Coastal Change and Shoreline Prediction using Deep Learning

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Abstract

Coastlines undergo continuous transformation due to natural forces and anthropogenic influences, resulting in considerable variability in shoreline positions across time. Tracking and forecasting these shifts is critical for sustainable coastal governance, hazard reduction, and safeguarding ecosystems. This research introduces a hybrid methodology for shoreline forecasting that leverages multi-date satellite data from Landsat 5, 7, and 8, acquired via Google Earth Engine, to examine extended shoreline dynamics across Indian coastal zones. Land–water delineation is accomplished through the Modified Normalized Difference Water Index (MNDWI) alongside K- Means clustering, subsequently refined using morphological processing to eliminate noise and improve accuracy. Shoreline contours are then derived from the processed imagery and subjected to temporal examination. A deep learning architecture incorporating ConvLSTM with an integrated attention mechanism is utilized to simultaneously capture spatial and temporal characteristics, enabling precise projection of future shoreline locations. Furthermore, linear regression is employed to assess overarching trends and validate the prediction reliability. The framework additionally produces change maps identifying zones of coastal erosion and sediment deposition. Experimental outcomes confirm that the developed system accurately predicts shoreline variability, delivers stable results, and serves as a dependable tool for coastal surveillance and informed decision-making in at-risk coastal communities.

Keywords: *Coastal Change Detection, Shoreline Prediction, Remote Sensing, Deep Learning, ConvLSTM, MNDWI.*

I. INTRODUCTION

Coastlines rank among the most actively changing and ecologically sensitive zones on the planet, perpetually shaped by physical forces such as tidal action, wave energy, and sediment dynamics, as well as human-driven pressures like urban expansion and infrastructural growth [10]. These combined influences drive substantial shifts in shoreline positions, giving rise to concerns such as land erosion, inundation risks, and deterioration of coastal habitats [5], [12]. Consequently, the systematic observation and projection of shoreline behavior has become indispensable for responsible coastal governance, risk mitigation, and ecological preservation [10].

Conventional approaches to shoreline identification, including manual boundary tracing and fixed-threshold image classification, tend to be labor-intensive and often yield inconsistent outcomes when extended to broad spatial scales or lengthy time spans [5]. The growing availability of orbital imagery has positioned remote sensing as a powerful means of examining coastal transformations [5], [11]. Notably, datasets spanning multiple acquisition dates allow for uninterrupted tracking of shoreline behavior across prolonged intervals [3], [4]. Nevertheless, a considerable number of prevailing techniques are constrained in their capacity to reliably replicate long-term shoreline evolution, primarily because they emphasize spatial characterization while neglecting the role of temporal continuity [12].

In the present investigation, multi-date imagery sourced from the Landsat 5, 7, and 8 satellite platforms is accessed through Google Earth Engine to examine shoreline transformations along Indian coastal zones [3], [4]. These archives offer extensive historical depth, rendering them well- suited for documenting shoreline shifts over successive years [4]. To strengthen the delineation of water bodies, the Modified Normalized Difference Water Index (MNDWI) is employed [1], supplemented by K-Means clustering to achieve reliable water–land boundary separation [2]. Although these methods enhance classification precision, they are inherently incapable of independently forecasting future shoreline conditions [5].

To overcome these shortcomings, the current work presents a deep learning-driven framework for shoreline forecasting, achieved by coupling Convolutional Long Short-Term Memory (ConvLSTM) [6] with a Convolutional Block Attention Module (CBAM) [7]. This integrated architecture equips the model to simultaneously encode spatial structures and temporal evolution within shoreline transition data [6], [7]. Additionally, linear regression is incorporated to examine overarching trends and quantify forecast reliability [8], [9]. The resulting system offers a more holistic solution than prior methods by unifying segmentation, trend analysis, and predictive modeling into a single coherent pipeline [12].

