

Article

Multi-Year Predictability of Sandy Shoreline Change from Remote-Sensing Reconstruction and a Spatiotemporal Transformer

Keyu Tao ^{1,2}, Fenzhen Su ^{1,2} , Fengqin Yan ^{1,2,*}, Vincent Lyne ^{3,†}  and Jiaojie Zhang ¹

¹ Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; taokeyu25@mailsucas.ac.cn (K.T.); sufz@reis.ac.cn (F.S.); 1202321144@cug.edu.cn (J.Z.)
² College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 101408, China
³ IMAS-Hobart, University of Tasmania, Hobart, TAS 7004, Australia; vinlyne@gmail.com
* Correspondence: yanfq@reis.ac.cn
† Retired Scientist.

Abstract

Most studies of sandy shoreline forecasting address relatively short time scales. Under limited annual observations and strong shoreline persistence, the added value of a Transformer over simple baselines and the influence of remotely sensed shoreline definitions remain insufficiently tested. Using Xichong Beach, Shenzhen, we constructed 40-year shoreline series for 80 transects from 284 quality-controlled Landsat waterlines acquired during 1986–2025. We compared a quality-controlled annual landward-envelope composite waterline with annual median waterlines and examined the effects of transect spacing and positional error on long-term change rates. We then developed a residual spatiotemporal Transformer that uses 10 years of shoreline states and historical wind–wave exposure to directly predict five future horizons, and compared it with persistence, rolling linear trend, and random forest models. The annual landward-envelope composite waterline was systematically landward of the annual median waterline (positional RMSE, 12.78 m), but their alongshore LRR patterns were strongly correlated ($r = 0.982$) and identified consistent major erosion–accretion zones. After Monte Carlo error propagation, the beach-mean LRR was -0.250 m yr^{-1} (95% interval, -0.299 to -0.203 m yr^{-1}), whereas the direction of change remained uncertain at 39 local transects. Across 400 year–transect locations in the independent 2021–2025 evaluation period, the Transformer produced the lowest RMSE, MAE, and Dynamic RMSE (9.403, 7.399, and 12.042 m, respectively), with an RMSE skill of 27.0% relative to persistence. Environmental features yielded a small gain during rolling validation but no stable improvement in the independent evaluation period. SHAP attribution identified recent shoreline state as the dominant predictive information, followed by wind–wave exposure. Direct forecasts for 2026–2030 gave a beach-mean displacement of -8.527 m in 2030 (95% conditional residual bootstrap interval, -12.514 to -4.950 m), although every local-transect interval crossed zero. Multi-year predictability is therefore scale dependent: beach-mean trends are more resolvable, whereas local change directions remain constrained by observation error and model residuals.



Academic Editor: Efthimios Karymbalis

Received: 27 June 2026

Revised: 29 July 2026

Accepted: 2 August 2026

Published: 5 August 2026

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Keywords: remote sensing; Landsat; CoastSat; sandy shoreline; spatiotemporal Transformer; multi-year forecasting; uncertainty

1. Introduction

Sandy shorelines are among the most dynamic geomorphic boundaries at the land–sea interface. Their positions are jointly affected by waves, tides, storms, sea level change,

sediment transport, coastal engineering, and human activities [1,2]. Global satellite observations and regional studies show that long-term erosion and accretion coexist widely on sandy coasts and that erosion may intensify under climate change and sea level rise [3–6]. Coastal protection can also alter local retreat rates [7]. Compound risks from sea level rise and tropical cyclones increase exposure of coastal ecosystems and socioeconomic assets [8,9]. Coastal research therefore needs both historical reconstruction and an assessment of the temporal and spatial scales at which future change can be forecast reliably.

Satellite Earth observation has greatly extended the temporal and spatial coverage of shoreline monitoring and has become an important complement to field surveys [10,11]. Reviews have compared shoreline change analysis and remote-sensing waterline extraction methods [12,13]. Long Landsat records, Google Earth Engine, and CoastSat v3.2 enable multi-decadal waterline extraction and regional comparison [14–16]. Morphological extraction, water indices, and deep learning edge detection can identify land–water boundaries [17–21], but their applicability varies with coast type and image conditions. Satellite imagery identifies the sand–water boundary at acquisition, rather than a fixed-elevation geomorphic shoreline. Its position is affected by image resolution, tide level, wave setup and runup, seasonal beach morphology, and image quality [22–25]. Reliability should therefore be assessed not only from single-image extraction accuracy but also from whether annual shoreline construction and spatial sampling alter long-term conclusions.

Aggregating multiple waterlines into annual shorelines can reduce the effect of irregular observation frequency, but different aggregation rules have different physical meanings. Annual mean or median shorelines represent central annual conditions, whereas the most landward waterline is more sensitive to tide, wave runup, extreme events, and the number of images available each year [23–27]. On curved beaches, transect orientation, spacing, and baseline smoothing also affect local intersections and estimated change rates. Before using remote-sensing shorelines to train forecasting models, it is therefore necessary to test how shoreline-proxy definition, transect sampling scale, and historical positional error affect long-term erosion–accretion patterns.

Shoreline forecasting has developed from persistence assumptions, linear trend extrapolation, and empirical equilibrium models to data-driven approaches such as random forests, support vector regression, recurrent neural networks, and Transformers [28–36]. Persistence and trend models are transparent and require few data, but they cannot represent nonlinear change. Process and equilibrium models can include wave–shoreline response relationships but commonly require field calibration and high-temporal-resolution forcing data [35,36]. Random forests handle multivariate nonlinear relationships but do not explicitly represent temporal order or alongshore spatial structure. LSTM, GRU, and related deep learning methods improve time-series fitting, yet shoreline studies often treat each transect as an independent series, and performance can depend strongly on sample size, forecast horizon, and data partitioning [29,31–34].

Transformers represent dependencies between time steps through self-attention [37] and have been applied to shoreline forecasting [30]. For continuous sandy beaches, relations among neighboring transects can also be represented as spatial structure. Greater model complexity, however, does not automatically improve temporal extrapolation. When shoreline persistence is strong, complex models may primarily continue the most recent state. A recent multi-site benchmark likewise showed that relative model performance varies with forecast horizon, observation conditions, and evaluation design [34]. The added value of a Transformer should therefore be tested against persistence, trend, and non-Transformer machine-learning baselines under a common temporal split, input window, forecast horizon, and evaluation grid.

The use of environmental information also raises a scale-matching problem. Waves and wind are important external controls on sandy-beach evolution, but aggregating hourly or event-scale processes into annual metrics can weaken information on storm sequencing, seasonal contrasts, and post-event recovery. Offshore reanalysis data projected onto transect orientation describe relative exposure among coastal segments, but they do not replace nearshore calculations of wave refraction, breaking, or sediment transport. SHAP and related methods describe statistical attribution within a fitted model, rather than independent physical causation. Existing forecasting studies also commonly report deterministic curves or a single aggregate error, with comparatively limited joint consideration of observation error, model residuals, and alongshore correlation.

Xichong Beach has a continuous Landsat record from 1986 to 2025, an approximately 4 km continuous sandy reach, an arcuate planform, and changing alongshore orientation. It is therefore suitable for testing a spatially explicit model with a limited annual series. The site is affected by monsoon conditions, typhoons, and human activity, allowing comparison of shoreline history and environmental exposure information. This is nevertheless a single-site analysis; the findings do not directly represent coasts with different tidal ranges, sediment types, nearshore morphology, or engineering interventions.

We combined remote-sensing shoreline reconstruction, DSAS transect analysis, a residual spatiotemporal Transformer, common baseline comparison, and uncertainty propagation to assess multi-year predictability of sandy shoreline change. We ask: (1) whether annual landward-envelope composite waterlines, annual median waterlines, and transect spacing alter the main spatial pattern and magnitude of long-term shoreline change; (2) how much forecast skill the residual spatiotemporal Transformer adds relative to persistence, rolling linear trend, and random forest during an independent evaluation period; (3) whether historical wind-wave exposure projected to transect orientation provides stable incremental information beyond shoreline history and spatial position; and (4) how the resolvability of future change differs between beach-mean and local-transect scales after accounting for historical observation error and model residuals.

