



Research Paper

Assessing tidal flat deposition potential using spatial analysis: A case study on the northern coast of Vietnam

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ARTICLE INFO

Keywords:

Tidal flats
Potential for deposition
Spatial analysis
Relative discriminatory influence
Forcing factors

ABSTRACT

The evolution of tidal flats is influenced by various forcing factors resulting from interactions among terrestrial, oceanic, and atmospheric environments. This study employs spatial analysis models to assess the potential for deposition of tidal flats along the northern coast of Vietnam. A series of 14 forcing factor maps, categorized into four groups sediment sources, oceanographic factors, coastal properties, and tidal flat properties, is derived. These forcing factors are analyzed using both heuristic and empirical approaches, and their relevance to deposition during the period 1989–2014 is evaluated using the Relative Operating Characteristic (ROC) method. The analysis quantifies the relative discriminatory influence of each factor on historical deposition. Subsequently, the Multi Criteria Evaluation (MCE) method is applied to integrate critical factors with varying weights, generating 9 scenarios of deposition potential. Scenario 5, produced using a weight series linearly proportional to the relative discriminatory influence of the forcing factors and showing the best fit to historical deposition, is selected to generate the potential map of future tidal flat deposition. This map achieves an accuracy of 77.6%, indicating high deposition potential around the Red River mouth and low potential along rocky coastal tidal flats. The study represents a significant advancement in applying complex spatial analysis methods to predict the potential for future changes of tidal flats within diverse coastal environments at a large scale.

1. Introduction

Tidal flats, the area is alternately submerged and exposed to the air due to tidal level variations, formed by the interactions between marine processes, freshwater, and land (Gao, 2019). Any variation in tidal flats serves as an indicator of changes in the physical, chemical, and biological processes occurring in both land and ocean environments (Wang et al., 2019). Tidal flat evolution under different conditions is controlled by various driving forces including wind climate, tidal range, sediment characteristics, coastal morphology, temporal variability, and human activities (Ostrowski et al., 2009; Zhu et al., 2024). Understanding the evolution of tidal flats is a key parameter for making plans for substantial development in terms of climate change and human impacts (Zhang et al., 2022).

The geomorphology of coasts, sediment characteristics and the properties of tidal flats are critical driving factors of tidal flat changes. A concave-upward profile enhancing the maximum ebb current is in cases

of erosion and a convex profile strengthening flood currents in cases of net deposition (Kirby, 2000; Pritchard and Hogg, 2003). Erosion and deposition occur throughout the entire water column in shallow waters, and these processes are influenced by the slope and width of the tidal flats (Wright et al., 1999). Sediments of various particle sizes are transported by the direction of tidal flow and waves to form tidal flat surfaces, which exhibit lenticular, wavy, and flaser bedding (Klein, 1985). Small grain sizes including silt and clay cause particles to aggregate, reducing erosion compared to sandy tidal flats (Dyer et al., 2000; Wang, 2012). Coarse sediments in tidal flats are characterized by less consolidation, making these flats more prone to erosion (Wang, 2012). Additionally, the cohesive properties of sediment are also influenced by the content of organic matter and carbonate components. Halophytic plants, algae, and microphytobenthos produce carbohydrates and they trap suspended sediment, increasing sediment stability and raising the elevation of intertidal flats (Fulweiler et al., 2015). Surface roughness of tidal flats measured by the scale of ripples, is

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Received 19 March 2025; Received in revised form 4 June 2026; Accepted 13 July 2026

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influenced by current speed, sediment grain size, and, to some extent, water depth (Wright et al., 1999). The smooth surface of muddy environments, with reduced turbulence and cohesive sediment properties, enhances deposition (van Ledden et al., 2004). Longer exposure of fine sediments in tidal flats to air and higher temperatures help stabilize the sediment, leading to a flatter surface and maximizing accretion (Nguyen et al., 2022).

Meteorological factors including seasonal variations, wind and storms inducing waves, directly influence sediment flux, leading to changes in tidal flats (Brigit, 2000). Offshore wind direction is a crucial factor affecting the deposition because it extends the aerial exposure time and increases the duration of slack water, which enhances the consolidation rate of sediments (Colosimo et al., 2023). Back-barrier settings, tidal-dominated estuaries, deltas, and adjacent chenier plains experience increasing wind and wave exposure (Daidu, 2013). During storms, sediment is predominantly transported seaward (Yang et al., 2003), however, tidal marsh grasses tend to accrete vertically as storm waves dissipate due to the presence of marsh grass (Friedrichs and Perry, 2001). The seasonal cycle between erosional and depositional states of tidal flats is influenced by meteorological variations that direct seasonal sediment conditions (O'Brien and McPherron, 2000).

According to the concept of dynamic equilibrium, a mudflat or other sediment-water system adjusts to a stable form if given sufficient time and consistent forcing conditions (Roberts and Whitehouse, 2001). Numerous studies have applied dynamic equilibrium theory to predict morphological changes in tidal flats, considering local factors such as waves, tides, sediment sources, and sinks (Friedrichs, 2011; Petti et al., 2019). Defining the appropriate type of equilibrium for a coastline is particularly difficult (Perillo, 2012), and many issues arise in quantifying and defining the relevant conditions (Perillo and Syvitski, 2010; Hu et al., 2015; Hu et al., 2018). In the field of machine learning, although artificial neural networks (ANNs) have shown strong performance in spatial data prediction, their application is often limited by challenges in interpretability and the need for large training datasets to achieve high accuracy (Nikparvar and Thill, 2021). Tidal flats, as a dynamic landcover class, can be analyzed for potential changes using spatial models within a geographic information system (GIS) (Lambin et al., 1994). Spatial models such as GEOMODE and Land Change Modeler have been widely applied to study land use, landcover, and forest changes (Agarwal et al., 2002; Hosonuma et al., 2012; Bax et al., 2016). However, tidal flats, a unique land cover shaped by interactions among terrestrial, oceanic, and atmospheric systems, pose challenges for spatial analysis, which require further methodological advancements, particularly in quantifying the relative discriminatory influence of individual forcing factors.

The physical mechanisms of sediment processes are well understood, predicting sedimentation remains challenging due to site-specific variations (Black et al., 2002). Furthermore, the evolution of tidal flats is highly dynamic due to the influences of both natural factors (Elmilady et al., 2022; Nguyen et al., 2022) and anthropogenic factors (Pan et al., 2022; Zhang et al., 2022). These previous studies have identified the forcing factors that drive the evolution of tidal flats; however, the comparative influence of these factors on tidal flat variations requires more comprehensive investigation. This study aims to optimize the spatial analysis proposed by Walker et al. (2013) for the tidal flat environment with the following objectives: (1) quantify the relative discriminatory influence of forcing factors on the deposition of tidal flats, and (2) construct scenarios of potential deposition by integrating forcing factor maps for tidal flats along the northern coast of Vietnam. This study pioneers the identification of the hierarchical influence of forcing factors on deposition and offers insights into future variations of tidal flats through spatial analysis models, thereby supporting decision-making and the sustainable management of intertidal zones.

2. Study area

Tidal flats in the north of Vietnam are formed along the 350 km coastline next to the Gulf of Tonkin, suffering a 3.5 m tidal range with a diurnal regime. The coastline, oriented at a 45° angle from northeast to southwest, faces a shallow sea averaging 50 m in depth. The coastline can be divided into the southern and northern parts, across 13 sections (Fig. 1). The southern part, from Kim Son to Yen Hung is an estuarine area where the tidal flats are predominantly composed of sediment from the Red River Delta. The Red River with the length of 1149 km annually carries an average of 82×10^6 tons of sediment, contributing to the development of extensive muddy tidal flats (Do et al., 2007). The strong interaction between river water and wave currents forms the estuarine back barrier tidal flats with series sand banks seaward in Kim Son, Giao Thuy, and Tien Hai. The northern part from Ha Long to Mong Cai is characterized by mountainous coastal regions with the steep slope of topography and high precipitation in monsoon climate to generate numerous short-lived, temporal rivers. The coastal area faces more than 2300 islands with a height reaching up to 400 m, as far as 10 km from the shoreline. The complex interplay of land, ocean, and atmospheric conditions gives rise to the diverse formations of tidal flats in northern Vietnam (Dang et al., 2020; Tong et al., 2020).

3. Data in use

3.1. Historical deposition of tidal flats

Historical vertical changes of tidal flats using in this study were investigated from multi-temporal satellite images through two periods 1989–2000 and 2000–2014 (Tong et al., 2020). Three maps of historical deposition are produced to coordinate the deposition areas for periods 1989–2000, 2000–2014, and 1989–2014. The maps consist of Boolean values with 1 or 0 corresponding to deposition or non-deposition area. Deposition areas are dominant in the southward area (block A and B) but less in the North (block D and E) indicated in Fig. 2.

3.2. Forcing factors influencing tidal flat deposition

Forcing factors are grouped into four categories consisting of sediment sources, oceanographic forcing factors, coastal properties, and tidal flat properties. Maps of factors are registered to the same projection WGS 84 zone 48 N with the pixel size of 30 m × 30 m to fit with the historical deposition maps. Consequently, forcing factors are represented on the extent of tidal flats in 2014 to generate 14 factor maps.

3.2.1. Forcing factors related to sediment sources

River mouth distance: Along the northern coast of Vietnam, 30 rivers with the length greater than 30 km are used to create river mouth distance map. The furthest distance from the river mouths is 9.9 km in Hai Hau (Fig. 3A) while the shortest distance is from Dam Ha to Mong Cai due to the high concentration of small river mouths.

River sediment source: A scheme of 10 sediment sources is relatively determined based on the separation of sediment distribution along the coast (Fig. 3B). Tidal flats in Kim Son developed in an embayment, are mainly fed by the mixed sediments from the Ma, the Ninh Co and the Day rivers. The Red River supplies sediment to tidal flats from Hai Hau to Thai Thuy. Tidal flats in Cam Pha are characterized by the clay coal sediments (Tong et al., 2020), but sediments in the tidal flats in Hai Ha are coarse particles due to the short, steep slope rivers.