The central contribution of this work lies in constructing a hybrid framework that bridges satellite-based remote sensing with advanced deep learning strategies [5], [12] to deliver precise shoreline projections. The system further produces spatial change maps that delineate zones of erosion and sediment accretion, yielding actionable knowledge for coastal infrastructure planning and ongoing environmental assessment [10].

II. RELATED WORK

Satellite-based observation has long served as a practical foundation for studying how coastlines behave over time, largely because it supports wide- area coverage and multi-decade data continuity [5], [11]. Among the various satellite platforms, Landsat missions have proven especially useful for examining shoreline trends, given their consistent revisit cycles and spectral richness [4]. Spectral water indices — particularly MNDWI [1] — have gained traction for distinguishing open water from land surfaces. That said, their reliability can degrade under challenging atmospheric conditions, including cloud contamination and seasonal spectral shifts, which introduce uncertainty into segmentation results [5].

Extracting accurate shoreline boundaries fundamentally depends on how well water and land can be separated in imagery. Simpler approaches such as edge-based filters and fixed thresholds offer ease of use but frequently break down in heterogeneous or ecologically complex coastal settings [5]. Clustering-based methods, notably K- Means [2], bring improvement by organizing pixels according to spectral likeness rather than fixed cutoffs, yielding cleaner separations. However, they are still prone to generating fragmented or noisy outputs that demand further refinement before reliable shoreline contours can be extracted [5].

The advent of deep learning has meaningfully advanced both the detection and forecasting of shoreline positions [12]. Architectures like CNNs and ConvLSTM [6] are particularly well-suited to this domain, as they can simultaneously process spatial structure and temporal change within sequential satellite imagery. Incorporating attention mechanisms such as CBAM [7] allows models to prioritize the most informative spatial and spectral channels, sharpening predictive accuracy. A practical drawback, however, is that these models are data-hungry and computationally demanding, which can hinder their adoption at scale [12].

Taken together, the literature reveals persistent gaps. Remote sensing methods remain vulnerable to environmental noise [5], classical techniques struggle with temporal modeling, and deep learning frameworks typically address either segmentation or prediction — rarely both in a unified system [12]. Noisy segmentation outputs further complicate shoreline extraction in intricate coastal environments [5].

These gaps point toward the need for an integrated pipeline capable of handling water–land delineation, temporal pattern learning, and future position forecasting within a single coherent system one that draws on the complementary strengths of remote sensing and deep learning while compensating for their respective weaknesses [5], [12].

To address this, the present study combines multi-temporal Landsat imagery accessed through Google Earth Engine [3], [4] with MNDWI-based segmentation [1] and K-Means clustering [2] for boundary delineation.

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A ConvLSTM and CBAM-based deep learning model [6], [7] then drives shoreline forecasting, while spatially explicit change maps identify regions of active erosion and accretion — forming a practical and end-to-end framework for coastal monitoring [12].

III. PROPOSED METHOD

The goal of the developed system is to identify and forecast shoreline shifts through a hybrid pipeline that brings together satellite remote sensing, classical machine learning, and modern deep learning [5], [12]. Multi-date imagery drawn from the Landsat 5, 7, and 8 platforms — retrieved via Google Earth Engine — forms the observational backbone of the framework, with attention directed toward Indian coastal zones [3], [4].

Architecturally, the system operates on a client– server model. The frontend layer presents an accessible interface through which users interact with the system, while the backend handles the heavier computational workload — encompassing image ingestion, spectral processing, segmentation, and model inference.

Raw input arrives as GeoTIFF files carrying multiple spectral channels, including Green, Near- Infrared (NIR), and Shortwave Infrared (SWIR). The MNDWI [1] is computed across these bands to accentuate water surfaces and attenuate land- associated reflectance. Pixel-level classification is then carried out using K-Means clustering [2], which partitions the image into distinct water and land zones based on spectral proximity. Morphological post-processing — including opening and closing operations — is subsequently applied to smooth boundaries and eliminate spurious noise from the segmented output.