2. Study Area and Data Sources

2.1. Study Area

Xichong Beach is located in Dapeng New District, Shenzhen, Guangdong Province, China (approximately 114.50–114.60° E and 22.45–22.50° N). It faces the outer waters of Daya Bay and has a subtropical monsoon climate. Mean annual temperature is approximately 23.0 °C and mean annual precipitation is approximately 1935.8 mm. Monsoon transitions and typhoons produce pronounced seasonal and event-scale wave conditions, which interact with tides to affect the position of the sand–water boundary.

The study coastline is approximately 5 km long and includes rocky, gravel, and sandy segments. We analyzed the continuous sandy beach, which is approximately 150 m wide, backed by mountains, and arcuate in planform. Its continuously changing orientation and exposure provide a clear setting for testing spatial dependence among neighboring transects (Figure 1).

The complete multi-decadal remote-sensing record, continuous sandy reach, and pronounced curvature make Xichong Beach an appropriate site-scale test of forecast skill. The site enables assessment of annual shoreline representation, alongshore coupling, and environmental exposure features, but its geomorphic setting and data sources are relatively limited. Extension to other coasts requires independent multi-site validation that considers differences in tidal range, beach slope, sediment grain size, wave climate, nearshore morphology, and human intervention.

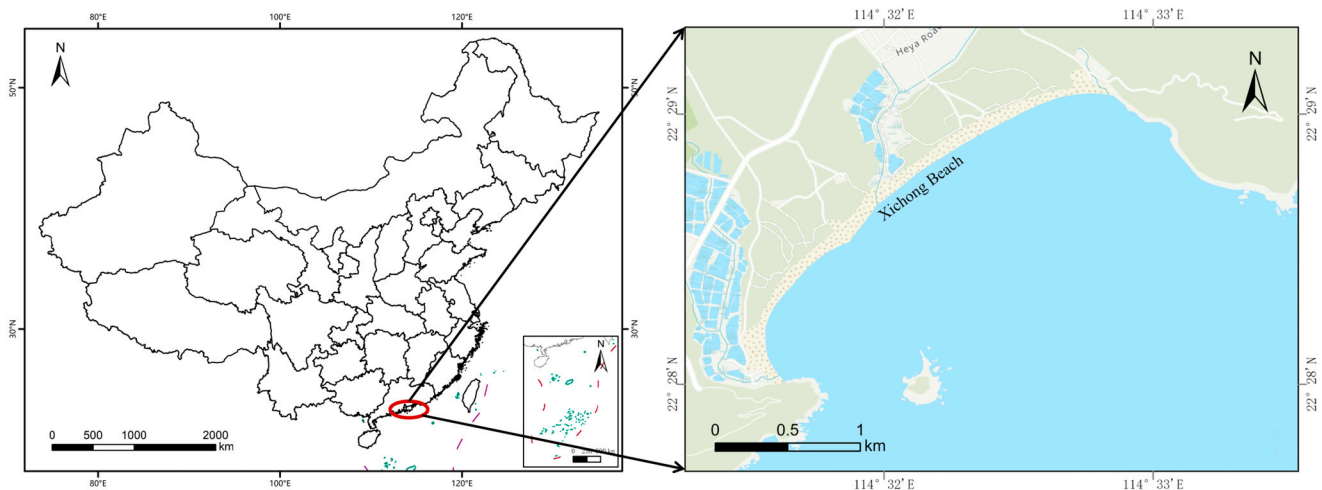


Figure 1. Geographic location of the study area in China.

2.2. Data Sources and Preprocessing

Shoreline data were obtained in Google Earth Engine (GEE) from Landsat 5 TM (1986–2011), Landsat 7 ETM+ (1999–2012), Landsat 8 OLI (2013–2025), and Landsat 9 OLI-2 (2021–2025) imagery [14]. The nominal spatial resolution of the multispectral bands is 30 m. Landsat 7, 8, and 9 images with 15 m panchromatic bands were pan-sharpened and resampled using principal component substitution [38], whereas Landsat 5 remained at 30 m resolution. After cloud masking, registration checks, and shoreline quality control, 284 individual waterlines were retained for 1986–2025.

Wind and wave data were obtained from hourly ERA5 reanalysis [39], including 10 m wind vectors, significant wave height, mean wave direction, and mean wave period. These variables were used to construct annual wind–wave exposure indices relative to transect orientation. The UTC acquisition time of each image was matched to predicted astronomical tide from TMD3/EOT20 [40] to describe observation conditions of individual waterlines; it was not used as an independent input to the forecasting model.

Image preprocessing included study area clipping, cloud masking with quality assurance bands, projection transformation, and pan-sharpening where necessary. Shoreline and transect analyses used WGS 84/UTM Zone 50N (EPSG:32650). Shoreline positions, environmental variables, and model targets were aligned by year–transect unit.

Annual environmental features included cumulative exposure, P95, P99, and hours of high exposure calculated from hourly records to retain long-term background conditions and part of the extreme exposure information. The model used only shoreline and environmental data available before the forecast origin; environmental observations from target years were excluded. Standardization parameters for continuous variables were fitted only within the corresponding training period and then applied unchanged to validation and evaluation periods.

3. Methods

The workflow comprised dataset construction, remote-sensing waterline extraction, spatiotemporal forecasting, and result interpretation with uncertainty assessment (Figure 2). It places observation, analysis, forecasting, and interpretation in one evaluation chain.

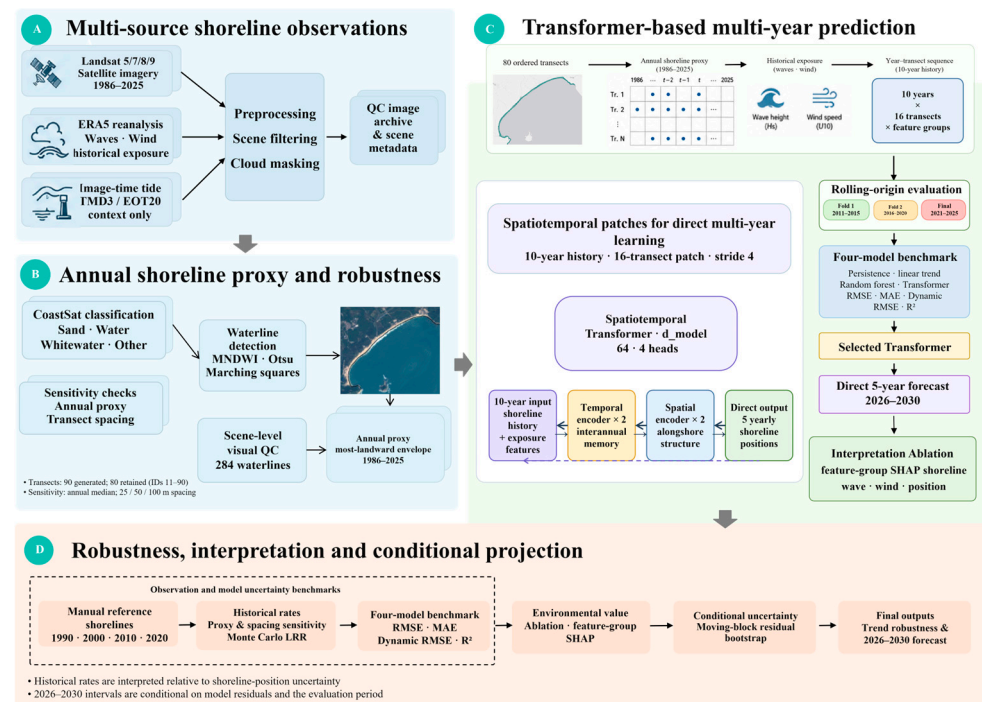


Figure 2. Workflow of the integrated shoreline reconstruction and Transformer-based forecasting framework.

3.1. Shoreline Extraction Using CoastSat

3.1.1. Waterline Extraction and Annual Shoreline Definition

We used the open-source CoastSat toolkit to semi-automatically extract sand–water boundaries from multi-temporal Landsat imagery [16]. CoastSat combines pretrained image classification, water index thresholding, and sub-pixel boundary tracking. Pixels are first classified as sand, water, whitewater, or other surface types, after which the sand–water boundary is identified within a candidate shoreline buffer.

