A Simulation of Shoreline Evolution with a Groin Structure Using an Alternative Machine Learning Algorithm

Surasak Manilam, and Nopparat Pochai

Abstract — **Uneven sediment transport is a major cause of coastal erosion. Using groin structures is one method to help slow the outflow of sediment from the shoreline. Studying coastal behavior and forecasting future shoreline changes are crucial for managing and assessing the viability of remediation strategies. This research presents simulations of shoreline evolution with a single groin structure using two different methods, such as mathematical modeling and an alternative machine learning. A mathematical model is a representation of a real-world shoreline evolution phenomenon using partial differential equations. A machine learning algorithm is designed to learn patterns and relationships directly from real data. In this research, an alternative machine learning algorithm is designed to learn patterns and relationships directly from mathematical simulation data and let the machine make a decision in a situation that it has never learned before. For mathematical modeling, we introduced a one-dimensional model to predict the shoreline evolution. The initial and the boundary conditions with related parameter settings are introduced. The Saulyev finite difference method is used to obtain the approximated solution. An alternative machine learning algorithm for unexpected shoreline evolution prediction is also proposed. For alternative machine learning simulations, we identified six suitable features for the training dataset and developed an alternative K-nearest neighbor algorithm. It provides a way of predicting the evolution of the shoreline with a single groin structure. Additionally, an exact solution in an ideal scenario is used to test the precision of the simulation as well. The results show that the Saulyev technique outperforms an alternative K-nearest neighbor algorithm due to the lower root mean square error value. Both results of them are closed together. According to the research, mathematical modeling outperforms the KNN regression technique in terms of computational effectiveness during time periods of 0.5, 1, 5, 10, 15, and 20 years. Based on the modeling configuration and parameter simplicity, the KNN algorithm is still a good option for non-expert users.**

Index Terms — **alternative, groin, K-nearest neighbors machine learning, Saulyev finite difference, shoreline evolution modeling**

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I. INTRODUCTION

EROSION is a natural phenomenon that has been intensifying continuously, with over 24% of global coastlines currently facing this issue at a rate of more than 0.5 m/yr, while only 28% are showing signs of recovery [1]. The causes of this erosion include climate change, rising sea levels, the increasing intensity of waves and currents, and the improper use of land and resources by humans [2], [3], [4], [5]. If this problem is not addressed promptly and appropriately, it could have significant impacts on ecosystems, quality of life, and the economy. Generally, there are two main approaches to addressing this problem: non-structural and structural approaches. Non-structural approaches include activities such as planting mangrove forests, beach nourishment, and implementing setback regulations. Structural approaches, on the other hand, involve constructing physical barriers such as breakwaters, groins, and seawalls. A groin is a medium-sized engineered structure that is placed perpendicular to the coastline and comes in various shapes, such as Y-shaped, I-shaped, and T-shaped. It is designed to capture sand moving along with the current, thereby slowing the movement of sediment and promoting its accumulation. Additionally, groins help dissipate wave energy and reduce the impact of currents [6].

Mathematical modeling and data analysis using machine learning are fundamental tools essential for the development of effective strategies, management, and planning e.g., air pollution, salinity in rivers and heat transfer within multi-layered walls (see [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]). This paper [17] presents contemporary logical design criteria for groin constructions. They are divided into three main categories: structural design, functional design, and coastal processes. The evaluation of the effectiveness, costs, and benefits of coastal defense was presented by integrating three models: the shoreline evolution model (to predict land area changes over time), the preliminary coastal structure design model (to estimate construction material volumes), and the cost-benefit evaluation model (to assess cost and benefit criteria). Additionally, the proposed methodology was applied to evaluate the performance of different grain scenarios through a case study, emphasizing the importance of physical and economic analysis. The results indicate that defining coastal defense interventions is complex, as the best physical solutions can be very costly, while the best economic scenarios may result in significant land loss. This approach demonstrates that integrated analysis of shoreline evolution, coastal intervention design, and subsequent costs and benefits improves the performance of coastal defense interventions [18]. In [19], they introduced a shoreline change model with an ensemble Kalman filter to forecast wave-induced coastal erosion and uncertainty at different time scales. They applied ensemble wave time series generated by a computationally effective statistical downscaling technique to assess shoreline change projections that were simulated with and without ensemble wave driving conditions. When compared to the impractical scenario of model predictions based on a single, deterministic realization of the wave forcing, the results show a significant (site-dependent) increase in model uncertainty. The well-developed ensemble modeling technique is used on a beach in Tairua, New Zealand, that is regularly observed. In [20], eight time-series forecasting methods are evaluated for predicting future shorelines based on historical satellite data. By analyzing over 37,000 global transects, the researchers found that traditional methods, along with certain probabilistic Machine Learning (ML) models, outperformed Ordinary Least Squares (OLS) regression at most sites. Over a seven-year forecasting period, these approaches yielded more accurate predictions for 54% of the sites, with an average reduction in Mean Squared Error (MSE) of 29%. While ML models did not significantly exceed traditional methods in accuracy, they were more efficient in computation time. The study also offers recommendations for enhancing ML models to enable them to surpass both OLS and traditional methods. These forecasting tools are essential for coastal engineers, managers, and researchers to predict future shoreline changes on a global scale and derive valuable insights. In paper [21], recurrent Artificial Neural Networks (ANNs), specifically NARNET and NARXNET, were introduced to model shoreline changes along the Narrabeen Coast in Australia from 1980 to 2014. The findings indicate that these models reliably predict shoreline changes based on historical data. Comparisons with other methods, including Radial Basis Function (RBF), General Regression Neural Network (GRNN), and Time Delay Neural Network (TDNN), reveal that NARNET produced the most accurate results, achieving a Mean Absolute Percentage Error (MAPE) of 17.18%, while NARXNET exhibited the highest correlation coefficient (CC) of 0.26. Overall, NARNET and NARXNET are preferred methods as they require less supplementary data beyond the shoreline position itself.

