

Reconstructing Significant Wave Height Fields from Sparse Observations Using Physics-Guided Virtual Observations

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Highlights

- T2S-W reconstructs high-fidelity wave height fields from sparse observations using physics-guided virtual observations.
- T2S-W achieves 0.20 m RMSE at 99.8% missing rate with strong robustness in monsoon and typhoon events.
- LightGBM learns nonlinear source-sink terms and decouples wind wave and swell dynamics.
- Perturbation experiments confirm the model learns propagation-dependent anisotropic diffusion aligned with group velocity.

Abstract

Real-time, high-precision significant wave height (SWH) fields are essential for ocean forecasting, disaster mitigation, and marine applications. However, extremely sparse observational coverage in vast ocean regions limits accurate reconstruction, as traditional spatial interpolation often produces overly smoothed fields that fail to capture fine-scale structures and sharp gradients. This study proposes the Time-to-Space Wave (T2S-W) Framework, a hybrid approach based on “filling space with time.” It advects historical time-series observations forward to the target time using group velocities to generate physics-guided virtual observations that fill spatial gaps. A lightweight LightGBM model learns nonlinear source and sink terms, applying corrections for dissipation and energy growth along ray paths without real-time wind fields. A CNN–Transformer architecture then performs high-precision continuous reconstruction. Results show strong accuracy and robustness under ~99.8% missing rates, achieving 0.20 m RMSE on test sets while preserving fine-scale structures across monsoon and typhoon conditions. Diagnostics confirm the framework learns wind sea/swell decoupling, shallow-water topographic dissipation, and propagation-dependent anisotropic diffusion. This provides a novel pathway for high-fidelity reconstruction under sparse data and indicates the potential extends to other advection-diffusion ocean fields like temperature, salinity, and tracers.

1 Introductions

Ocean waves constitute one of the most active and destructive dynamic elements in the marine environment. High spatiotemporal resolution significant wave height fields have become core foundational data for a wide range of operational domains, including ocean numerical forecasting, engineering design and maintenance, offshore wind power development, maritime safety, and disaster early warning (Houghton et al., 2023; Nasir et al., 2023; Ningsih et al., 2023; Valamanesh et al., 2015; H. Yang et al., 2024). For instance, Ningsih et al. (2023) demonstrated in Indonesian waters that tropical cyclone activity can markedly elevate the probability of extreme high waves

in adjacent seas, directly threatening fisheries and shipping safety. Nasir et al. (2023) showed along the South China Sea coast that accurate significant wave height modeling and simulation are essential for understanding coastal dynamic processes.

In practical applications, however, a persistent challenge arises between the “point-wise acquisition” of wave observations and the “areal representation” demanded by end-user applications. Currently, high precision in-situ wave observations rely primarily on fixed buoys and shore-based monitoring stations. Although these platforms deliver extremely high temporal resolution and rigorously calibrated data sequences, their spatial distribution remains highly uneven. Moreover, the number of stations is severely limited by substantial construction and maintenance costs(Beckman & Long, 2022; Duan et al., 2024). In numerous sea areas of strategic importance for shipping and oil-and-gas development, long-term operational wave buoys are extremely scarce, leaving most regions in a state of persistently sparse data or even observational blind zones(Ardhuin et al., 2025; Lv et al., 2025). Such sparse and inhomogeneous observational networks struggle to capture the fine-scale spatial structures of wave fields under complex dynamic processes. This limitation becomes especially severe during non-local swell propagation or under the influence of extreme weather systems such as typhoons, where data from isolated stations cannot adequately represent true sea states over large domains(Balakrishnan Nair et al., 2025; Morales-Márquez et al., 2023).

Satellite remote sensing can partially compensate for the spatial coverage deficiencies of in-situ observations by supplying large-scale surface wind and wave height information. Nevertheless, its applications remain subject to significant constraints. Satellite altimeters measure only along nadir tracks, producing discrete strip-like data with relatively long revisit cycles; consequently, they cannot satisfy the stringent requirements of real-time applications for temporal continuity and high-resolution refinement(Le Traon et al., 2025; Y. Yang et al., 2024). Other remote-sensing techniques, such as synthetic aperture radar (SAR), can furnish two-dimensional wave-spectrum information, yet they are hampered by complex inversion

algorithms, cloud and fog interference, and non-synchronous data acquisition, rendering them unsuitable for independently constructing high-frequency, seamless full-domain wave height fields (Ehlers et al., 2023; R. M. Asiyabi et al., 2023).

Under conditions of extremely high observational missing rates, the rapid and high-precision reconstruction of continuous two-dimensional wave height fields from isolated, scattered observation nodes has emerged as a key technical challenge limiting marine economic development and disaster risk prevention. Traditional spatial interpolation methods (e.g., kriging, inverse-distance weighting) extend point measurements to unobserved grids by constructing semi variograms or distance-decay weights, thereby enabling rapid spatial continuity of discrete observations. These techniques are therefore widely employed in operational ocean monitoring, data-quality control, and preprocessing pipelines(Altunkaynak, 2005; Lu & Wong, 2008; H. Yang et al., 2024). However, such methods implicitly rely on assumptions of spatial stationarity, local correlation, and isotropy, which hinder their ability to represent the nonlinear, non-local propagation of wave energy along characteristic rays(Raissiun et al., 2024; Workneh et al., 2024). Data assimilation systems based on mature spectral or phase-averaged wave models can, when observations are relatively abundant, propagate point or along-track information across larger spatial scales through dynamical constraints, background error covariances, and multi-source data fusion while preserving energy conservation and dispersion relations(Almeida et al., 2016). For example, techniques coupling the ensemble Kalman filter with higher-order spectral methods have proven effective for reconstructing and forecasting phase-resolved surface waves(Wang & Pan, 2021). Nevertheless, numerical assimilation approaches incur high computational costs that conflict with the demand for rapid updates in operational settings(Patanè et al., 2024). They also depend heavily on real-time wind forcing and parameterized source functions(Siadatmousavi et al., 2024; Umesh & Behera, 2020; Zhou et al., 2022). Under extremely sparse in-situ conditions, although assimilation systems can diffuse point observations into surrounding regions via background error covariances, the extremely low

observational coverage restricts the spatial influence of the corrections. The system therefore remains dependent on background field quality and struggles to constrain regions far from observation sites(S. Chen et al., 2024; Smit et al., 2021; Wang et al., 2022b). This challenge is exacerbated in operational scenarios lacking quasi-real-time, high accuracy wind forcing, where biases in the background field itself limit the effectiveness of assimilation corrections(Hu et al., 2024).

In recent years, deep learning methods have attracted considerable attention in the field of sparse wave height field reconstruction owing to their powerful nonlinear mapping capabilities. Duan et al.(2024) developed a regional wave reconstruction (RWR) model based on fully connected networks and convolutional neural networks, enabling rapid reconstruction of wave height distributions in the Hawaiian and Mexican seas from sparse buoy observations. They systematically analyzed the influences of reconstruction domain boundaries and buoy density on accuracy. Lv et al.(2025) constructed an Actor-Critic framework fusing U-Net and GAN architectures to achieve joint multi-variable wave field reconstruction and identified an adaptive observation point selection strategy that significantly outperforms uniform deployment at 1% observational density. Shi et al.(2026) proposed the AUWave hybrid deep learning framework, which employs a station-level MLP encoder and a self-attention enhanced U-Net decoder to reconstruct high resolution regional significant wave height fields rapidly from sparse buoy observations. Through Optuna based automated hyperparameter optimization and cross Atlantic Pacific transfer validation, the framework demonstrated superior accuracy and portability relative to the RWR baseline. However, the aforementioned approaches perform static spatial completion at a single time instant and do not dynamically exploit historical observations in the temporal dimension. Consequently, their ability to recover high-frequency structures and frontal features remains limited under extremely high missing rate scenarios. Other studies have focused on imputing missing values and extending records in fixed-buoy time series: Bujak et al.(2023) combined neural networks with an integrated surface database to fill gaps and prolong

significant wave height measurements. Chen et al.(2022) proposed a low-rank tensor completion model for gap filling of wave records. Patanè et al.(2024) developed a deep hybrid network for significant wave height estimation. Çelik(2026) employed a lightweight recurrent neural model to reconstruct complete wave-height sequences from sparse observations. Tan et al.(2026) built a graph-neural-network model that fuses spatiotemporal information for buoy-data imputation. All of these works address temporal dimension recovery at fixed buoy locations rather than generating complete two-dimensional spatial wave field distributions over entire sea domains. Furthermore, existing deep learning approaches for wave data completion generally lack physical interpretability or mechanism diagnostics, making it difficult to ascertain whether the models have genuinely learned ocean dynamical laws. Physical consistency therefore remains a notable deficiency.

To address the limitations of traditional methods (loss of high frequency information), numerical models (dependence on parameterization schemes and external forcing), and current deep learning approaches (insufficient physical guidance and interpretability), this study proposes Time to Space-Wave (T2S-W) Framework, the innovative design concept of “filling space with time.” The aim is to overcome information gaps arising from large-scale observational voids and to achieve high precision wave field reconstruction under extremely low observational coverage. The core contributions of this paper are threefold:

(1) Development of an adaptive wave field reconstruction framework suited to varying data conditions: In severely data limited scenarios with only extremely sparse wave height observations, a purely data driven base spatial-completion model is constructed. In scenarios with additional physical parameters, the framework is extended to a hybrid architecture that integrates “kinematic forward propagation—nonlinear wave-height correction—spatial reconstruction,” achieving high precision reconstruction at an approximately 99.8 % data missing rate.

(2) Breakthrough of information gap limitations at extremely low

observational coverage via virtual observations: The proposed T2S-W Framework exploits wave kinematic priors by advecting historical time series observations forward along group velocity rays to the current time, thereby filling spatial blind zones and supplying information increments to the spatial completion model. Physical feature based nonlinear corrections are further applied to the virtual observations, effectively mitigating systematic biases introduced by the simple wave energy conservation assumption and substantially improving reconstruction quality under realistic, complex marine environments.

(3) Enhancement of the interpretability of AI models through physical

diagnostics: By means of spatial diagnostics, SHAP feature attribution, and single-point targeted perturbation experiments, the study verifies that the model learns genuine ocean dynamical laws. It reveals that, even without wind field input, the model autonomously learns morphological evolution of wind sea and swell, nearshore topographic dissipation, and spatial diffusion covariance mechanisms characterized by anisotropy and propagation dependence.

The remainder of this paper is organized as follows. Section 2 systematically describes dataset construction, the sparse wave height reconstruction framework, and feature engineering design. Section 3 presents statistical evaluation of the framework on internal and external test sets together with morphological diagnostics under conventional monsoon sea states and extreme typhoon events. Section 4 provides physical mechanism interpretation and discussion of propagation direction dependent spatial diffusion responses of the reconstruction model, as well as shallow water topographic dissipation and wind-sea/swell dynamical decoupling within the wave height correction model. Section 5 summarizes the main conclusions and outlines future research directions.

2. Data and Methodology

This chapter systematically describes the datasets employed and the proposed T2S-W Framework. It first introduces data acquisition and variable selection, followed by a detailed exposition of the framework's three core components: the purely data driven base spatial completion model, virtual observation generation based on wave kinematic priors, and nonlinear dynamic correction of wave height via LightGBM.

2.1 Data Set Construction

2.1.1 Training and internal test datasets (CMEMS)

The training and internal evaluation data for this study originate from the global ocean wave reanalysis dataset provided by CMEMS (European Union Copernicus Marine Service, 2019). This dataset is driven by an advanced third-generation spectral wave model and assimilates extensive satellite altimetry observations, enabling high-fidelity reproduction of the complex evolutionary processes of real ocean waves. The dataset features a spatial resolution of $0.2^\circ \times 0.2^\circ$ and a temporal resolution of 3-hourly intervals, encompassing long-term historical records since 1993. It supplies abundant samples for the framework to learn multi-scale ocean climate rhythms and wave dynamical laws. To ensure rigorous evaluation, the extracted long-term historical wave height field samples were strictly partitioned into training (1 January 1993 – 12 October 2018), validation (13 October 2018 – 17 April 2020), and internal test (18 April 2020 – 30 April 2023) sets in an 8.5:0.5:1 ratio. The training set was used for parameter optimization of the base model and the LightGBM module, the validation set for hyperparameter tuning and early-stopping control, and the internal test set exclusively for final objective quantitative performance assessment.