The modified normalized difference water index (MNDWI) was calculated as

$$\text{MNDWI} = (\text{Green} - \text{SWIR1}) / (\text{Green} + \text{SWIR1})$$

where Green and SWIR1 are the reflectances of the green and shortwave-infrared bands, respectively. An Otsu threshold was derived from the MNDWI histogram within the candidate region [41], and a continuous sub-pixel boundary was then generated using Marching Squares [42]. Classification, thresholding, and boundary results were visually checked.

Quality-controlled, landward valid waterline segments from different images in the same year were combined into an annual shoreline, here termed the annual landward-envelope composite waterline. This composite does not correspond to one image date, one tide level, or a fixed elevation and is therefore not described as a fixed high-water shoreline [1,23,24,27]. Because the composite contains segments from multiple dates and no synchronous, spatially representative beach slope was available, no uniform tide–slope horizontal correction was applied. Its representativeness was evaluated through single-image observation statistics, comparison with annual median waterlines, and historical rate sensitivity analyses.

3.1.2. Extraction Workflow and Quality Control

Landsat images were first selected in GEE by study area, time range, and quality assurance bands, with a scene cloud-cover threshold of 0.3. Xichong Beach is dominated by

light-colored sand, so the CoastSat beach color parameter was set to “bright”. A reference shoreline was manually digitized from clear images, and the maximum search distance was set to 100 m to constrain candidate waterlines.

After automated extraction, each result was inspected for cloud-edge effects, white-water misclassification, registration anomalies, duplicate segments, and implausible positions. Results failing quality requirements were removed. Individual waterlines were allowed to be spatially discontinuous; where no valid transect intersection existed, the value was recorded as missing and was neither extended nor interpolated. Independently digitized shorelines for 1990, 2000, 2010, and 2020 were used for positional-accuracy validation. Figures 3 and 4 show the reference shoreline constraint and CoastSat extraction procedure, respectively.

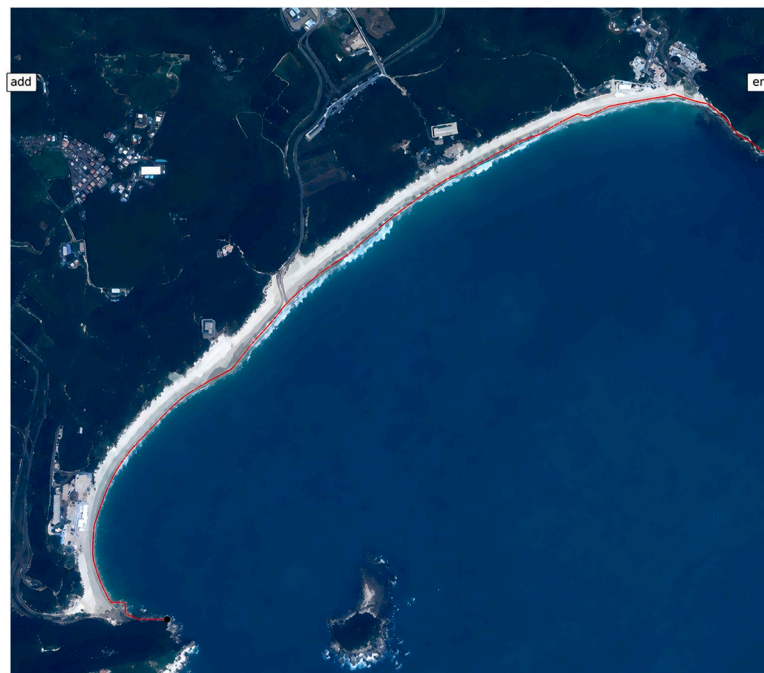


Figure 3. Manually digitized reference shoreline used to constrain the CoastSat search. (The red line represents the manually digitized reference coastline, and black dots represent the endpoint of the line).

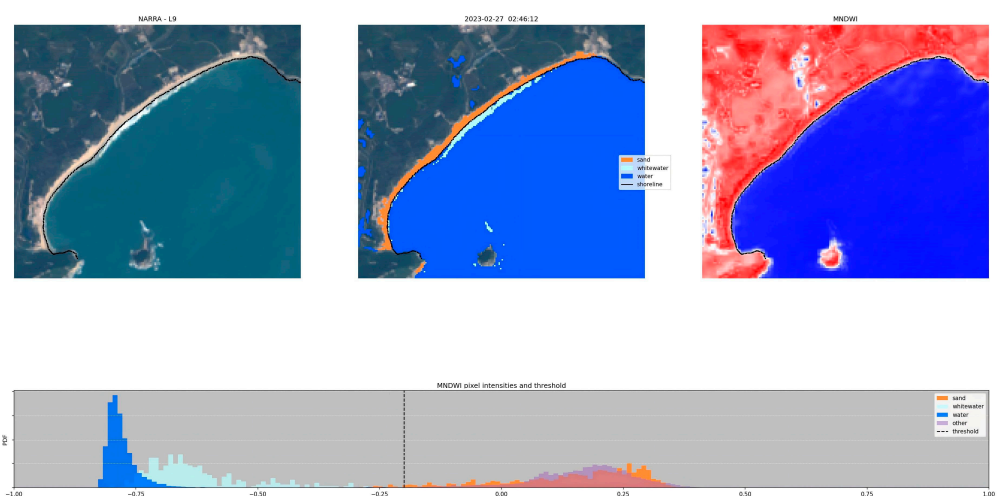


Figure 4. Example CoastSat waterline extraction, including the source image, pixel classification, MNDWI, and threshold segmentation result.

A total of 284 unique individual waterlines were retained for 1986–2025, with 2–16 images per year. Each waterline retained its image date, season, sensor, and predicted astronomical tide at acquisition. The annual landward-envelope composite waterline was used in the main analysis, and transect-level annual median waterlines were used for sensitivity testing of shoreline definition.

3.2. DSAS-Based Spatial Representation and Historical Change Analysis

3.2.1. Baseline, Transects, and Shoreline Change Metrics

The Digital Shoreline Analysis System (DSAS 6.0.170) was used to convert annual shoreline vectors to cross-shore distance series along transects [43]. This baseline and regular transect approach is widely used for shoreline change rate calculation, and its implementation in a GIS plugin supports baseline construction, transect generation, and automated metrics [44]. All annual shorelines during 1986–2025 were overlaid; the landward-most valid segments from each reach were selected and joined to create a continuous reference baseline. The baseline was placed landward of the shorelines to define transect origins and alongshore order consistently.

DSAS generated cross-shore transects at 50 m spacing along the baseline. Baseline smoothing was set to 200 m, transect length to 250 m, and orientation approximately normal to the local baseline. Ninety transects were generated initially. Transect IDs 1–10 at the study area ends did not form complete intersections with all 40 annual shorelines and were excluded. The final sample retained 80 valid transects (IDs 11–90) spanning approximately 3.95 km of coastline (Figure 5).

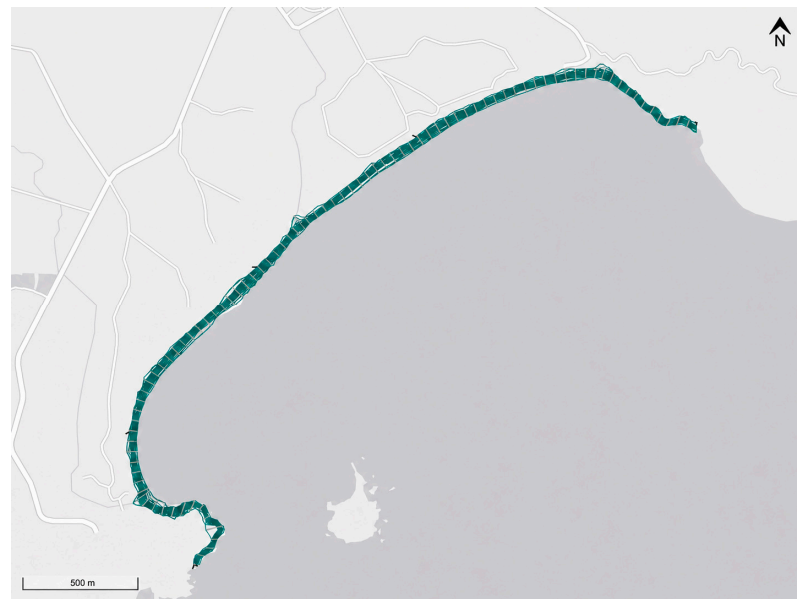


Figure 5. Digital Shoreline Analysis System (DSAS) transect layout at Xichong Beach.