In [22], [23], [24], [25] and [26], they developed a one-line theory and presented analytical solutions for shoreline evolution, which are highly valuable for understanding the characteristics of long-term coastal changes. However, these analytical solutions have limitations, as they cannot predict scenarios with complex conditions. In practice, numerical methods for modeling shoreline evolution are more suitable. In [27], [28] and [29], they introduced an approximation of the solution of a one-dimensional coastal evolution model with a groin structure using two explicit finite difference methods, namely the Forward Time Centered Space (FTCS) method and the Saulyev method. In [30] and [31], they developed a non-dimensional model based on the one-dimensional model for predicting shoreline changes associated with both single and twin groin structures, which can reduce computational time and cost. They also described the concept of model transformation, including setting conditions and tuning various physical parameters to improve the model performance. The results show that shoreline evolution accelerated annually when the engineering structure was installed on the nearby shorelines. Better simulations are produced by the Saulyev finite difference technique since it is not constrained by the stability criteria.

This paper presents a novel approach compared to the above literature. This research aims to predict changes in the coastline due to a single-groin structure by employing two distinct methods and assessing the performance of each through root mean square error (RMSE). The structure of this paper is as follows: Section II introduces the mathematical modeling. In Section III, we explore the development of an alternative machine learning algorithm and the creation of the training dataset. Section IV describes the performance measurement of the simulation. Section V explains the simulation of coastal evolution, integrating both a mathematical model and an alternative machine learning algorithm. Section VI offers a presentation and discussion of the simulation results. Finally, Section VII provides the research conclusions.

II. Mathematical Modeling

A. Shoreline Evolution Model

Coastal dynamics were developed as a mathematical model under the sand volume conservation law and two general assumptions: 1) The coastline moves parallel to itself without changing its sh[ape during erosion, although it is constantly moving. Any position on the profile can be determined using the baseline. Therefore, a contour line is used for the convenience of identifying the coastline; and 2) the sand transfer on the profile is between two elevations, i.e., the depth of closure and the berm height. This measurement uses the mean sea level (MSL) as a reference.

A one-dimensional mathematical model for shoreline evolution is defined by (1):

$$\frac{\partial y}{\partial t} = D\frac{\partial^2 y}{\partial x^2} , \tag{1}$$

for all $(x,t)\in\Omega$ such that $\Omega=[0,L]\times[0,\tau]$, $\tau = 360t_Y$, $D=\frac{2Q_0}{D_B+D_C}$, where the variables and parameters of (1) are defined in Table I and Figs. 1-2. The coefficient D is the value describing the time scale of the shoreline change after wave action. Therefore, a high amplitude of long-shore sand transport rate Q_0 will enable rapid shoreline responses. On the other hand, a large depth of closure D_C will slow the response of the shoreline.

Assume the initial shoreline contour has the same breaking wave angle at every site and is in equilibrium when it is parallel to the x-axis. Therefore, the expression of the initial condition is

$$y(x,0) = 0 \quad \text{at } t = 0 , \tag{2}$$

for all $x\in[0,L]$. The incident angle of the breaking wave crests affects the change in coastline at the groin. Therefore, the expression of left-boundary condition and right-boundary condition are defined by

$$y(0,t) = f(t) \text{ at } x = 0 \ , \tag{3}$$

and

$$y(L,t) = g(t) \text{ at } x = L \ , \tag{4}$$

for all $t \in [0,\tau]$, where $f(t)$ and $g(t)$ are given interpolation functions.

TABLE I
VARIABLES AND PARAMETERS

Symbol	Description (Unit)
y	Shoreline position (m)
x	Long-shore distance (m)
t	Time (day)
Q_0	Amplitude of the long-shore sand transport rate (m^3/day)
D_B	Berm height (m)
D_C	Depth of closure (m)
α_0	Angle between breaking wave crests and the x-axis (deg)
L	Shoreline distance (m)
t_Y	Number of years (yr)

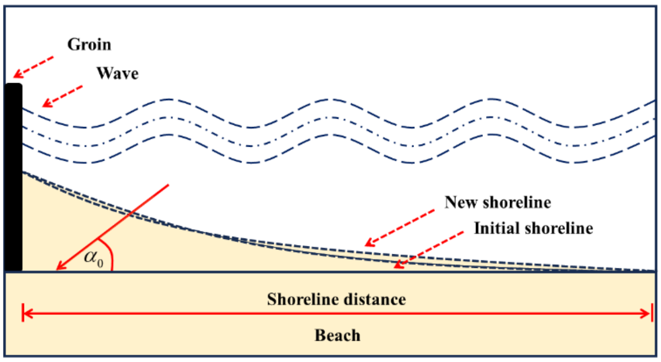

Fig. 1. Initial shoreline with a straight groin structure.