2.1.2 External independent test dataset (ERA5)

To verify whether the model overfits to a single reanalysis system, this study introduces the completely independent ERA5 wave reanalysis dataset (Copernicus Climate Change Service, 2018). This dataset differs from CMEMS in physical forcing

mechanisms, assimilation schemes, and spatiotemporal grids, thereby serving as an important benchmark for evaluating the model's generalization and transfer capability. The study extracted four consecutive complete years (2020–2023) of ERA5 data. These data participated in neither model training nor hyperparameter selection and were reserved entirely for external independent validation. To maintain grid consistency, the native 0.5° coarse resolution ERA5 fields were interpolated onto the target 0.2° grid, and the hourly time series were averaged to 3-hourly intervals to match the model's physical spatiotemporal resolution.

2.1.3 Study area and physical variables

The South China Sea (SCS) was selected as the experimental domain. This region is characterized by alternating monsoon regimes and frequent typhoon activity, exhibiting typical complex air–sea coupling dynamics; it is also an area of strategic importance for international shipping and offshore oil-and-gas development. The study domain spans 106.0°E – 120.0°E and 9.0°N – 23.0°N .

The primary physical variables employed by the model include significant wave height (VHM0), mean wave period (VTM10), mean wave direction (Dir), and the partitioned wind-sea and swell components of each variable. In addition, local group velocity, computed from wave period and static water depth, serves as the key prior for propagation calculations.

2.2 Pure Data Driven Base Model for Spatial Reconstruction

Under extremely sparse observational conditions, conventional spatial interpolation methods become ineffective because of large-scale spatial information gaps. To bridge vast unobserved regions and extract complex wave spatial structures, this study designed a hybrid deep learning architecture that fuses convolutional modules and transformer encoder layers, incorporating progressive mask updating and dynamic physical constraint losses to guarantee spatial continuity and physical consistency of the reconstructed fields.

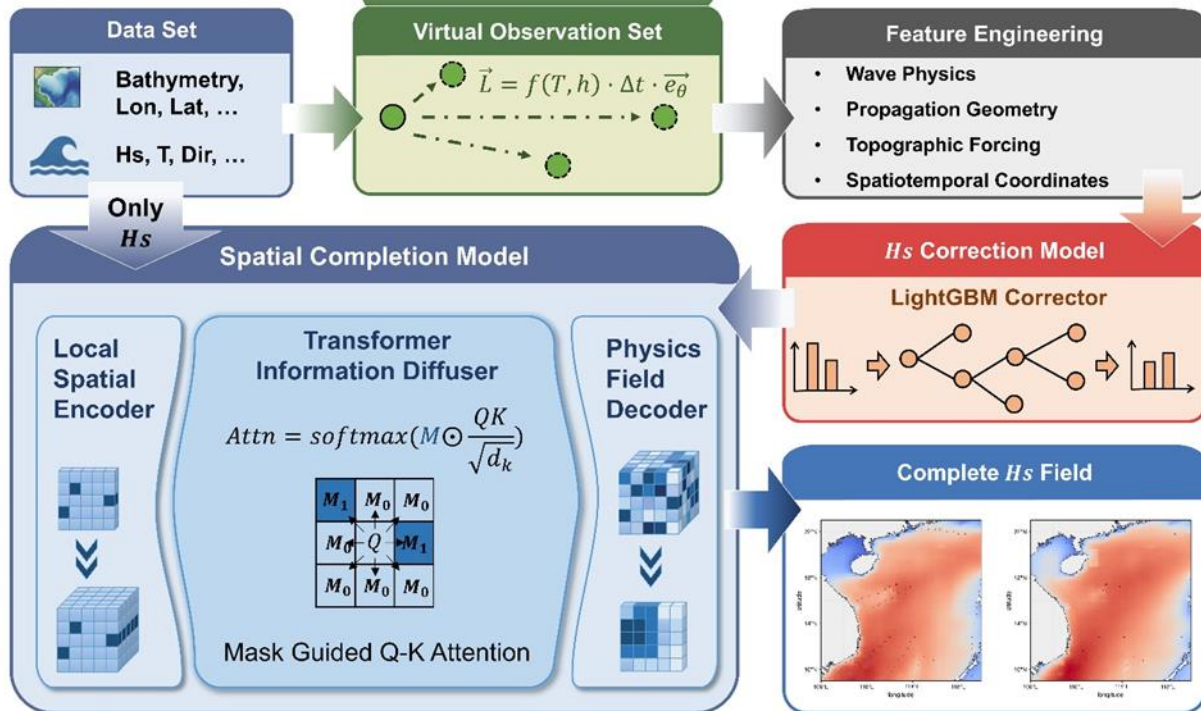
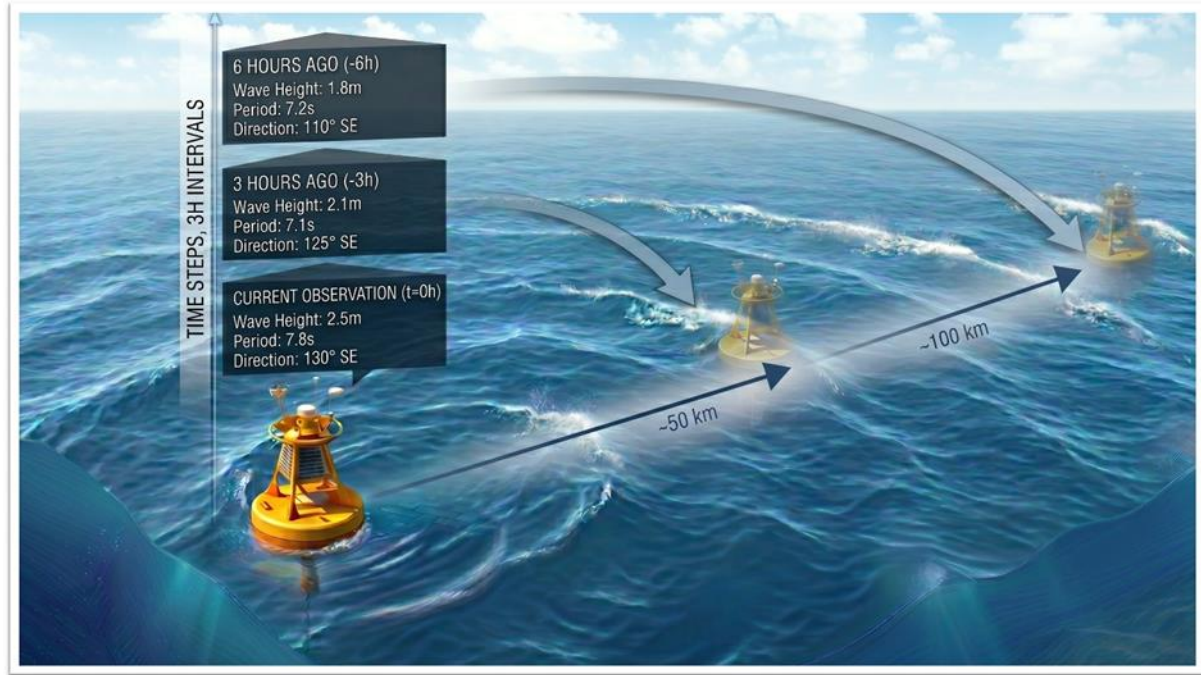


Figure 1 Schematic diagram of base spatial completion model and the physics-enhanced significant wave height field reconstruction framework (T2S-W). The blue modules (Dataset, Spatial Completion Model, Complete Field) constitute the workflow of the base model (purely data-driven spatial completion); the remaining components form the complete

pipeline of virtual-observation enhancement T2S-W Framework, including kinematic virtual observation generation, feature engineering, and LightGBM nonlinear correction. The top panel illustrates the kinematic prior driven virtual observation forward propagation process, in which observations from different historical moments are advected along group-velocity rays to the target time.

2.2.1 Basic Reconstruction Model

The base model adopts a “CNN encoder–Transformer–CNN decoder” architecture comprising three principal modules:

Local spatial encoder: The input sparse wave height field is first processed by a CNN encoder that extracts local features and maps the single physical scalar field (H_s) into a high dimensional latent feature space.

Global spatial covariance modeling: To address information gaps over extensive unobserved domains, a Transformer network containing 12 encoder layers operates in latent space as a global information propagator and completion model. The multi head self-attention mechanism learns data driven, non-stationary spatial covariances—i.e., nonlinear long-range correlations between any pair of spatial grid points—from large volumes of historical wave height fields, thereby realizing spatial information transfer analogous to background error covariances in advanced data assimilation.

Physics-aware wave height field decoding and reconstruction: The high dimensional features after Transformer interaction and fusion are restored to two-dimensional grid form and decoded by a CNN decoder into a continuous significant wave height field possessing physical meaning.

2.2.2 Progressive Soft-Mask Diffusion Mechanism

Because observational platforms are extremely sparse, large unknown blind zones exist across the spatial grid. Compared with conventional binary masks (known points = 1, unknown points = 0), the present model employs a continuous dynamic

confidence mask mechanism that more effectively guides information diffusion across blind zones.

The mask matrix represents the confidence level of each grid point. In the initial state, real observation points are assigned a confidence of 1.0, while unobserved regions receive a small initial prior confidence, like 0.01. During the layer-by-layer forward propagation of the Transformer encoder, mask confidence values are updated by successive square-root operations following an exponential schedule. As network depth increases, mask values in low-confidence regions progressively approach 1.0. This design ensures that the network prioritizes definite real observation points in shallow layers and gradually diffuses high-confidence inferred information smoothly across the entire fluid domain in deeper layers, thereby avoiding the introduction of errors from initial attention noise in shallow layers.

2.2.3 Physics-Aware Dynamic Normalized Loss

Relying solely on mean-squared error (MSE) as the loss function easily leads the model to produce overly smoothed outputs that suppress extreme sea states and frontal gradients present in the real ocean. Consequently, this study introduces a multi-dimensional physical-constraint loss together with a dynamic exponential moving-average (EMA) normalization mechanism.

The overall loss function comprises three components:

$$\mathcal{L}_{total} = \mathcal{L}_{MSE} + \lambda_{grad}\mathcal{L}_{Grad} + \lambda_{spec}\mathcal{L}_{Spec}$$

Where $\mathcal{L}_{MSE}$ is the wave height amplitude loss constraining absolute magnitude errors; $\mathcal{L}_{Grad}$ is the spherical gradient loss that accounts for actual physical distances on the latitude–longitude grid and enforces retention of wave-front sharpness; and $\mathcal{L}_{Spec}$ is the local frequency domain energy spectrum loss that, via fast Fourier transform (FFT), ensures the energy cascade of the reconstructed field across spatial scales conforms to real ocean dynamical laws.

Dynamic normalization mechanism: Because the three loss terms differ substantially in magnitude and physical dimensions, fixed weights easily cause training instability. After a warm-up period the model establishes a dynamic tracker based on EMA that continuously captures the historical median statistics of each loss component ($\mu_{mse}, \mu_{grad}, \mu_{spec}$). In subsequent optimization, the model computes dynamic denominators ($\lambda_{grad} = \mu_{grad}/\mu_{mse}$) in real time to anchor the gradient and spectral losses to a scale comparable to the MSE loss. This adaptive balancing strategy effectively prevents “spurious convergence” caused by large-magnitude loss terms dominating gradient updates while precisely capturing high-frequency wave structures and nonlinear features.

2.3 Virtual Observation Enhancement based on Wave Kinematic Priors

The base spatial completion model utilizes only sparse observations at a single instant and therefore fails to exploit historical time-series observations effectively. To fill spatial gaps with historical observations, this study proposes a virtual observation enhancement component of the T2S-W, which is grounded in wave kinematic priors. The T2S-W Framework applies the physical laws of wave propagation to “forward advect” measured data from past moments to the target time, thereby substantially increasing the information density and spatial coverage of the input field.

2.3.1 Kinematic Propagation of Historical Observations

This stage employs idealized wave propagation assumptions to map data from the temporal to the spatial domain: each observed wave is assumed to be narrow-banded and unimodal, with significant wave height, period, and direction conserved during propagation. For any historical observation point within a sliding time window, the wave state is defined jointly by wave height, group velocity, and wave direction. Virtual observation generation proceeds as follows:

Propagation position estimation: From the group velocity and time interval of the historical observation, the propagation distance on the sphere is calculated.

Combined with the wave propagation direction, spherical trigonometry yields the theoretical arrival latitude and longitude.

Grid-point mapping: The theoretical position is mapped to the nearest model grid point. If the landing point lies outside the computational domain boundary or on a land mask, the trajectory is discarded. Otherwise, a “virtual observation” equal in magnitude to the historical wave height is generated at that location.

Through the above physical forward propagation process, historical data originally fixed at sparse buoy locations are transformed into a virtual observation network distributed across the domain at the target time, effectively filling spatial blind zones.