All distances were calculated in EPSG:32650, with the landward transect endpoint as origin and positive values seaward. Where multiple intersections occurred, one intersection associated with the main beach waterline was retained; incomplete or ambiguous intersections were recorded as missing without temporal interpolation. DSAS shoreline position uncertainty was set uniformly to 10 m and the confidence level to 99.7%. Shoreline change envelope (SCE) is the distance between the two most separated shorelines; net shoreline movement (NSM) is the difference between first and last positions; endpoint rate (EPR) is NSM divided by elapsed time; linear regression rate (LRR) is the least-squares slope of all valid shoreline positions against time; and weighted linear regression rate (WLR) weights

positions by shoreline uncertainty. Because all years used the same 10 m weight, WLR and unweighted LRR were numerically identical here.

Transect ID retained a fixed alongshore order, which was used for historical comparisons, construction of spatial patches, and spatial block resampling of residuals. Historical results focus on LRR from the complete annual series, with EPR and WLR reported as supplementary indicators.

3.2.2. Shoreline Definition, Transect Spacing, and Historical Rate Uncertainty

Shoreline definition sensitivity used the same 80 transects. For each year–transect combination, an annual median position was calculated when at least three unique individual waterline intersections were available; missing intersections remained missing. EPR and LRR for annual landward-envelope composite and annual median waterlines were calculated using the same valid years. Absolute position and rate differences were evaluated with signed difference, MAE, RMSE, correlation, and agreement in erosion–accretion direction.

Transect-spacing sensitivity was tested at 25, 50, and 100 m. The 25 m configuration contained 159 transects and the primary 50 m configuration contained 80. The 100 m configuration was created by alternating subsamples of the 50 m transects, giving two starting phases of 40 transects each. LRR required at least 20 valid years in each configuration. Beach-mean rates, correlations between alongshore curves, and local hotspot boundaries were compared.

Historical rate uncertainty was propagated by Monte Carlo simulation. Comparison with independent reference shorelines produced 1831 valid distance-error points and a pooled RMSE of 16.095 m. In each simulation, zero-mean Gaussian perturbations $N(0, 16.095^2)$ were added at valid year–transect positions, while missing values remained missing; 10,000 simulations were run. The 2.5th and 97.5th percentiles of simulated LRRs define a 95% interval. Intervals entirely below zero, entirely above zero, and crossing zero were classified as robust erosion, robust accretion, and directionally uncertain, respectively. This empirical error was used for Monte Carlo propagation and has a different purpose from the uniform 10 m DSAS weight.

3.3. Historical Wind–Wave Exposure Projected to Transect Orientation

Wave and wind directions were transformed to the local coordinate system of each transect. The seaward transect direction defined the local normal and the alongshore direction defined the tangent. Directional differences used the smallest circular angle to avoid treating 359° and 1° as 358° apart. Offshore wave-flux proxy was represented as H_s^2T and decomposed into cross-shore and alongshore components according to relative direction; 10 m wind vectors were projected in the same way. These variables represent offshore exposure relative to shoreline orientation, not actual nearshore energy flux after refraction, breaking, bathymetric sheltering, or sediment transport calculations.

The complete environmental configuration contained seven annual features: cumulative cross-shore wave-flux proxy, cumulative absolute alongshore wave-flux proxy, cumulative onshore wind energy, cumulative absolute alongshore wind energy, cross-shore wave-flux P95 and P99, and hours of high cross-shore exposure. Cumulative metrics describe annual background exposure, while P95, P99, and high-exposure hours retain some high-energy event information.

Shoreline state features included shoreline distance, annual change, a change availability flag, and normalized alongshore position. The full model used 11 input features. The environmental ablation configuration removed the seven wind–wave variables and retained the four shoreline state and spatial position features. All thresholds and standardization parameters were derived from training data.

3.4. Spatiotemporal Transformer, Baselines, and Evaluation

The spatiotemporal Transformer used 10 consecutive historical years to directly forecast the next five years. Each sample comprised 16 neighboring transects with an alongshore stride of 4. The complete-model input tensor was $10 \times 16 \times 11$ (time $\times$ transect $\times$ feature), compared with $10 \times 16 \times 4$ without environmental features; outputs were future shoreline distances for 5×16 positions. The model used Transformer attention [37], first extracting temporal dependencies within each transect and then learning spatial relations among transects. Targets were cumulative residuals relative to the last observed shoreline. Five independent output heads produced the forecast horizons in one pass, and an annual-increment auxiliary loss constrained the interannual trajectory. This direct multi-horizon design does not feed one forecast year back into the following year. Key hyperparameters are given in Table 1.

Table 1. Hyperparameter configuration of the Transformer model.

Parameter	Description	Value
Historical input window	Consecutive input years	10 years
Forecast horizon	Direct output in one pass	5 years
Spatial patch	Number of adjacent transects	16
Sliding stride	Alongshore transect stride	4
d_model	Hidden feature dimension	64
Number of attention heads	nhead	4
Temporal encoder layers	Temporal layers	2
Spatial encoder layers	Spatial layers	2
Feed-forward dimension	dim_feedforward	128
Dropout	Dropout rate	0.1
Learning rate	Initial learning rate	0.0003
Incremental loss weight	Auxiliary term for annual increments	0.5
Training epochs	Selected by cross-validation	20

Models were implemented in Python 3.10.15 and PyTorch 2.0.1 with CUDA 11.8, and were trained on an NVIDIA GeForce RTX 4060 Laptop GPU. The Transformer and random forest each used five random seeds (42, 123, 2024, 2025, and 2026), and final results are ensemble means. Data, preprocessing configurations, and outputs were stored with hash values to ensure that all models used the same data version.

Model selection used rolling-origin cross-validation. In the first fold, samples with forecast origins during 1995–2005 were used for training, and 2010 was used as the validation origin to forecast 2011–2015. In the second fold, training origins were extended to 2010, and 2015 was used as the validation origin to forecast 2016–2020. The final independent evaluation used observations during 2011–2020 to directly forecast 2021–2025. After model selection, observations during 2016–2025 were used to directly forecast 2026–2030.

Baseline models were persistence, rolling linear trend, and random forest [45]. Persistence held the shoreline at its forecast origin position. The rolling linear trend extrapolated a line fitted to each transect’s 10-year history. Random forest used the same features and direct forecast targets as the Transformer. All four models were evaluated on the same five horizons, 80 transects, and 400 year–transect positions.

Evaluation metrics were root mean square error (RMSE), mean absolute error (MAE), Dynamic RMSE, R^2 at evaluation locations, and skill relative to persistence. Dynamic RMSE was calculated for 162 larger-change locations defined before evaluation. Skill was defined as $1 - \text{Error_model}/\text{Error_persistence}$. The environmental feature ablation retained model structure, data partition, random seeds, loss function, and evaluation grid and removed

only historical environmental variables. It is a feature group ablation, not a full ablation of positional encoding, attention layers, or other architectural components.

3.5. Model Attribution and Future Forecast Uncertainty

3.5.1. SHAP Model Attribution

Deep SHAP was used to interpret the final complete-environment Transformer. SHAP is an additive feature attribution framework that assigns input contributions to individual forecasts [46]. The background distribution comprised 100 training-period patches, and 500 scalar forecasts from the independent evaluation period were explained; evaluation samples were not used to select the background. Inputs were grouped in advance as shoreline memory, spatial position, wave exposure, and wind exposure. SHAP values describe attribution within the fitted model and are not used to infer independent physical causation.

3.5.2. Direct Forecasts for 2026–2030 and Conditional Residual Bootstrap

Observed sequences during 2016–2025 were used to produce all five forecast horizons for 2026–2030 in one pass. Future displacement was referenced to the observed 2025 shoreline; negative values indicate landward displacement and positive values indicate seaward displacement.