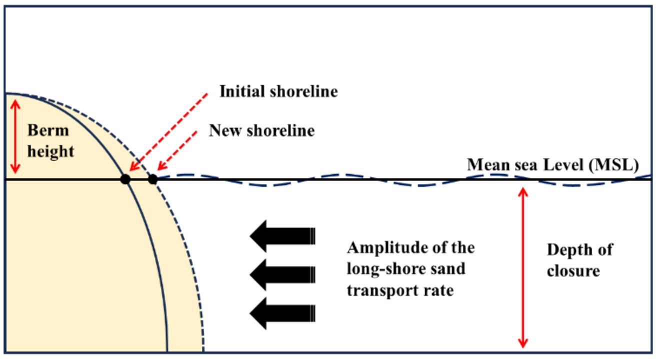

Fig. 2. Cross section of coastal changes and morphology.

B. Unconditionally Stable Saulyev Finite Difference Method

The Saulyev finite difference (Saulyev) method is an explicit unconditionally stable finite difference method, so it is convenient and does not have strict limitations on the size of the time increment compared with other methods [32]. To solve (1) using the Saulyev method, the first step is to create a meshing grid over the domain Ω, which is done by dividing the space-interval $[0,L]$ into M sub-intervals and the time-interval $[0,\tau]$ into N sub-intervals, in which the values $\Delta x = L/M$ and $\Delta t = \tau/N$ are the x-axis increment and the t-axis increment, respectively. Any point on this meshing grid is accessed using coordinates $(x_m,t_n) = (m\Delta x, n\Delta t)$ for each $m = 0,1,\ldots,M$ and $n = 0,1,\ldots,N$. Therefore, the approximation of shoreline evolution y at any point on the grid is defined by the notation $y(x_m,t_n) = y_m^n$.

We have the following finite difference approximation [33], [34]:

$$y \cong y_m^n \ , \tag{5}$$

$$y_m^n \cong y(x_m,t_n) \ , \tag{6}$$

$$y_m^{n+1} \cong y(x_m,t_n+\Delta t) \ , \tag{7}$$

$$y_{m+1}^n \cong y(x_m+\Delta x,t_n) \ , \tag{8}$$

$$y_{m-1}^{n+1} \cong y(x_m-\Delta x,t_n+\Delta t) \ , \tag{9}$$

$$\frac{\partial y}{\partial t} \cong \frac{y_m^{n+1}-y_m^n}{\Delta t} \ , \tag{10}$$

$$\frac{\partial^2 y}{\partial x^2} \cong \frac{y_{m+1}^n - y_m^n - y_m^{n+1} + y_{m-1}^{n+1}}{(\Delta x)^2} \ . \tag{11}$$

Next, substitute (5)-(11) into (1), and we obtain the following.

$$\frac{y_m^{n+1}-y_m^n}{\Delta t} = D\left[\frac{y_{m+1}^n - y_m^n - y_m^{n+1} + y_{m-1}^{n+1}}{(\Delta x)^2}\right] ,$$

$$y_m^{n+1}-y_m^n = \frac{D\Delta t}{(\Delta x)^2}\left[y_{m+1}^n - y_m^n - y_m^{n+1} + y_{m-1}^{n+1}\right] ,$$

$$y_m^{n+1} = \lambda y_{m+1}^n - \lambda y_m^n - \lambda y_m^{n+1} + \lambda y_{m-1}^{n+1} + y_m^n \ . \tag{12}$$

The equation (12) can be written in the explicit Saulyev finite difference form as follows.

$$y_m^{n+1} = (1+\lambda)^{-1}\left[\lambda y_{m+1}^n + (1-\lambda)y_m^n + \lambda y_{m-1}^{n+1}\right] , \tag{13}$$

where $m = 1,2,\ldots,M-1$, $n = 0,1,\ldots,N-1$ and $\lambda = \dfrac{D\Delta t}{(\Delta x)^2}$.

The Saulyev finite difference method can be written as pseudocode 1.

C. Exact Solution for Shoreline Evolution Model

The exact solution for the shoreline evolution model is defined by [35]:

$$y(x,t) = \sqrt{(B\pi)^{-1}}\tan(\alpha_0)\left[e^{-Bx^2} - x\sqrt{B\pi}\, erfc\left(x\sqrt{B}\right)\right], \tag{14}$$

where $B = \dfrac{1}{4Dt}$, and $erfc\left(x\sqrt{B}\right) = 1 - \dfrac{2}{\sqrt{\pi}}\displaystyle\int_0^{x\sqrt{B}} e^{-t^2}dt$ is the complementary error function of $x\sqrt{B}$.

III. ALTERNATIVE MACHINE LEARNING ALGORITHM

A. K-Nearest Neighbors Algorithm for Shoreline Evolution Prediction

The K-nearest neighbors (KNN) algorithm is a supervised machine learning method that applies to clustering and regression [36], [37]. There are five advantages of this method: 1) Simple and uncomplicated – KNN is a simple and easy-to-understand algorithm because it uses only three required parameters, i.e., number of K-nearest neighbors, distance function and average of nearest neighbors; 2) Wide selection of distance functions – KNN provides flexibility in choosing distance functions such as Manhattan distance, Euclidean distance, Minkowski distance and Weighted distance; 3) No assumption related to data – KNN is a non-parametric algorithm unlike mathematical modeling that requires assumptions about large amounts of data; 4) No training model generation – KNN is a lazy algorithm with no model reconstruction. Instead, it uses a method of labeling newly entered data based on learning from past training data; and 5) Fast response to input data changes – Data classification and data regression are instantly changed when new training data is added or removed.