2.3.2 Temporal-Decay Confidence Masking

Virtual observations are generated under the idealized “source and sink free” assumption. As forward propagation time increases, accumulated nonlinear deformation and dissipation errors inevitably grow. Consequently, the spatial completion model must distinguish “real observations” from “virtual observations that contain error.” This study constructs an initial confidence mask assignment based on the temporal difference of virtual observations: real observation points receive the highest mask value (1.0); virtual observation mask values lie in the interval $[0, 1]$ and obey a “temporal-decay principle”—the closer the observation is to the target time (smaller temporal difference), the higher its mask value. This arrangement allows high confidence virtual observations to be activated preferentially in the shallow layers of the Transformer, dominating information diffusion into surrounding blind zones, while low confidence distant historical virtual observations participate in spatial interaction only after deeper layer iterations.

2.4 Non-linear Wave Height Correction via LightGBM

Real wave propagation is governed by source and sink terms that include wind-energy input, nonlinear wave–wave interactions, bottom-friction dissipation, white-capping dissipation, and shallow-water breaking. The idealized wave energy

conservation assumption underlying virtual observations therefore introduces systematic errors in realistic environments. For application scenarios in which real-time complete wind fields are difficult to obtain, this study introduces a lightweight LightGBM(Ke et al., 2017) wave height corrector to construct a nonlinear correction module that learns the source and sink terms of wave propagation through readily available physical feature proxies. LightGBM approximates the true wave height correction values by integrating multiple regression decision trees. Its objective function is:

$$\mathcal{L}^{(t)} = \sum_{i=1}^N \left(y_i - \left(\hat{y}_i^{(t-1)} + f_t(x_i) \right) \right)^2 + \Omega(f_t)$$

where $\hat{y}_i^{(t-1)}$ is the cumulative prediction of the previous trees, $f_t(x_i)$ is the output contributed by the current decision tree being optimized, and $\Omega(f_t)$ is the regularization term controlling model complexity (penalizing the number of leaves and leaf weights). To suppress local spatial noise in the gridded data and improve generalization, the model restricts each tree to a maximum of 63 leaves, a maximum depth of 8, and a minimum of 120 samples per leaf.

To enable the model to capture wave energy attenuation and input patterns effectively and in a lightweight manner, this study avoids blind high-dimensional inputs. Instead, a physically guided feature set is constructed from a small number of readily obtainable variables: single point wave observation elements (initial wave height, period, wave direction), spatiotemporal coordinates (latitude, longitude, and seasonal phase) and wave spectrum partition information (wind sea/swell energy ratio). This feature engineering allows LightGBM to learn the nonlinear dynamics of wave source and sink terms effectively even in the absence of real time wind field input.

3 Results

To evaluate the performance of the proposed Base model and the physics-enhanced T2S-W framework under extremely sparse observational conditions, this chapter systematically presents reconstruction results on the CMEMS internal test set and the ERA5 external validation set under a 99.8 % data missing rate (only nine observation platforms within the SCS study area). The locations of the known observation points were completely randomly selected once at the outset and held fixed throughout the entire dataset to emulate the fixed-position operational mode of anchored mooring buoys. This design provides a realistic testbed for persistently sparse and geographically static observational coverage. Section 3.1 compares statistical metrics and spatial visualizations of the Proposed T2S-W framework, the Base model, U-Net, and conventional interpolation methods during the regular monsoon period and the entire test set, thereby verifying the contribution of virtual observations to blind-zone information filling and fine-scale structure recovery. Section 3.2 assesses robustness and extreme value reconstruction accuracy of typhoon period samples under strongly nonlinear conditions. Section 3.3 independently evaluates the error evolution of the LightGBM wave height correction module relative to the benchmark.

3.1 Conventional Sea Conditions: Statistical Metrics and Spatial Visualization

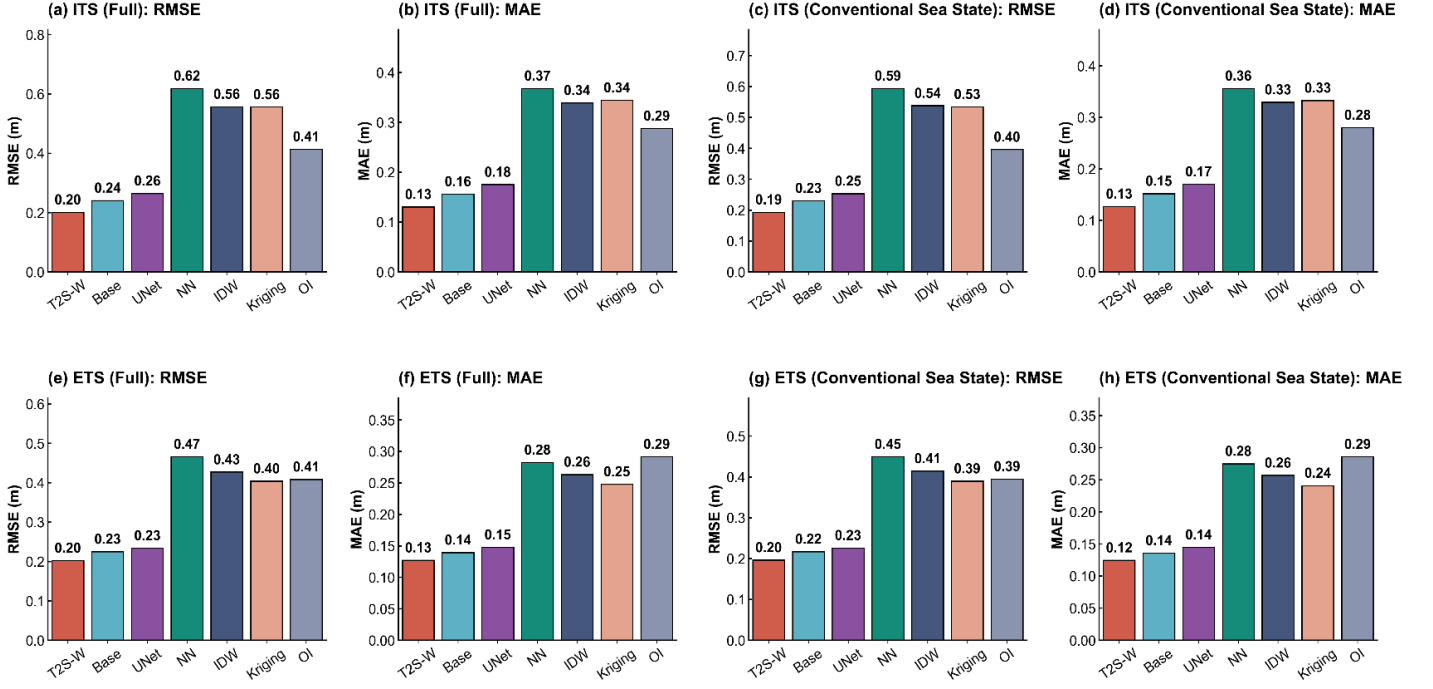


Figure 2. Comparison of reconstruction performance on the internal test set (ITS) and external validation set (ETS) for the full test set and conventional sea states. (a) ITS full test set RMSE; (b) ITS full test set MAE; (c) ITS conventional sea state RMSE; (d) ITS conventional sea state MAE; (e) ETS full test set RMSE; (f) ETS full test set MAE; (g) ETS conventional sea state RMSE; (h) ETS conventional sea state MAE. Methods compared include the complete Framework proposed in this study (T2S-W), the purely data-driven base model (Base), a mainstream deep learning model (U-Net), and conventional interpolation methods (NN, IDW, Kriging, OI).

On both the internal test set and the independent external validation set, the complete framework (T2S-W), the purely data-driven base model (Base), a representative mainstream deep learning baseline (U-Net), and four conventional methods (local distance weighted approaches NN and IDW together with geostatistical methods Kriging and OI) were systematically compared under extremely sparse observational conditions. Evaluation metrics comprised RMSE and MAE for both the full test set and conventional (non-typhoon) sea states. This section focuses on statistical metrics and spatial-visualization case studies for the non-

typhoon period. Dedicated results for typhoon extreme events are presented separately in Section 3.2.

As shown in Figure 2(c)–(d), under extremely sparse observational conditions traditional local interpolation methods (NN, IDW, Kriging) exhibit severe errors because spatial correlations are broken, RMSE exceeds 0.50 m. OI, which incorporates a static background field, reduces RMSE to 0.40 m but remains limited by the isotropy assumption. In contrast, deep learning models demonstrate excellent spatial completion capability across large blind zones: U-Net lowers RMSE substantially to 0.25 m, while the Base model developed in this study, leveraging a global long-range attention mechanism, achieves an advantage at 0.23 m. Among all models the T2S-W Framework exhibits the strongest adaptability to sparse data, attaining the lowest global RMSE of 0.19 m. MAE and MAPE metrics likewise indicate that T2S-W is optimal (0.13 m and 14.69 %, respectively). On the external validation set (Figure 2(e)–(h)), because ERA5 fields possess smoother spatial structures the reconstruction task is somewhat easier and a modest reduction in error appears for some traditional interpolation methods. The T2S-W Framework nevertheless maintains the best performance, with RMSE = 0.20 m, MAE = 0.12 m and MAPE = 11.82 %, outperforming the Base model (0.22 m), U-Net (0.23 m) and all conventional methods.

On the full test set (Figure 2(a)–(b) and (e)–(f)) the relative ranking of the models remains essentially identical to that observed for conventional sea states. The T2S-W Framework continues to deliver the best performance, although errors increase slightly, indicating that the framework retains good robustness when the complete test set—including extreme events—is considered.

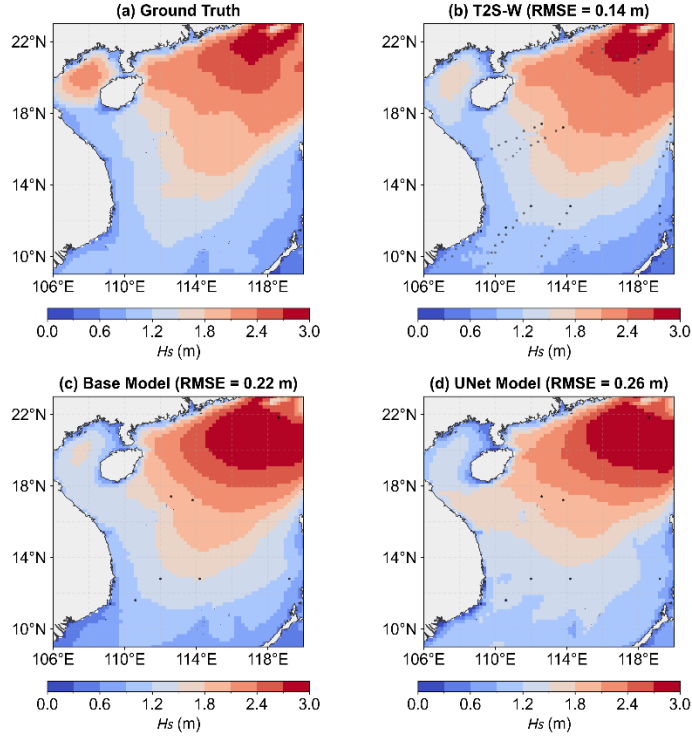


Figure 3. Multi-scale physical structure reconstruction comparison for a monsoon period wave height field. (a) Ground truth wave height field. (b) Reconstruction by the proposed framework (T2S-W). (c) Reconstruction by the purely data driven base model (Base Model). (d) Reconstruction by the mainstream deep learning baseline (U-Net). Black dots denote real observation locations; Grey dots represent virtual observation trajectories of varying confidence.

Figure 3 presents a multi-scale physical structure reconstruction comparison for a typical monsoon period wave height field on 14 December 2020. In the ground truth field (Figure 3a) a high energy wave region excited by the monsoon exists in the northeastern South China Sea, exhibiting fine-scale spatial energy distribution. Under extremely sparse observational conditions the purely data driven deep learning baselines U-Net (Figure 3d) and the Base model (Figure 3c) can recover only large-scale features during spatial reconstruction because they lack data anchors over the extensive unobserved domain, both exhibits pronounced overestimation and outward diffusion of wave energy at smaller scales. Although the Base model, benefiting from its global long range attention mechanism, achieves a marginally lower error (RMSE = 0.22 m) than U-Net (RMSE = 0.24 m), both reveal the inherent limitation of relying solely on deep learning

for large area information gap reconstruction: they struggle to delineate local energy gradients accurately.

The complete T2S-W Framework proposed in this study (Figure 3b) achieves the best reconstruction accuracy, with global RMSE reduced dramatically to 0.14m and spatial pattern in close agreement with the ground truth. The figure clearly shows that the T2S-W Framework benefits from the virtual observation points (grey dot trajectories in Figure 3b) distributed by kinematic forward propagation, which augment information content in observational blind zones. These physically constrained priors along wave rays successfully suppress the unrealistic overestimation in the northeastern South China Sea that the Base and U-Net models produce under large-scale data gaps. This result strongly demonstrates that the T2S-W Framework, relying on the physical information increment supplied by “filling space with time,” not only controls global statistical error but also compensates for the tendency of purely data driven models to generate spurious energy diffusion in unobserved blind zones, thereby furnishing more accurate fine-scale wave structures and energy distribution boundaries.