Net sediment distribution represents the relative distribution of suspended sediment on tidal flats, interpolated linearly based on the distance from river mouths and the sediment load transported by rivers from Kim Son to Thai Thuy (Hoa, 2001) and from Do Son to Mong Cai (Pham, 2005) (Fig. 3C). The sediment distribution (Fig. 3D) provides a relative comparison of the suspended sediment distribution across tidal flats rather than the actual amount of sediment deposition. The values

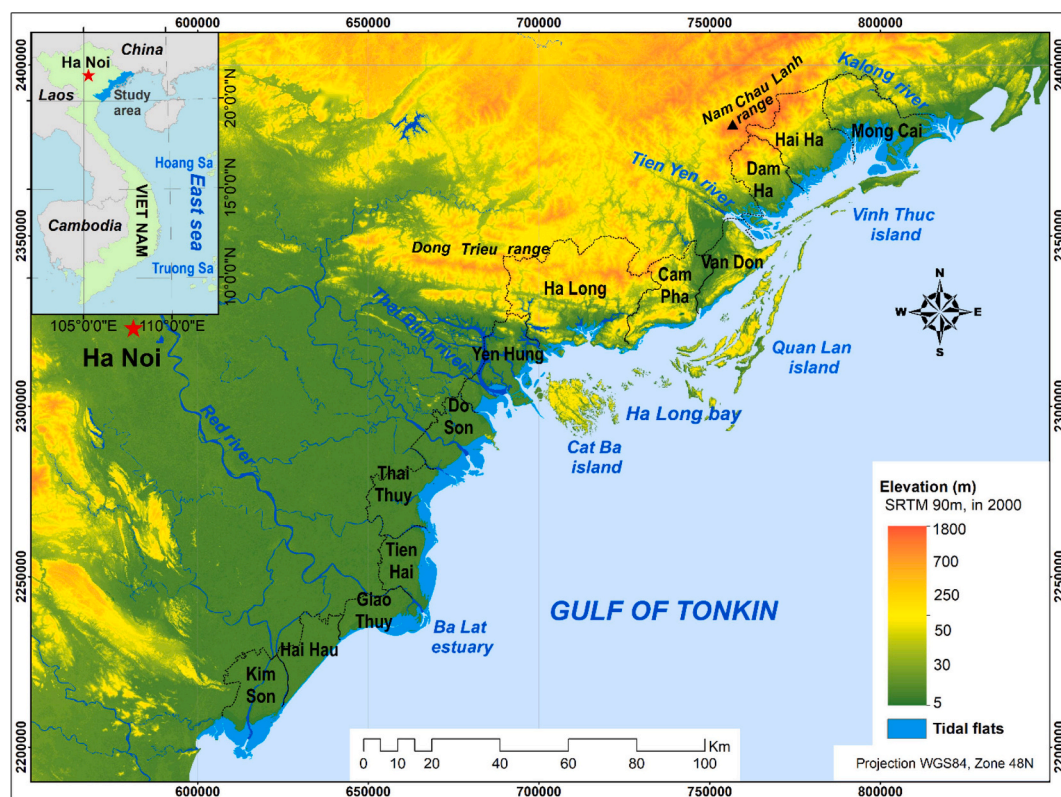


Fig. 1. Geographical map of the study area with the Red River delta surrounded by mountainous topography in the North and the West, and Gulf of Tonkin in the East and the South. Tidal flats (light blue area) formed along the coast with corresponding names of coastal sections. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

indicated in Fig. 3D represent the annual sediment load from rivers distributed over a 900 m² area (30 m × 30 m pixel size) on tidal flats.

3.2.2. Oceanographic forcing factors

Wind, wave effect: The wind-wave forcing factor is mapped based on the exposure of tidal flats to wind, and waves from the Gulf of Tonkin with the 3 levels the high, medium, and low effects (Fig. 4A). The low effect area covers the tidal flats from Ha Long to Mong Cai due to the presence of seaward islands, reducing the influence of wind and waves. The tidal flats surrounding the Red River mouth are categorized as medium effect because of the sandbars with 4 m height forming the back-barrier tidal flats. High effect of wind, waves is at the open-coast tidal flats.

Sea water velocity: Velocity and direction of sea surface water are monthly composited from the altimetry satellite sources of the National Oceanic and Atmospheric Administration (NOAA) organization. An average of sea surface water velocity with a spatial resolution of 0.25 degrees in the 2010–2013 period is collected to map the forcing factor of sea water velocity impacting to the tidal flats. The map of sea water velocity forcing factor shows the strongest impact (0.8 m/s) in Hai Hau (Fig. 4B).

3.2.3. Forcing factors related to coastal properties

Coastline length: A coastline segment is defined as a relative straight line starting from a point on shoreline and ending at a river mouth or at a point which changes the coastline orientation. The length of the coastline is determined as the projection of the coastal segment onto the meridian. The coastline lengths are in the range of 159 m - 27,770 m, represented on the tidal flat (Fig. 5B).

Coastline orientation is known as the direction of a coastline segment, presenting the level of seaward facing. The wave direction, assumed to be uniform with the wind direction, exerts the most

significant coastal erosion force when forming a 45° angle with the shoreline and decreases on either side (Ashton and Murray, 2006). Coastline orientation ranges from 0° to 90°, which is relative to the prevailing wind (the NE-SW direction) (Fig. 5A).

Coastal land-cover refers to the physical characteristics of coastal areas. The coastal land-covers are categorized into closed mangrove, open mangrove, rocky coast, aquaculture areas, sand bars/islands, and concrete dyke. The coastal land-cover map was constructed using supervised classification of Landsat 8 satellite imagery captured in 2014 (Fig. 5C).

Near-shore slope: The slope of the seabed counted from tidal flats to the depth of −20 m is mentioned as near-shore slope, which is represented on tidal flats (Fig. 5D). The −20 m depth contour is extracted from topographic maps of the sea floor at the scale 1/100,000.

3.2.4. Forcing factors of tidal flat properties

Tidal flat width is generated from the extent of tidal flats in 2014 (Tong et al., 2020). The tidal flats surrounding the Red River mouths are the largest with a maximum width of 7819 m, but the narrowest tidal flat is in Van Don with a 43 m wide (Fig. 6A).

Tidal flat slope: The DEM of tidal flats in 2014 (Tong et al., 2020) is used to generate the slope map. The slope value of a pixel in the DEM is calculated by the maximum change rate in elevation values from that pixel to its 8 surrounding neighbors. The slope of tidal flats is generally very low with a range of 0.000° – 0.099° (Fig. 6B).

Exposure time of tidal flats is the amount of time in a year that tidal flats are exposed to the air. Hourly tide data at the Do Son gauge station in 2014 is used to investigate the correlation between exposure time and tide levels (Fig. 6C). The exposure time of tidal flats (Fig. 6D) is the result of integrating the elevation of the tidal flat DEM in 2014 and the amount of time at a specific tide level.

Tidal flat roughness and tidal flat moisture: The roughness of the

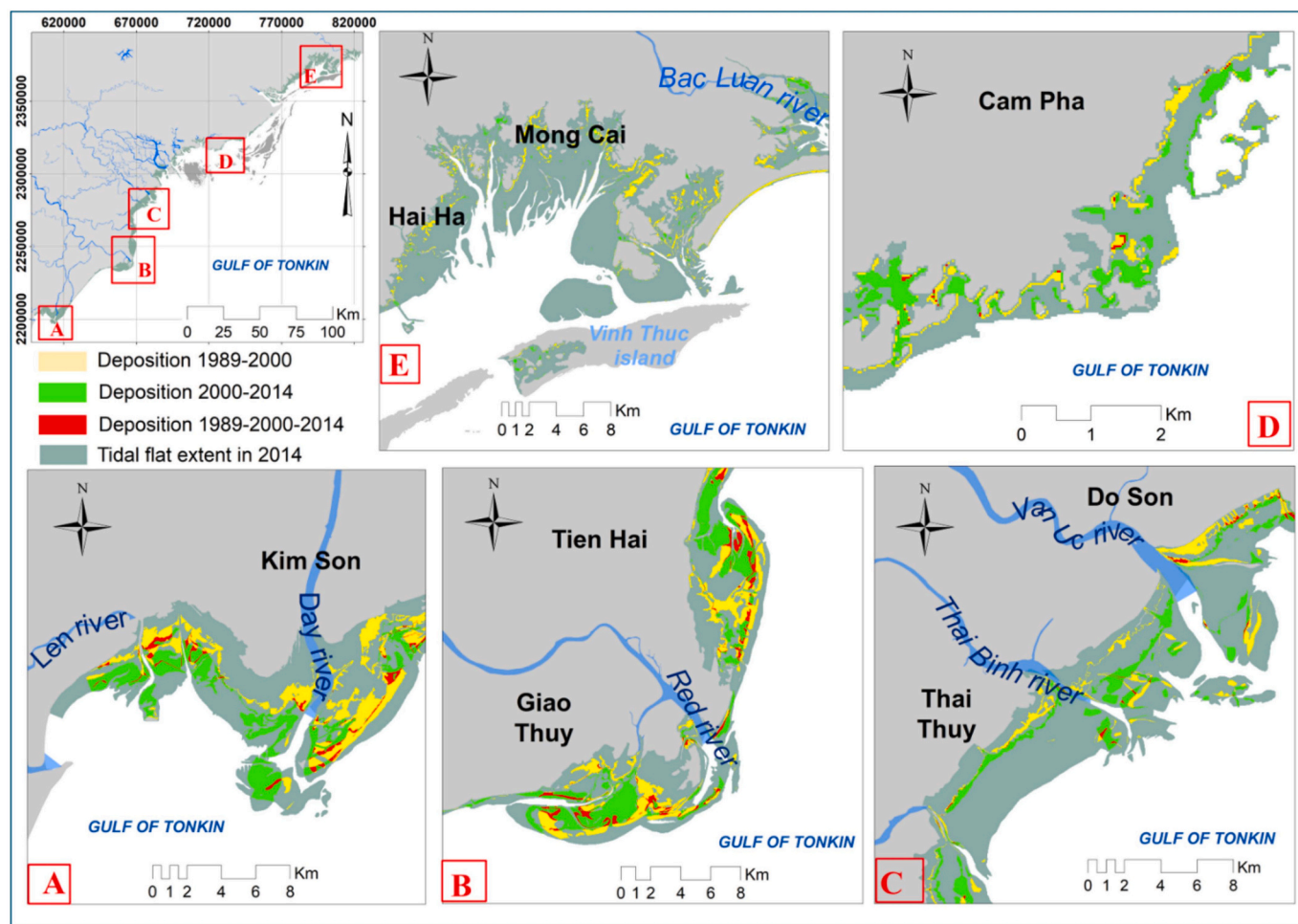


Fig. 2. Deposition map of tidal flats in periods 1989–2000 (yellow area), 2000–2014 (green area), and during the entire 1989–2014 period (red area). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

tidal flat surfaces is the mean height of crests on tidal flats within an area while the tidal flats expose to the air. The surface roughness (Fig. 5E) and soil moisture (Fig. 5F) are calculated by the Oh model (Oh, 2004) applied for Sentinel-1 A SAR images acquired on July 2015, detailed in our previous study (Tong et al., 2017).

