Review Article

Shoreline Prediction Models: A Review of the Evolution from Empirical to AI Machine Learning Approaches

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The dynamic nature of coastal zones is characterized by continuous change in shoreline position due to natural and anthropogenic processes. These changes present challenges for coastal management and conservation efforts. Traditionally, shoreline change analysis relied mainly on empirical observations and numerical models which was limited in dealing with complex, multi-dimensional interactions along our coasts. Recent decades have witnessed an integration of machine learning (ML) techniques into coastal studies to predict shoreline changes. This review aims to provide a general overview of the development of shoreline modeling and the evolution of ML applications in the field. The review synthesizes findings from 18 research papers, tracing the development of shoreline prediction methodologies from early empirical models to modern ML-based frameworks. The analysis highlights a shift from deterministic approaches to data-driven models that leverage multiple ML techniques for improved predictions. By comparing different modeling approaches over time, this study evaluates the effectiveness of ML in capturing shoreline dynamics and enhancing predictive capabilities. The review shows that new methods can significantly enhance shoreline modeling, offering improved predictive power and new insights into coastal dynamics. The findings suggest future research directions in the context of climate change and increasing human interventions.

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1. Introduction

Understanding shoreline changes and the natural activities along the coast is very important for taking care of our coastal areas. These areas are affected by many natural factors like waves, tides, rising sea levels, and the amount of sediment, as well as human activities such as coastal structures, dredging, and beach nourishment. These factors make coastal areas one of the most dynamic and special places on Earth[1]. These influences can strongly change the nature of the shoreline, leading to erosion, accretion, and changes along our coasts[2]. The importance of studying these changes is due to the vulnerability of shorelines to the climate change, including sea-level rise and increased storm intensity, which needs effective coastal management strategies to protect coastal communities, and ecosystems[3]. Moreover, the economic and social implications of shoreline change are crucial, considering that coastal areas have important infrastructures and a significant portion of the world's population[4].

Many anthropogenic activities may lead to sediment erosion by disrupting sediment supply or changing the natural coastal processes[5]. Similarly, sea-level rise, caused by climate change, has a significant threat to low-lying areas like deltas, which need management strategies to mitigate these impacts[6]. In recent decades, the study of coastal processes and shoreline change has been improved a lot by integrating computational modeling, satellite imagery analysis and machine learning (ML) approaches. This development provided tools for analyzing complex and large data sets, improving prediction abilities, and developing better shoreline management steps[7].

Studying coastlines has changed a lot over time. Field measurements along the shoreline was hard work to do, especially for large scale projects and only gave a little bit of information in terms of time because shorelines are dynamic. Then, computers got better, and scientists started using computer models that could guess how the shoreline would change under different conditions. This was a big step because it helped scientists understand more with less fieldwork, as a result, the field shifted towards numerical and statistical models with more systematic ways to predict shoreline behavior and simulate future scenarios. At the same time, these models were limited by the simplifications needed to make complex coastal processes computationally manageable[8][9]. Integrating this with satellite imagery was another big step to study shorelines and coastal areas because it gave a lot more information with easier access. Scientists were able to see how shorelines changed over time along much longer distances. The latest big change was using ML where computers were able to learn from data to make guesses. For studying coastlines, ML was used to look at the data from satellites and computer models and predict how the shoreline might change, dealing with complex data and giving accurate predictions. This is why ML is considered a big help for scientists trying to understand and protect our coasts, especially as the climate changes and coastal management becomes more challenging[10].

The objective of this review is to discuss the development and integration of ML approaches in the predicting shoreline change and coastal processes over time. The selected papers were intended to cover the journey from the traditional methodologies, including physical and numerical modeling, to the application of ML techniques, like neural networks, support vector machines, and DL algorithms as convolutional neural networks. The main goal is to show how these ML techniques have not only enhanced the accuracy and efficiency of predicting shoreline changes but also our understanding of the complex relations between natural and anthropogenic activities affecting coastal zones.

While a significant portion of ML research in this field was focused on the identification and extraction of shorelines from satellite imagery, less focus was directed to predicting shoreline position changes and erosion-accretion processes along the coast. This review addresses the contribution and development of ML in shoreline change and coastal processes prediction and shows the evolution of these approaches. Additionally, the paper is exploring the challenges and limitations, including data availability and models complexity. The paper is trying to provide an overview, to guide potential future research directions in managing and understanding dynamic shorelines.

1.1. Background

ML today is a big part of computer science that helps dealing with big, complex types of data and allowing computers to learn patterns and relationships without being told exactly what to do. It started in the 1950's as artificial intelligence. Instead of being programmed step by step, in ML computers get better at tasks through training. While there is an overlap between ML and traditional statistical methods, the main difference is in their philosophies and objectives. ML tends to be more about prediction and classifying data, rather than understanding the relationships between variables and this is why usually it is a black box.

Over the past few decades ML has witnessed significant capability improvements, driven by developments in computational power, and the availability of large datasets. These improvements have led to the widespread usage of ML techniques across different fields and applications[11][12][13].

Supervised learning is one of the main branches of ML that involves algorithms that learn from labeled training examples to make predictions for other input datasets[14]. In unsupervised learning, the goal is to identify patterns or structures from data without any labels provided with the training data to catch the similarities in the data[15]. Reinforcement Learning is another branch of ML where the algorithm

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optimizes its actions in a dynamic environment to maximize cumulative rewards over time, guided by a predefined reward function that evaluates the desirability of its state-action output[16] (Figure 1).

Linear regression models the relationship between a dependent variable y and one or more independent variables X. When there is just one independent variable, it's called simple linear regression while if there are multiple independent variables, the model is called multiple linear regression model. The model is built by estimating coefficients for the independent variables that minimize the difference between the predicted and actual values of the dependent variable. This is done through a method called ordinary least squares. The simplicity of linear regression makes it an excellent model for forecasting and understanding the linear relationship between variables[17].