Once segmentation is complete, the water–land boundary is interpreted as the shoreline contour for each time step. The temporal evolution of these contours is then examined by quantifying changes in water and land coverage across the image sequence. Linear regression is fitted to these measurements to characterize long-term directional trends, with the R^2 statistic serving as a gauge of model fit and forecasting reliability [8], [9].

Shoreline forecasting itself is handled by a deep learning architecture that pairs ConvLSTM [6] with CBAM [7]. ConvLSTM is well-suited to this task because it jointly encodes spatial structure and sequential variation within the input data, while CBAM refines the learned representations by selectively weighting the most discriminative spatial locations and spectral channels. Together, they enable the system to generate temporally coherent and spatially precise shoreline projections. The system additionally produces change detection maps that juxtapose historical observations with model predictions, visually delineating zones of active erosion and sediment accretion.

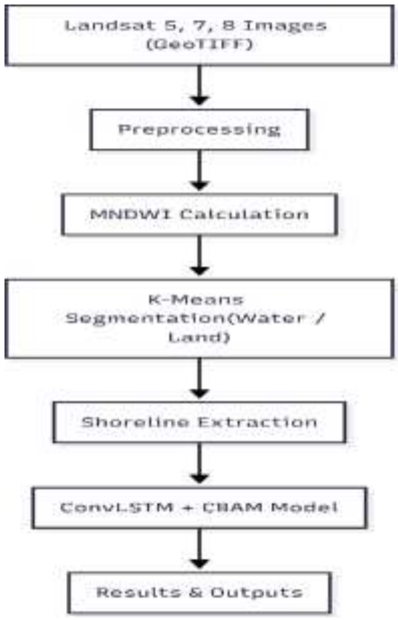


Fig. 1: Proposed System Architecture

The central strength of this framework lies in its end-to-end design, which unifies detection, temporal reasoning, and prediction within a single system rather than treating them as disconnected tasks. This cohesion translates into higher accuracy and more actionable outputs for coastal decision- making. The pipeline progresses through well- defined stages including data acquisition, spectral segmentation, shoreline delineation, trend analysis, and predictive modeling, each building upon the last to ensure consistency throughout.

A. DATA COLLECTION

Satellite imagery spanning multiple time periods is acquired from the Landsat 5, 7, and 8 platforms through Google Earth Engine [3], [4]. Indian coastal zones serve as the geographical focus of this work, where the extensive temporal depth of these archives supports meaningful long-term shoreline investigation.

B. PREPROCESSING

Input images in GeoTIFF format carry several spectral bands, of which Green, NIR, and SWIR are selected for downstream processing. Before analysis begins, all images undergo normalization and spatial resizing to establish uniform input dimensions. Residual noise is suppressed and band formatting is standardized to ensure the pipeline operates consistently across acquisitions from different sensors and dates..

C. WATER-LAND SEGMENTATION

Delineating water from land begins with the application of MNDWI [1], which amplifies the spectral signature of water bodies while diminishing the response of vegetated and built-up surfaces. The resulting index image is then fed into K-Means clustering [2], which assigns each pixel to a water or land class based on its spectral characteristics. Morphological operators such as opening to remove small foreground objects and closing to fill gaps are applied afterward to produce clean and well-defined region boundaries.

D. SHORELINE EXTRACTION AND CHANGE ANALYSIS

The shoreline is defined as the boundary between water (pixel value 255) and land (pixel value 0) regions in the segmented binary mask. This boundary represents the coastline for each time period and serves as the basis for further analysis.To analyze shoreline changes over time, the system calculates variations in water and land areas from the segmented masks. Linear regression is applied to model temporal trends, and the R- squared (R^2) value is used to evaluate prediction confidence [8], [9].

E. DEEP LEARNING MODEL

Shoreline forecasting is performed using a ConvLSTM network [6] augmented with a CBAM attention block [7]. ConvLSTM processes sequences of segmented images, learning how spatial patterns in shoreline position evolve across time steps. CBAM complements this by directing the network's attention toward spatially and spectrally informative regions, improving the quality of extracted features and ultimately sharpening prediction accuracy.