Let the training dataset be in the format:

$$\Gamma = \left\{ \left(X^j, y^j \right) \middle| j = 1,2,\ldots,p \right\}, \tag{15}$$

where each $X^j = \left\{ x_1^j, x_2^j, x_3^j, \ldots, x_q^j \right\} \in \mathbb{R}^q$ is the training data with q attributes, $y^j \in \mathbb{R}$ is the output (label) of each training data and p is the number of training data. The new data will be given as X. Let $X \in \mathbb{R}^q$ be new data with q attributes and not yet labeled. The process of K-nearest neighbor regression (KNN regression) algorithm consists of three steps: distance measurement, nearest neighbors sorting and prediction.

- Step 1: Find the Euclidean distance between the training data X^j and the new data X by using the equation below:

$$d\left(X^j, X \right) = \sqrt{\sum_{i=1}^{q} \left(x_i^j - x_i \right)^2}. \tag{16}$$

- Step 2: Determine the set of K-nearest neighbors of X in the form:

$$R_X^K = \left\{ \left(X^r, y^r \right) \middle| r = 1,2,\ldots,K \right\}, \tag{17}$$

which is obtained by arranging the new order of $\left(X^j, y^j \right)$ in the training dataset Γ according to their ascending Euclidean distance and K is the number of nearest neighbor vectors.

- Step 3: Estimate the output y for X by using the arithmetic mean of the output values $y^r \in R_X^K$ according to the equation below:

$$y = \frac{1}{K} \sum_{r=1}^{K} y^r. \tag{18}$$

The K-nearest neighbor regression (KNN regression) algorithm can be written as pseudocode 2.

Pseudocode 1: Saulyev FDM

Input: 1) number of sub-intervals M, N; 2) number of years t_Y; 3) shoreline distance L; 4) coefficient D; 5) initial condition y_m^0; and 6) boundary conditions y_0^n, y_M^n

Output: approximated shoreline y_m^n

Begin
Compute λ, Δx, Δt and create a meshing grid over the domain Ω
for $n \leftarrow 0$ **to** N **do**
  if $n \leftarrow 0$ **then**
    Compute y_m^n using the IC in (2)
  else
    for $m \leftarrow 0$ **to** M **do**
      if $m \leftarrow 0$ **then**
        Compute y_m^n using the left-BC in (3)
      else if $m < M$ **then**
        Compute y_m^n using the Saulyev equation in (13)
      else
        Compute y_m^n using the right-BC in (4)
      end
    end
  end
end
return y_m^n

Pseudocode 2: KNN regression

Input: 1) training dataset Γ; 2) new data X; and 3) number of nearest neighbors K

Output: approximated shoreline y

Begin
for $j \leftarrow 1$ **to** p **do**
  Compute the distance $d\left(X^j, X \right)$ between the training data X^j and the new data X by using the Euclidean formula in (16)
end
Rearrange the new order of $\left(X^j, y^j \right) \in \Gamma$ according to their ascending distance
for $j \leftarrow 1$ **to** p **do**
  if $j \le K$ **then**
    Add $\left(X^j, y^j \right)$ to the set R_X^K
  end
end
Estimate the average y from the value $y^r \in R_X^K$ using the arithmetic mean in (18)
return y

B. An Alternative Algorithm for Unexpected Shoreline Evolution Prediction

Sometimes the rankings given to individual training datasets are redundant, and neglecting this issue can result in poor performance. Therefore, in this section, we introduce an alternative prediction algorithm bias averaging in step 3 of the previous section, which is detailed below. Let k_r be the number of nearest neighbor vectors that share r-rank, r be the number r-rank and $K = k_1 + k_2 + \ldots + k_r$. If some ranks have more than one nearest neighbor vector (share ranks), then a general bias average is

$$y = \frac{1}{K}\left(\sum_{h=1}^{k_1} y^{1,h} + \sum_{h=1}^{k_2} y^{2,h} + \ldots + \sum_{h=1}^{k_r} y^{r,h}\right), \quad (19)$$

where $r < K$.

In special cases, if every rank has only one nearest neighbor vector ($k_1 = k_2 = \ldots = k_r = 1$), then a general bias average is (18), where $r = K$.

C. Generated Shoreline Evolution Dataset

The dataset for shoreline evolution consists of six attributes as listed in Table II, where note that A1 = x^j_1, A2 = x^j_2, A3 = x^j_3, A4 = x^j_4, A5 = x^j_5, and A6 = x^j_6. Let each attribute A1-A6 have the following values: amplitude of the long-shore sand transport rate A1 is 6375, 7500, and 8625 m^3/day; berm height A2 is 1, 2, and 3 m; depth of closure A3 is 24, 28, and 33 m; angle of the breaking wave crest along the shoreline A4 is 0.02, 0.03, and 0.04 deg; step size of distance is 250 m; step size of time is 60 days; and number of years is 20 years. In Table III, the 166,617-training dataset was generated by three steps: 1) using a linear permutation method with the values of the attributes defined above (not permuting the positions of attributes A1-A6); 2) using the Saulyev method in (13) with the case of linear permutations obtained; and 3) reshaping the solutions and assigning them as labels. Note that the testing dataset or new dataset has the same attributes as the training dataset.