4. Methodology

This study employs spatial analysis methods to assess the potential deposition of tidal flats (Fig. 7). Input data for the model includes 14 forcing factor maps and deposition maps through periods 1989–2000, 2000–2014, and 1989–2014. Each forcing factor is critically assessed for its relevance to the historical deposition through both heuristic approach and empirical approach to generate heuristic factors and empirical factors. The Relative Operating Characteristic (ROC) statistic method is used to evaluate the effect of these factors on the historical deposition. The factors with significant influences are integrated in the Multi Criteria Evaluation (MCE) method to generate maps of the potential deposition. The proposed framework is positioned as complementary to process based models, offering a computationally efficient means of regional scale screening where detailed hydrodynamic data and numerical solvers are not available. The model does not solve hydrodynamic or sediment transport equations and should therefore be interpreted as a spatial susceptibility assessment rather than a physically based morphodynamical simulation.

4.1. Mapping heuristic factors and empirical factors

The heuristic approach assesses the relevance of a factor map covering the changes based on a theoretical base. Factor values are linearly rescaled to integers from 0 to 255, with 0 and 255 representing the lowest and highest contributions to deposition. For example, the further away from river mouths is, the lower suspended sediment transports that tend to decrease the deposition rate. Comprehensive rules of how forcing factors affecting the deposition are listed in Table 1. Heuristic factors are ranked as a continuous data type, and hence the factors measured in categorical data (River sediment sources, Wind-wave effects, Coastal land-cover) are not a heuristic factor. The normalization of heuristic factors to a 0–255 scale supports a data driven susceptibility assessment rather than a process-based simulation at the regional scale; thus, the method is suitable for comparative analysis but does not explicitly resolve local nonlinear or threshold-controlled morphodynamical processes.

The empirical approach ranks areas based on the spatial relationship between forcing factors and historical changes (real changes). For this approach, forcing factors are overlaid to the 1989 tidal flat area to analyze their relationship with actual deposition. The 1989 tidal flats are assumed to result from historical deposition processes. However, only the remained areas after subtracting the 1989–2014 deposition from tidal flats in 1989 are overlaid with the forcing factors. The factor's values are categorized into equal intervals. A cross-tabulation analysis compares forcing factors with the remaining tidal flats in 1989 by counting pixels fully belonging to each category. Depositional

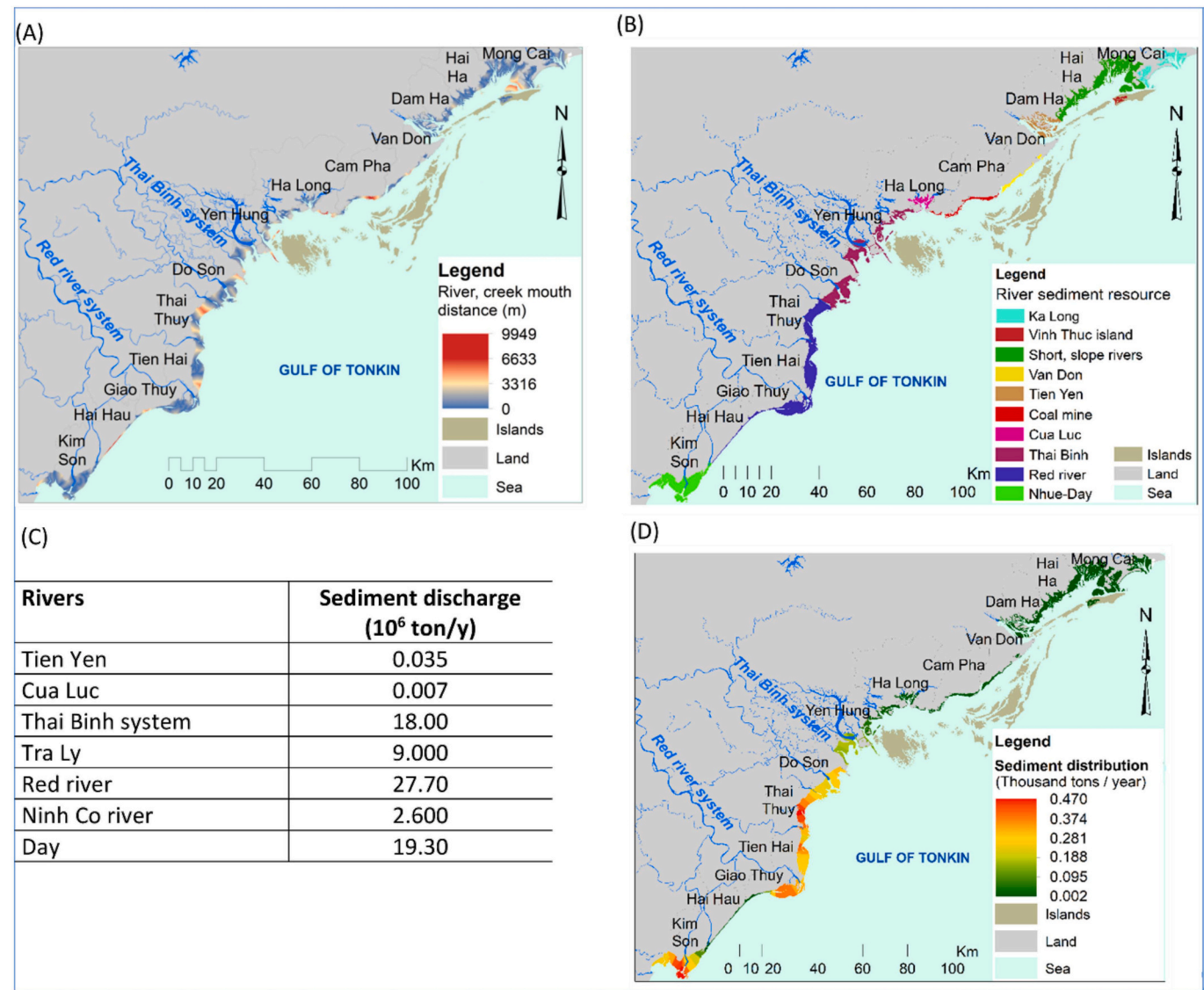


Fig. 3. (A) Map of river mouth distances, (B) Map of river sediment source, (C) Annual sediment discharge of rivers, and (D) Map of the annual relative distribution of suspended sediment transported from rivers on the tidal flat (ton/year/900 m²).

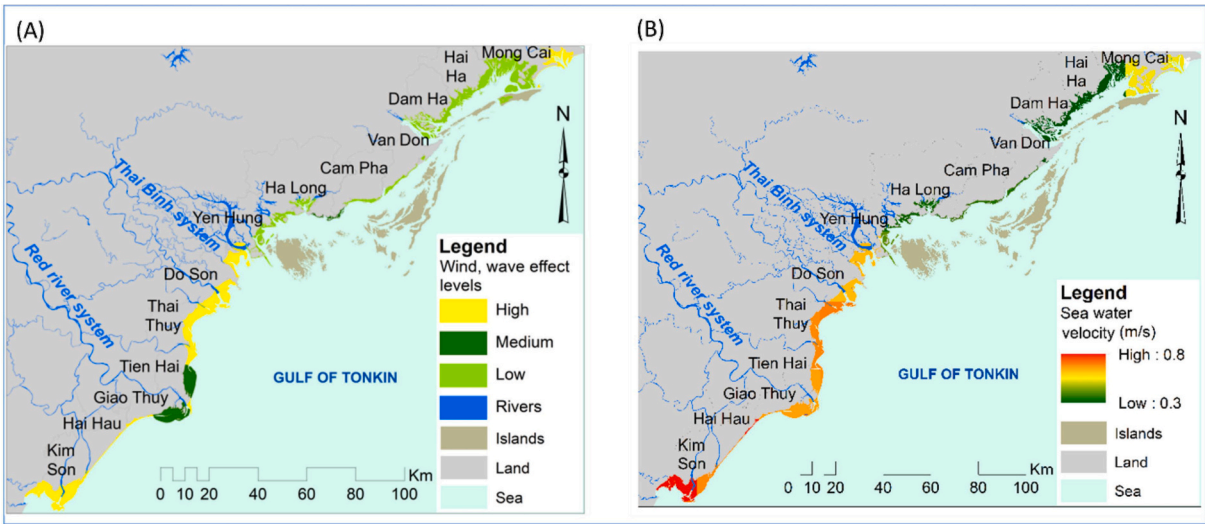


Fig. 4. (A) Map of wind-wave effect, and (B) Map of sea water velocity affecting tidal flats.