3.2 Typhoon Period: Statistical Metrics and Spatial Visualization

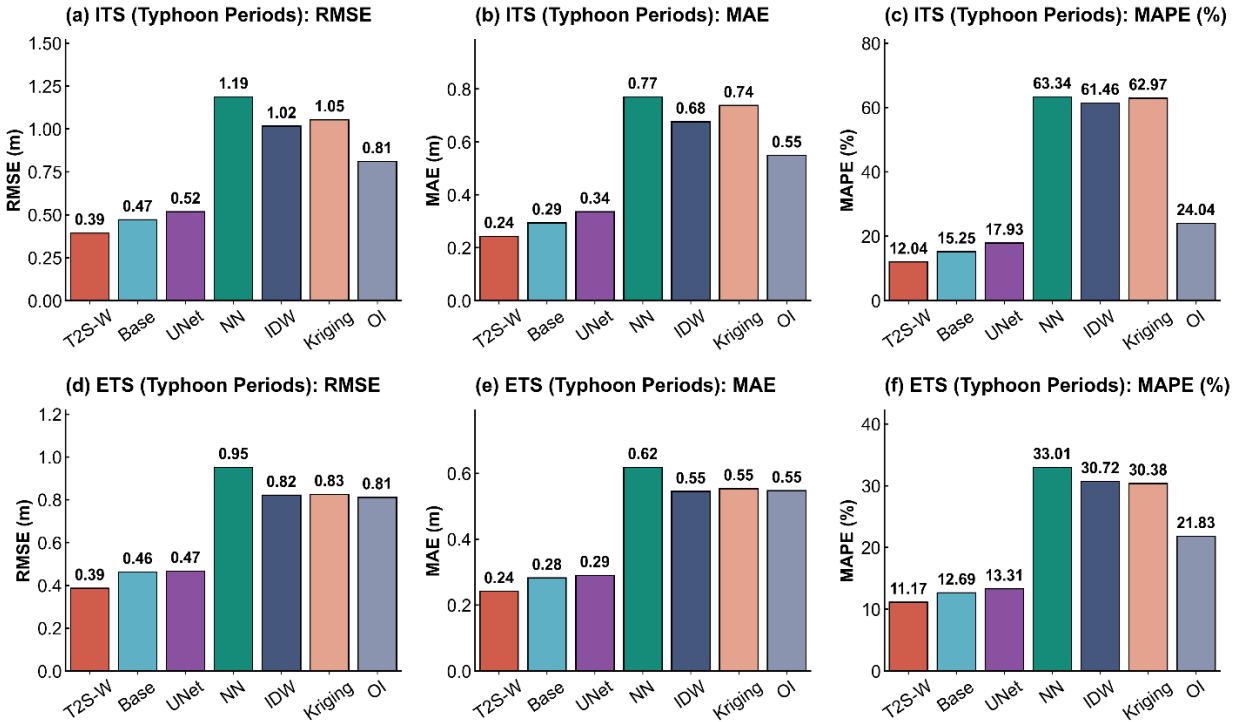


Figure 4. Comprehensive comparison of spatial reconstruction performance on the internal test set (ITS) and external validation set (ETS) during the typhoon period. (a) ITS typhoon periods RMSE; (b) ITS typhoon periods MAE; (c) ITS typhoon periods MAPE (%); (d) ETS typhoon periods RMSE; (e) ETS typhoon periods MAE; (f) ETS typhoon periods MAPE (%). Methods compared include the complete framework proposed in this study (T2S-W), the purely data driven base model (Base), the mainstream deep learning architecture (U-Net), and conventional interpolation methods (NN, IDW, Kriging, OI).

To assess reconstruction performance under typhoon extreme sea states, this section separately analyzes statistical metrics and presents spatial visualization case studies for typhoon period samples. As shown in Figure 4(a)–(c), on the typhoon period internal test set, conventional interpolation methods (NN, IDW, Kriging) perform poorly, with RMSE reaching approximately 1m and MAPE exceeding 60%. Purely data driven deep learning models also experience clear performance degradation, although they keep errors within a manageable range: U-Net yields a typhoon-period RMSE of 0.52 m and the Base model 0.47 m. Notably, the T2S-W Framework maintains good reconstruction skill even during typhoon periods, achieving a typhoon period RMSE of only 0.39 m, MAE of 0.24 m and MAPE as low as 12.04 %—all lower than the other models. In the independent typhoon validation on the external set (Figure 4(d)–(f)), the T2S-W Framework (RMSE 0.39 m, MAE 0.24 m, MAPE 11.17 %) again substantially outperforms the Base model (0.46 m), U-Net (0.47 m) and all conventional methods, reconfirming the superior robustness of the physics augmented hybrid reconstruction framework under extreme events.

Relative to conventional sea states, errors for all models increase during the typhoon period, yet the relative advantage of the T2S-W Framework is further amplified, demonstrating that the virtual observation scheme based on “filling space with time” exerts stronger constraining power on extreme high gradient, nonlinear sea states.

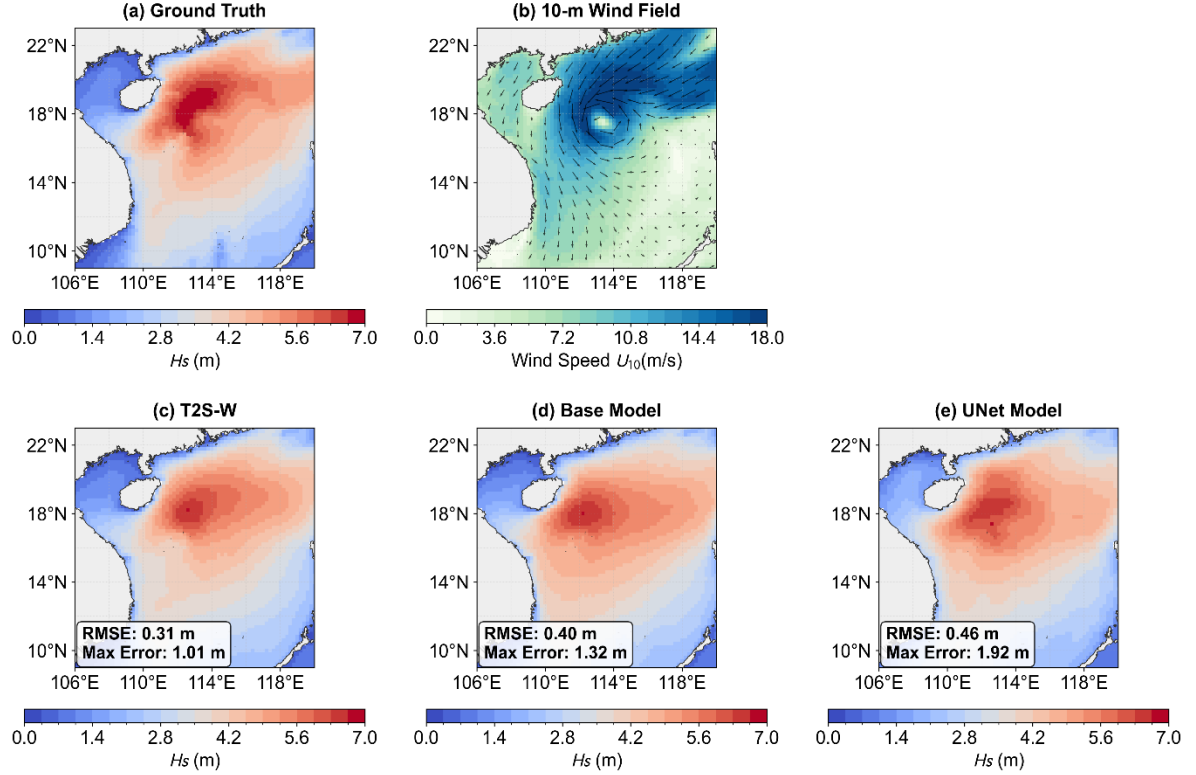


Figure 5. Spatial diagnostics of an extreme typhoon event (Super Typhoon Molave). (a) Ground truth significant wave height field; (b) 10 m wind field, illustrating the strong cyclone and typhoon-eye structure responsible for the extreme sea state; (c) Reconstruction by the proposed framework (T2S-W); (d) Reconstruction by the purely data driven base model (Base Model); (e) Reconstruction by the deep learning baseline (U-Net). Black dots denote real observations; Grey dots denote virtual observations. Panels (b)–(d) are annotated with sample RMSE and maximum absolute error within the sample.

To visualize the framework’s ability to reconstruct strongly nonlinear extreme weather systems, Figure 5 displays the extreme sea state and model diagnostics during the passage of Super Typhoon Molave (Category 3, peak wind speed approaching 165 km/h) on 24 October 2020. In this event the sea surface was excited to produce disaster-level giant waves exceeding 7.0 m. Reconstructions by the purely data driven deep learning models (U-Net and Base) are compared with the physics-enhanced framework (T2S-W) with respect to recovery of spatial features.

Inspection of Figure 5(d) and (e) shows that, even when relying solely on the extremely few isolated observation points available at a single instant, the purely data

driven deep learning models can still recover the main physical extent and distributional trend of the typhoon waves to a certain degree. However, because they lack guidance from physical priors and temporal evolution information, purely data driven reconstruction of typhoon high order modes readily produces spatial smoothing, causing highly concentrated extreme wave peak energy to diffuse outward. The mainstream U-Net architecture (Figure 5e) yields a maximum absolute error as high as 1.92 m and an RMSE of 0.46 m. The Base Model (Figure 5d), which constitutes the component of the present study, leverages its global modeling advantage and performs slightly better than U-Net in recovering the typhoon energy field, constraining the maximum absolute error to 1.32 m and reducing RMSE to 0.40 m. Nevertheless, it still fails to overcome the physical limitation of energy smoothing.

Constrained by the extremely sparse observational conditions and the complete absence of real-time wind or other atmospheric forcing data, the physics enhanced hybrid framework (T2S-W, Figure 5c) does not perfectly reconstruct the small scale “typhoon eye” structure (visible in the wind-field center of Figure 5b). However, in the broad high wave region surrounding the typhoon eye the spatial pattern and extreme value distribution reconstructed by the model are almost identical to the ground truth. The T2S-W Framework demonstrates outstanding extreme value reconstruction accuracy, further suppressing the global RMSE of the typhoon field to 0.31 m and markedly reducing the maximum absolute error to 1.01 m. Tracking the virtual observation trajectories in the figure reveals that the model successfully overcomes the smoothing artifacts of purely data driven models under extreme data gaps by exploiting the physical information increment generated by the time-to-space conversion, thereby producing steeper and more accurate small scale energy gradient structures in the high wave region surrounding the typhoon eye and improving the reconstruction quality of hazardous sea states.