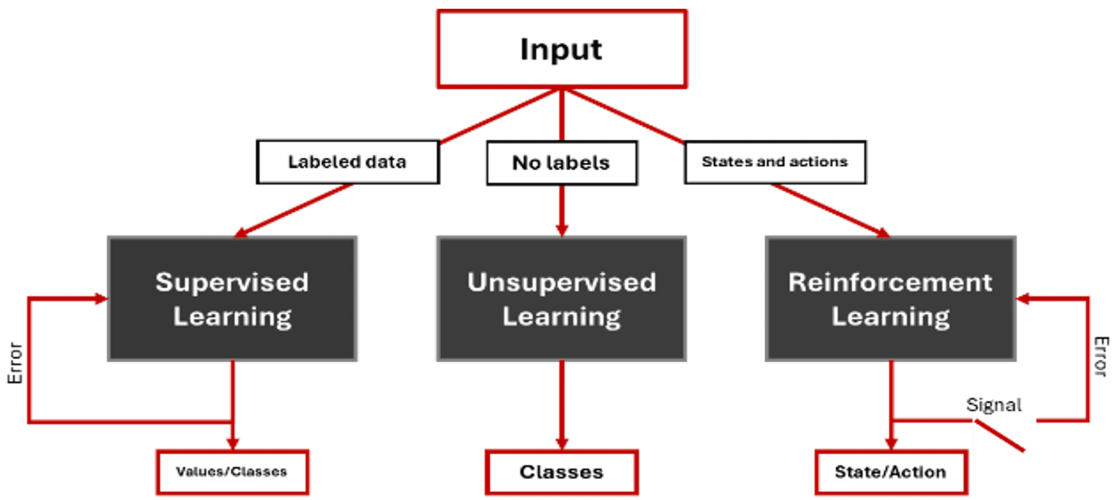

Figure 1. *A visual representation of the main branches of machine learning, categorizing methods based on input data type and learning outcomes. Supervised learning uses labeled data to map inputs to outputs, unsupervised learning identifies patterns in unlabeled data, and reinforcement learning optimizes actions based on rewards and feedback signals.*

Logistic regression on the other hand is usually used to predict binary outcomes by assigning a probability to each observation and how different variables influence the likelihood of a binary event to happen[18]. Another type of regression is gaussian process regression (GPR) is different from traditional regression techniques, as GPR calculate confidence levels or intervals with its predictions[19]. Neural networks are systems with connected layers of information that process the learning process. These layers include an input data layer for variables, an output layer for responses, and one or more hidden

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layers in the middle. The design allows neural networks to learn and to make predictions or decisions based on what they learned. The learning process involves adjusting the network's weights based on the input data inside the neuron (Figure 2).

The network tries to match its output with the correct answer based on the training data then to adjusts its weights based on the difference or error between its output and the correct output. This adjustment process repeats many times, with the weights until the network's error is the lowest[20][21]. To avoid overfitting in this type of model, the data is divided into three sets, training, validation, and testing. The training data is set to learn the relationships between inputs and outputs.

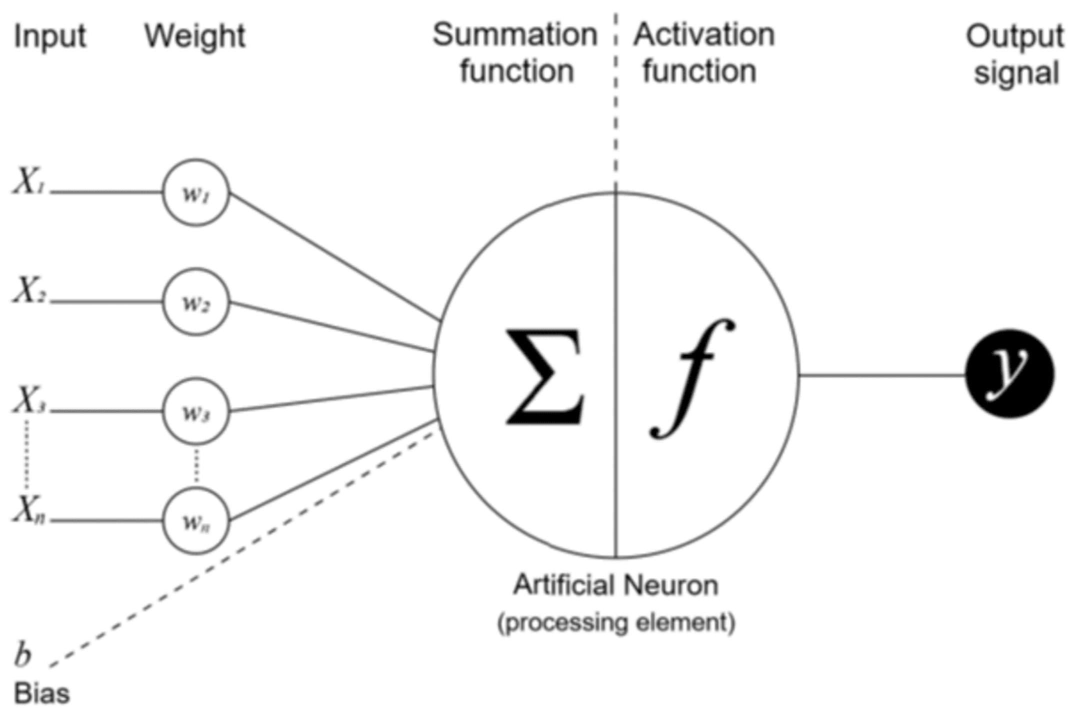

Figure 2. *A schematic representation of an artificial neuron, illustrating how weighted inputs are summed and passed through an activation function to produce an output signal, forming the basis of neural network computations.*

The validation set is used to determine the model that has the lowest error using a dataset different from the one used for training. After validation, the testing set is used further to evaluate the model's performance on another dataset to ensure its generalizability to new, unseen data. This systematic sequence of steps of model validation and testing ensure that neural network models are reliable by

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avoiding overfitting[22]. Deep Learning (DL) is considered a subclass of Artificial Neural Networks (ANNs), using multi-layered computational structure, which includes input, hidden, and output layers. Convolutional Neural Network (CNN) is another subclass of ANN characterized by integrating convolutional layers, pooling layers, and fully connected layers, as shown in figure 3. CNNs are designed to utilize the two-dimensional structure of its input data effectively. With their higher computational cost, CNNs reduce the need for manual feature extraction by identifying essential features automatically, making them more robust and advanced than standard ANNs[23]. Support Vector Machine (SVM) is a classification method that works by finding the hyperplane that best divides a dataset into classes. SVM works well in complex situations with multiple dimensions. It can handle different types of data using different kernel functions with its ability to model complex nonlinear boundaries. Therefore, it is widely used in fields like image and text recognition[24] (figure 4).

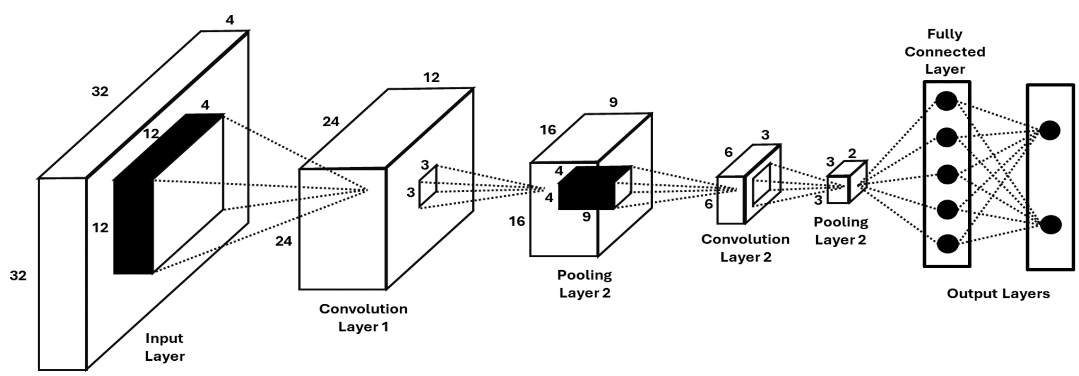

Figure 3. *A detailed representation of a Convolutional Neural Network (CNN) architecture, illustrating the sequential flow of data through multiple layers. The input layer receives an image, which is processed through convolutional layers that extract key features using filters. Pooling layers reduce the spatial dimensions while retaining important information, enhancing computational efficiency. Additional convolutional and pooling layers further refine feature extraction. The final fully connected layer integrates extracted features and maps them to specific output classes, demonstrating how CNNs process visual data for classification and recognition tasks.*