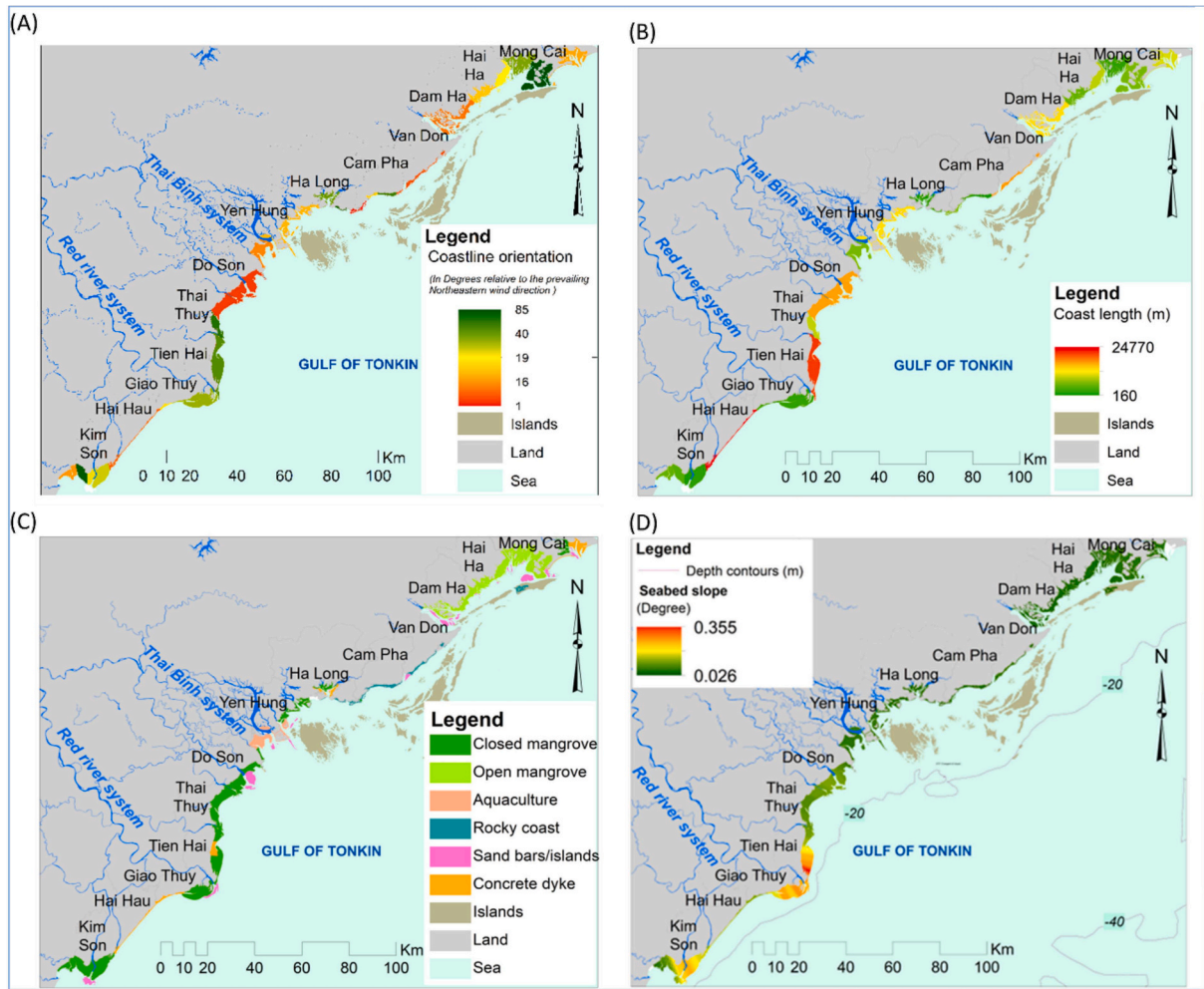


Fig. 5. (A) Coastline orientation relative to the predominant Northeastern wind direction, (B) Map of coastline length, (C) Coastal land-cover, (D) Map of near-shore seabed slope represented on tidal flats.

proportions are then assigned to the corresponding forcing factor categories. Empirical factors are created by scaling assigned values to a 0–255 range. Unlike heuristic factors, empirical factors are generated for all 14 forcing factors, including both continuous and categorical data types.

4.2. ROC and MCE methods

The ROC is the primary method used to evaluate how well a forcing factor represents historical deposition without quantifying the changes precisely (Pontius and Schneider, 2001). Forcing factor maps are segmented by ROC using multiple thresholds. The ROC compares simulated images (forcing factor maps) with the reference image (historical deposition map), generating summary statistics from multiple two-by-two contingency tables, each corresponding to a threshold. For each threshold, false positive (x) and true positive (y) percentages are calculated to form data points (x, y), which collectively create the ROC curve. The Area Under the ROC Curve (AUC) provides a summary measurement, where a higher AUC indicates the forcing factor portraying better the location of historical deposition map. The AUC is calculated using the following equation.

$$AUC = \sum_{n=1}^n (x_{i+1} - x_i) \left\{ y_i + \frac{(y_{i+1} - y_i)}{2} \right\} \quad (1)$$

Where x_i , y_i are the percentage of false positives and the percentage of true positives for threshold i , respectively. n is the number of

thresholds.

The MCE is a decision support method which attempts to combine a set of criteria to achieve a single composition according to a specific objective. The MCE method is implemented for various combinations of forcing factor maps with different sets of weights to achieve the highest potential for deposition. Each factor is multiplied with its weight and then added to the results. Weights for factors are defined in constraining that the sum of factor weights is equal one.

$$D = \sum_{i=1}^{14} w_i a_i \quad (2)$$

Where D is a potential for deposition, w_i is a weight corresponding to forcing factor a_i .

4.3. Assessment process for future deposition potential of tidal flats

Heuristic factors, empirical factors, and historical deposition maps serve as input data to assess tidal flat deposition potential. The analysis occurs in two phases. In the first phase, 11 heuristic and 14 empirical factors are evaluated against 1989–2014 deposition using the ROC method. Each forcing factor has two versions (heuristic and empirical), but only the one with the higher AUC value is selected. In the second phase, the MCE method combines selected factors with weight sets based on AUC values. Each weight set generates a potential deposition scenario, which is then evaluated using ROC to determine the best match with historical deposition from 1989 to 2000 and 2000–2014. For all scenarios, weights were renormalized following perturbation to ensure

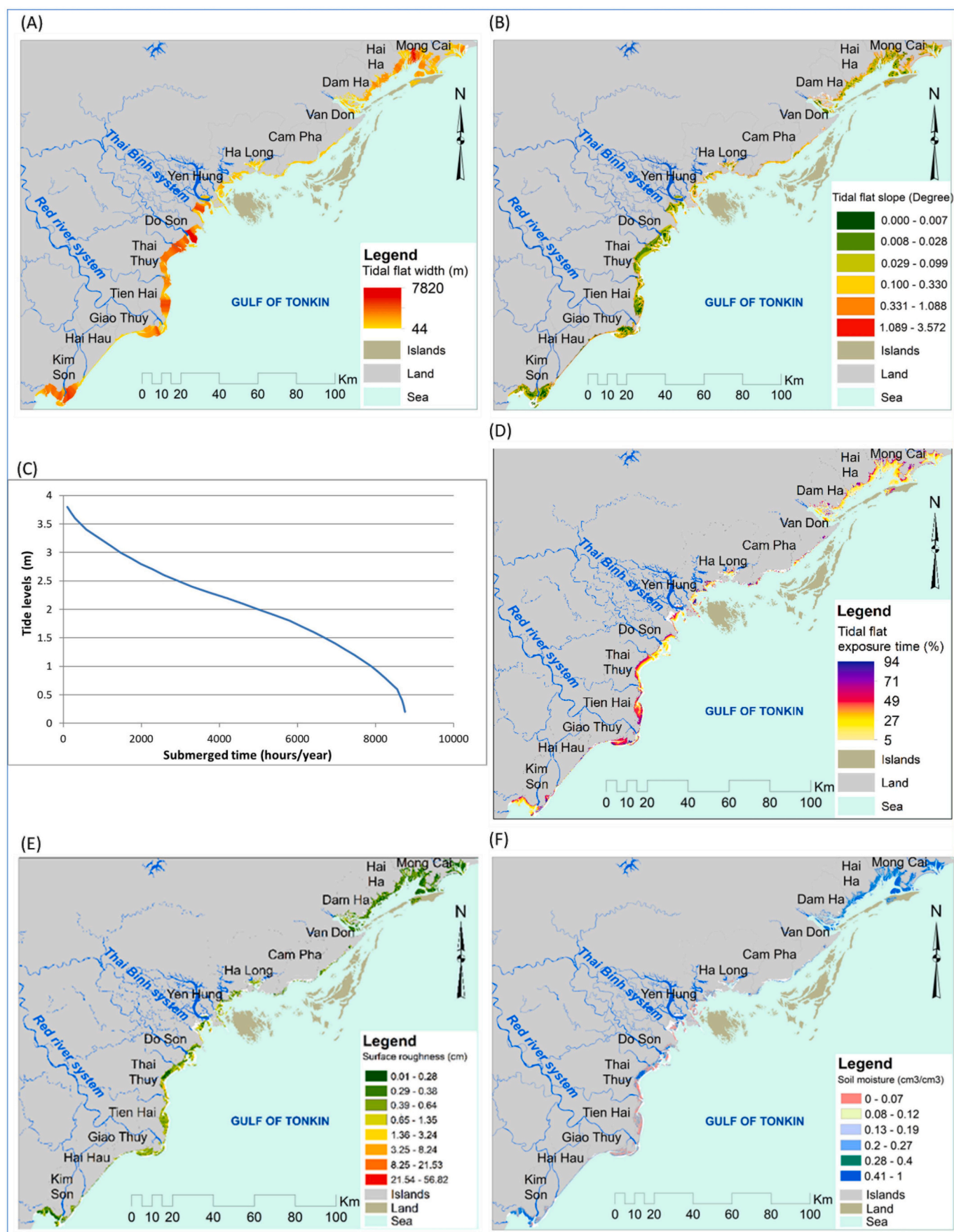


Fig. 6. (A) Map of tidal flat width, (B) Map of tidal flat slope, (C) The correlation between the tide levels and the exposure time, (D) Map of the percentage of tidal flats exposure time throughout the year, (E) Surface roughness map of tidal flats, (F) Soil moisture map of tidal flats.