F. PREDICTION AND OUTPUT

The trained model predicts future shoreline conditions using historical data. The system generates shoreline maps, change detection maps, and future prediction outputs. Change maps highlight regions of erosion and accretion by comparing historical and predicted results, providing valuable insights for coastal monitoring and management.

IV. RESULTS AND DISCUSSION

The developed shoreline forecasting framework is assessed through a set of standard segmentation evaluation metrics. Across all measures, the model exhibits consistent capability in learning coastal boundary patterns and generating reliable projections of future shoreline positions.

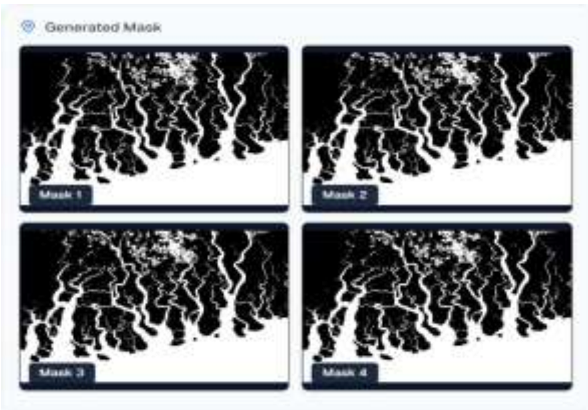
Performance Metrics:

Metric	Value
IoU	0.86
Dice	0.88
Accuracy	0.89

The system performs well across all evaluation criteria. An IoU of 0.86 indicates strong spatial agreement between predicted and reference boundaries. The Dice coefficient of 0.88 reflects high overlap between predicted outputs and ground truth annotations. An overall accuracy of 0.89 establishes the robustness and dependability of the proposed approach.

Shoreline Analysis for Different Coastal Regions:

Sundarbans Coastal Region



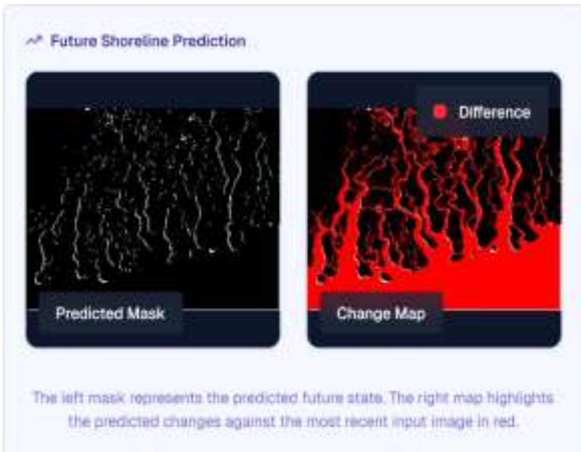


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Fig. 2: Sundarbans Coastal Region – Water–Land Segmentation, Predicted Shoreline, Change Detection Map, and Temporal Trend Analysis

The results for the Sundarbans coastal region highlight dynamic shoreline behavior over time. The segmentation and prediction outputs accurately represent the coastal boundary, while the change map indicates active erosion and accretion zones. The trend analysis shows an overall increase in water area of +4.14 sq km and a corresponding decrease in land area of −4.14 sq km, reflecting noticeable shoreline shifts in this region.