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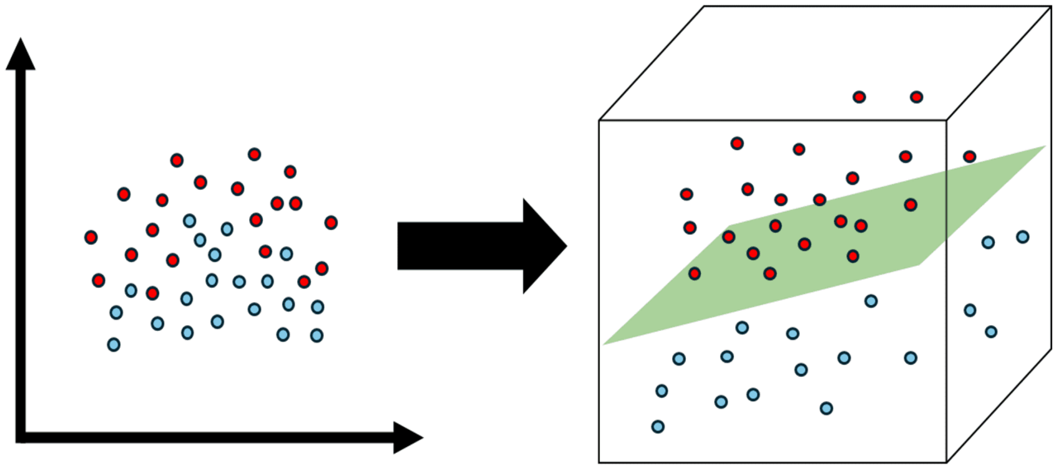

Figure 4. *A conceptual illustration of Support Vector Machine (SVM) modeling, showing how data is transformed into a higher-dimensional space for optimal separation. The left side depicts data points in two dimensions, while the right side illustrates the resulting hyperplane (green) that separates the classes in a multi-dimensional space, demonstrating SVM's classification mechanism.*

Decision Trees are non-parametric models used mainly for classification. A decision tree builds a model in the form of a tree structure, breaking down a dataset into smaller subsets, and at the same time developing an associated decision. The simplicity of decision trees makes it easy to interpret and in explaining the decision-making process. However, they can be prone to overfitting, especially with complex trees[25]. Random forests on the other hand, can solve the overfitting issue in decision trees by averaging multiple deep decision trees, trained on different parts of the same training set, aiming to reduce variance. This model is highly scalable and can handle large datasets and can provide estimates of what variables are important in the classification[26].

K-means Clustering is an unsupervised method for separating data into a set number of distinct clusters. It works basically by randomly selecting initial centroids in the data and then changing these centroids by assigning data points to the nearest cluster then recalculate the centroids. The method is widely used because of its simplicity and efficiency, and it's particularly effective when the structure of the clusters is hyper-spherical. However, K-means can be very sensitive to the initial placement of centroids and may be less accurate with clusters of different sizes and densities[27]. Self-Organizing Maps (SOM's) are a type of ANN that is trained using unsupervised learning to produce a low-dimensional, discretized

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representation of the inputs. SOM's can preserve the topological properties of the inputs, making them useful for visualization and for finding hidden structures in complex data[28].

Principal Component Analysis (PCA) is another unsupervised method that converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. PCA is widely used as a tool in exploratory data analysis and to simplify data and identify directions of levels of variance in high-dimensional datasets[29] (Figure 5).

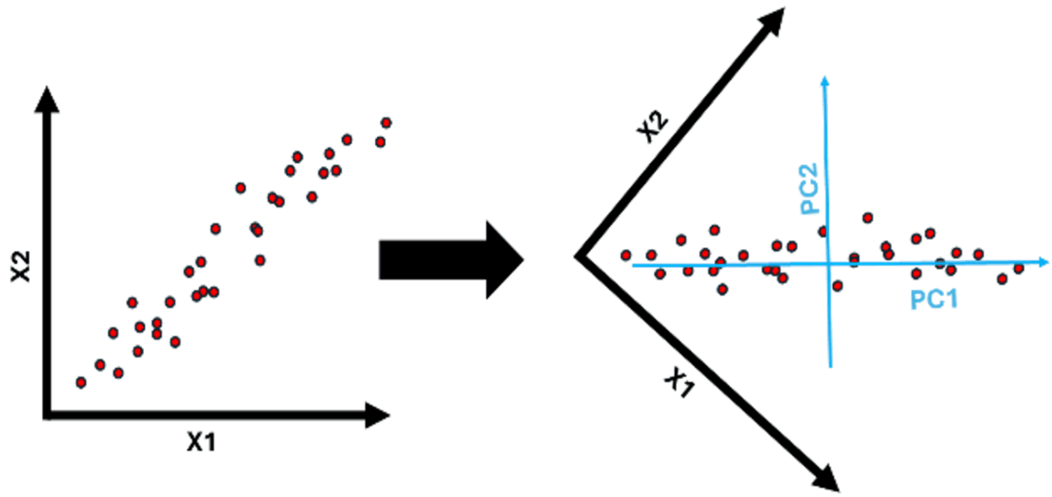

Figure 5. *A representation of Principal Component Analysis for a two-dimensional system, illustrating how data points are transformed from the original coordinate space (X1, X2) into a new axis system defined by principal components (PC1, PC2). The transformation maximizes variance along PC1, enabling dimensionality reduction while preserving key data patterns.*

2. Review Methodology

A systematic five-step process was developed to review the evolution of shoreline prediction methods, with particular emphasis on the integration of machine learning approaches (Figure 6). The initial literature search was conducted across scientific databases, utilizing key search terms including "shoreline prediction," "machine learning," and "coastal modeling." Following preliminary screening through titles and abstracts, papers were evaluated against three primary criteria: publication timeframe, machine learning applications in shoreline prediction, and research impact. A comprehensive temporal scope spanning five decades, from the 1970s to present, was established to capture the methodological evolution in the field. This timeframe was selected to demonstrate the transition from traditional prediction methods to advanced computational approaches. From the identified literature pool, 18 representative papers were selected, documenting the progression from early mathematical models of the late 20th century to sophisticated machine learning applications in recent years. In the final phase, these papers were systematically analyzed and synthesized, with focus placed on both chronological development and technical comparison, thereby establishing a comprehensive understanding of the field's evolution from empirical to machine learning-based prediction techniques.