3.3 LightGBM Wave Height Correction Model: Statistical Results

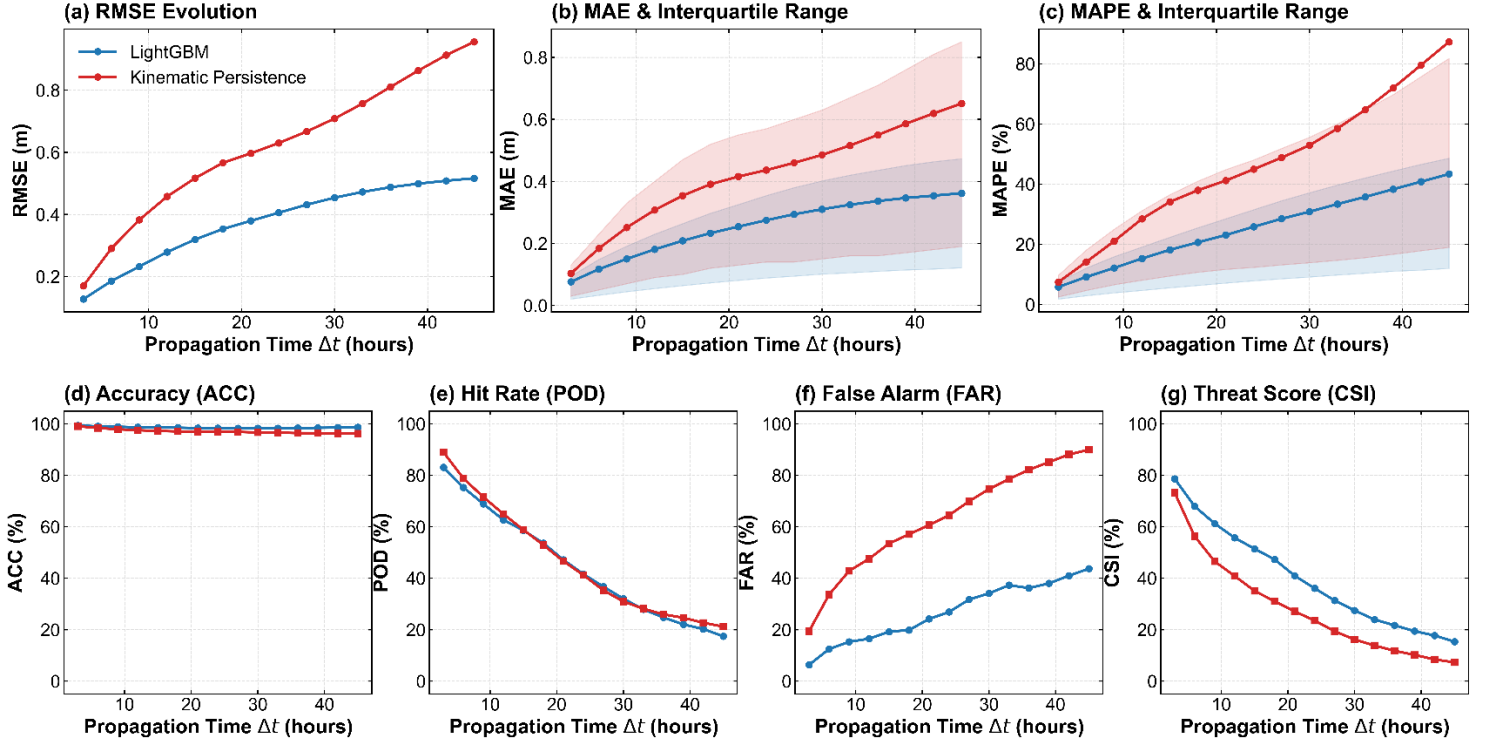


Figure 6. Comprehensive performance comparison of wave height prediction as a function of forward propagation time (t). Panels (a)–(c) show the temporal accumulation of root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), respectively. Shaded regions indicate interquartile range. Panels (d)–(g) present binary classification metrics for extreme high sea state conditions (significant wave height $\geq 4.0\text{m}$): accuracy (ACC), probability of detection (POD), false alarm rate (FAR) and critical success index (CSI). The blue line represents LightGBM correction results; the red line represents the kinematic persistence (KP) benchmark based on the wave energy conservation assumption.

To evaluate independently the performance of the LightGBM nonlinear dissipation correction module, this study compares it against an idealized virtual observation benchmark. The benchmark assumes narrow band unimodal waves whose energy is absolutely conserved during group velocity propagation, and defined here as the Kinematic Persistence (KP) scheme. Skill is assessed at different propagation times (t), with emphasis on cumulative error evolution and the ability to capture extreme sea states. The extreme sea state threshold is set at significant wave height =

4.0m (consistent with the disaster-onset criterion in the China Marine Disaster Bulletin and corresponding to Grade 6 “huge waves” and above in GB/T 42176-2022). The problem is converted to a binary classification task and evaluated with accuracy (ACC), probability of detection (POD), false alarm rate (FAR) and critical success index (CSI).

As shown in Figure 6(a)–(c), the cumulative error of the KP scheme grows rapidly with propagation time, reaching nearly 1.0m RMSE at 48h. In contrast, the error growth of the LightGBM correction module is markedly slower; at 48h RMSE is approximately 0.5m, MAE remains below 0.4m, and the interquartile range is substantially narrower, demonstrating adaptability to dynamic wave environments.

For the binary classification of extreme sea states the four verification metrics are defined on the basis of hits (H), misses (M), false alarms (F) and correct negatives (N) as follows:

$$ACC = \frac{H + CN}{H + M + FA + CN}$$

$$POD = \frac{H}{H + M}$$

$$FAR = \frac{FA}{H + FA}$$

$$CSI = \frac{H}{H + M + FA}$$

In the extreme sea state binary metrics (Figure 6(d)–(g)) both schemes yield ACC values close to 100 %. However, because extreme samples are highly imbalanced, the large number of correct negatives (N) from calm sea states dominates the ACC calculation and the metric therefore has limited discriminative power. POD declines from approximately 85% to 20% with increasing lead time for both schemes, reflecting the common dependence on identical kinematic ray-tracing to locate historical wave sources, their “hit” capability for existing high waves is therefore governed by the same kinematic relations. Clear advantages for LightGBM appear in

FAR and CSI. The FAR of the KP scheme rises rapidly from 20% to nearly 90% with propagation time, exposing the limitation of the pure energy conservation assumption: when high energy waves propagate long distances and enter shallow water regions, they undergo intense dissipation, yet the KP scheme blindly retains the initial wave height, generating numerous false alarms. By contrast, LightGBM, which perceives physical features such as propagation distance, bathymetric gradient and wave steepness, substantially reduces unreasonable wave heights, even at the 48h lead time FAR remains around 40%. The CSI metric further indicates that LightGBM maintains a significant and persistent skill advantage while balancing misses and false alarms, proving that it effectively learns the nonlinear energy attenuation laws governing wave propagation.

It is noteworthy that the LightGBM module already exceeds 0.20 m RMSE within the first 10h of propagation, whereas the T2S-W Framework evaluated in Section 3.1 achieves an overall test-set RMSE of 0.20m. This result reveals the internal synergistic mechanism of the framework: the outer CNN–Transformer spatial completion model does not mechanically replicate the local corrections produced by LightGBM. Instead, through the temporal decay confidence mask mechanism it treats the LightGBM output as a high-value physical constraint. Leveraging the global spatial topology and propagation dependent covariance learned by the self-attention mechanism, the outer model intelligently diffuses the local information into surrounding and downstream regions. The core value of the LightGBM module therefore lies in its explicit learning—under the constraint of no real-time wind field input—of the nonlinear growth and dissipation of wave energy via physically guided features, thereby supplying a physical information increment to the outer model rather than furnishing the final correct answer directly. The ultimate high precision continuous field reconstruction emerges from the deep fusion and dynamic interplay between the inner local physical constraints and the outer global spatial-geometric constraints.

4 Discussion

To further verify the reliability and scientific validity of the proposed T2S-W Framework under complex marine dynamical environments, this chapter conducts a systematic assessment of the framework's physical consistency. Diagnostics range from the large-scale propagation response of the spatial field completion model to the per-trajectory energy modulation performed by individual virtual observations. Section 4.1 first examines the base completion model through single-point targeted perturbation experiments, verifying whether the model goes beyond the isotropic assumptions of traditional mathematical interpolation and learns dynamical diffusion characteristics aligned with wave group velocity propagation directions. Sections 4.2–4.5 then shift focus to the wave height correction model, dissecting in depth the LightGBM module's learning mechanisms for nonlinear source and sink terms. Section 4.2 quantifies the relative contributions of topographic forcing and spectral-partition physical priors via feature ablation experiments, confirming the necessity of introducing explicit physical constraints. Building on this foundation, the subsequent three sections analyze the specific roles of these features across multi-scale physical scenarios: nearshore energy dissipation induced by seafloor topography in shallow-water regions (Section 4.3), dynamical decoupling of wind waves and swells evolution (Section 4.4), and the response of wave height change rates to the macro-scale monsoon seasonal cycle in the South China Sea (Section 4.5). Through the above multi-dimensional mechanism diagnostics, the physical consistency of the wave height completion framework in capturing complex wave evolution is substantiated.

4.1 Propagation Dependent Anisotropic Spatial Diffusion in the Reconstruction Model

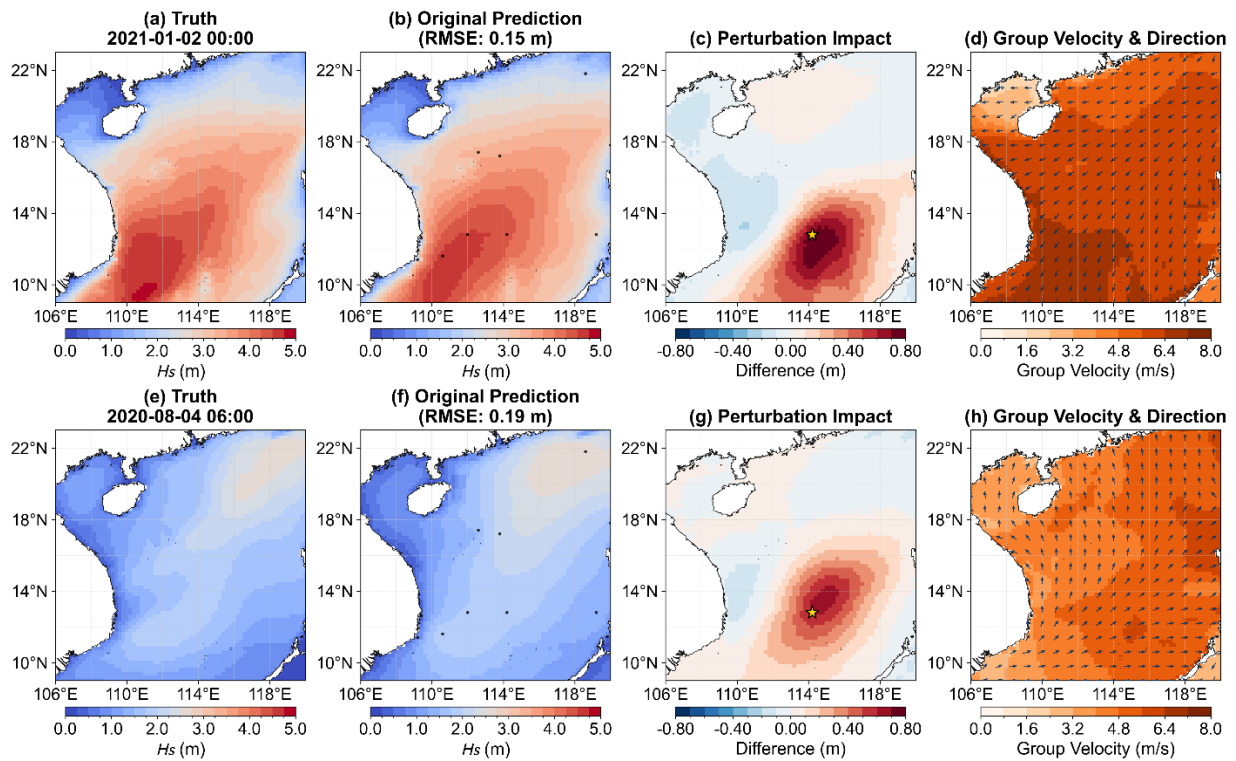


Figure 7. Propagation dependent spatial response analysis based on single point observation perturbation in the Base model. The figure illustrates the spatial response mechanism after a positive wave height perturbation is applied to a single node (yellow pentagram). Panels (a)–(d) show the dynamical response pattern for 2 January 2021 (winter northeasterly monsoon period): (a) ground truth wave height field, (b) original predicted wave height field before perturbation, (c) perturbation influenced field (i.e., prediction increment), (d) corresponding real wave motion characteristics (background color represents group velocity magnitude; arrows indicate wave propagation direction). In this regime the perturbation increment (panel c) exhibits an elliptical elongation aligned with the real group velocity path toward the southwest downstream. Panels (e)–(h) display the dynamical response pattern for 4 August 2020 (summer southwesterly monsoon period), with sub-panel layout identical to the upper row. Facing the opposite monsoon background, the perturbation increment (panel g) reverses and diffuses toward the northeast downstream region.

In the reconstruction of marine spatial physical fields, the rational extension of innovation from a limited number of observation points into spatial blind zones is the core issue determining reconstruction quality. Traditional interpolation methods usually rely on geometric distance or isotropy assumptions and readily produce “bull’s-eye artifacts” that violate dynamical law. Although modern advanced data assimilation algorithms introduce flow dependent background error covariances that evolve dynamically with weather regimes, their construction cost is high. They not only require explicit external background flow fields (e.g., ocean currents, wind fields) as constraints but also rely on expensive physical adjoint models or dozens of ensemble members for real-time online computation, imposing a severe computational bottleneck on operational high-frequency deployment.

To investigate the implicit spatial covariance characteristics of the present framework during information extension, single-point targeted perturbation experiments were performed (Figure 7). It should be emphasized that these experiments were deliberately conducted on the Base Model without virtual observations. If perturbations were applied only to real observation points within the virtual observation scheme, the dense surrounding virtual observation nodes would create excessively large local spatial gradients, forcing the response to be squeezed onto the lee side of the virtual observations. Conversely, joint perturbation of real and virtual observations would easily be misinterpreted as arising solely from the geometric contribution of the explicit virtual forward propagation scheme. Performing diagnostics on the Base Model therefore purely reveals the spatial response pattern induced by single point input perturbation under extremely data sparse conditions. The results demonstrate that the model’s spatial pattern response exhibits anisotropic and propagation dependent spatial diffusion characteristics. Even under the stringent condition of wave height-only input, the model autonomously decodes implicit seasonal features and wave propagation directions.