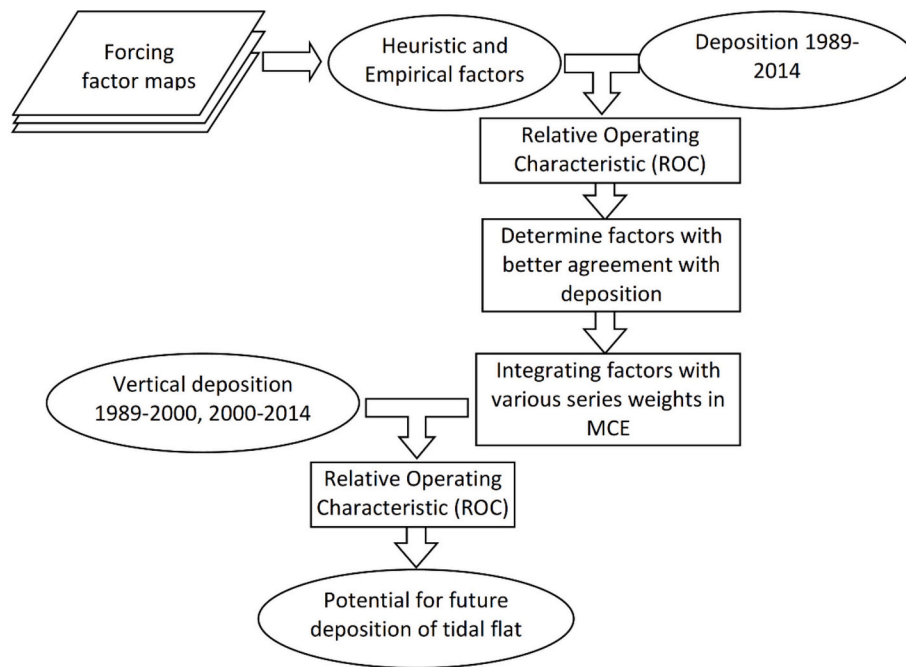


Fig. 7. Flow chart to assess the potential for deposition of tidal flats.

Table 1
Comprehensive rules of forcing factors affecting the deposition of tidal flats.

Factors	Range of values (unit)	Comprehensive rules
River mouth distance	0–9949 (m)	Higher value, lower deposition
Net sediment distribution	2–470 (ton/year/900m ²)	Higher value, higher deposition (Cao et al., 2023)
Sea water velocity	0–0.8 (m/s)	Higher value, lower deposition (Zhou et al., 2022a; Zhou et al., 2022b)
Coastline orientation	0°–45°	Higher value, higher deposition (Ashton and Murray, 2006)
	45°–90 °	Higher value, lower deposition (Ashton and Murray, 2006)
Coastline length	159–24,770 (m)	Higher value, lower deposition
Near-shore seabed slope	0.026–0.355 (degree)	Higher value, lower deposition (Wright et al., 1999)
Tidal flat width	43–7919 (m)	Higher value, higher deposition (Wright et al., 1999)
Tidal flat slope	0–3.572 (degree)	Higher value, lower deposition (Wright et al., 1999)
Exposure time	5–94 (%)	Higher value, higher deposition (Colosimo et al., 2023)
Tidal flat moisture	0–0.34 (m3/m3)	Higher value, higher deposition
Tidal flat roughness	0–35.2 (cm)	Higher value, lower deposition (van Ledden et al., 2004)

that their sum remained equal to one, thereby preserving comparability among aggradation potential maps. The scenario with the highest Root Mean Square (RMS) of AUC values across both periods is chosen as the future deposition potential map. The ROC analyses were conducted using the scikit-learn library implemented in the Python programming language, with input images of uniform dimensions (7587 columns × 6724 rows) and 256 equally spaced threshold intervals. Consequently, the map of future deposition potential is classified into three levels the high, medium, and low potential based on the Natural break method. Above all, the historical deposition maps for 1989–2000 and 2000–2014 were used to quantify the relative discriminatory influence of individual forcing factors through ROC analysis and to support the development of weighting scenarios. The resulting deposition potential scenarios were

subsequently compared with the historical deposition patterns over the entire 1989–2014 period to evaluate internal spatial agreement, without implying independent or time-forward predictive validation. The final deposition potential map was validated using temporally independent elevation and positions of waterline derived from satellite imagery acquired in 2021 and 2022. Waterline elevations were referenced to the corresponding water levels at the time of image acquisition, enabling an independent assessment of the spatial agreement between predicted deposition potential and depositional areas observed after model construction.

5. Results

5.1. Forcing factors versus depositions in the period 1989–2014

Fig. 8 presents the ROC assessment of 14 empirical and 11 heuristic maps against tidal flat deposition from 1989 to 2014. Overall, AUC values are relatively low, with 16 of 25 factors scoring below 0.5. The sediment sources group has the highest explanatory power, particularly the net sediment distribution, which peaks at 0.70 for the heuristic factor and 0.65 for the empirical factor. The tidal flat properties group follows, with the exposure time (0.68) and the tidal flat width (0.58) showing strong correlations with deposition. In contrast, the oceanographic forcing and coastal properties groups provide weaker explanations. The lowest AUC values belong to near-shore bottom slope (0.30 heuristic, 0.31 empirical) and tidal flat moisture (0.37 heuristic, 0.39 empirical). The exposure time shows a higher heuristic factor (0.68) compared to its empirical counterpart (0.38), whereas sea water velocity has a higher empirical factor (0.54) than heuristic (0.33).

Based on ROC evaluation, 7 selected heuristic factors are net sediment distribution, river mouth distance, coastal orientation, tidal flat width, surface roughness, tidal flat slope, and exposure time. The selected 5 empirical factors are sediment source, sea water velocity, wind-wave effect, coastline length, and coastal landcover. Due to insufficient AUC values, the near-shore bottom slope and the tidal flat moisture are excluded from the potential deposition model.

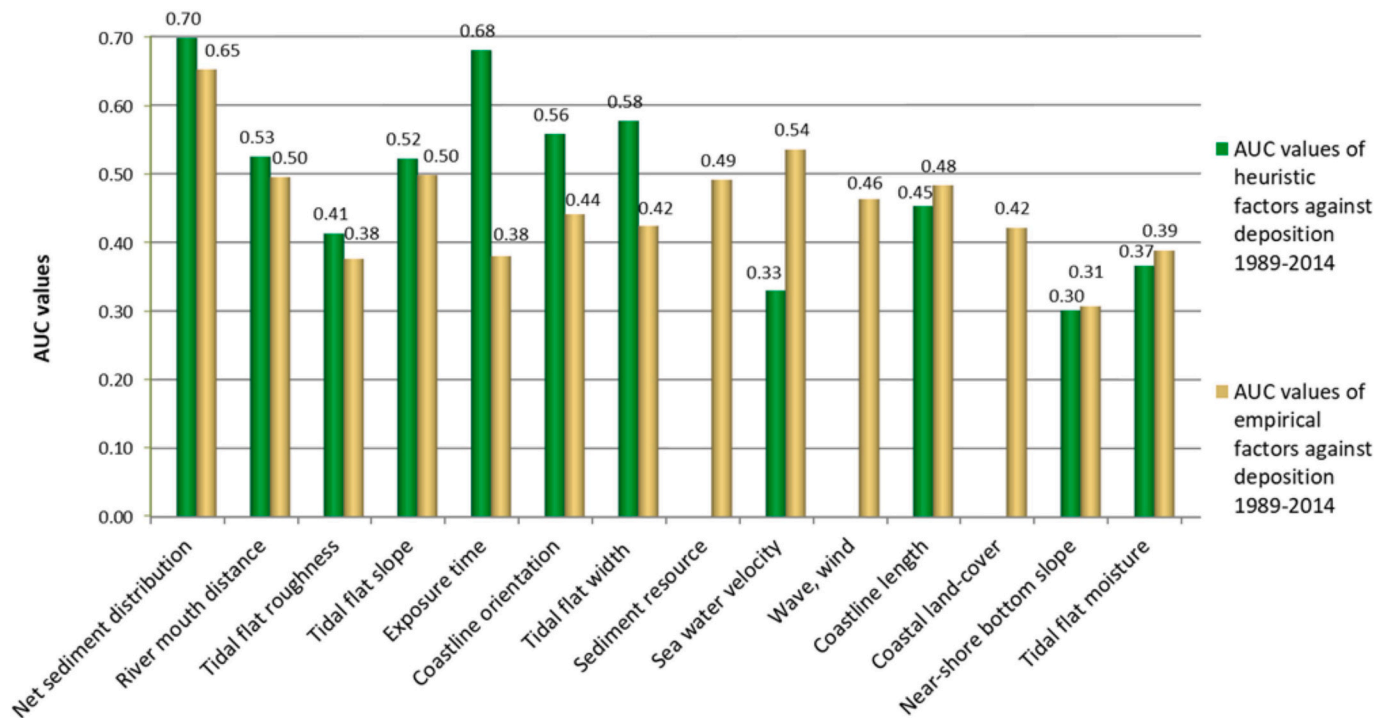


Fig. 8. AUC values of heuristic and empirical factors against tidal flat deposition in the period 1989–2014.

5.2. The relative discriminatory influence of factors on deposition potential

Heuristic and empirical factors are separately applied in the MCE method to generate potential deposition maps. Factors are evaluated against historical deposition from 1989 to 2000 and 2000–2014 using the ROC tool. To assess the relative discriminatory influence of a factor on the deposition potential, the factor is tested twice with different weights. Initially, the heuristic factor is assigned a weight of 20% while the other factors are set to 13.3%. In the second test, the heuristic factor's weight increases to 40%, and the remaining heuristic factors are adjusted to 10%. The difference in AUC values between these tests measures the factor's influence, with the RMS index summarizing AUC variations across both periods (Table 2). Overall, the influence of individual factors is relatively low, with RMS differences ranging from -0.047 to 0.002 . The tidal flat width factor shows the weakest contribution, with an RMS difference of -0.047 , indicating that even when its weight is doubled, it has minimal impact on deposition potential. The

corresponding potential map (Fig. 9A) shows high deposition potential concentrated in wide tidal flats. Coastal orientation and tidal flat slope also have low influence, with RMS differences of -0.021 and -0.020 , respectively. Conversely, river mouth distance and exposure time exhibit the highest influence, with a positive RMS difference of 0.002 . Notably, the exposure time factor significantly enhances deposition potential maps, showing the strongest agreement with historical deposition. When assigned weights of 20% and 40% for the exposure time factor, the resulting maps yield RMS of 0.720 and 0.722 , respectively, the highest among all factors.