IV. Simulation Performances

The root mean square error (RMSE) is one of the popular tools to measure the difference between the exact solution and the approximated solution. The model with the lowest RMSE value is the best performer. The formula of RMSE is

$$RMSE = \sqrt{\frac{1}{w}\sum_{i=1}^{w}\left(y_i - \tilde{y}_i\right)^2}, \quad (20)$$

where y_i is the exact solution, $\tilde{y}_i$ is the approximated solution, and w is the number of solutions.

V. Simulations of Shoreline Evolution

In this paper, we used two methods to investigate long-term shoreline evolution: mathematical modeling and alternative machine learning algorithm, which are detailed below.

In testing with mathematical modeling, we determine the physical parameters as illustrated in Table IV and employ the Saulyev method.

In testing with alternative machine learning, we load the training dataset as illustrated in Table III and generate the testing dataset using the physical parameters as illustrated in Table V. We employ the KNN regression method with both datasets. The actual and approximated values of local shoreline growth over 0.5, 1, 5, 10, 15, and 20 years are illustrated in Tables VI-XI and Figs. 3-6.

The root means square error values of each method is illustrated in Table XII. The root means square error values of the KNN regression method when changing the K-nearest neighbor number is illustrated in Table XIII.

TABLE II
Attributes of Dataset

Symbol		Attribute (Unit)
A1	Q_0	Amplitude of the long-shore sand transport rate (m^3/day)
A2	D_B	Berm height (m)
A3	D_C	Depth of closure (m)
A4	α_0	Angle between breaking wave crests and the x-axis (deg)
A5	x	Long-shore distance (m)
A6	t	Time (day)

TABLE III
Coastal evolution training dataset

No.	Attributes						Label
	A1	A2	A3	A4	A5	A6	y
1	6375	1	24	0.02	0	0	0.00000
2	6375	1	24	0.02	0	60	3.94824
…	…	…	…	…	…	…	…
55538	6375	3	33	0.04	4000	7140	2.71103
55539	6375	3	33	0.04	4000	7200	2.77335
55540	7500	1	24	0.02	0	0	0.00000
55541	7500	1	24	0.02	0	60	4.28247
…	…	…	…	…	…	…	…
111077	7500	3	33	0.04	4000	7140	4.12845
111078	7500	3	33	0.04	4000	7200	4.21405
111079	8625	1	24	0.02	0	0	0.00000
111080	8625	1	24	0.02	0	60	4.59244
…	…	…	…	…	…	…	…
166616	8625	3	33	0.04	4000	7140	5.73966
166617	8625	3	33	0.04	4000	7200	5.84898

TABLE IV
Parameter Setting for Mathematical Modeling

Description (Unit)	Symbol	Value
Shoreline distance (m)	L	4000
Amplitude of the long-shore sand transport rate (m^3/day)	Q_0	7900
Berm height (m)	D_B	1.8
Depth of closure (m)	D_C	26
Angle between breaking wave crests and the x-axis (deg)	α_0	0.025
Step size of shoreline distance (m)	Δx	500
Step size of time (day)	Δt	90

TABLE V
Parameter Setting for An Alternative Machine Learning

Description (Unit)	Symbol	Value
Number of nearest neighbors	K	3
Shoreline distance (m)	L	4000
Amplitude of the long-shore sand transport rate (m^3/day)	A1	7900
Berm height (m)	A2	1.8
Depth of closure (m)	A3	26
Angle between breaking wave crests and the x-axis (deg.)	A4	0.025
Step size of shoreline distance (m)	Δx	500
Step size of time (day)	Δt	90

VI. Result and Discussion

Under the assumptions described in the previous section, we used two methods, namely mathematical modeling, and alternative machine learning, to test the long-term coastline evolution, which obtained the following results:

The computational efficiency of the KNN regression algorithm is shown in Table VI and Fig. 4 when the number of K-nearest neighbors is varied using the RMSE value. It can be shown that K = 3 provides better computing efficiency in comparison to other cases. As a result, K = 3 will be selected for this research.

Table VII and Fig. 5 illustrate the comparison of the local shoreline's actual and approximate values over a haft-year period, where the highest value is 9.02460 m, the lowest value is 0.0000 m, the Saulyev's RMSE value is 0.28497, and the KNN regression's RMSE value is 0.31751.

Table VIII and Fig. 6 illustrate the comparison of the local shoreline's actual and approximate values over a 1-year period, where the highest value is 12.76271 m, the lowest value is 0.0000 m, the Saulyev's RMSE value is 0.32256, and the KNN regression's RMSE value is 0.39723.

Table IX and Fig. 7 illustrate a comparison of the local shoreline's actual and approximate values over a 5-year period, where the highest value is 28.53829 m, the lowest value is 0.05510 m, the Saulyev's RMSE value is 0.43020, and the KNN regression's RMSE value is 0.85744.

Table X and Fig. 8 illustrate the comparison of the local shoreline's actual and approximate values over a 10-year period, where the highest value is 40.35924 m, the lowest value is 0.91247 m, the Saulyev's RMSE value is 0.42264, and the KNN regression's RMSE value is 1.34167.

Table XI and Fig. 9 illustrate the comparison of the local shoreline's actual and approximate values over a 15-year period, where the highest value is 49.42977 m, the lowest value is 2.78261 m, the Saulyev's RMSE value is 0.34930, and the KNN regression's RMSE value is 1.81389.