In the winter northeasterly monsoon sample (Figure 7a–d, 2 January 2021), when a positive wave height perturbation is applied to an observation point in the central-

southern South China Sea, the influence region is not a concentric circle but an elongated ellipse whose major axis is parallel to the wave group velocity direction (northeast–southwest). In the summer southwesterly monsoon sample (Figure 7e–h), facing the opposite climatic regime, the perturbation increment also reverses and diffuses toward the downstream region in the northeast direction. The above single-point perturbation experiments provide strong evidence that, even when only wave height is supplied as input and without any explicit physical equations or historical time-series injection, the purely data driven Base Model can transcend simple “spatial interpolation.” From the spatial distribution of discrete inputs, it autonomously decodes wave propagation direction and seasonal variation features, forming an anisotropic spatial diffusion mechanism aligned with real group velocity paths and thereby realizing flow dependent background error covariance characteristics analogous to those obtained in advanced ensemble Kalman-filter data assimilation at far higher computational cost.

4.2 Feature Ablation and Physical Interpretability of the Correction Model

To validate the roles of the individual feature groups in the LightGBM-based nonlinear wave height correction module, this section presents a feature ablation experiment on the input feature system. The features were partitioned into three groups: basic parameters (Base: initial wave height, period, direction, propagation duration, wave steepness), topographic forcing features (Topography: initial water depth, final water depth, water depth difference, offshore distance), and spectral partition energy features (Spectral Partition: wind-sea and swell energy proportions). The root-mean-square error (RMSE) evaluation results of the ablation experiment on the test set are shown in Table 1; the error reduction percentages are calculated relative to the error obtained when only the Base group was used. To further reveal the targeted improvement each feature group provides under different sea states, the 100 samples with the largest prediction differences were subjected to feature-mean analysis.

Table 1. Feature ablation study for the wave height correction model.

Base	Topography	Spectral Partition	RMSE (m)	Reduction (%)
✓	✗	✗	0.423	-
✓	✓	✗	0.386	8.72%
✓	✗	✓	0.406	3.90%
✓	✓	✓	0.380	10.07%

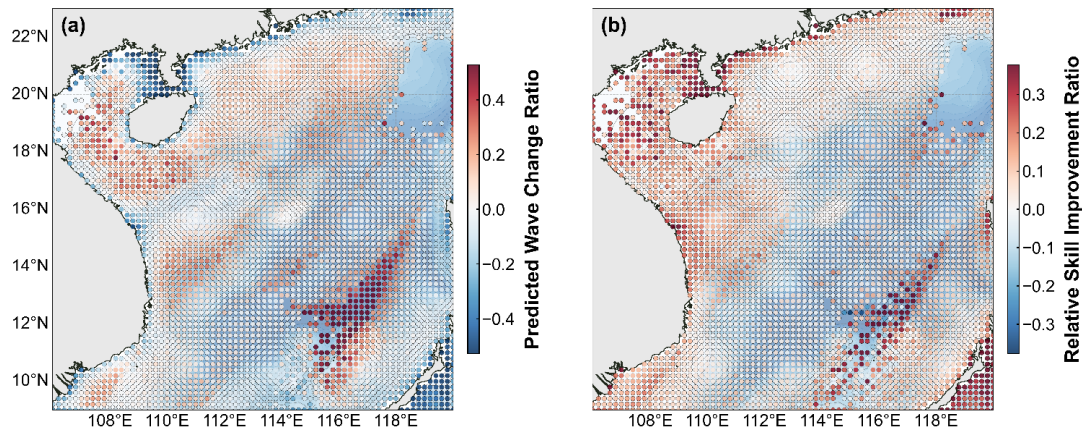
When the model relies solely on basic parameters (Base), prediction RMSE reaches 0.423 m. Addition of the topographic forcing feature group reduces the error by 8.72 %, this group yields the most significant improvement on samples propagating from deep to shallow water. This indicates that, relying only on wave height, period and propagation distance, the model cannot simulate real-ocean energy changes, especially nearshore energy attenuation processes. After the topographic-forcing features (Topography) are introduced, model error decreases markedly by 8.72 % (RMSE falls to 0.386 m). Topographic features enable the model to successfully capture bottom friction during nearshore wave propagation and depth-induced breaking dissipation triggered when waves cross the continental slope.

Compared with the baseline experiment that judges wave nature solely from mean initial period (T), introduction of wind sea and swells energy proportion features reduces RMSE by 3.90 %; this group produces the largest improvement on samples in which wind sea and swells energies are roughly equal. This reveals the physical value of spectral-partition features: when confronted with bimodal spectra in which wind waves and swells energies are comparable (mixed sea states), a single T value easily leads the model to misjudge energy attributes. Spectral-partition features endow the model with the ability to decouple long waves (swell) from short waves

(wind wave), enabling differentiated responses to wave components possessing distinct dispersion relations.

The full-feature combination yields optimal model performance, with RMSE reaching 0.380 m—a 10.07 % reduction relative to the baseline. The topographic-forcing group constructs external physical boundary conditions for wave propagation, while the spectral partition group resolves the internal energy composition of the wave system. Their deep synergy allows the LightGBM module, even in the absence of wind field input, to reconstruct source and sink term dynamics that are relatively consistent with real wave dynamics, thereby supplying reliable physical information increments and prior constraints to the outer CNN–Transformer spatial completion model.

4.3 Representation of Topographic Dissipation in Shallow Water



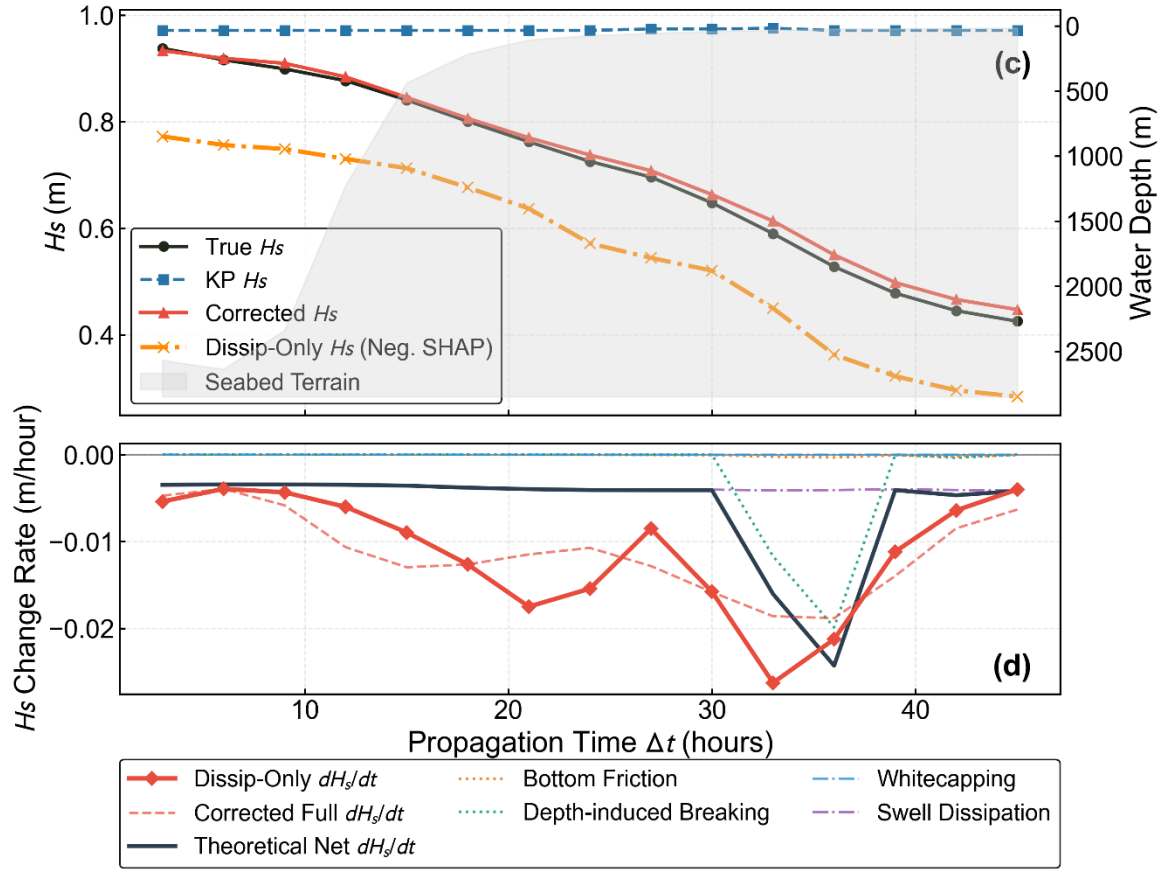


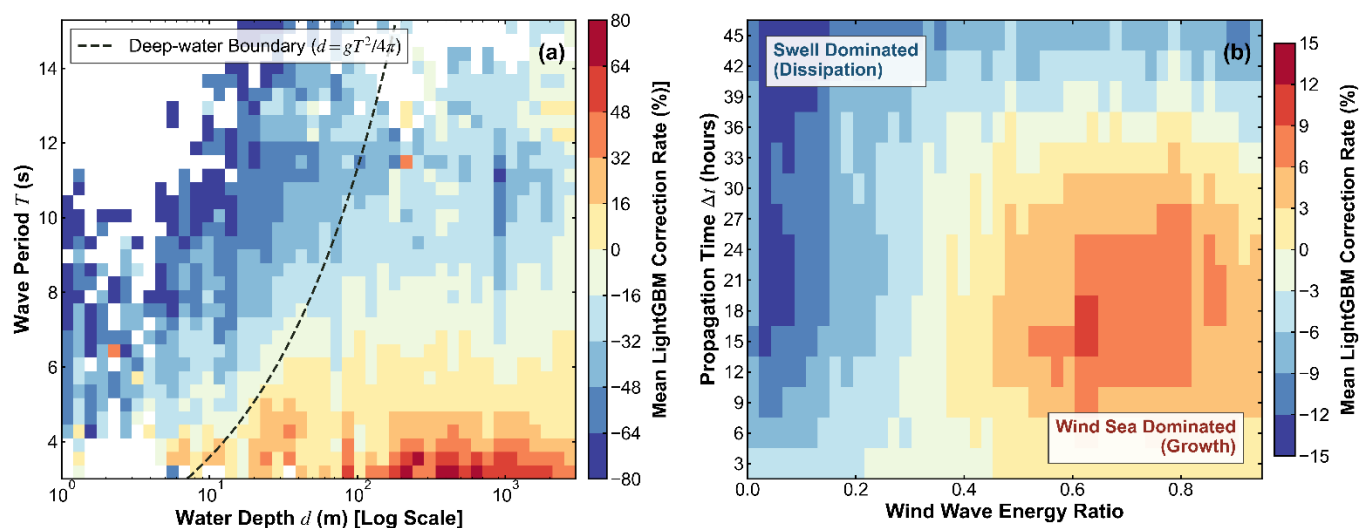
Figure 8. Spatial distribution of wave height correction and nearshore propagation profile diagnostics. (a) Grid averaged predicted wave height change rate, red represents growth and blue represents dissipation. (b) Grid averaged relative skill-improvement rate, highlighting the key regions where the LightGBM correction module significantly outperforms the uncorrected kinematic benchmark. (c) Average wave height profile extracted from nearshore wave samples, showing the evolution of significant wave height (H_s) with propagation time (t) under different water depths (gray shaded region, right axis). Real observed values (black line), uncorrected KP values (blue dashed line), full LightGBM predictions (red line), and pure dissipation profiles isolated via negative SHAP values (yellow dash dotted line) are compared. (d) Average dissipation rate comparison, showing the dissipation rate calculated from LightGBM pure dissipation isolation (red solid line) versus the theoretical net dissipation rate (black solid line) and its individual physical branches, including bottom friction, depth-induced breaking, wave-steepness white-capping, and swell attenuation.

This study finds that the model goes beyond pure statistical fitting and learns real wave dynamical laws. Spatial diagnostics (Figure 8a–b) indicate that the LightGBM correction module functions within the overall framework as a nonlinear source and sink term learning model. Through physical features it effectively distinguishes monsoon driven wind sea growth from topography induced energy dissipation. Over the open ocean domain of the South China Sea the model primarily applies positive corrections, successfully capturing local wind sea growth driven by the monsoon. In transitional regions such as the entrance to the Beibu Gulf, it captures wave height growth induced by gradually shoaling water depth. The continental-shelf edge and coastal zone exhibit dense, sharply negative corrections, corresponding mainly to intense energy dissipation dominated by depth-induced breaking.