Five empirical factors are applied the same method as heuristic factors. Each empirical factor is assigned weights range from 30% to 54% to invest the changes in AUC values (Table 3). AUC values for 1989–2000 are higher than those for 2000–2014. The wind-wave effect factor has the lowest AUC values for both periods with 0.459 and 0.423 of RMSs, respectively, indicating minimal impact on deposition potential, with an RMS difference of -0.036 . The wind-wave factor is set the weight at 54%, while other factors are set to 11.5%, the resulting

Table 2

Relative discriminatory influence of heuristic factors measured by the difference of AUC values achieved from adjusting factor's weights.

Weights (%) of heuristic factors for combination in MCE							AUC	AUC	RMS of	Different RMS
Net sediment distribution	River mouth distance	Coastline orientation	Tidal flat width	Tidal flat roughness	Tidal flat slope	Exposure time	1989–2000	2000–2014	AUCs	of AUCs
20.0	13.3	13.3	13.3	13.3	13.3	13.3	0.637	0.777	0.710	
40.0	10.0	10.0	10.0	10.0	10.0	10.0	0.629	0.767	0.701	–0.009
13.3	20.0	13.3	13.3	13.3	13.3	13.3	0.635	0.776	0.709	
10.0	40.0	10.0	10.0	10.0	10.0	10.0	0.641	0.775	0.711	0.002
13.3	13.3	20.0	13.3	13.3	13.3	13.3	0.635	0.765	0.703	
10.0	10.0	40.0	10.0	10.0	10.0	10.0	0.629	0.731	0.682	–0.021
13.3	13.3	13.3	20.0	13.3	13.3	13.3	0.632	0.755	0.696	
10.0	10.0	10.0	40.0	10.0	10.0	10.0	0.617	0.679	0.649	–0.047
13.3	13.3	13.3	13.3	20.0	13.3	13.3	0.634	0.770	0.705	
10.0	10.0	10.0	10.0	40.0	10.0	10.0	0.635	0.745	0.692	–0.013
13.3	13.3	13.3	13.3	13.3	20.0	13.3	0.627	0.771	0.703	
10.0	10.0	10.0	10.0	10.0	40.0	10.0	0.605	0.753	0.683	–0.020
13.3	13.3	13.3	13.3	13.3	13.3	20.0	0.629	0.801	0.720	
10.0	10.0	10.0	10.0	10.0	10.0	40.0	0.594	0.831	0.722	0.002

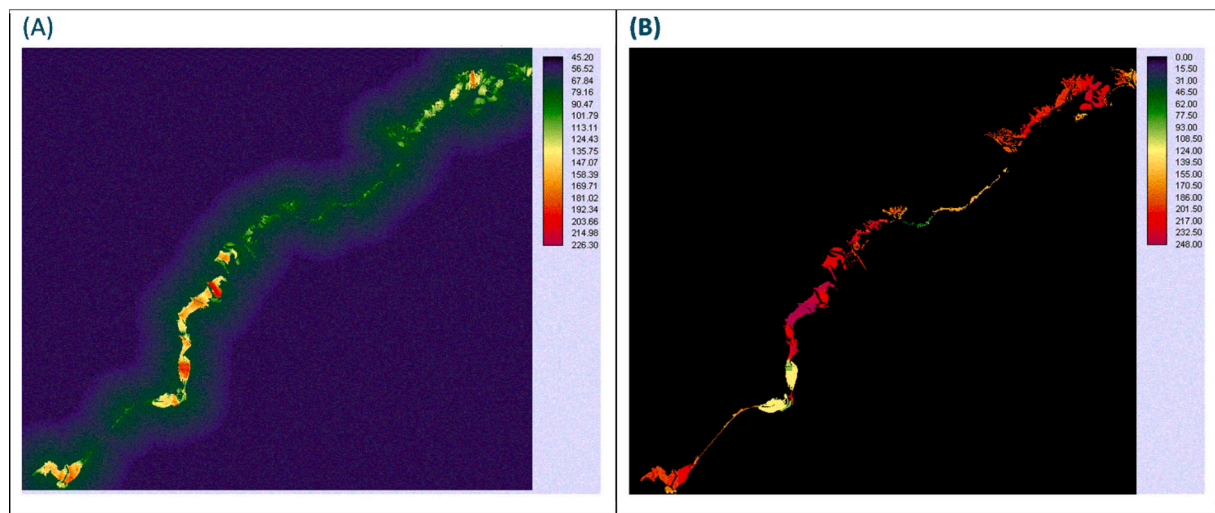


Fig. 9. Potential maps for deposition generated from the combination of (A) 7 heuristic factors with the weight of 40% assigned to the tidal flat width factor and the weight of 10% for the other factors, (B) 5 empirical factors with the weight of 54% assigned to the wind, wave effect factor and the weight of 11.5% for the remaining empirical factors.

Table 3

Relative discriminatory influence of empirical factors measured by the difference of AUC values achieved from the variation of factors' weights.

Weights (%) of empirical factors for combination in MCE					AUC 1989–2000	AUC 2000–2014	RMS of AUCs	Different RMS of AUCs
River sediment sources	Sea water velocity	Wave, wind	Coastline length	Coastal land- cover				
30.0	17.5	17.5	17.5	17.5	0.489	0.472	0.481	–0.014
54.0	11.5	11.5	11.5	11.5	0.459	0.474	0.467	
17.5	30.0	17.5	17.5	17.5	0.527	0.493	0.510	0.012
11.5	54.0	11.5	11.5	11.5	0.540	0.503	0.522	
17.5	17.5	30.0	17.5	17.5	0.475	0.442	0.459	–0.036
11.5	11.5	54.0	11.5	11.5	0.440	0.405	0.423	
17.5	17.5	17.5	30.0	17.5	0.503	0.471	0.487	–0.007
11.5	11.5	11.5	54.0	11.5	0.487	0.473	0.480	
17.5	17.5	17.5	17.5	30.0	0.561	0.538	0.550	0.031
11.5	11.5	11.5	11.5	54.0	0.590	0.571	0.581	

potential map (Fig. 9B) shows high deposition potential across most of the study area. The relative discriminatory influence gradually increases with RMS differences of –0.014, –0.007, and 0.012 for river sediment sources, coastline length, and sea water velocity, respectively. The coastal landcover factor has the highest influence, with an RMS difference of 0.031. The relative discriminatory influence of both heuristic and empirical factors provide ideas for determining factor weights in constructing scenarios for the deposition potential.

5.3. Deposition scenarios of tidal flats

Seven heuristic and five empirical factors are integrated into the MCE method to map tidal flat deposition potential. A total of nine combinations, each with a distinct set of weights, are applied across twelve forcing factors to generate nine scenarios of future deposition. Table 4 outlines the weight assignments for each combination. Each potential deposition scenario is then assessed for its alignment with

Table 4

Weights used to generate deposition potential and the agreement between potential maps and historical deposition.

Potential deposition scenarios		Sce1	Sce2	Sce3	Sce4	Sce5	Sce6	Sce7	Sce8	Sce9
Factors	Weights (%)									
Empirical factor	River sediment source	7.0	8.0	6.0	7.0	5.0	1.0	8.0	8.0	6.0
	Sea water velocity	5.0	8.0	17.0	8.0	17.0	22.0	12.0	8.0	16.0
	Wave, wind	17.0	8.0	3.0	7.0	0.0	0.0	4.0	7.0	0.0
	Coastline length	3.0	8.0	10.0	7.0	10.0	6.0	9.0	8.0	9.0
	Coastal land-cover	15.0	8.0	22.0	8.0	19.0	39.0	16.0	7.0	24.0
	Net sediment distribution	4.0	8.0	9.0	11.0	9.0	4.0	9.0	11.0	8.0
Heuristic factor	River mouth distance	0.0	8.0	0.0	0.0	15.0	14.0	11.0	8.0	12.0
	Coastal orientation	10.0	8.0	4.0	10.0	1.0	0.0	6.0	9.0	3.0
	Tidal flat width	22.0	8.0	1.0	10.0	0.0	0.0	2.0	9.0	0.0
	Tidal flat roughness	6.0	8.0	7.0	10.0	7.0	1.0	8.0	6.0	6.0
	Tidal flat slope	9.0	8.0	5.0	10.0	2.0	0.0	7.0	8.0	4.0
	Exposure time	1.0	8.0	15.0	11.0	15.0	14.0	11.0	11.0	12.0
AUC of scenarios and deposition 1989–2000		0.579	0.598	0.625	0.614	0.631	0.630	0.623	0.611	0.628
AUC of scenarios and deposition 2000–2014		0.560	0.670	0.691	0.701	0.706	0.671	0.692	0.706	0.687
RMS of AUC 1989–2000 and AUC 2000–2014		0.570	0.635	0.659	0.659	0.670	0.651	0.658	0.661	0.658

historical deposition from 1989 to 2000 and 2000–2014. Scenario 1 (Sce1); weights are assigned in proportion to the absolute relative discriminatory influence, excluding the river mouth distance factor, as its influence is like exposure time. Scenario 2 (Sce2); all factors receive equal weights of 8%. Scenario 3 (Sce3) is like Sce1, but weights are adjusted based on the relative discriminatory influences. Scenario 4 (Sce4); a slight variation of Sce2, also the scenario excludes river mouth distance. Scenario 5 (Sce5); weights increase with relative discriminatory influences, but wind-wave effect and tidal flat width are excluded due to their minimal impact. Scenario 6 (Sce6); uses the sets of weights wherein factors exhibit a relative discriminatory influence greater than -0.014 . Scenarios 7, 8, and 9 test different weight assignments aligned with the increase of relative discriminatory influences. Fig. 10 illustrates the weight variations for each scenario in relation to relative discriminatory influences.

Table 4 presents the evaluation of deposition potential maps derived from 12 forcing factors. Scenario 1 shows the least agreement with historical deposition, as indicated by the lowest AUC values: 0.579 in the 1989–2000 period and 0.560 in the 2000–2014 period). The RMS of AUC of Scenario 1 is the lowest (0.570) among all scenarios. Seven of the nine scenarios exhibit similar RMS values, ranging from 0.635 (Sce 2) to 0.661 (Sce 8). Scenario 5 emerges as the optimal deposition scenario, achieving the highest RMS value (0.670) by assigning the highest weight (19%) to coastal land cover while excluding the wind-wave effect and

tidal flat width factors, which had the lowest influence. Scenario 5 also shows the strongest agreement with historical deposition, with AUC values of 0.631 in the 1989–2000 period and 0.706 in the 2000–2014 period.