Table XII and Fig. 10 illustrate the comparison of the local shoreline's actual and approximate values over a 20-year period, where the highest value is 57.07658 m, the lowest value is 5.26681 m, the Saulyev's RMSE value is 0.27204, and the KNN regression's RMSE value is 2.28108.

When analyzing each year, as illustrated in Tables VII-XII and Figs. 5–10, we observe that the shoreline evolution is generally increasing.

Table XIII illustrates the computational efficiency of each method based on the RMSE value. These results indicate that the Saulyev method has higher computational efficiency than the KNN regression algorithm over periods of 0.5, 1, 5, 10, 15, and 20 years. However, the KNN regression algorithm remains a suitable choice for practical applications due to its simplicity, as it relies on only three parameters: the number of K, the distance function, and the averaging of the nearest neighbors.

TABLE VI
ROOT MEAN SQUARE ERROR (RMSE) OF THE KNN REGRESSION METHOD WHEN CHANGING THE K-NEAREST NEIGHBOR NUMBER

K	Time (years)					
	0.5	1	5	10	15	20
1	0.60375	0.84184	2.15726	3.42521	4.55798	5.61270
3	0.31751	0.39723	0.85744	1.34167	1.81389	2.28108
5	0.45389	0.62692	1.41965	2.08250	2.61032	3.07218
7	0.49451	0.68973	1.59822	2.37041	2.99363	3.54111
9	0.43018	0.58946	1.31002	1.90549	2.37619	2.78746

TABLE VII
EVOLUTION OF THE LOCAL SHORELINE OVER 0.5 YEARS
(K = 3 AND A6 = 180 DAYS)

Distance (m)	Method		
	Exact	Saulyev	KNN
0	9.02460	9.02460	8.31884
500	1.53582	2.27980	2.07989
1000	0.10721	0.51410	0.43401
1500	0.00271	0.10887	0.08135
2000	0.00002	0.02215	0.01422
2500	0.00000	0.00438	0.00237
3000	0.00000	0.00085	0.00038
3500	0.00000	0.00016	0.00006
4000	0.00000	0.00000	0.00000

TABLE VIII
EVOLUTION OF THE LOCAL SHORELINE OVER 1 YEAR
(K = 3 AND A6 = 360 DAYS)

Distance (m)	Method		
	Exact	Saulyev	KNN
0	12.76271	12.76271	11.76462
500	3.97171	4.61991	4.28042
1000	0.81042	1.45040	1.31768
1500	0.10263	0.41199	0.35677
2000	0.00777	0.10878	0.08754
2500	0.00034	0.02717	0.01990
3000	0.00001	0.00650	0.00426
3500	0.00000	0.00148	0.00086
4000	0.00000	0.00000	0.00000

TABLE IX
EVOLUTION OF THE LOCAL SHORELINE OVER 5 YEARS
(K = 3 AND A6 = 1800 DAYS)

Distance (m)	Method		
	Exact	Saulyev	KNN
0	28.53829	28.53829	26.30649
500	17.76165	18.10173	16.67494
1000	10.23635	10.82549	9.97430
1500	5.42788	6.10825	5.63213
2000	2.63341	3.25720	3.00575
2500	1.16342	1.64307	1.51721
3000	0.46615	0.77788	0.71898
3500	0.16882	0.32254	0.29831
4000	0.05510	0.05510	0.04699

TABLE X
EVOLUTION OF THE LOCAL SHORELINE OVER 10 YEARS
(K = 3 AND A6 = 3600 DAYS)

Distance (m)	Method		
	Exact	Saulyev	KNN
0	40.35924	40.35924	37.20299
500	29.08324	29.32719	26.99058
1000	20.18738	20.63899	18.97138
1500	13.46526	14.05205	12.90691
2000	8.61186	9.24227	8.48671
2500	5.27069	5.85169	5.37275
3000	3.08146	3.53082	3.23762
3500	1.71822	1.96912	1.79151
4000	0.91247	0.91247	0.79739

TABLE XI
EVOLUTION OF THE LOCAL SHORELINE OVER 15 YEARS
(K = 3 AND A6 = 5400 DAYS)

Distance (m)	Method		
	Exact	Saulyev	KNN
0	49.42977	49.42977	45.56417
500	37.93037	38.11912	35.07818
1000	28.39723	28.75082	26.41508
1500	20.71455	21.18428	19.43447
2000	14.70437	15.22368	13.94540
2500	10.14586	10.63931	9.72709
3000	6.79742	7.18961	6.54981
3500	4.41767	4.64089	4.19334
4000	2.78261	2.78261	2.46098

TABLE XII
EVOLUTION OF THE LOCAL SHORELINE OVER 20 YEARS
(K = 3 AND A6 = 7200 DAYS)

Distance (m)	Method		
	Exact	Saulyev	KNN
0	57.07658	57.07658	52.61298
500	45.44352	45.58825	41.95014
1000	35.52331	35.79495	32.88025
1500	27.23961	27.60218	25.30790
2000	20.47271	20.87630	19.10146
2500	15.06953	15.45611	14.10456
3000	10.85577	11.16555	10.14848
3500	7.64832	7.82600	7.06390
4000	5.26681	5.26681	4.69078

TABLE XIII
ROOT MEAN SQUARE ERROR OF EACH METHOD

Time (years)	Method	
	Saulyev	KNN
0.5	0.28497	0.31751
1	0.32256	0.39723
5	0.43020	0.85744
10	0.42264	1.34167
15	0.34930	1.81389
20	0.27204	2.28108