To further open the “black box” of topography-driven correction, this study tracks the dynamic evolution of waves propagating from deep to shallow water (Figure 8c). The corrected wave height given by the model (red line) agrees well with the true wave height (black line). Using the SHAP method, features contributing negatively to wave height were isolated, thereby excluding positive source-term contributions such as wind energy input and extracting the empirical wave height propagation profile driven solely by dissipation (yellow dash dotted line). From this profile the actual dissipation rate learned by the machine learning model was calculated (Figure 8d, red line). To verify its physical accuracy, a theoretical dissipation rate benchmark was constructed (Figure 8d, black line). This benchmark discards idealized assumptions and, along each propagation trajectory, extracts real local water depth, period, wave direction and wind-field data at every point to compute the energy contributions from the four classical theoretical sink terms of energy dissipation: bottom-friction dissipation, depth-induced breaking dissipation, white-capping dissipation, and swell dissipation. The detailed formulas, parameter selections, and narrow-band assumption adaptations for each physical branch are provided in Appendix A. Comparison results (Figure 8d) show that the empirical dissipation rate isolated by SHAP and the theoretical net dissipation rate exhibit

consistency in key dynamical features. Both successfully capture the intense energy attenuation in nearshore regions dominated by depth-induced breaking. However, the two evolutions are not perfectly identical. The most prominent difference lies in the spatial/temporal offset of the depth-induced breaking peak: the data-driven model (LightGBM) triggers the maximum dissipation rate at an earlier time step than the theoretical formula. This offset arises primarily from differences in data grid resolution and physical threshold triggering mechanisms. In complex nearshore topography, LightGBM—trained on real data—can sense sub-grid scale abrupt shoaling and therefore triggers breaking dissipation earlier. The theoretical formula relies strictly on grid-averaged depth and only exhibits abrupt cliff-like decay in the next integration step once wave height reaches the rigid theoretical breaking threshold ($H \approx \gamma h$). In addition, residual deviations in certain non-extreme dissipation intervals are mainly attributable to the fact that the current trajectory-tracked theoretical formulae do not account for wave refraction effects under complex shallow water topography, and the one-dimensional idealized spectrum does not include directional spreading losses or cross-compensation of incoming energy from a realistic multi-directional spectrum.

4.4 Decoupling of Wind and Swell Wave through Source-Sink Term Learning



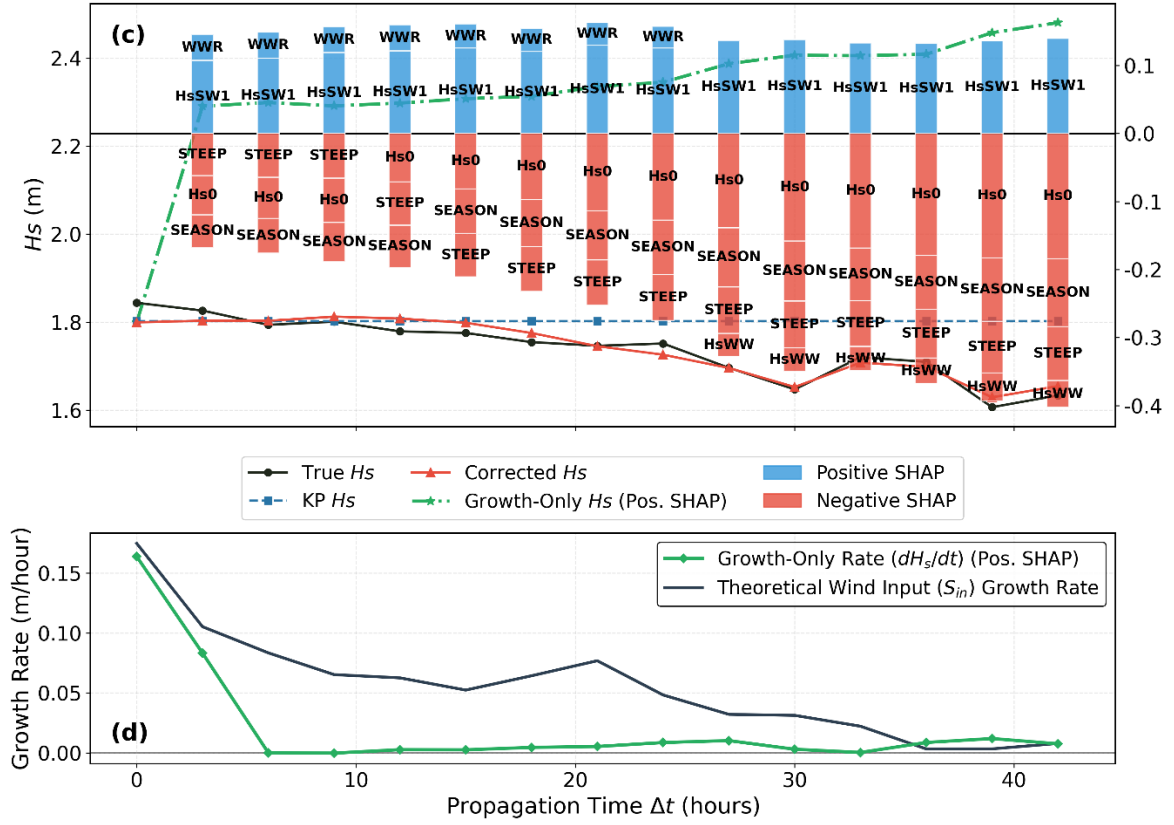


Figure 9. LightGBM learning of wave dispersion relations and source and sink terms. (a) Distribution of LightGBM wave height correction rate in the “water depth-period” parameter space. The black dashed line represents the classical deep water boundary theoretical curve ($d = gT^2/4$). (b) Distribution of wave-height dynamic evolution in the “wind wave energy proportion (WWR)–propagation time (t)” space. (c) Dynamic SHAP feature contribution analysis of the average propagation profile for high wind wave proportion entries, illustrating the positive–negative contribution game that drives the full “growth then decay” process of waves under the condition of no explicit wind field input. Features shown are initial wave height (H_{s0}), wave steepness (STEEP), swell wave height (H_{sSW1}), wind wave ratio (WWR), and seasonal phase (SEASON) as an environmental proxy variable. (d) Diagnosis of wave height growth rate evolution for this propagation profile, comparing the wind energy input wave height change rate isolated via positive SHAP values (green solid line) with the theoretical wind energy input growth rate calculated from the Snyder formula driven by real wind fields (black solid line).

Having confirmed the model’s precise capture of shallow-water topographic dissipation, we further examine whether the model can autonomously distinguish the dynamical-behavior differences between wind-sea and swell without explicit input of the wave energy balance equation. Projecting the model averaged correction rate onto the “water depth–wave period” parameter space (Figure 9a) yields a clear physical demarcation that closely follows the classical deep-water boundary theoretical curve ($d = gT^2/4$). In the deep-water short period region to the lower right of the theoretical curve, corrections are predominantly positive growth, corresponding to the rapid growth stage of local wind wave. In the deep-water region characterized by long-period features (upper right), the model applies mild negative corrections, depicting the weak natural attenuation experienced by mature swell after it has detached from wind-energy replenishment. Once the shallow-water/long-period region (left of the theoretical curve) is entered, the model immediately imposes significant negative dissipation, with dissipation increasing further toward the upper left, indicating that the model has to a certain extent grasped the wave dispersion relation—longer waves feel the bottom and experience friction earlier, whereas shorter waves are restricted only in extremely shallow water.

In the two-dimensional “wind wave energy ratio (WWR)–propagation time” diagram (Figure 9b), the model further exhibits the ability to decouple wave source and sink terms: the swell-dominated region (low WWR) primarily receives negative corrections, consistent with dissipation-attenuation under the absence of local wind-energy replenishment. The leftmost column in the figure, the magnitude of negative correction is relatively small. This corresponds to the “leading swell” that, after dispersion sorting, possesses extremely long wavelengths and travels at the leading edge of the wave system—its intrinsic physical properties dictate extremely low energy dissipation, enabling it to maintain wave height for prolonged periods. The wind-sea-dominated region displays a complete life cycle of “initial positive growth followed by negative dissipation,” depicting the process whereby wind sea absorbs

wind energy, grows, reaches energy saturation, and then becomes dominated by white-capping and nonlinear interactions that drive dissipation.

To further verify the model's decoupling capability for the wind-energy input term (S_{in}), Figure 9c presents a dynamic feature attribution analysis of the average profile for high wind wave proportion samples. By isolating features with positive SHAP contributions, the wind sea growth driven prediction profile was reconstructed (green line in Figure 9c), and its temporal change rate (green line in Figure 9d) was quantitatively compared with the theoretical wind energy input rate calculated from real wind fields (black line in Figure 9d). On the positive driving side, wind wave ratio (WWR) and main swell wave height (H_{SW1}) play core roles. Wind wave proportion acts directly as a proxy feature for local wind-energy input and dominates the rapid early rise in wave height. Swell wave height provides a sustained, consistent positive contribution throughout the entire propagation cycle, accurately reflecting the marine physical characteristic that low-frequency swell dissipates extremely slowly and can maintain background wave height over long periods. On the negative-suppression side, initial wave height (H_{s0}), wave steepness (STEEL) and seasonal phase (SEASON) together constitute the energy sink terms for wave growth. The nonlinear dissipation effect brought by initial energy state H_{s0} accumulates and intensifies gradually with time during wind wave evolution. Simultaneously, high wind wave proportion is often accompanied by large wave steepness (STEEL), which directly triggers intense white-capping dissipation and manifests as significant negative feature contribution. In addition, combining the seasonal characteristic ($\cos \approx -0.85$) of the sample with its southwest-to-northeast propagation trajectory, the model accurately perceives the offshore attribute of the prevailing summer southwesterly monsoon in the South China Sea. Confronted with the inherent "short-fetch" geometric limitation and relatively weak climatic background of offshore winds, the model actively applies negative penalties that synergistically suppress excessive growth of short-fetch wind-sea.

The change rate comparison in Figure 9d further confirms the physical consistency of the reconstruction framework. To quantitatively verify the positive feature contributions learned by the model, we compared the empirical wave height growth rate isolated via positive SHAP values (green solid line in Figure 9d) with the theoretical input rate calculated from classical physical equations (deep-blue solid line in Figure 9d). Detailed parameterization derivation is referred to Appendix A. Comparison results show that, under the condition of no explicit wind field input, the empirical growth rate derived from positive SHAP values of the model matches the theoretical input rate calculated from the real physical equations (deep-blue line) in both trend and magnitude. In the later propagation stage, as waves gradually mature, the green curve obtained through positive SHAP isolation represents the source-term contribution captured by the model. Given that the framework operates without explicit wind-field forcing and that SHAP attribution reflects statistical feature contributions rather than direct physical separation, this isolation primarily reflects the dominant positive source signals while inherently incorporating some balancing influence from dissipation processes that are statistically coupled in the training data. Nevertheless, the model effectively captures the dynamical transition of wind-sea evolution from a rapid growth phase dominated by wind input to a source-term balanced saturation phase, consistent with the physical mechanisms governing wave development.