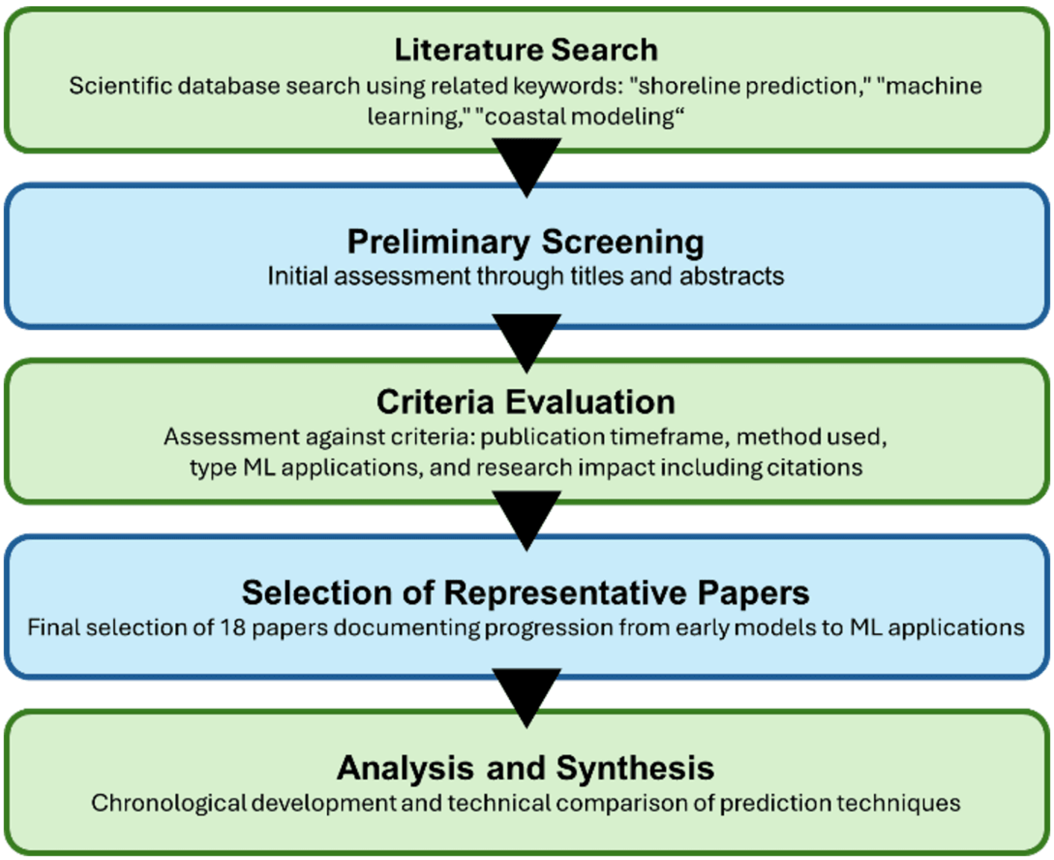

Figure 6. *A systematic review methodology flowchart showing the five-step process used to select and analyze 18 key papers on the evolution of shoreline prediction modeling techniques.*

2.1. Early Approaches (1970's to 1980's)

The paper *"**Spatial and Temporal Analyses of Shoreline Variations**"*[30] presented a shoreline change analysis using historical aerial photography data. The authors calculated the rates of change and variance along a segment of the U.S. mid-Atlantic coast. The methodologies developed relied on measuring and calculating the rates of shoreline change using an orthogonal coordinate system with a transect spacing of 100 m intervals along the coast recording where the shoreline and storm surge penetration line at each transect. Then the mean rate of shoreline change ($S-L$) was calculated using the formula:

$$S-L=\frac{1}{N_p}\sum_{i=1}^{N_p}SL_i$$

where SL_i is the rate of shoreline change between the times of two consecutive aerial photographs and N_p is one minus the number of historical aerial photographs used. Then the standard deviation of $S-L$ was later calculated to account for the variance in the rates of shoreline change.

They found that the shoreline erosion rates average along the U.S. mid-Atlantic coast was 0.6 m/yr but varied significantly along the coast and over time.

The paper ***"Numerical Model of the Shoreline Change at Oarai Beach"***[31] introduced a numerical model to study long-term shoreline evolution. The study used an empirical model to predict the influence of coastal structures like groins and breakwaters on sand transport and shoreline dynamics. They used the following formula to estimate the rate of sand volume transport along a shoreline:

$$Q=(H^2\cdot g^{\frac{1}{2}})\cdot(\beta_1\cdot sin(2\alpha_{bs})-\beta_2\cdot cos(\alpha_{bs})\cdot H\cdot\partial H/\partial x)$$

where Q is the rate of sediment transported along the shore, H is the wave height, \(x\\)is the distance along the shoreline, and α_{bs} is the wave breaking angle on the shoreline. The coefficients β_1 and β_2 are factors in the breaking angle and the wave height gradients along the shoreline.

2.2. 1990's to 2000's

The paper ***"Analytical Solutions of One-Line Model for Shoreline Change Near Coastal Structures"*** [32] introduced another numerical model to analyze the impacts of coastal structures including groins, jetties, and breakwaters on shoreline changes. The model simulates the shoreline change based on longshore transport of sand affected by these structures. The aim is to provide a predictive tool for understanding and managing the effects of these structures on shoreline behavior. The model inputs include wave and sediment properties, and the geometry of coastal defenses. The model provided a clear, mathematical understanding of the processes driving shoreline evolution near coastal structures to assess potential impacts of coastal defenses on shoreline positions.

The paper ***"Do Storms Cause Long-Term Beach Erosion along the U.S. East Barrier Coast?"***[33] tested the assumption that severe storms are the primary drivers of long-term beach erosion along the U.S. East Coast. Based on an analysis of historical shoreline data, the authors thought that beaches tend to recover and maintain their original erosion trends after the storm, suggesting that sea-level rise and sediment supply variations have a more significant impact on shoreline recession than storm events. This study was following the same modeling trend of using the numerical analysis approach, rather than newer techniques like ML, to evaluate shoreline changes over time.

The model target was to estimate the long-term trend of shoreline change using linear regression analysis on non-storm-influenced shoreline positions and comparing the storm impact changes with this trend. This paper was one of the papers to highlight the need to consider broader geological and environmental factors when modeling shoreline changes including sediment supply to the shoreline.