Conditional uncertainty was constructed from Transformer ensemble residuals in the independent 2021–2025 evaluation period. Residuals were defined as observed minus predicted shoreline distance and were centered separately by forecast horizon. A non-circular moving-block bootstrap was then applied along ordered transect IDs to retain alongshore spatial correlation [47]. The primary block length was 16 and the sensitivity block length was 8, with 2000 simulations. The 2.5th and 97.5th percentiles define 95% conditional residual bootstrap intervals. These intervals describe the range of model error conditional on continuation of historical evaluation residual structure; they do not include systematic shoreline bias, model parameter uncertainty, unknown future environmental forcing, or geomorphic regime change.

3.6. AI-Assisted Application and Scope

The AI-assisted application comprised three components: the CoastSat classifier assisted candidate waterline identification; automated scripts aligned shoreline, transect, and environmental data in space and time; and data-driven models supported baseline comparison, multi-year forecasting, and model attribution. This application layer improves the consistency of long-record processing, experiment reproduction, and updating with new observations, but it does not change the distinct roles of CoastSat extraction, DSAS change analysis, and Transformer forecasting.

Expert supervision was retained for reference shoreline definition, removal of anomalous waterlines, assessment of multiple intersections, missing value handling, and interpretation. The current workflow does not include near-real-time data assimilation, coupled nearshore process modeling, or automated management decisions. It is therefore an expert-supervised, AI-assisted shoreline-monitoring and forecasting application.

4. Results

4.1. Observation Conditions, Positional Accuracy, and Annual-Shoreline Sensitivity

A total of 284 unique individual waterlines were retained for 1986–2025. All 40 years had observations, with 2–16 images per year and a mean of 7.1. Spring, summer, autumn, and winter accounted for 14.1%, 21.5%, 37.3%, and 27.1% of images, respectively; autumn and winter together accounted for 64.4%. Predicted astronomical tide at acquisition ranged

from -0.562 to 0.960 m. Observation number, seasonal composition, and tide sampling were uneven among years (Figure 6).

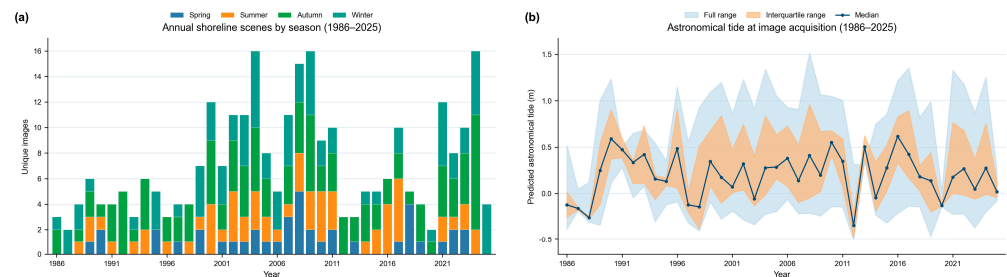


Figure 6. Annual number and seasonal composition (a) of individual waterlines, and predicted astronomical tide at acquisition (b), 1986–2025.

RMSEs between annual landward-envelope composite waterlines and independently digitized reference shorelines in 1990, 2000, 2010, and 2020 were 19.29, 11.41, 14.14, and 18.23 m, respectively (Table 2). These results quantify positional agreement between annual shorelines and external references. The effect of shoreline-proxy definition was evaluated separately through annual-median sensitivity.

Table 2. Accuracy assessment of extracted shorelines.

Year	Mean (m)	Standard Deviation (m)	RMSE (m)	Theoretical Maximum Allowable Error (m)
1990	17.31	8.52	19.29	28.28
2000	9.50	6.33	11.41	28.28
2010	11.87	7.69	14.14	28.28
2020	15.88	8.96	18.23	28.28

For year–transect combinations with at least three individual waterline intersections, 2917 valid combinations were obtained, representing 91.16% of 3200 theoretical combinations. The annual landward-envelope composite waterline was, on average, 10.66 m landward of the annual median waterline (MAE, 10.66 m; RMSE, 12.78 m; median absolute difference, 9.47 m). The two positions remained correlated (Pearson $r = 0.829$; Spearman $\rho = 0.779$), indicating consistent relative spatial variation but non-equivalent absolute positions (Figure 7).

4.2. Robustness and Uncertainty of Historical Shoreline Change

The two annual shoreline representations produced broadly consistent long-term change patterns. EPR direction agreed at 96.2% of transects when fixed 1986–2025 endpoints were used. Alongshore LRR distributions calculated from common valid years were strongly correlated (Pearson $r = 0.982$; Spearman $\rho = 0.920$), and 78 of 80 transects retained the same erosion–accretion direction. Mean LRR changed from -0.2570 m yr^{−1} for the annual landward-envelope composite waterline to -0.1760 m yr^{−1} for the annual median waterline. Shoreline definition thus affected rate magnitude more than the main spatial zoning.

After Monte Carlo propagation, beach-mean LRR had a median of -0.250 m yr^{−1} and a 95% interval of -0.299 to -0.203 m yr^{−1}. At the local-transect scale, central LRR was negative at 65 transects, but only 34 showed robust erosion. In total, 7 showed robust accretion, and 39 intervals crossed zero (Figure 8). The long-term landward-change signal is more resolvable at the beach-mean scale than the direction classification at individual transects.

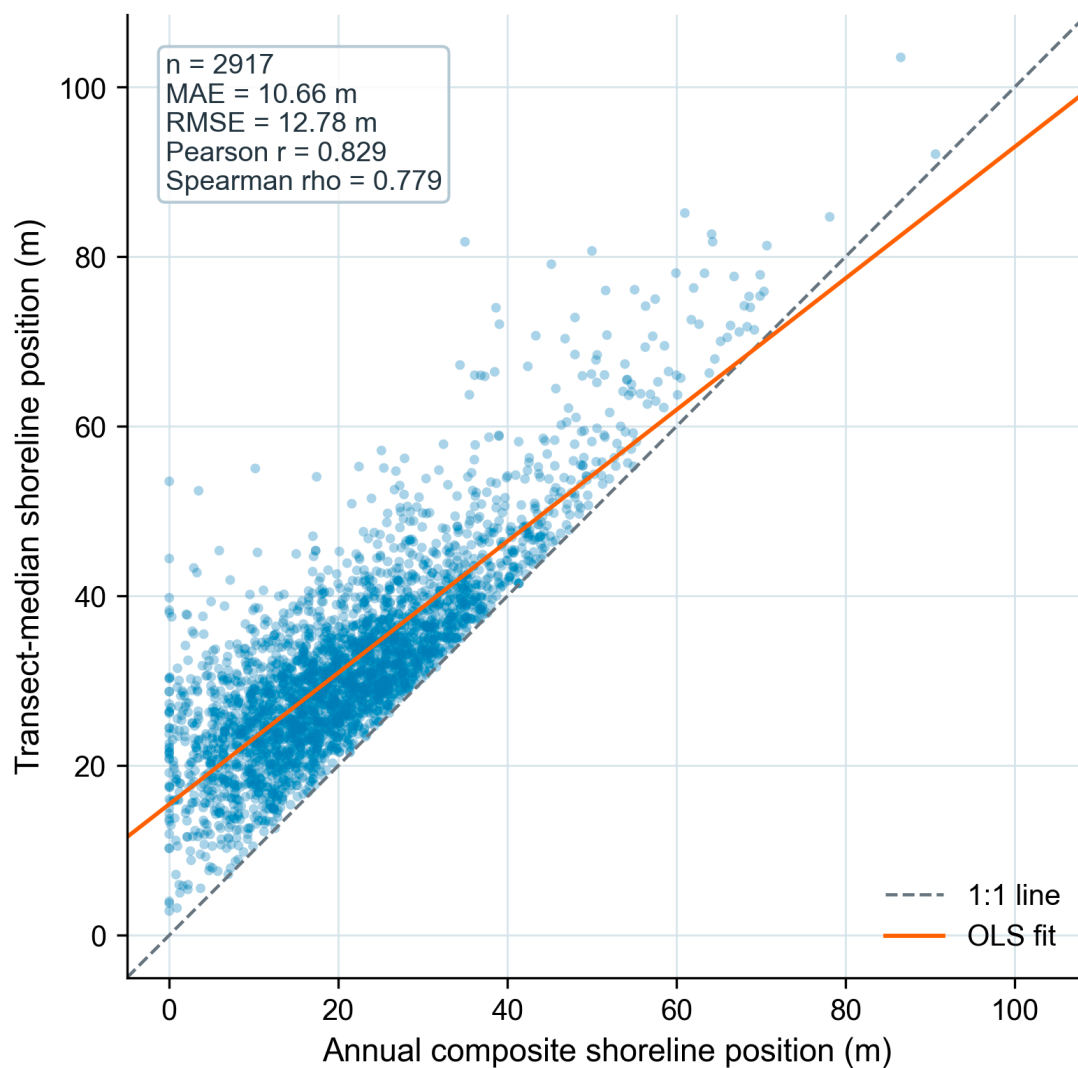


Figure 7. Comparison of annual landward-envelope composite waterlines and transect-level annual median waterlines.