Puri (Odisha) Coastal Region

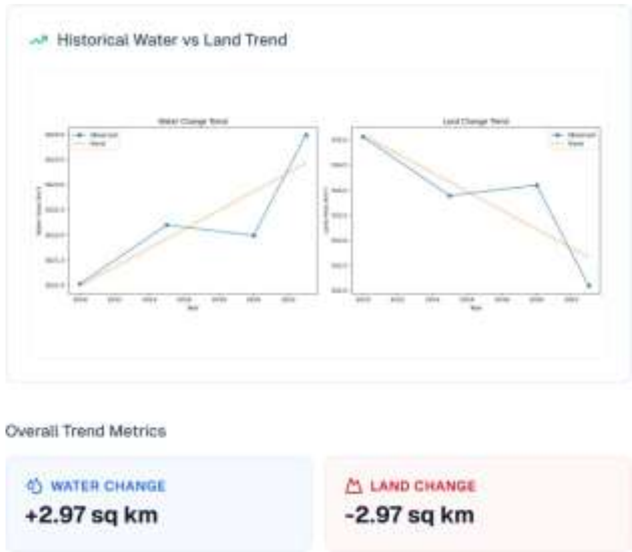


Fig. 3: Puri (Odisha) Coastal Region – Water–Land Segmentation, Predicted Shoreline, Change Detection Map, and Temporal Trend Analysis

The results for the Puri (Odisha) coastal region show noticeable shoreline changes over time. The segmentation and prediction outputs represent the coastal boundary, while the change map indicates erosion and accretion. The trend analysis shows an increase in water area of +2.97 sq km and a decrease in land area of −2.97 sq km, reflecting moderate shoreline shifts.

Gujarat coastal region

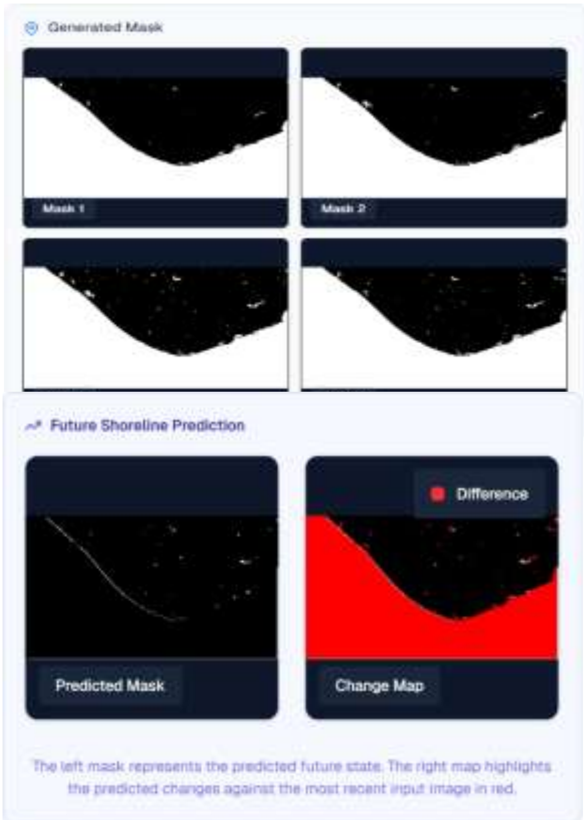
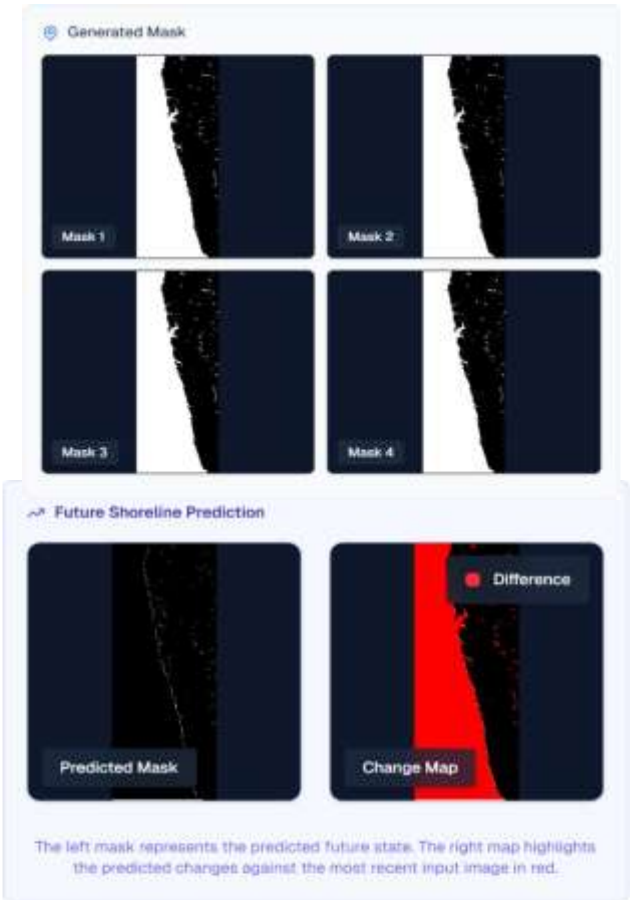