The paper ***"A Simple New Shoreline Change Model"***[34] applied a numerical model predicting the shoreline changes due to the cross-shore processes. This model required minimal input data considering primarily wave and water-level data to predict shoreline movements over time. The model's main assumption was that the shoreline approaches an equilibrium position exponentially over time. The main mathematical concept in the model can be represented by an equilibrium relationship, where the rate of shoreline position change ($dy(t)/dt$) is proportional to the difference between the current shoreline position ($y(t)$) and an equilibrium shoreline position ($y_{eq}(t)$).

The paper ***"Detection, measurement and prediction of shoreline recession in Accra, Ghana"***[35] applied a model called Soft Cliff And Platform Erosion (SCAPE) to analyze and predict shoreline changes. Although SCAPE is a numerical model not a ML model, and it uses linear regression to fit the model, it has a data-driven nature similar to ML models by calibrating the model against known data to increase its performance. The prediction of the future shoreline positions was done by adjusting a rock strength calibration coefficient K ensuring the model's predictions align with the actual observed data as shown in the equation:

$$\Delta y / \Delta t = K \cdot f1 \cdot (f3(t) - z) \cdot tan(f2(z))$$

where $\Delta y / \Delta t$ indicates the rate of change in the profile elevation over time, with $f1$, $f2$,and $f3$ representing the functions that modify this rate based on wave action, the slope, and tidal elevation, respectively.

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The paper *"**Neural Network Modelling of Planform Geometry of Headland-Bay Beaches**"*[36] was one of the early examples of using ANNs (ANNs) to model and predict the shoreline geometry which is different from traditional empirical models. The method does not rely on a predefined equation to describe beach shapes, but instead, the ANN learned from examples of existing beach planforms as the training set in terms of waves direction, wave height, and sediment grain size, then applied this knowledge to predict the geometry of other shorelines. The Authors selected 23 beaches worldwide, divided the data into training (16 beaches) and test (7 beaches) sets, to train the neural network. The study's experimental design tested different network architectures and algorithms to get the best model predictive accuracy. Using ANN was flexible to adapt to various beach geometries without being limited by the assumptions of the traditional models.

The model's prediction capability of the network is defined by the connected neurons and weights gained through the training process. This represents a significant departure from conventional methods, where knowledge of beach geometry is predefined and limited by the accuracy of the chosen mathematical model allowing for better prediction of complex coastal geomorphological processes.

2.3. Early 2010's

The paper *"**A hybrid approach to model shoreline change at multiple timescales**"*[37] applied a technique to integrate behavior-oriented and data-driven approaches to predict shoreline evolution. And this was the main unique point about this paper as the model used a physics-based equation with a data-driven approach to predict how the beach shape changes over time. The model was applied on Colwyn Bay beach in North Wales, UK, and used historical wave measurements and shoreline surveys to calibrate the model.

The model focused on two parameters, the diffusion coefficient, and the source function. The diffusion coefficient accounts for the morphodynamic response of the shoreline and was calculated in this paper using historic wave data to reflect longshore sediment transport's impact on the shoreline changes. The source function accounts for the residual impacts of waves, tides, and anthropogenic stresses, and was calculate in this paper using the short-term wave events, seasonal variations in wave properties, tides, wave-induced currents, and anthropogenic impacts. The paper presented a methodology using these components in predicting shoreline changes, focusing on understanding the combined effects of cross-shore and longshore transport on shoreline evolution for more effective coastal management.

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The paper *"Investigating Nonlinear Shoreline Multiperiod Change from Orthophoto Map Information by Using a Neural Network Model"*[38] presented an application of ANNs to predict future shoreline changes based on orthophoto map data from three different years (1990, 2001, and 2010). This paper used spatial data of 6 beaches around Taiwan and predicted shoreline variations for 2015 and 2020 by developing two networks then comparing between them using different configuration of the data between training, testing, and validation. The inputs for the network included the coordinates of the historical shoreline's position at different times, while the outputs were the predicted shoreline coordinate positions for future years. Then the models' performance was evaluated using correlation coefficient and root-mean-square error to indicate and compare their effectiveness in predicting future shoreline changes. This method applied data-driven prediction of shoreline changes without relying on complex physical process models. But at the same time relying on one parameter and ignoring many other ones that might have an impact on the shoreline changes specially at the eastern and western sides of Taiwan may affect the models' ability to generalize predictions at different coastal settings or under changing environmental conditions.

The Paper *"Nonlinear forecasting of intertidal shoreface evolution*"[39] applied an ANN model to predict future changes in the intertidal shoreface. The model used inputs derived from remote sensing imagery, specifically, shoreline positions over time, to understand and predict the changes along the shoreface. The training inputs of the model also included wave direction, height, and sediment characteristics. Authors assumed a smooth transition in shoreline evolution from day to day. Then they applied a nonlinear time series analysis to detect change patterns. To evaluate the model, the study introduced an energy equilibrium model to account for long-term shoreline variations due to wave activities. This equilibrium model calculated the shoreline responses to wave energy disequilibrium. By using this model, elevation changes at each cross-shore position were predicted to identify the model parameters variations across the shoreline to finely tune predictions.

Thes paper highlighted the limitations of numerical models that simulate shore evolution based on the local conditions of each shoreline and used parameter tuning against historical data. However, this paper provided predictions without the necessity of detailed local conditions or extensive parameter tuning.

The study *"Predicting Future Shoreline in Red Sea Area: Geomatics Study"*[40] used a simple method of predicting future shorelines in response to sea-level changes on the Red Sea coast between El-Quseir and Marsa Alam. The method used a combination of remote sensing, tide gauge data, and digital elevation models (DEMs), to predict shoreline. The key in this model was in its use of sea-level change data, topographical information, and satellite imagery to model the interaction between land and sea dynamically. This method did not use any ML techniques to understand the coastal dynamics but considered changing climate conditions, offering a simple one variable tool for coastal zone management. However, it can only predict shoreline changes for limited locations and cannot be considered effective for complex coastal zones with longshore sediment transport or anthropogenic impacts.

2.4. From 2017 to Current

The paper ***"A model integrating longshore and cross-shore processes for predicting long-term shoreline response to climate change"***[41] developed a model called CoSMoS-COAST (Coastal One-line Assimilated Simulation Tool), a numerical model designed to predict short-term and long-term shoreline changes in response to climate changes. This model integrated process-based models of shoreline evolution due to longshore and cross-shore sediment transport with sea level rise impacts. The model was applied to a 500 km stretch of the Southern California coast, with a diverse range of beach settings, to demonstrate the model's broad applicability. The model captured the change in shoreline position over time $\frac{dy}{dt}$ as a function of several physical processes presented by this formula:

$$\frac{dy}{dt} = -\frac{1}{d} * \frac{\partial Q}{\partial X} + CE^{1/2} * \frac{\partial^2 y}{\partial X^2} - \frac{c}{\tan(\beta)} * \frac{\partial S}{\partial t} + V_{lt}$$

$-\frac{1}{d} * \frac{\partial Q}{\partial X}$ represents the longshore sediment transport, where Q is the volumetric transport rate, X is the alongshore coordinate, and d is the average depth of active sediment transport. This part of the formula shows that the change in the shoreline position is partly due to gradients in the longshore transport. $CE^{1/2} * \frac{\partial^2 y}{\partial X^2}$ accounts for cross-shore sediment transport, where C is a coefficient related to wave energy dissipation, E is wave energy, and y is the cross-shore coordinate to consider the curvature of the shoreline impact on cross-shore transport $\frac{\partial^2 y}{\partial X^2}$ and wave energy. $-\frac{c}{tan(\beta)} * \frac{\partial S}{\partial t}$ represents the shoreline migration due to sea-level rise, with c as the rate of sea-level rise, β as the beach slope, and S as the cross-shore position of the shoreline suggesting that the retreat of shoreline is affected by the slope of the beach. V_{lt} stands for the long-term shoreline trend due to unresolved processes including factors like sediment supply, human interventions, and other processes that are not captured by the other terms in the model.