Fig. 11 presents nine potential deposition scenarios for tidal flats, with Scenario 5 producing the most accurate potential map. Pixel values in Scenario 5 range from 0 to 249.3, where higher values (dark red) indicate greater deposition potential. The highest deposition potential is concentrated in concave coastline sections, aligning with findings from (Kirby, 2000). Areas in light red or orange represent moderate deposition potential, while dark green regions, mainly found in narrow tidal flats along straight coastlines, indicate the lowest deposition potential.

The optimal deposition potential (Scenario 5), as shown in Fig. 11, is classified into three levels as high (169–247), medium (125–168), and low potential (94–124) using the natural breaks method. This approach groups similar pixel values while maximizing differences between classes. Areas with vertical erosion exceeding 0.288 m (1989–2014) are classified as having no future deposition potential. The map of the future deposition potential is presented in Fig. 12. High potential areas (34%) are concentrated around the Red River and Thai Binh River mouths, where historical accretion has occurred due to high sediment input (Tong et al., 2020). In Kim Son, high and medium potential areas intermingle, while in Mong Cai, high potential zones appear as narrow strips on high tidal flats. Medium potential areas (38%), the largest

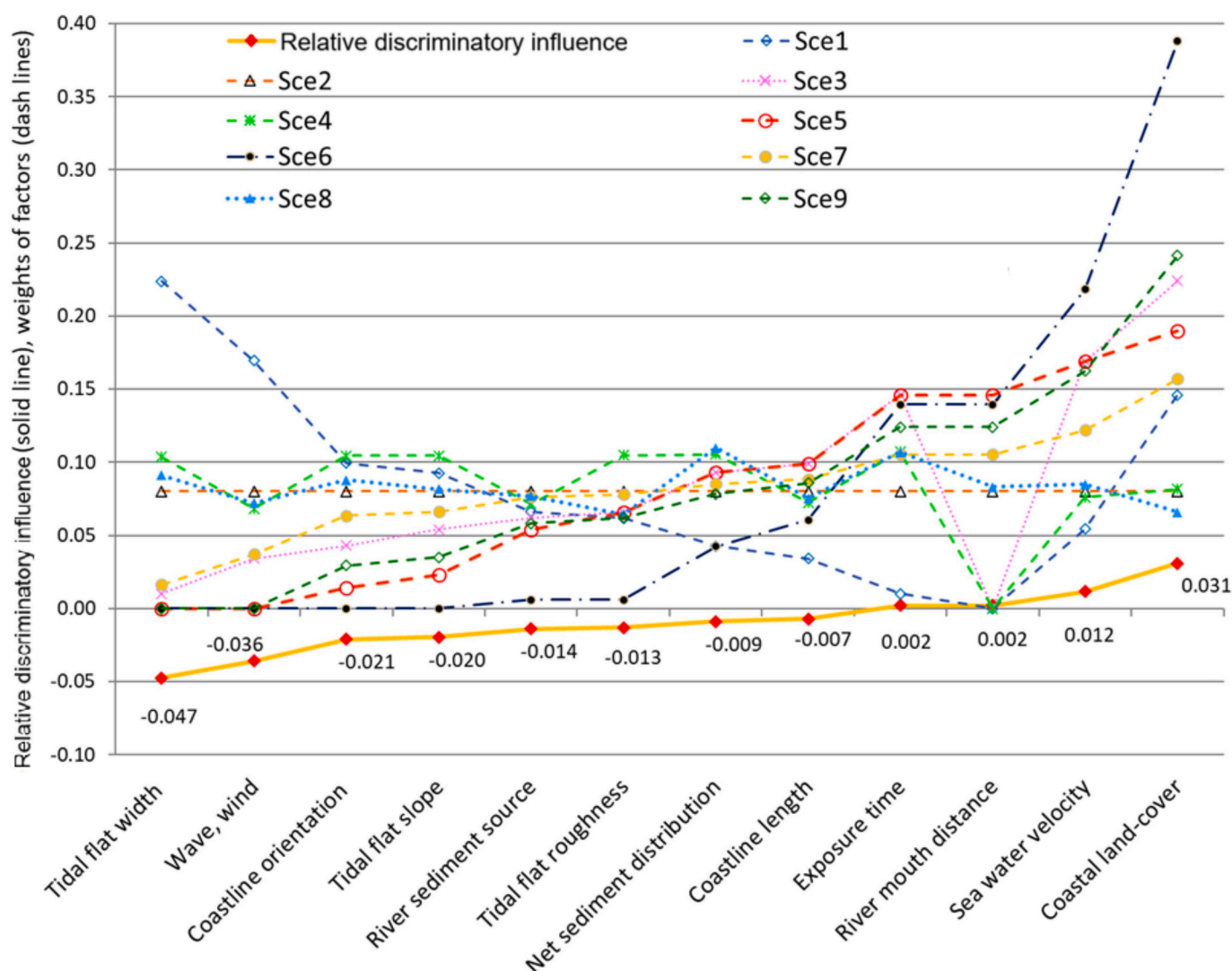


Fig. 10. Relative discriminatory influence of forcing factors (solid line) and the distribution of weights employed in potential deposition scenarios (dashed lines).

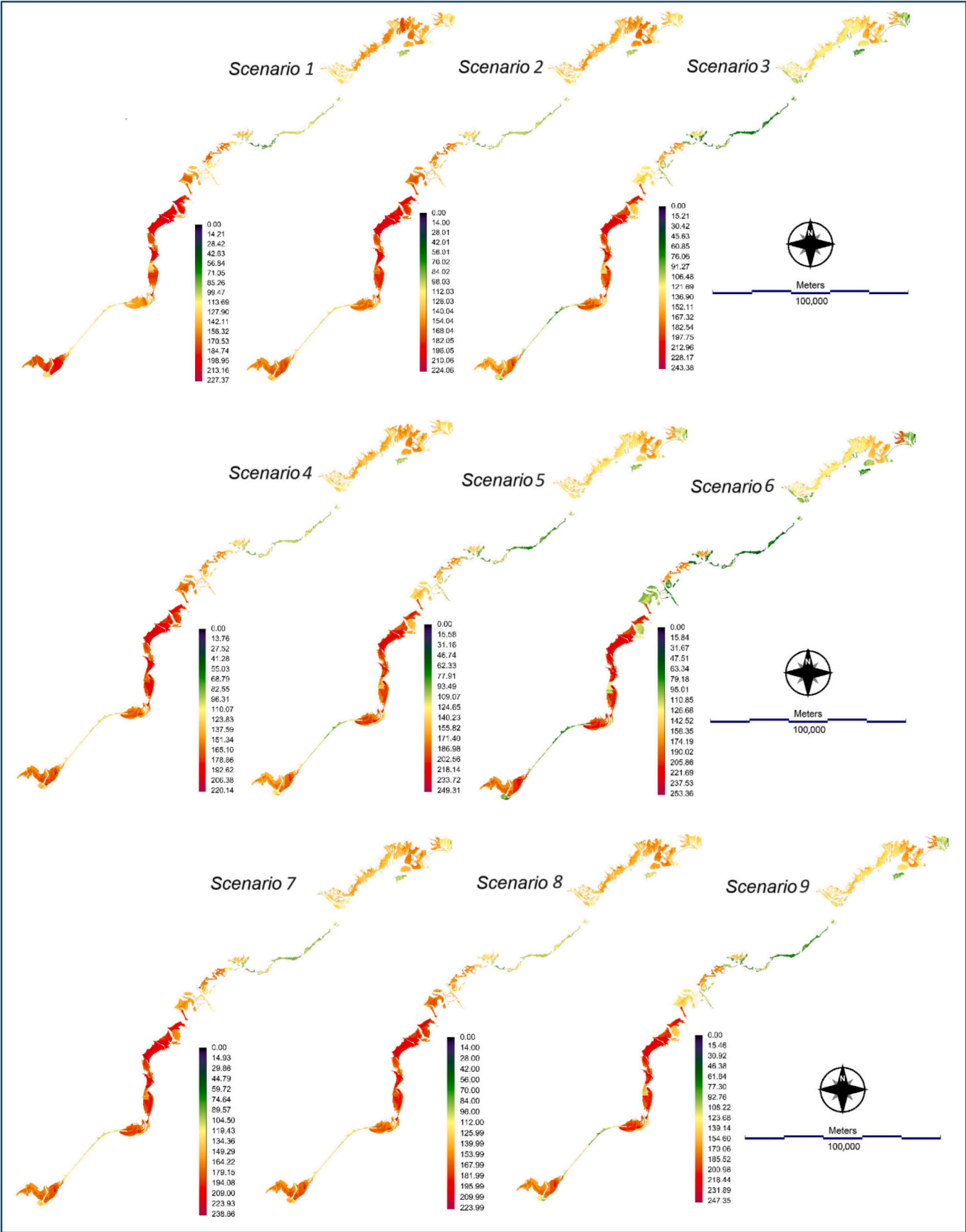
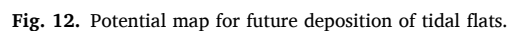


Fig. 11. Nine potential scenarios for future deposition of tidal flats.



5.4. Accuracy of potential map for future deposition of tidal flats

Table 5

Portions of checking points on potential classes for future deposition.

within each potential class of tidal flats. The largest portion of deposition points are in high potential with 53%, followed by medium potential with 12.7% and low potential with 5.6%. Erosion points occupy 12.1% with 6.3% falling within the no potential class. Overall accuracy of the future deposition potential map is 77.6%, based on correctly classified points (bold values in [Table 5](#)).

6. Discussions

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sources. This approach overcomes challenges encountered by numerical equilibrium models. By integrating 14 distinct forcing factors in this study, spatial analysis models represent a novel approach to assess deposition potential for such a complicated domain as tidal flats at a regional scale. Successful application of the model at a global scale depends critically on the availability of historical data on tidal flat dynamics and associated forcing factors. Historical data can be derived from multitemporal satellite imagery (Murray et al., 2019; Murray et al., 2022). Global forcing factors are accessible from various sources; for instance, oceanic and atmospheric data can be obtained from NOAA, while riverine data are available through HydroSHEDS (Ouellet Dallaire et al., 2019). These datasets can be integrated into the model, enabling its application beyond local contexts to global scales and enhancing its predictive capacity for both alongshore and cross-shore tidal flat dynamics (Fig. 12). It is important to emphasize that the MCE framework assumes additive and conditionally independent factor contributions and does not explicitly resolve cross-factor interactions or feedback mechanisms.