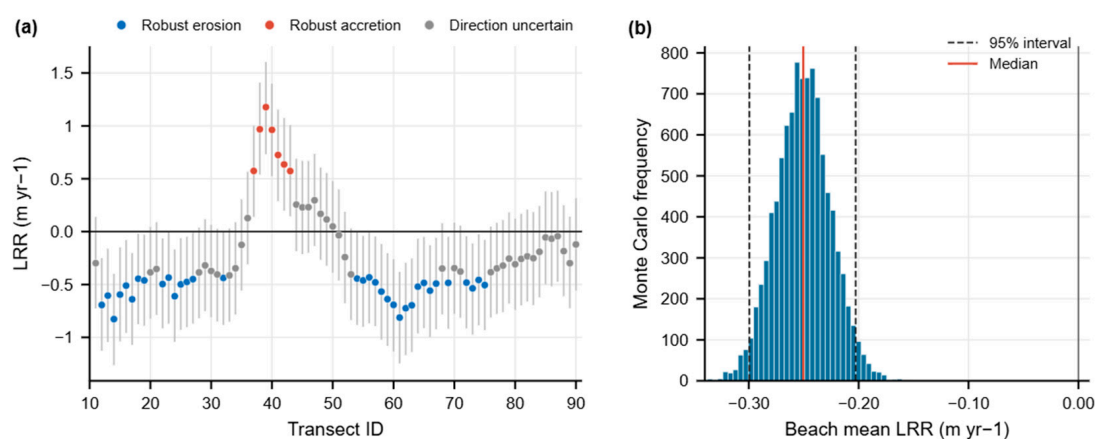


Figure 8. Historical LRR uncertainty propagation: (a) central estimates and 95% Monte Carlo intervals for 80 transects; (b) simulated distribution of beach-mean LRR.

Annual shorelines showed pronounced alongshore variability (Figures 9 and 10). Some reaches changed landward over the long term, whereas others were near stable or changed seaward. Transect sensitivity was examined at 25, 50, and two 100 m phases;

mean LRR ranged from -0.2457 to -0.2579 m yr $^{-1}$. Pearson correlations between the 25 and 50 m alongshore curves and between the 50 m curve and the two 100 m phases were 0.9974, 0.9848, and 0.9744, respectively. Thus, 50 m spacing represented the main beach-scale pattern stably, although sparse 100 m sampling shifted some local hotspot boundaries. The pattern is consistent with combined effects of waves, morphology, and sediment exchange, but no nearshore hydrodynamic or sediment transport simulation was conducted; no causal attribution is made to specific processes.

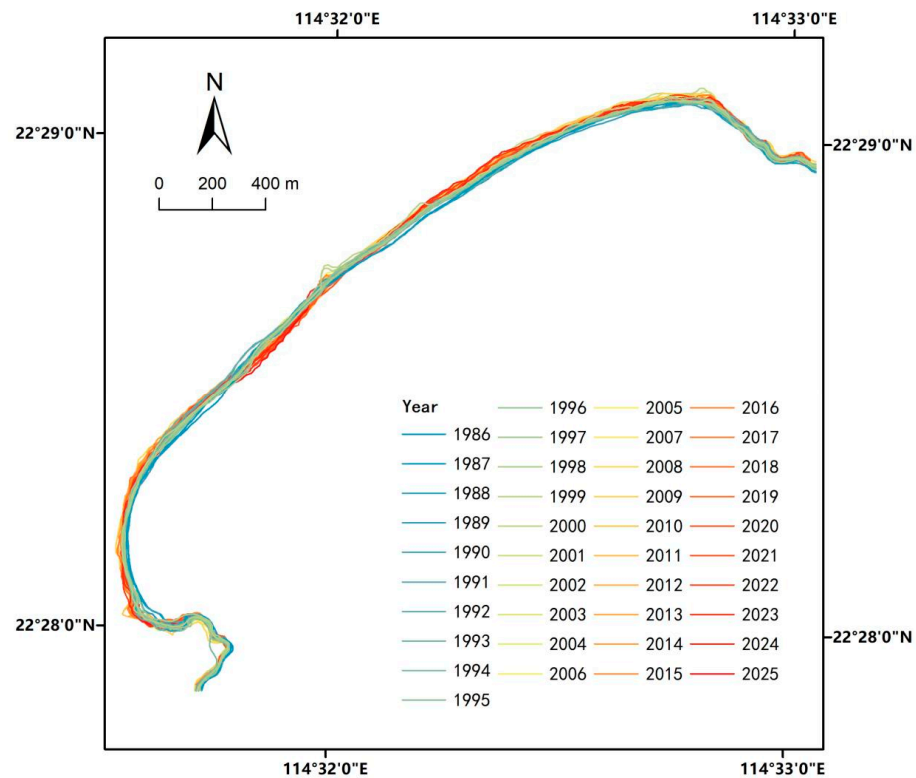


Figure 9. Annual landward-envelope composite waterlines at Xichong Beach, 1986–2025.

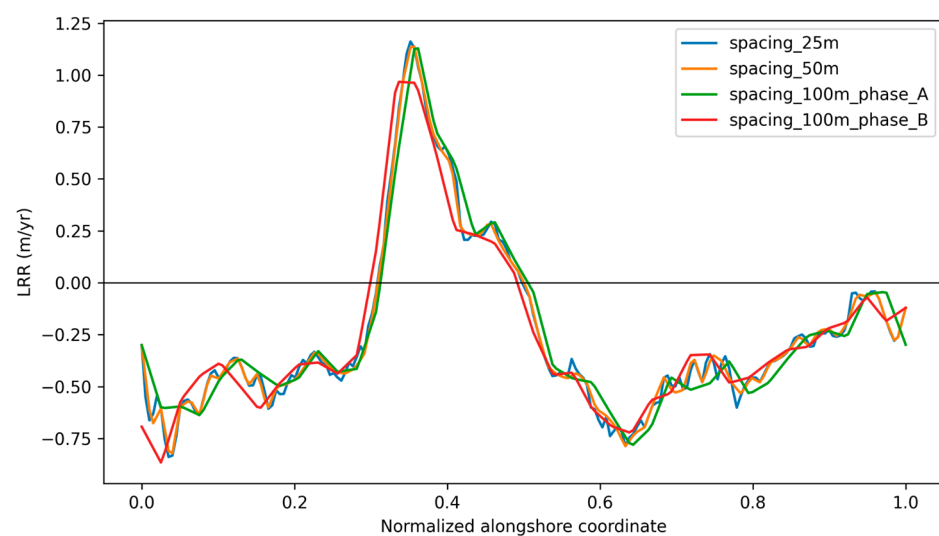


Figure 10. Alongshore LRR curves for 25, 50, and two 100 m phase configurations.

4.3. Multi-Year Forecast Skill and Environmental Information

4.3.1. Comparison of Four Models

The four models were evaluated on the same 2021–2025 grid of 400 year–transect locations. The residual spatiotemporal Transformer produced the lowest RMSE, MAE, and Dynamic RMSE (9.403, 7.399, and 12.042 m, respectively), with $R^2 = 0.451$ (Table 3). Relative to persistence, its RMSE skill and Dynamic-RMSE skill were 27.0% and 16.5%. Random forest had intermediate performance, whereas rolling linear trend and persistence had similar errors. Compared with random forest, the Transformer reduced RMSE by 13.5% but Dynamic RMSE by only 4.3%, indicating a clearer gain for absolute shoreline position. Performance was not identical across horizons: Transformer RMSE was lower than persistence during 2021–2024, but its 2025 RMSE was 10.963 m, above the persistence value of 7.779 m.