This model stands out for its comprehensive consideration of multiple factors affecting shoreline changes and its integration of diverse data types, providing a tool for coastal management and climate

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change adaptation strategies. The model was tested on Southern California, predicting that up to 67% of the beaches may experience significant erosion by 2100 under certain sea level rise scenarios, highlighting the need to plan for coastal management strategies to mitigate the impacts of climate.

The paper ***"Shoreline change analysis and erosion prediction using historical data of Kuala Terengganu, Malaysia"***[42] presented an empirical approach to predict coastal erosion using the Bruun Rule model on the coastal area of Kuala Terengganu, Malaysia. The model evaluated the rate of shoreline erosion resulting from sea-level rise on sandy beaches from 2013 to 2020 using this equation:

$$R = G\frac{L}{B + h^*} - S$$

The model calculated the horizontal retreat of the shoreline R based on the beach profile characteristics, sea-level rise, and the material's overfill ratio. The Depth of Closure h^*, the berm height B, beach profile length to the active zone L, and the vertical sea-level rise S. Then the model was evaluated using coefficient of determination, and MSE with historical shoreline data for the years 1980 and 2005.

The paper ***"Application of ML Methods for the Prediction of River Mouth Morphological Variation: A Comparative Analysis of the Da Dien Estuary, Vietnam"***[43] went through different ML techniques to predict morphological changes at river mouths, focusing on the Da Dien Estuary in Vietnam. In the study, logistic regression sets a basic predictive framework, while neural networks bring complexity and depth to model non-linear interactions between factors. Ensemble methods like bagging and boosting (AdaBoost, LogitBoost) enhanced model performance, with bagging focusing on reducing overfitting through averaging multiple models and boosting methods refining predictions. Random Subspace method was used to predict the estuary throat width changes. Predictions were made based on input including wind energy and direction, swell energy and direction, tidal prism, and river discharge, which were derived from satellite data and local hydrological measurements.

A key component of this paper was choosing input features. The authors focused on six parameters wind energy and direction, wave energy and direction, tidal prism, and river discharge. Due to the complexity of the area, they checked how important each of these parameters was for predicting changes at the river mouth. They employed a feature selection approach using Spearman correlation coefficient to assign weights to each input feature and select what factors most significantly influence the morphology of the estuary. This method allowed the model to use fewer features compared to other models especially in estuaries as complex systems.

For evaluation, authors used the Mean Squared Error, Root Mean Squared Error, Kappa index, ROC, and AUC to evaluate how closely the predicted changes matched the observed data. Cross-validation was also used to make sure that the models generalized well to unseen data and to prevent overfitting. The unique aspect of this paper was its comparative analysis of multiple ML techniques and critically evaluating their performance against each other. Using these multiple methods, showed how a well-designed approach can perform well in predicting changes at such complicated coastal areas like the river mouths.

The paper ***"Advanced ML Techniques for Predicting Nha Trang Shorelines"***[44] applied several ML models to predict shoreline changes using surveillance camera images. The paper compared the performances of a statistical forecasting model, the Seasonal Auto-regressive Integrated Moving Average (SARIMA), and two ML models, Neural Network Auto-Regression (NNAR) and Long Short-Term Memory (LSTM), against the commonly used Empirical Orthogonal Function (EOF) model. The models performed well in detecting shoreline changes from video cameras even under extreme weather conditions. The data consisted of daily shoreline positions at five locations along the coast, from May 2013 to December 2015, as the first two years from May 2013 to May 2015 used for training, and the remaining data until December 2015 set aside for testing.

The evaluation was performed using four performance metrics including Pearson Correlation Coefficient (R), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), to assess the accuracy of the predictions. These metrics helped in comparing the actual shoreline positions with the positions predicted by the models. The study concluded that the SARIMA, NNAR, and LSTM models significantly outperform the EOF model in terms of prediction accuracy for both long and short-term predictions particularly in dealing with noisy and missing data due to extreme weather conditions, which is usually a common challenge in monitoring coastal changes through camera systems.

The paper ***"ANN for the prediction of shoreline changes in Narrabeen, Australia"***[15] used Nonlinear Autoregressive Neural Networks (NARNET) and Nonlinear Autoregressive Neural Networks with Exogenous Inputs (NARXNET) to model shoreline changes in Narrabeen Coast, over a period from 1980 to 2014. The study used historical shoreline data to train these recurrent ANNs, comparing their performance against other methods like Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN), and Time Delay Neural Network (TDNN).

The models were structured to predict shoreline changes using historical positions as input data. The NARNET did not require additional external data other than the shoreline positions, while the NARXNET used tidal variation data as well. The networks included four hidden layers with 40-50 neurons per layer, and a time delay parameter was set to 20 steps (months) for NARNET and 10 steps for NARXNET. The input data was divided 90% for training, 9% for testing, and 1% for validation. The models′ evaluation used the trained networks to estimate monthly shoreline positions from January 2014 to October 2014 then assessed using RMSE, Coefficient of Efficiency, and Correlation Coefficient. The paper concluded that NARNET, which relies solely on historical shoreline positions, delivered the most accurate predictions of future shoreline positions, and confirmed the importance of having long-term historical data for training reliable and accurate predictive models, which may not always be available for all coastal regions globally.

The paper ***"On the use of convolutional DL to predict shoreline change"***[45] explored the application of DL algorithms, specifically CNNs and hybrid CNN-Long Short-Term Memory (CNN-LSTM) networks, for predicting interannual shoreline positions. The study employed an approach to evaluate the performance of DL models against traditional shoreline change models. CNNs and CNN-LSTMs were calibrated and tested using shoreline position data derived from camera system. The model inputs included averaged significant wave height, peak period, and direction obtained from the SWAN wave model and validated with field measurements. Additionally, the first 10 principal components derived from sea level pressure PCA, with a shoreline time series as the output. The data was split into 14 years for training, 2 years for development, and 2 years for testing. The CNN and CNN-LSTM architectures were tested against other models like SPADS and ShoreFor, using RMSE, correlation, and Mielke's index to assess their predictive capabilities.