4.5 Wave Height Response to Monsoon Variability and Topographic Constraint

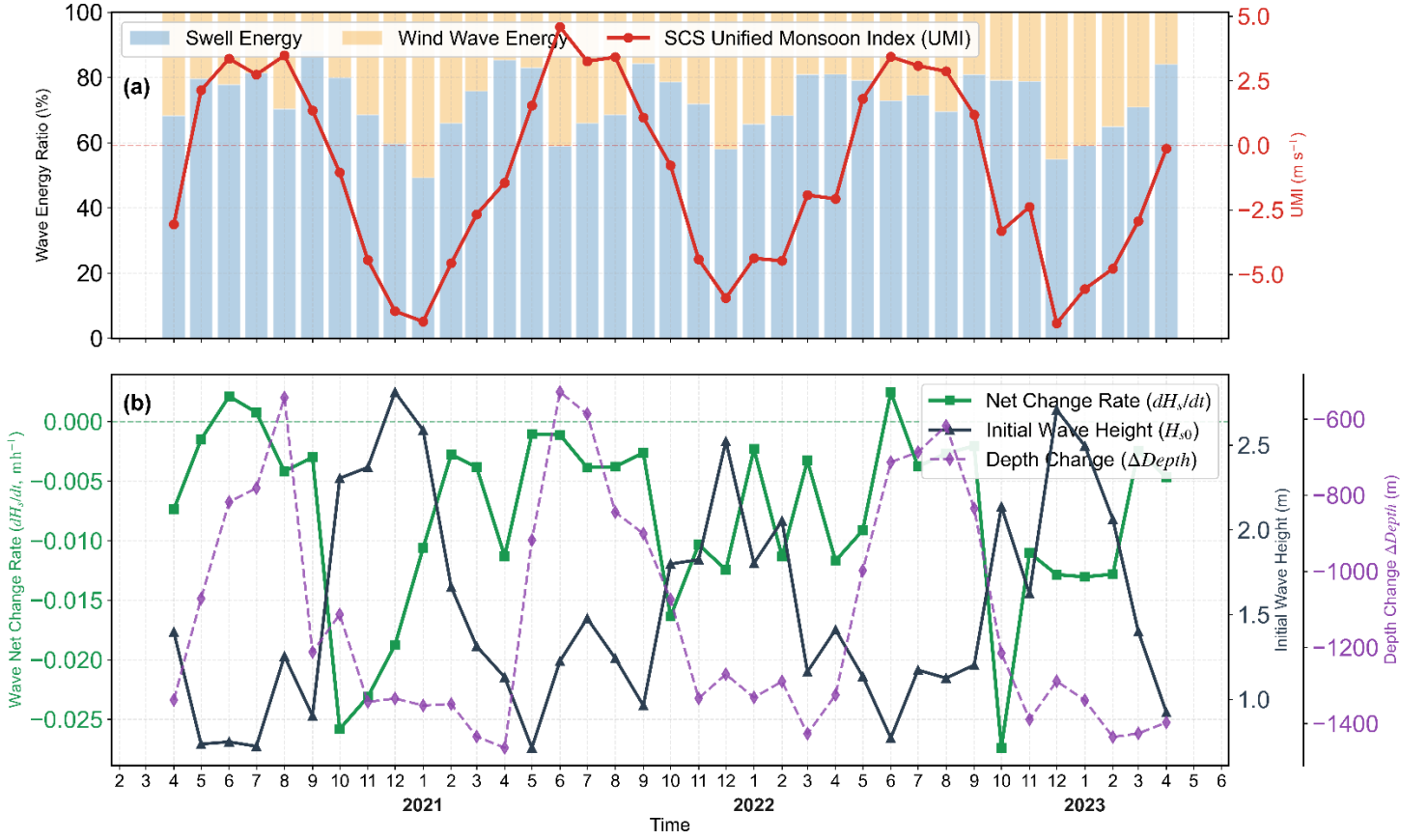


Figure 10. Dynamic response of the LightGBM wave height correction model to South China Sea monsoon alternation. (a) Evolution of the unified monsoon index (UMI, red solid line) and wind sea/swells energy proportions on a monthly basis. (b) Comparison of monthly-mean net wave height change rate (green solid line) calculated from model output, average initial wave height (black solid line), and average propagation water-depth change (purple dashed line).

This section evaluates the physical consistency of the wave height correction model on the seasonal variation scale. Figure 10 shows that the monthly-mean net wave height change rate calculated by the model, and exhibits a highly consistent seasonal rhythm with the unified monsoon index (UMI) of the South China Sea. During the summer-monsoon period (UMI positive), overall wind forcing over the South China Sea is relatively mild and initial wave height is smaller. Summer monsoon winds are southwesterly; wave propagation paths in the South China Sea are

predominantly directed from shallow to deep water, overall dissipation is weak, and net change rates frequently become positive, accurately depicting the dynamical characteristic of net growth under mild wind forcing. During the winter-monsoon period (UMI negative), strong northeasterly monsoon winds excite large initial wave heights, and waves propagate mainly from deep to shallow water (northeast to southwest), bottom friction and depth-induced breaking therefore produce larger dissipation rates than in summer. Meanwhile, the strong and directional winds continuously inject energy, maintaining wave height at a certain level through dynamic equilibrium. The annual maximum dissipation rate occurs during the monsoon-transition period (approximately October), when frequent autumn typhoons generate high initial wave heights, yet the stable winter monsoon has not yet been fully established. Giant waves subsequently lose sustained wind-energy support during propagation and, superimposed on their own extremely high nonlinear dissipation rates, ultimately produce the most intense energy attenuation of the year. Even in the complete absence of wind-field input, LightGBM—relying solely on environmental proxy features—captures this complex air–sea coupling phenomenon.

The above results indicate that the T2S-W Framework can accurately recover the differences in topographic propagation paths caused by different monsoons as well as the dynamic balance between wind-energy input and topographic dissipation under varying climatic backgrounds.

5 Conclusion

The contradiction between the “point-wise acquisition” of wave observations and the “areal representation” required by practical applications has long constrained the refined development of ocean forecasting and disaster prevention under extremely sparse observational conditions. Targeting the limitations of traditional spatial interpolation, numerical models, and purely data-driven methods in extremely constrained scenarios, this study proposes the T2S-W Framework based on the concept of “filling space with time.” The Framework couples wave kinematic priors,

LightGBM nonlinear wave-height correction, and a CNN–Transformer deep learning model, achieving high precision significant wave height reconstruction at an approximately 99.8 % data-missing rate.

The core conclusions of this study are as follows:

- **Spatial constraints fused with wave propagation priors and optimization of fine-scale wave structure reconstruction:** This study utilizes group velocity forward propagation of historical observations to construct a virtual observation network input, injecting physical information increments into extensive unobserved blind zones. This physical prior, aligned with wave-ray propagation, forms a powerful spatial energy distribution constraint that effectively suppresses the spurious energy diffusion, overestimation, and smoothing phenomena that purely data driven models readily produce under sparse conditions. It successfully reconstructs multi scale wave surface physical structures possessing more realistic energy distribution boundaries.
- **Learning of wave energy budget balance and dynamical decoupling of wind sea and swells mechanisms:** Under operational scenarios lacking real-time complete wind-field input, the LightGBM model autonomously learns the nonlinear source and sink terms of waves through physically guided features, realizing dynamical decoupling of wind sea and swells as well as proxy learning of wind-energy input. The shallow-water dissipation rate evolution trends it produces are in good agreement with classical theoretical parameterization formulae on key features, demonstrating that the model can effectively capture the complex dynamical processes of the real ocean.
- **Learning of propagation direction guided wave energy spatial distribution responses:** Single-point input perturbation experiments indicate that the purely data-driven Base model can autonomously decode wave propagation direction and seasonal features, forming an anisotropic spatial diffusion mechanism aligned with group velocity paths. This realizes flow-dependent background error covariance

characteristics analogous to those obtained in data assimilation at high computational cost.

Although this study has made progress in wave height field reconstruction under extremely sparse observations, further optimization space remains. For example, the model achieves relatively high reconstruction accuracy in the peripheral and central high wave regions of typhoons, yet restoration of the extremely small-scale “typhoon-eye” structure remains limited by the scarcity of meteorological boundary conditions. Future work may explore the fusion of high-resolution satellite data or the nesting of local high-resolution networks to enhance the depiction of extreme spatial gradients. In addition, the framework can be extended to other ocean basins or to the global domain to test its generalization performance, and the feasibility of embedding the generated high precision wave height fields as background fields into existing numerical forecasting and assimilation systems can be explored. Furthermore, because the framework has already demonstrated the ability to decode seasonal features from extremely sparse inputs and to construct propagation direction dependent spatial diffusion mechanisms, it can be further promoted to the reconstruction of other ocean physical fields governed by advection diffusion processes, such as temperature–salinity fields or tracer fields. In these scenarios the model is expected to learn flow-dependent anisotropic covariance structures, providing computationally efficient background error estimation pathways for data assimilation and thereby significantly expanding the application potential of artificial intelligence methods in ocean state reconstruction.

CRedit authorship contribution statement:

CRedit authorship contribution statement Shuang Xu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization; Hailong Liu: Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization; Qi Shu: Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A: Parameterization of Theoretical Source and Sink Terms and Regional Adaptation Schemes Based on the Narrow-Band Unimodal Assumption

In the constrained scenario of fusing extremely sparse observations with virtual observations, complete two-dimensional directional wave spectra $E(f, \theta)$ cannot be obtained in real time. Therefore, when constructing the physical theoretical benchmark, this study introduces the narrow-band unimodal assumption widely adopted in parameterized wave models.

Under this framework, the temporal evolution of the zero-order moment of wave energy ($m_0 = H_s^2/16$) is controlled not only by the wave energy flux convergence induced by kinematic shoaling but is also dominated by the balance of local source and sink terms. Its governing equation can be simplified as:

$$\frac{dm_0}{dt} = S_{\text{bot}} + S_{\text{br}} + S_{\text{wc}} + S_{\text{swell}} + S_{\text{in}}$$

Addressing the regional marine environmental characteristics of the South China Sea (SCS) and the limitations of the 0.2° model grid resolution, this study performs specific adaptations and sub-grid calibrations for each classical parameterized term. The detailed expressions are as follows:

1. Bottom Friction Dissipation (S_{bot})

When wave groups propagate from deep water to the continental shelf, friction in the benthic boundary layer leads to wave energy dissipation. This study adopts the classical JONSWAP empirical formula proposed by Hasselmann et al. (1973), combined with the finite-depth dispersion relation $\omega_p^2 = gk \tanh(kh)$, to express the local bottom friction dissipation as:

$$S_{\text{bot}} = -C_{\text{bot}} \frac{\omega_p^2}{g^2 \sinh^2(kh)} m_0$$

where C_{bot} adopts the standard constant of $0.038 \text{ m}^2/\text{s}^3$. A grid-resolution adjustment factor is applied to both the bottom-friction and depth-induced breaking dissipation terms. This minor adjustment ensures that the one-dimensional theoretical

benchmark produces dissipation magnitudes broadly consistent with those implicit in the 0.2° CMEMS reanalysis fields used for model training and validation.

2. Depth-Induced Breaking Dissipation (S_{br})

In extremely shallow waters, rapidly decreasing water depth triggers intense wave breaking. This study employs the bulk dissipation model by Battjes & Janssen (1978):

$$S_{br} = -\alpha_{bj} Q_b \frac{H_{\max}^2}{4T} \times f_{\text{sub}}$$

where $\alpha_{bj} = 1.0$ and T is the period. The maximum allowable wave height is determined based on the Miche criterion as $H_{\max} = \gamma_{bj} h$ (with the breaking parameter adopting the conventional default value of $\gamma_{bj} = 0.73$).

3. Whitecapping Dissipation (S_{wc})

In deep water or during strongly wind-driven stages, whitecapping induced by excessive wave steepness serves as a primary energy sink. Based on the pulse-theory framework of Hasselmann (1974), its expression is:

$$S_{wc} = -C_{wc} \omega_p s^2 m_0$$

where the wave steepness parameter is defined as $s = H_s/L$ (L being the local wavelength), and the dissipation coefficient C_{wc} follows the parameter calibration benchmark in the WAM Cycle 3 scheme, set to 2.36×10^{-5} .

4. Swell Dissipation (S_{swell})

For swells propagating over long distances out of the wind fetch, interactions between the viscous atmospheric boundary layer and turbulence induce weak attenuation:

$$S_{swell} = -C_{swell} \max\left(0, 1 - \frac{U_{\text{rel}}}{C_p}\right) \omega_p m_0$$

where U_{rel} is the relative wind speed aligned with the wave direction. While classical global ocean models typically employ a higher swell dissipation coefficient, the South China Sea represents a typical semi-enclosed marginal sea with a broad continental shelf, where swells are frequently mixed with monsoon-driven wind waves. To prevent energy distortion resulting from overly rapid dissipation over coarse grids and semi-enclosed topography, regional adaptation was conducted in this study by reducing C_{swell} to 2.0×10^{-6} . This reflects the dynamic characteristic that non-breaking swells over the broad, shallow continental shelf of the SCS can sustainably maintain the regional background wave heights.

5. Wind Energy Input (S_{in})

As the core mechanism driving the positive growth of wave heights, this study adopts the Komen et al. (1984) scheme widely used in third-generation wave models. To rigorously characterize the air-sea momentum flux, the 10-meter wind speed (U_{10}) is converted into the sea surface friction velocity u_* based on the empirical formula by Wu (1982):

$$u_* = \sqrt{(0.8 + 0.065U_{10}) \times 10^{-3}} U_{10}$$

Under the constraint of the narrow-band unimodal wave age, the wind energy input term is expressed as:

$$S_{\text{in}} = C_{\text{in}} \frac{\rho_a}{\rho_w} \max\left(0, 28 \frac{u_{* \text{proj}}}{C_p} - 1\right) \omega_p m_0$$

where the dimensionless coefficient adopts the classical value $C_{\text{in}} = 0.25$, the air-sea density ratio $\rho_a/\rho_w = 1.2 \times 10^{-3}$, and $u_{* \text{proj}}$ is the projection of the friction velocity in the wave propagation direction. The constant 28 represents the classical upper limit of wave age under fully developed sea states.