional channel processes, sediment transport processes and hydrodynamic interactions underrepresented. Furthermore, differences in the resolution of the data, selection of training samples, and accuracy assessment methods make it difficult to compare the results from different studies. Standardised, transferable DSAS–machine learning frameworks, applicable in a variety of riverine settings, should be developed for future research. The use of higher resolution satellite data, time-series analysis and ancillary data, e.g. hydrological and sediment data, would further improve the morphological assessments. Furthermore, the application of advanced machine learning and automation technologies is promising for real-time monitoring and early-warning systems of the rivers. In general, the integration of DSAS and machine learning represents a promising approach for the more reliable and sustainable monitoring and management of river morphology.

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