The models comprised two convolutional layers and two fully connected layers, with a sub-sampling operation (max pooling) applied. Dropout regularization was applied between the fully connected layers to prevent overfitting. The LSTM layer was designed to remember what was predicted at the previous step and reuse the information in the following step. This hybrid approach aimed to combine spatial learning from CNN with the temporal learning from LSTM.

The study was a step forward in the application of DL for coastal research. By demonstrating the performance of CNN and CNN-LSTM models in predicting shoreline change, the paper showed the power and the importance of the network design. The findings show that the DL capability in accurately predicting shoreline behaviors over traditional models, especially in capturing seasonal and short-term trends in this paper.

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The paper ***"On the role of hydrodynamic and morphologic variables on neural network prediction of shoreline dynamics"***[46] combined hydrodynamic and morphological variables and used an ANN on data collected from Biscarrosse beach, on the French Atlantic coast over a 3-year period to predict shoreline responses. The study focused on evaluating if a small dataset could still offer reliable predictions for shoreline changes. The model applied a shallow feedforward network with one hidden layer and 10 neurons, optimized through testing different configurations. The reason for that was to avoid the complexities of increasing the number of hidden layers. This decision was explained as authors wanted to give more importance for input selection over network complexity.

The model had 10 input variables covering both hydrodynamic conditions including wave heights, cumulated longshore wave energy, and tidal ranges and morphological characteristics including offshore bar properties, beach states, and break pint position. Then for evaluation RMSE, efficiency coefficient, and correlation coefficient were used showing a good performance in predicting shoreline behaviors capturing seasonal and short-term trends. The study explored the impact of increasing input variables on model performance and concluded that the choice of relevant inputs is more important than the quantity. Moreover, using hydrodynamic and morphological parameters together was found to enhance model accuracy. A notable aspect of this research is that it is relying on simple measured parameters that could be collected by community beach programs.

3. Discussion

In the 1970s and 1980s, the approaches to model shoreline changes were empirical, focusing on spatial and temporal data to understand and predict coastal processes. The methodologies used during this period prepared for more complex models to be developed later. Both studies in this review were based on empirical observations feeding more complicated numerical models. They provided a base to understand the natural of shoreline changes and the impacts of man-made structures on these processes. These papers reflect the progression from the simple empirical methodologies to the more sophisticated, data-driven numerical models, as an intro to the computational methods of coastal processes and shoreline prediction studies.

From the 1990s to the 2000s, the methodology for modeling and predicting shoreline changes experienced a slight shift. The early part of this era was characterized mainly by the use of numerical models, which relied on empirical data and mathematical equations to understand the dynamics of shoreline behavior. And to understand the influence of natural and anthropogenic factors. These models provided understanding of the impact of coastal structures on sand transport and erosion processes, using variables like wave characteristics and sediment properties to simulate shoreline evolution. As the understanding of coastal processes increased, there was a growing recognition of the limitations of the traditional modeling techniques, particularly their inability to capture the complex, non-linear interactions within coastal environments.

Entering the late 1990's and early 2000's, the use of ML and ANNs was new to the field. However, these techniques introduced a new approach to coastal studies, moving beyond the limitations of predefined equations and to use data-driven models that could learn from inputs. This period showed a development of models capable of predicting shoreline changes with greater accuracy and flexibility. And analyzing patterns within data sets to predict the geometry of shorelines under many different conditions.

During the early 2010's, shoreline change prediction showed more integration of ML techniques with traditional modeling approaches compared to before. This period experienced a switch from solely relying on empirical and numerical models with little ML, by applying new non-linear approaches to capture complex coastal dynamics. However, the models' predictive capability was sometimes limited by the complexity of coastal environments and different influencing factors, including sediment properties, transport mechanisms and other impacts of waves, coastal structures, and sea-level rise. Most of the ML approaches were using ANNs because of their ability to learn from data, identify patterns and relationships that seem hard to catch. This period showed more development of hybrid models that integrate the strengths of traditional models with the adaptability and of ML. Models used historical data, remote sensing imagery, and environmental variables that may affect shoreline changes.

The early 2010's period marked a period of another significant improvement in shoreline and coastal studies, with more focused and complicated ML models and opened a broader research trend towards integrating different approaches to solve complex environmental issues.

From 2017 to the present, applying ML approaches in shoreline prediction showed a big transformation, marked by an evolution towards more complex model architectures, the use of expansive datasets, and applying approaches for input selection. Compared to earlier periods, where models were simpler and often relied on singular ML techniques, recent developments have seen the integration of multiple ML approaches within a single predictive framework. Each component of these composite models is designed to perform specific functions such as handling temporal sequences, spatial patterns, or nonlinear relationships within the dataset.

Moreover, the era has been characterized by a significant expansion in the volume and variety of data employed. Models now are able to handle large, complex datasets that encompass a broader range of input variables, including detailed, geologic, hydrodynamic conditions, geomorphologic features, and anthropogenic factors, providing better understanding of shoreline dynamics. This period also showed a systematic direction towards model comparison and optimization, with extensive focus on evaluating the performance of various models against one another to identify the most effective predictive model. Techniques such as cross-validation, hyperparameter tuning, and the use of multiple performance metrics have become standard practices, aimed at enhancing model accuracy and ensuring robustness of models.

Shoreline change prediction has come a long way with the use of machine learning, bringing new ways to study coastal dynamics. Researchers now work with a wide range of data, including satellite images, tide gauge records, sediment properties, and past shoreline positions. Combining these different sources has improved model accuracy and helped uncover the complex factors that shape shoreline evolution. Machine learning is also being applied in different coastal regions, capturing the unique processes driving erosion and accretion. As these methods continue to develop, they offer better predictive tools while also revealing challenges related to data availability, model accuracy, and reliability.

Even with these advancements, there is still no single ML model or framework that works for all shoreline predictions. Researchers use different approaches based on the data they have and the specific goals of their studies. The choice of input variables also varies depending on coastal conditions and the type of analysis being performed. This variety shows the flexibility of ML in shoreline studies but also underscores the fact that the field is still evolving. While models are improving, there is still room for growth, with researchers actively exploring new ways to refine predictions and make models more reliable and easier to interpret. As studies continue, comparing different modeling approaches and improving their accuracy will be essential for shaping more effective and standardized shoreline prediction methods.

A structured overview of these studies, categorized by publication year, model type, input data, and geographic scope, offers a comprehensive perspective on the evolving landscape of shoreline change prediction (Table 1).