Table 3. Overall performance of four models on the independent 2021–2025 evaluation set.

Model	RMSE (m)	MAE (m)	Dynamic RMSE (m)	R ²
Persistence	12.886	10.602	14.428	−0.032
Rolling linear trend	12.850	10.527	14.272	−0.026
Random forest	10.871	8.715	12.577	0.266
Spatiotemporal Transformer	9.403	7.399	12.042	0.451

4.3.2. Environmental Feature Ablation and SHAP Attribution

To assess the incremental contribution of environmental variables, we compared the complete model containing environmental drivers with a model based only on historical shoreline position series. The complete-environment Transformer had a mean RMSE of 9.720 m in rolling cross-validation, slightly lower than the shoreline history configuration (9.815 m). In the independent 2021–2025 evaluation, however, removing environmental features reduced Transformer RMSE, MAE, and Dynamic RMSE from 9.403, 7.399, and 12.042 m to 8.515, 6.465, and 10.596 m; random forest changed in the same direction (Table 4). Historical wind–wave exposure therefore supplied complementary information during some validation periods, but its forecast gain did not transfer consistently to the final evaluation period.

Table 4. Environmental feature group ablation on the independent 2021–2025 evaluation set.

Model	Feature Configuration	RMSE(m)	MAE (m)	Dynamic RMSE (m)
Transformer	Complete environmental features	9.403	7.399	12.042
Transformer	Shoreline history only	8.515	6.465	10.596
Random forest	Complete environmental features	10.871	8.715	12.577
Random forest	Shoreline history only	9.847	7.785	11.459

SHAP feature group attribution was greatest for shoreline memory (mean absolute SHAP value, 15.394), followed by wave exposure (4.426), wind exposure (3.123), and spatial position (0.505) (Figure 11). Shoreline distance was the highest-contributing individual variable; among environmental features, cross-shore wave-flux P99 had the highest attribution. Together with the ablation results, recent shoreline state was the most stable predictive information, while annual wind–wave exposure provided a secondary and period-dependent statistical contribution.

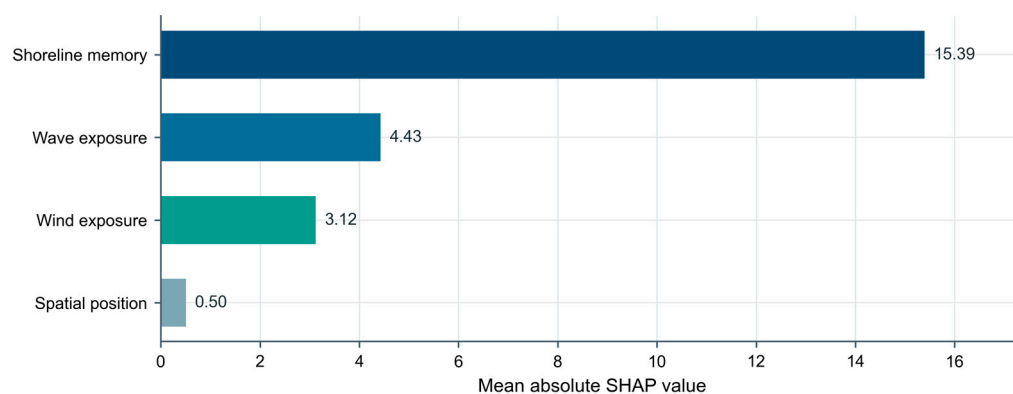


Figure 11. SHAP feature group attribution for the complete-environment Transformer.

4.4. Shoreline Forecasts for 2026–2030 and Conditional Uncertainty

Using observations during 2016–2025, the model generated five forecast horizons for 2026–2030 in one pass. Beach-mean central displacements were -5.923 , -6.599 , -11.564 , -8.046 , and -8.527 m for forecast horizons 1–5, respectively (Table 5; Figure 12). The 95% conditional residual bootstrap intervals were below zero at the beach-mean scale for all horizons. For 2030, central displacement was -8.527 m with an interval of -12.514 to -4.950 m.

Table 5. Beach-mean direct forecast displacements for 2026–2030 and 95% conditional residual bootstrap intervals.

Year	Forecast Horizon	Central Displacement (m)	Conditional Residual Bootstrap Median (m)	95% Lower Bound (m)	95% Upper Bound (m)
2026	1	−5.923	−5.580	−8.330	−2.807
2027	2	−6.599	−7.429	−10.806	−3.777
2028	3	−11.564	−12.535	−16.157	−8.621
2029	4	−8.046	−8.608	−12.352	−5.559
2030	5	−8.527	−8.896	−12.514	−4.950

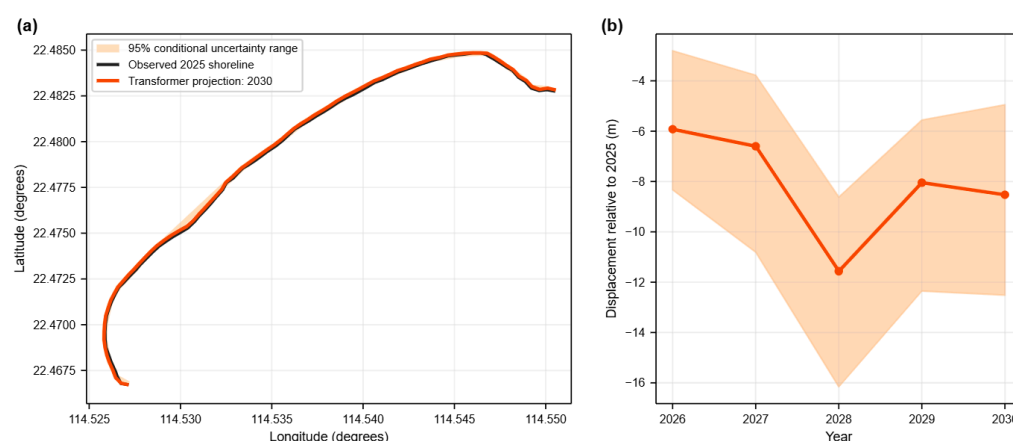


Figure 12. Direct forecasts and conditional uncertainty for 2026–2030: (a) observed 2025 shoreline, central 2030 forecast, and conditional spatial range; (b) beach-mean displacement and 95% conditional interval. In panel (b), the orange line shows the beach mean central displacement forecast relative to 2025, and the shaded band shows the 95% conditional residual-bootstrap uncertainty range.

A beach-mean interval below zero does not mean that every local reach can be assigned a landward direction. All 80 local-transect 95% intervals crossed zero, and block lengths of 8 and 16 gave the same beach-mean direction. The present model therefore gives a

conditional beach-mean landward-displacement signal, whereas local erosion or accretion direction remains unresolved.

5. Discussion

5.1. Remote-Sensing Shoreline Uncertainty and the Resolvable Scale of Historical Change

Long Landsat records provide a stable data source for multi-decadal shoreline analysis, but the conclusions they support depend on the size of change signals relative to observation error. RMSE against independent reference shorelines was 11.41–19.29 m, and RMSE between the annual landward-envelope composite and annual median waterlines was 12.78 m. These measures describe external positional agreement and differences caused by annual shoreline definition, respectively, and cannot substitute for one another. Both indicate that sub-10 m absolute displacements and near-zero local changes are readily affected by image resolution, water level, wave setup, and annual compositing. This is consistent with error sources identified in studies of remote-sensing shoreline definition, annual statistical shorelines, and algorithm benchmarks [1,22–27].

Shoreline definition clearly affected absolute position and LRR magnitude, but along-shore rate distributions from the two annual representations were strongly correlated and 97.5% of transects retained the same change direction. The annual landward-envelope composite waterline can therefore describe the main erosion–accretion zones stably, although its rate magnitude should not be treated as fully interchangeable with other annual representative lines. Transect-spacing analysis gave a similar result: 25–100 m configurations had little effect on beach-mean LRR, whereas local hotspot boundaries were more sensitive to sparse sampling. Beach-scale spatial patterns are consequently more robust than the absolute rate at a single location.