Fig. 4: Gujarat Coastal Region – Water–Land Segmentation, Predicted Shoreline, Change Detection Map, and Temporal Trend Analysis

The Gujarat coastal region exhibits moderate shoreline variations over the observed period. The model effectively captures the coastal boundary, while the change map highlights regions of erosion and accretion. The trend analysis indicates an increase in water area of +2.11 sq km and a corresponding decrease in land area of −2.11 sq km, reflecting gradual shoreline changes.

Mumbai coastal region



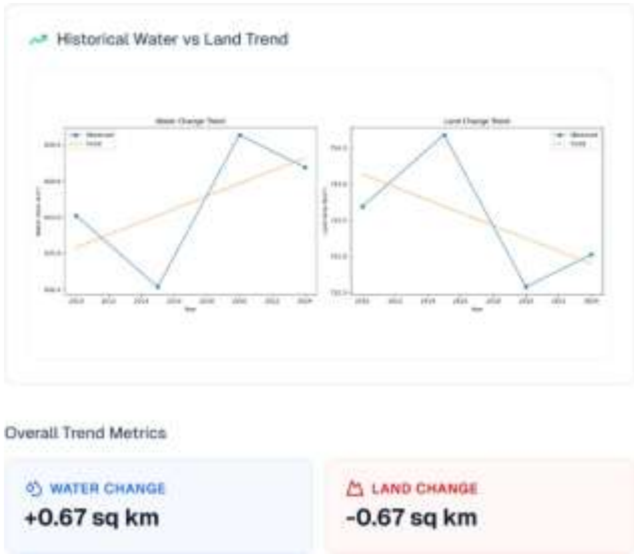


Fig. 5: Mumbai Coastal Region – Water–Land Segmentation, Predicted Shoreline, Change Detection Map, and Temporal Trend Analysis

The Mumbai coastal region exhibits irregular shoreline variations over the observed period. The segmentation and prediction outputs capture the coastal boundary effectively. Unlike other regions, the trend graph shows noticeable fluctuations, with values increasing and decreasing over time. This variation may be attributed to factors such as human activities like land reclamation, urban development, and other environmental influences. The trend analysis indicates a slight increase in water area of +0.67 sq km and a decrease in land area of −0.67 sq km, reflecting minor but inconsistent shoreline changes. These observations suggest that shoreline behavior in this region is less stable and influenced by both natural and anthropogenic factors.

V. CONCLUSION

This study presents an effective approach for shoreline prediction by combining remote sensing techniques with deep learning methods. Multi- temporal satellite imagery was used to analyze shoreline variations, while segmentation and temporal analysis helped in understanding coastal changes. The proposed model successfully captures both spatial and temporal patterns, enabling accurate prediction of future shoreline positions. The results demonstrate strong performance and consistent predictions across different coastal regions, indicating that the approach is reliable for monitoring shoreline dynamics. Overall, the system provides a practical framework for coastal analysis and can support decision-making related to coastal management.

Future research can be directed toward enhancing the model's performance by utilizing higher- resolution satellite imagery and adopting more advanced deep learning architectures.

Incorporating real-time shoreline monitoring capabilities would further improve the system's practical usability. Additionally, integrating the proposed model with GIS platforms can strengthen visualization and spatial analysis. Evaluating the approach across a wider range of coastal regions with diverse geographical characteristics would help assess its robustness and improve its applicability in real-world scenarios.

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