VII. CONCLUSION

Study of shoreline evolution prediction of a single-groin structure by using two completely different methods: mathematical modeling and alternative machine learning. For the mathematical modeling, we present the one-dimensional mathematical equation for shoreline evolution derived from the conservation law of sand volume. The techniques for defining boundary conditions and physical parameters affecting the shoreline with a single-groin structure, which is installed on the left side of the coastline, are presented. Then, we use the unconditionally stable Saulyev finite difference technique to predict the long-term shoreline evolution. The analytical solution to this mathematical model is also given. For alternative machine learning, we present the appropriate attributes to construct the training and testing datasets for long-term shoreline evolution. The definition and process of the K-nearest neighbor machine learning algorithm are presented. Then, we use the K-nearest neighbor machine learning algorithm to also predict the long-term shoreline evolution as well. The results of the study found that the evolution of the local coastline with a groin structure tends to increase continuously every year. Next, both introduced methods can be used to predict the evolution of local coastlines. Finally, the Saulyev technique has better computational efficiency than the K-nearest neighbor machine learning algorithm. Both results are closed together. However, in terms of ease of use, the K-nearest neighbor machine learning algorithm is more convenient due to the fact that the specialist who can implement the problem in the mathematical models is not required.

According to this research, the mathematical modeling outperforms the KNN regression algorithm with respect to computing efficiency for time periods of 0.5, 1, 5, 10, 15, and 20 years. Based on the modeling configuration and parameter simplicity, the KNN algorithm is still a good option for non-expert users. In addition, the results highlight the capabilities and limitations of applying mathematical models and machine learning techniques for shoreline evaluation forecasting.

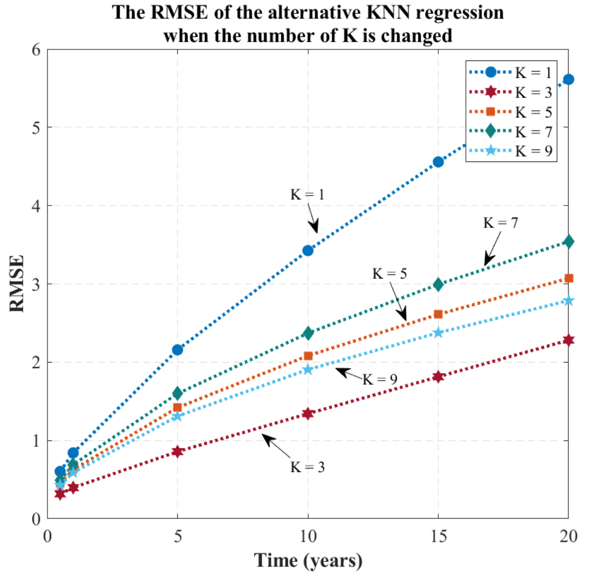

Fig. 4. The RMSE of the alternative K-nearest neighbor regression algorithm when the number of K is changed.

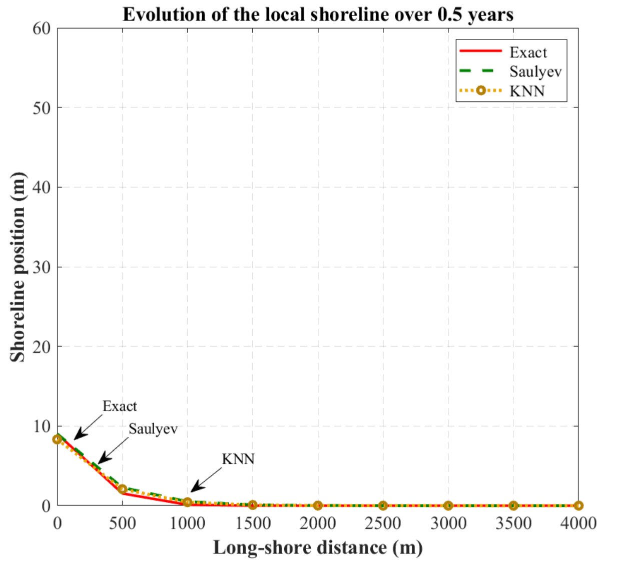

Fig. 5. Evolution of the local shoreline over 0.5 year (K = 3 and A6 = 180 days).

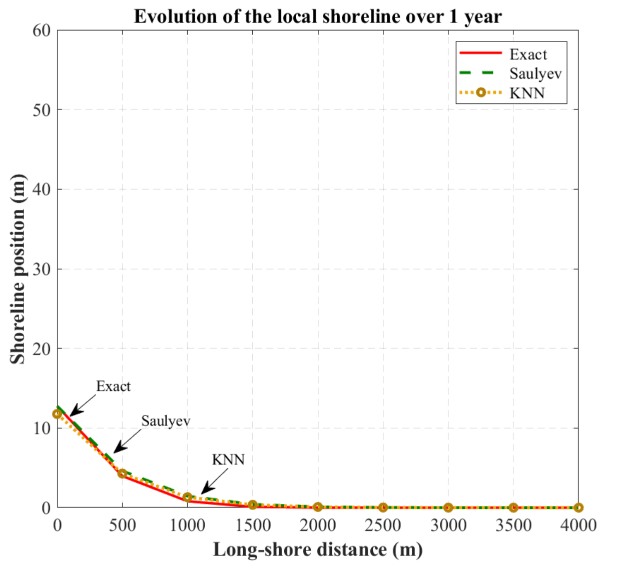

Fig. 6. Evolution of the local shoreline over 1 year (K = 3 and A6 = 360 days).