Year	Paper Title	Model Type	Input Data	Data Years and/or Locations	Authors
1978	Spatial and Temporal Analyses of Shoreline Variations	Numerical	Historical aerial photography data	Years not specified, U.S. mid-Atlantic coast	Hayden, B., Dolan, R., Felder, W.
1983	Numerical Model of the Shoreline Change at Oarai Beach	Numerical	Coastal structures impact on sand transport	Years not specified, Oarai Beach, Japan	Kraus, N. C., Harikai, S.
1997	Analytical Solutions of One-Line Model for Shoreline Change Near Coastal Structures	Numerical	Wave and sediment properties, coastal defenses geometry	Not specified	Larson, M., Hanson, H., Kraus, N. C.
2002	Do Storms Cause Long-Term Beach Erosion along the U.S. East Barrier Coast?	Numerical	Historical shoreline data	Years not specified, U.S. East Coast	Zhang, K., Douglas, B., Leatherman, S.
2004	A Simple New Shoreline Change Model	Numerical	Wave and water-level data	Not specified	Miller, J. K., Dean, R. G.
2008	Detection, measurement and prediction of shoreline recession in Accra, Ghana	Linear regression, Numerical (SCAPE Model)	Rock strength calibration coefficient K	Years not specified, Accra, Ghana	Addo, K. A., Walkden, M., Mills, J. P.
2009	Neural Network Modelling of Planform Geometry of Headland-Bay Beaches	ANN	Wave direction, wave height, sediment grain size	Training set from various global beaches	Iglesias, G., López, I., Castro, A., Carballo, R.
2013	A hybrid approach to model shoreline	Hybrid Model (physics-based	Historical wave measurements,	Years not specified, Colwyn	Karunarathna, H., Reeve, D. E.

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Year	Paper Title	Model Type	Input Data	Data Years and/or Locations	Authors
	change at multiple timescales	and data-driven)	shoreline surveys	Bay beach, North Wales, UK	
2014	Investigating Nonlinear Shoreline Multiperiod Change from Orthophoto Map Information by Using a Neural Network Model	ANN	Coordinates of the historical shoreline's position at different times	1990-2001; predictions for 2015-2020, Taiwan beaches	Kerh, T., Lu, H., Saunders, R.
2015	Predicting Future Shoreline in Red Sea Area: Geomatics Study	Numerical	Remote sensing, tide gauge data, digital elevation models (DEMs)	Years not specified, Red Sea coast between El-Quseir and Marsa Alam	El-Ashmawy, N., Hosny, M., El Shouny, A., Haggag, G.
2015	Nonlinear forecasting of intertidal shoreface evolution	ANN	Remote sensing imagery, wave direction, height, sediment characteristics	Recent imagery, location not specified	Grimes, D. J., Cortale, N., Baker, K., Mcnamara, D. E.
2017	A model integrating longshore and cross-shore processes for predicting long-term shoreline response to climate change	Numerical	Longshore and cross-shore sediment transport, sea level rise	Years not specified, Southern California coast, USA	Vitousek, S., Barnard, P. L., Limber, P., Erikson, L., Cole, B.
2019	Shoreline change analysis and erosion prediction using historical data of Kuala Terengganu, Malaysia	Numerical (Bruun Rule Model)	Beach profile characteristics, sea-level rise, overfill ratio of material	1980-2005; prediction for 2013-2020, Kuala Terengganu, Malaysia	Bagheri, M., Zaiton Ibrahim, Z., Bin Mansor, S., Abd Manaf, L., Badarulzaman, N., Vaghefi, N.
2019	Application of Machine Learning Methods for	Multiple ML Techniques	Wind energy and direction, swell	1988-2015, Da Dien Estuary,	Pham, D. H. B., Hoang, T. T., Bui, Q. T., Tran, N.

Year	Paper Title	Model Type	Input Data	Data Years and/or Locations	Authors
	the Prediction of River Mouth Morphological Variation: A Comparative Analysis of the Da Dien Estuary, Vietnam	(Regression, ANN, AdaBoost, LogitBoost)	energy and direction, tidal prism, river discharge	Vietnam	A., Nguyen, T. G.
2021	Advanced Machine Learning Techniques for Predicting Nha Trang Shorelines	Multiple ML Techniques (SARIMA, NNAR, LSTM)	Surveillance camera images	May 2013-December 2015, Nha Trang, Vietnam	Yin, C., Binh, L. T., Anh, D. T., Mai, S. T., Le, A., Nguyen, V. H., Nguyen, V. C., Tinh, N. X., Tanaka, H., Viet, N. T., Nguyen, L. D., Duong, T. Q.
2021	ANN for the prediction of shoreline changes in Narrabeen, Australia	ANN (NARNET, NARXNET)	Historical shoreline data, tidal variation data	1980-2014, prediction for Jan 2014 - Oct 2014, Narrabeen Coast, Australia	Zeinali, S., Dehghani, M., Talebbeydokhti, N.
2023	On the use of convolutional DL to predict shoreline change	DL (CNN-LSTM)	Wave height, peak period, direction, sea level pressure PCA	14 years for training, 2 years for development, 2 years for testing, location not specified	Gomez-De La Peña, E., Coco, G., Whittaker, C., Montaño, J.
2024	On the role of hydrodynamic and morphologic variables on neural network prediction of shoreline dynamics	ANN (Shallow Feedforward Network)	Hydrodynamic conditions, morphological characteristics	Collected over a 3-year period, Biscarrosse beach, France	Senechal, N., Coco, G.

Table 1. Summary of reviewed papers (1978-2024) showing the progression of shoreline prediction modeling techniques from numerical to machine learning approaches, including model types, input data, study periods, and locations.

4. Conclusion

The journey of shoreline prediction methodologies from empirical observations in the 1970’s and 1980’s to the well-developed ML applications of the present day represents a great evolution in coastal research. Initially was limited within empirical data and simplistic numerical models. However, early research introduced the foundational understanding necessary for the development of more complex prediction approaches from relying on direct observations to computational methods capable of dealing with the multi-dimensional dynamics of coastal processes.

Since the 1990’s the use of ML brought a new era of shoreline prediction. During this time, traditional approaches gradually gave way to data-driven approaches that made use of ML models′ capability to identify patterns in large data sets. The application of ML increased predictions flexibility and accuracy while also highlighting the limitations of earlier approaches in handling the nonlinear relationships of shoreline dynamics. The use of DL and other advanced ML techniques for predicting changes along coasts has significantly increased in the last few years. The use of large data sets and different model architectures signifies this present phase and makes it easier to comprehend shoreline evolution.

This overview highlights the trend of modeling techniques evolving into more advanced ML applications. Each phase of this evolution has advanced our knowledge of coastal behaviors and pushed the field toward more understanding and useful management strategies. The combination of various ML techniques to perform multiple roles within the model, which is an increasing trend recently will assist coastal research and the sustainable management of shoreline settings, enabling us to improve our prediction skills more and more. However, applying these models on different coastal areas may need specific modifications depending on the forces that are affecting different areas.

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Data Availability

This study is based on published research and does not involve new experimental data.

Conflicts of Interest

The authors declare no competing interests

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