The ROC method evaluates how well forcing factor maps portray a location of historical depositions based on the AUC value. In general, an AUC value greater than 0.5 and closer to 1 suggests that the forcing factor has relatively strong discriminatory power in explaining the observed changes. Higher AUC values indicate a stronger agreement between the simulated and actual maps, whereas lower values reflect weaker correspondence (Petrova et al., 2013). In other words, the factor map with the highest AUC depicts the most relative discriminatory correspondence between individual forcing factors and tidal flat deposition patterns. This study employs the ROC method in two phases. Initially, ROC is used to individually test each forcing factor's agreement with historical deposition to determine whether heuristic or empirical factors affecting the deposition. The second ROC process aims to assess the relative discriminatory influence of a specific factor when considered in combination with other factors. Previous studies attempted to explain the roles of forcing factors on the deposition of tidal flats including: wind speed and direction, and exposure time introducing over-consolidation process (Colosimo et al., 2023), air temperature and exposure period stabilizing the sediment and promoting the deposition (Nguyen Minh et al., 2022), sediment size and permeability (Mfikili et al., 2022). However, these studies did not quantify the comparatively relative discriminatory influence of these factors. Therefore, this study introduces a spatial analysis approach based on AUC values to rank the relative discriminatory influence of forcing factors on deposition for the first time. The ranking, from highest to lowest influence, includes Coastal land-covers, Sea water velocity, River mouth distance, Exposure time, Coastline length, Net sediment distribution, Surface roughness, River sediment source, Coastal orientation, Wave, wind effect, and Tidal flat width (Fig. 10).

ROC analysis is widely used in classification models due to its ability to evaluate true positive and false positive rates across various thresholds, making it particularly suitable for binary classification tasks common in environmental studies (Kwon et al., 2012). However, ROC analysis does not support the integration of multiple criteria. In contrast, Multi-Criteria Evaluation (MCE) enables the synthesis of diverse factors into a comprehensive spatial decision-making framework and is known for its flexibility and adaptability in environmental decision making (O'Byrne, 2022; Zhu et al., 2018). Besides, various methods have been applied to environmental prediction, including fuzzy logic, Naïve Bayes (NB), random forest (RF), binary logistic regression (BLR), multilayer perceptron (MLP), back-propagation neural network (BPNN), and support vector machine (SVM) (Huang et al., 2020; Ali et al., 2021; Nikparvar and Thill, 2021). For instance, in landslide susceptibility prediction, machine learning models often outperform statistical and heuristic approaches by delivering higher accuracy and more robust spatial predictions, owing to their capacity to model non-linear relationships. In contrast, statistical models are constrained by linear assumptions, while heuristic models depend on subjective weight

assignments (Huang et al., 2020; Ali et al., 2021). This study presents the first application of the MCE method combining both heuristic and empirical approaches to assess deposition potential in tidal flats. The integration of machine learning techniques for predicting tidal flat dynamics offers a promising direction for future research.

It should be noted that the MCE framework employed in this study integrates multiple forcing factor rasters as thematic evidence layers and therefore does not explicitly enforce statistical independence among input variables. In coastal and tidal flat environments, forcing factors are often inherently interrelated due to coupled geomorphic and hydrodynamic processes (e.g., elevation, inundation frequency, sediment supply, and flow dynamics), making complete orthogonality difficult to achieve in practice. While multicollinearity is a critical assumption in parametric regression based inference models, MCE is primarily a decision support and spatial suitability approach, where partial dependence among variables is commonly tolerated and interpreted as process coupling rather than redundancy. Nevertheless, the absence of formal orthogonality diagnostics (e.g., variance inflation factor or spatial autocorrelation metrics) may allow some degree of compounded influence and spatial signal reinforcement in the integrated depositional model. As a limitation, future studies may benefit from incorporating explicit intervariable dependence diagnostics or dimensionality reduction techniques to further constrain redundancy among forcing factors.

The most challenging aspect of the MCE method is determining the appropriate set of weights for factors to generate potential deposition scenarios. The Analytic Hierarchy Process (AHP) method is commonly used to address this challenge by ranking factors based on expert knowledge (Kordi and Brandt, 2012; Pham et al., 2023). However, the AHP approach may introduce bias due to subjective opinions that might not accurately reflect the true relationships between factors (Greene et al., 2011; Kordi and Brandt, 2012). In this study, factor weights are determined based on the measured relative discriminatory influence derived from spatial analysis referring to historical deposition. This objective approach enhances reliability in generating potential maps. It has been demonstrated that the optimal scenario for potential deposition (Scenario 5 in Fig. 10) is derived from weights that are directly correlated with the comparative influence ranking of factors.

This study utilizes ROC–AUC values to measure the spatial relationship between the factor maps and historical deposition rather than focusing on the underlying physical mechanisms or causal strength. Consequently, the physical interactions between factors are not directly addressed. From a global perspective, the approach represents a linear combination of forcing factors considering certain criteria: 1/ Simultaneous mapping: All forcing factors and tidal flats should be mapped concurrently to investigate their simultaneous and synthetic interactions on tidal flats; 2/ Independence and stability of factors: Forcing factor maps are treated as independent variables, while historical depositions are dependent variables. In this experiment, all forcing factors were mapped in 2014 to adapt the first criteria. Additionally, the variation in factors related to sediment sources, oceanography, and coastal properties was insignificant during the period 1989–2014 due to their modulation by mesoscale processes, which occur over decades (Sherman, 1995). Factors belonging to the tidal flat property group mutually interact with deposition. Tidal flat property factors integrate with other factors to drive changes in tidal flats. Conversely, the evolution of tidal flats forces back the variations in these factors. To accurately assess the sole impact of each factor of the tidal flat property group, these factors should be updated frequently throughout the study period (ideally annually from 1989 to 2014). Due to limited yearly topography data of tidal flats, the study accepts using factor maps of tidal flat properties generated in 2014. Above all, the analysis is retrospective and spatial in nature; forcing factors are treated as representative or slowly varying controls and are not intended to resolve time-forward causal relationships at interannual scales.

It is important to note that the potential deposition maps generated in this study do not account for potential sea level rise. If sea levels were

to increase greater than the accuracy of the DEM constructed in 2014 for tidal flats (0.144 m) (Tong et al., 2020), the applicability of these potential deposition maps would be invalid. According to Nguyen et al. (2022), the rate of sea level rise in the study area is 3.56 mm/year (Nguyen Minh et al., 2022), which means it would take approximately 40.4 years for sea levels to rise by 0.144 m. Therefore, the validity of the potential deposition scenarios in this study is limited to the next 40 years from 2014.

The synthetic approach integrating forcing factors for the northern part of Vietnam produced a potential map for vertical accretion of tidal flats with an accuracy of 77.6%. However, as a limitation of the study, the factor of tropical storms is not included due to insufficient data on their specific impacts in the study area, despite their critical role in sediment exchange in tidal flats (Georgiou et al., 2024; Zhou et al., 2022a; Zhou et al., 2022b). Forcing factors associated with ongoing economic development activities such as urbanization, road construction, the establishment of concrete sea dikes, and the expansion of aquaculture ponds can induce abrupt and unpredictable changes in tidal flat dynamics that fall outside the predictive capacity of the spatial model. These anthropogenic influences and sudden alterations in tidal flats should be excluded from the model, as its framework is based on linear regression processes, which assume gradual and systematic variation. Additionally, while the study focuses on deposition, it does not address erosion, which occurs concurrently in tidal flats. In future research, multitemporal satellite imagery will be utilized to analyze erosion patterns, while the impacts of historical tropical storms characterized by parameters such as average duration, affected areas, and storm intensity can be effectively mapped (Takagi, 2019). The spatial analysis framework developed in this study provides a basis for integrated assessments of erosion risk in relation to tropical cyclone activity and associated forcing factors.

7. Conclusions

This study successfully applies spatial analysis to integrate 14 forcing factors for mapping the potential deposition of tidal flats, marking the first implementation of this approach. The method enables quantification of deposition levels along both alongshore and cross-shore dimensions across various spatial scales, from local to global extents. A key strength of this spatial analysis method is its ability to incorporate a large number of forcing factors into the modeling process. However, a critical step is the evaluation of each factor's agreement with historical deposition, ensuring that only the most influential factors are selected. Another novel aspect of this study is the determination of factor weights in the MCE method based on their observed comparative influence ranking on deposition. Among various weighting strategies, ensuring a linear correlation between weights and comparative influence ranking is essential for generating reliable potential deposition scenarios. Despite these advances, challenges remain. Incorporating anomalous factors such as tropical cyclones, tsunamis, and earthquakes into the model presents a significant challenge. Additionally, the scarcity of historical data limits the effectiveness of such models, particularly for highly dynamic environments like tidal flats. Findings from this study highlight coastal land cover as the most influential factor affecting deposition rates. Conversely, wave and wind exposure, along with tidal flat width, are identified as key drivers of erosion. Spatially, tidal flats from Giao Thuy to Do Son exhibit the highest potential for deposition, whereas those in Dam Ha to Mong Cai show no potential for deposition. While the potential deposition maps provide valuable insights for coastal conservation and management, future research should aim to integrate anomalous factors into the model. This will enhance the comprehensiveness of accretion and erosion assessments in tidal flats, improving predictions for coastal resilience and planning.

CRedit authorship contribution statement

Thi Lan Pham: Writing – original draft, Methodology, Formal analysis, Data curation. **Si Son Tong:** Writing – review & editing, Writing – original draft, Validation, Data curation, Conceptualization. **Pham-Duc Binh:** Methodology, Data curation. **Tong Thi Huyen Ai:** Software, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research is implemented in the REMOSAT laboratory, University of Science and Technology of Hanoi (USTH). We express heartfelt thanks to these valuable supports. We thank also colleagues in the department of Space and Applications, USTH, who give us the advantage of experience in processing spatial data. We thank the anonymous reviewers for their very constructive reviews.

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