The Monte Carlo results further show this scale difference. The beach-mean LRR interval lies entirely below zero, so the long-term landward-change signal remains resolvable after spatial averaging. The 39 local intervals that cross zero show that direction classification is more sensitive to positional perturbation at the transect scale. Historical shoreline predictability is therefore not simply predictable or unpredictable; it varies jointly with spatial aggregation, change magnitude, and observation precision.

The Monte Carlo procedure used independent, zero-mean Gaussian perturbations. It propagates point position error but does not explicitly represent common displacement of an entire shoreline in a given year or non-Gaussian tails. The resulting intervals should therefore be interpreted as robustness ranges conditional on this error model. Synchronous topography, measured total water level, and higher-resolution imagery could help separate tide, wave setup, seasonal morphology, and image registration errors in future work.

5.2. Added Value of the Spatiotemporal Transformer and Sources of Multi-Year Predictability

The common baseline comparison shows that the residual spatiotemporal Transformer had the lowest position error in the present single-site overall evaluation. This result indicates that a 10-year history, spatial structure among neighboring transects, and direct multi-horizon residual representation extract information beyond persistence and rolling trend. Random forest also clearly performed better than the two simple baselines, showing that nonlinear shoreline history itself contains substantial predictive signal. The Transformer further reduced overall RMSE, although its improvement in Dynamic RMSE was smaller.

The model advantage was also horizon dependent. The Transformer performed better in 2021–2024 but not in 2025 relative to persistence. This reversal shows that rankings in short annual records vary with evaluation period and shoreline state; a mean metric cannot establish a general advantage for every year or site. Previous shoreline forecast

studies and the recent multi-site benchmark likewise show that performance of complex data-driven models depends on time scale, training samples, forcing information, and baseline design [28–34]. The contribution here is to quantify the added forecast value and limits of a residual spatiotemporal Transformer in a common single-site evaluation.

SHAP attribution and environmental ablation both identify recent shoreline state as the most stable information source. This result reflects path dependence at the multi-year scale: beach morphology has continuity, so future position is first constrained by recent state. Spatial patches enable the model to use shared changes among neighboring transects and thereby improve prediction of overall shoreline form. Because positional encoding, spatial attention, and annual-change features were not removed separately, the current evidence evaluates only the incremental contribution of the environmental feature group and cannot partition the contribution of all architectural components.

Transformer RMSE was lower than the shoreline error for some of the four independent reference years, but model error and observation error are not independent quantities that can be directly subtracted. Observation error occurs in both input sequences and evaluation targets and jointly constrains the attainable error floor. Further improvement will require better shoreline observation, temporal resolution, and process information, not simply a larger network.

5.3. Forecast Contribution of Environmental Information and Limits of Physical Interpretation

Environmental processes have clear coastal dynamic relevance, but physical association does not necessarily translate into forecast gain across periods. The complete-environment model improved slightly in rolling validation, whereas the shoreline history configuration performed better in the independent evaluation; random forest showed the same direction of change. This consistency suggests that the result is not specific to the Transformer and more likely reflects annual aggregation and distributional transfer of the environmental features.

Annual cumulative exposure, P95, P99, and high-exposure hours were derived from hourly ERA5 data [39]. These features retain more high-energy information than simple annual means but do not represent storm sequence, seasonal beach state, or post-event recovery. ERA5 variables also represent offshore grid cell exposure and were not transformed through nearshore refraction, breaking, sheltering, or depth effects. These factors may weaken the direct correspondence between environmental signals and annual shoreline response.

Wave and wind features received secondary SHAP attribution, meaning that the fitted model used them for some forecasts; their attribution values do not rank independent physical drivers. Correlation among environmental variables can also redistribute contributions across features. Without nearshore hydrodynamic, beach profile, and sediment transport observations, environmental results are limited here to statistical contributions in the fitted model rather than specific sediment transport mechanisms.

5.4. Future Forecasts, AI-Assisted Application, and Scope of Transfer

The direct multi-horizon design avoids feedback error from recursively reinserting prior forecasts. Beach-mean conditional intervals for 2026–2030 were below zero, indicating a beach-scale landward displacement signal conditional on the model structure and continuation of historical evaluation residuals. The forecast trajectory was not monotonic: displacement was largest in 2028 and then weakened, reflecting the joint influence of historical state and spatial relations in the model output.

Because all local-transect intervals crossed zero, the beach-mean signal cannot be converted directly into deterministic erosion boundaries for individual reaches. Spatial

averaging can reduce some local residuals of opposing sign, whereas individual transects remain affected by substantial interannual variability. The forecasts are therefore suited to identifying beach-scale change tendencies and monitoring needs. Local engineering design still requires field topography, hydrodynamics, sediment, and human activity information.

The conditional residual bootstrap propagates the random residual structure of the independent evaluation period only. It does not include initial shoreline systematic bias, forecast period bias, model parameter uncertainty, unknown future typhoons or engineering activity, or potential geomorphic regime shifts. The future intervals are therefore not a complete probabilistic forecast or a total uncertainty budget.

Evaluation was conducted only at Xichong Beach. Its continuous record and arcuate sandy shoreline support method testing but also limit the scope of transfer. Independent multi-site validation is still needed across different tidal ranges, slopes, sediment types, wave climates, and engineering settings.

The AI-assisted workflow improves shoreline processing, experimental reproducibility, and model update efficiency, but key steps remain expert supervised. Future work could incorporate higher-resolution shorelines, field beach slopes, nearshore waves, storm events, and engineering records, together with process constraints and continuous data assimilation. Until multi-source updates, external validation, and a fuller uncertainty budget are completed, the workflow should be viewed as a site-scale AI-assisted monitoring and forecasting application rather than a complete coastal digital twin.

6. Conclusions

Using Landsat waterlines from the period 1986–2025, this study evaluated multi-year predictability of sandy shoreline change at Xichong Beach through annual shoreline representation, historical change robustness, model baselines, and future conditional uncertainty. The annual landward-envelope composite waterline was systematically about 10 m landward of annual median waterlines and produced a more negative mean LRR. Nevertheless, their alongshore rate distributions were strongly correlated, and changes in transect spacing did not alter the main beach-scale erosion–accretion zones. After positional-error propagation, long-term beach-mean landward change remained resolvable, whereas change direction remained uncertain at 39 local transects.

Under a common 2021–2025 evaluation protocol, the residual spatiotemporal Transformer had the lowest overall RMSE, MAE, and Dynamic RMSE among the four models, with an RMSE skill of 27.0% relative to persistence. Random forest captured a moderate predictive signal, whereas rolling linear trend was close to persistence. The Transformer's advantage was clearest for overall shoreline position and varied by forecast horizon. It therefore represents added value at the present site and evaluation period, rather than a general advantage across all years or coastal settings.

Recent shoreline state was the most important and stable predictive information. Historical wind–wave exposure received secondary model attribution but did not provide a consistent overall accuracy gain in the independent evaluation period. Beach-mean conditional intervals for 2026–2030 indicated landward displacement, while all local-transect intervals crossed zero. Multi-year sandy shoreline predictability should thus be expressed by spatial scale and uncertainty: beach-mean trends are more resolvable, whereas local change direction requires higher-quality observations, nearshore process data, and multi-site validation.

Author Contributions: Conceptualization, K.T., F.S. and F.Y.; methodology, K.T. and F.Y.; software, K.T.; validation, K.T. and J.Z.; formal analysis, K.T.; investigation, K.T.; resources, F.S. and F.Y.; data curation, K.T. and J.Z.; writing—original draft preparation, K.T.; writing—review and editing, F.S.,

F.Y., V.L. and J.Z.; visualization, K.T.; supervision, F.S. and F.Y.; project administration, F.Y.; funding acquisition, F.S. and F.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China (No. 42476195) and Youth Innovation Promotion Association of Chinese Academy of Sciences (2023060).

Data Availability Statement: The source datasets used in this study are publicly available from the repositories cited in the manuscript. The processed shoreline dataset, derived results, and model outputs generated during the study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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