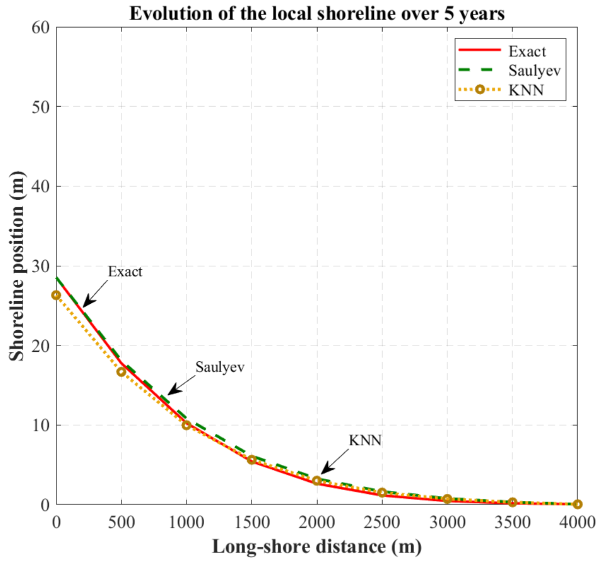

Fig. 7. Evolution of the local shoreline over 5 years (K = 3 and A6 = 1800 days).

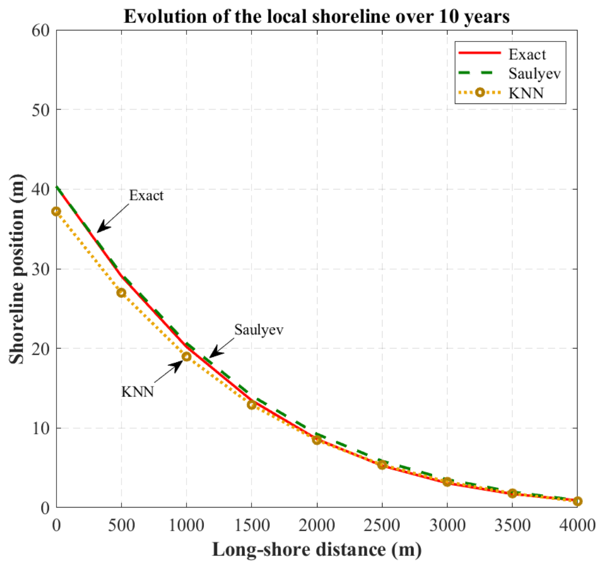

Fig. 8. Evolution of the local shoreline over 10 years (K = 3 and A6 = 3600 days).

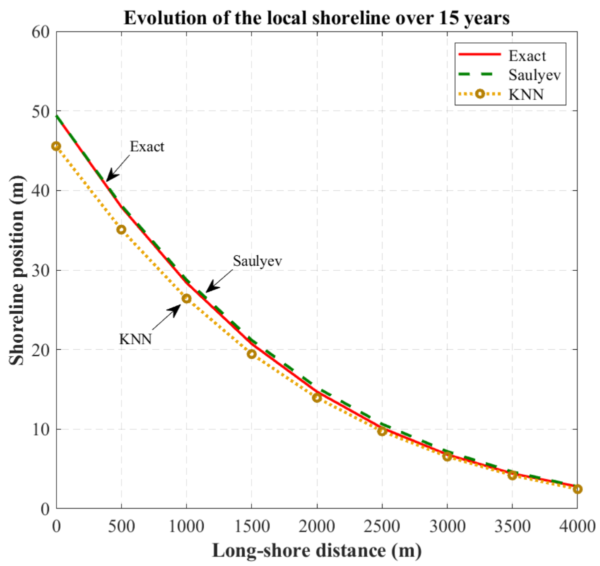

Fig. 9. Evolution of the local shoreline over 15 years (K = 3 and A6 = 5400 days).

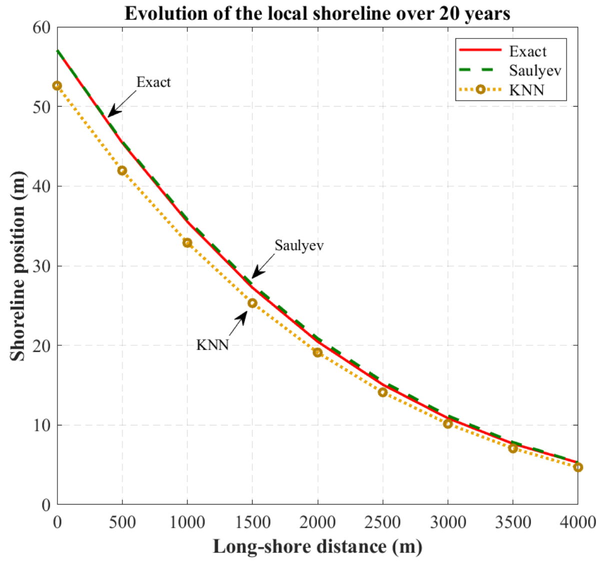

Fig. 10. Evolution of the local shoreline over 20 years (K = 3 and A6 = 7200 days).

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