

Numerical Simulation of Storm Surge-Induced Water Level Rise in the Bohai Sea with Adjoint Data Assimilation

Liqun Jiao ¹, Youqi Wang ¹, Dong Jiang ^{2,*} , Qingrong Liu ³, Jing Gao ³ and Xianqing Lv ¹ 

¹ State Key Laboratory of Physical Oceanography, Ocean University of China, Qingdao 266100, China; jllq8554@stu.ouc.edu.cn (L.J.); wangyouqi@stu.ouc.edu.cn (Y.W.); xqinglv@ouc.edu.cn (X.L.)

² School of Basic Sciences for Aviation, Naval Aviation University, Yantai 264000, China

³ North China Sea Marine Forecast and Hazard Mitigation Center, Ministry of Natural Resources, Qingdao 266100, China; liuqingrong@ncs.mnr.gov.cn (Q.L.); gaojing@ncs.mnr.gov.cn (J.G.)

* Correspondence: jd_nau@163.com

Abstract: This study applied an adjoint data assimilation model capable of integrating wind fields to investigate a temperate storm surge event in the Bohai Sea region during October 18 to 21, 2024. Based on in situ water level measurements from five tide gauge stations, the model simulated the spatial distributions of water levels under different wind stress drag coefficients (C_D) schemes driven by reanalysis wind fields and interpolated wind fields. The results demonstrated that the scheme without the adjoint data assimilation exhibited relatively low accuracy. Upon integrating the adjoint data assimilation method, the errors of the reanalysis wind fields were reduced by 44%, while those of the interpolated wind fields experienced a 74% decrease in error magnitude. Overall, this study provides a reference for enhancing the accuracy of water level predictions during storm surge events.

Keywords: adjoint assimilation; numerical simulation; storm surge; Bohai Sea



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1. Introduction

Storm surge is a phenomenon in which strong air disturbances, such as strong winds and sudden changes in air pressure, cause the sea surface to rise and fall abnormally. Storm surges are generally categorized into two main groups caused by tropical storms (such as typhoons, hurricanes, etc.) and temperate cyclones [1]. When it occurs, it often causes significant impact and damage to coastal levees and infrastructure [2–4]. Over recent decades, losses from storm surges have outpaced all other marine disasters in China, demonstrating a persistent upward trajectory [5]. Historically, between 2014 and 2023, China experienced 137 storm surge events, including 88 typhoon-induced surges and 49 extratropical surges, which averaged annual economic losses of approximately 5.52 billion yuan. In 2024, the coastal sea level in China rose 96 mm above the long-term average (1993–2011), exacerbating erosion in monitored coastal zones and intensifying seawater intrusion [6,7]. For instance, from October 2 to 6, 2022, a cold front from the northwest triggered storm surges along the Bohai coast, with most tide gauge stations recording water level rises of more than 1 m, and even more than 2 m in local areas [8]. Therefore, in-depth research on storm surges is of great significance to safeguard people's lives and properties.

Traditional studies on storm surges were limited to observations from tide gauges, which suffered from inherent spatiotemporal constraints [9]. In recent years, the continuous development and refinement of two-dimensional and three-dimensional numerical models for storm surge simulation have rendered numerical modeling an effective and widely

adopted research methodology [10]. This numerical simulation integrates atmospheric dynamics, oceanic hydrodynamics, and coastal geomorphology, with model outcomes primarily driven by atmospheric flow [11]. Atmospheric flow is represented as wind stress within numerical models. Wind stress serves as the primary driving force for the generation and evolution of storm surges and is parameterized through the wind stress drag coefficient (C_D) to quantify this momentum transfer [12]. In the early studies, the wind stress drag coefficient was usually assumed to be constant [13]. Later, it was empirically proposed that the wind stress drag coefficient is linearly related to the wind speed at a height of 10 meters above the sea surface [14–16]. There are differences in the setting of wind stress drag coefficients among different scholars, which leads to a certain degree of deviation in the accuracy of numerical simulations of storm surges. In view of this, some scholars have continuously compared various wind stress drag coefficient assumptions with a view to determining stable conclusions for numerical simulations of storm surges [17–20]. At the same time, the accuracy of numerical simulation results depends largely on the quality of wind field data [21]. With the increasing abundance of wind field products and the significant improvement of their accuracy, various types of reanalyzed wind field products have been gradually adopted in the field of numerical simulation of storm surge to drive the models in order to break through the limitations of field measurements [22]. However, the reanalyzed wind field products have a certain scope of application and specific error characteristics due to resolution and other reasons, and they cannot completely replace the measured data [23]. For example, Xiong et al. (2022) conducted numerical simulations of storm surges and wind speed analysis for eight historical typhoon events based on ECMWF Reanalysis v5 (ERA5) data, but the results indicated that the storm surge forcing derived from the ERA5 wind fields was systematically smaller compared to observations, and the deviation increased progressively as wind speeds intensified [22]. Therefore, methodological improvements are required to enhance the accuracy of the product wind fields and address this problem. For example, Liu and Sasaki (2019) used two hybrid methods, which is determined from the typhoon center to a certain radius, to superimpose the ERA-Internal reanalysis data, and it was found that the hybrid model can be easily adapted for each storm surge scenario, which greatly improves the accuracy of storm surge hindcasts [24]. Xiong et al. (2022) improved ERA5 by overlaying wind fields from the Dutch Tropical Cyclone Model onto ERA5 to create hybrid wind fields, which significantly enhanced wind speed representation and storm surge simulation accuracy near the typhoon center in two numerical experiments [22].

While numerical simulation currently serves as an effective methodology for examining storm surges, the determination of optimal parameters is also a critical issue. This issue can be efficiently achieved by adopting an adjoint data assimilation method [24–27]. The adjoint data assimilation method integrates the measured data with the numerical model, and the use of the adjoint assimilation method allows the model trajectory to be continuously adjusted in order to obtain the optimal parameters [28]. For instance, Lionello et al. (2006) designed for the operational prediction of storm surge in northern Adriatic Sea, which adopts the adjoint model for the computation of its gradient with respect to the initial condition. It is capable of efficiently improving the results of a storm surge prediction model in the Adriatic Sea [29]. With the help of the concomitant assimilation method, Liu and Lv (2011) inverted the spatially distributed wind stress drag coefficients by using the measured data. The study showed that the spatially distributed wind stress drag coefficients obtained from the inversion can effectively reduce the error between the simulated water level and the observed water level and improve the numerical simulation accuracy of storm surge [12]. Peng et al. (2013) employed the adjoint method to optimize wind stress drag coefficients in a 3D Princeton Ocean Model (POM) model, enhancing storm surge

predictions through twin experiments with varied error sources. The results demonstrated that this approach effectively reduces forecast inaccuracies regardless of error origins [30]. Li et al. (2013) employed the adjoint technique to simultaneously adjust the initial conditions and parameters of wind stress drag coefficient in the three-dimensional POM for improving storm surge forecasts [31]. Zheng et al. (2018) employed the Delft3D modeling framework to establish a storm surge model for the German Bight, demonstrating the efficacy of data assimilation in enhancing simulation accuracy through the adjustment of the wind drag coefficient (C_d) via a linear parameterization scheme [32]. Wang et al. (2021) employed data assimilation incorporating an adjoint method to estimate spatially and temporally varying bottom friction coefficients (BFCs), which closely align with observations, while significantly reducing mean absolute errors (MAEs) and vector discrepancies in tidal constituents between simulated outputs and independent tidal gauge measurements [33]. Gao et al. (2023) improved the inversion of open boundary conditions for the M2 tidal constituent in the Bohai and Yellow Seas based on a data assimilation framework, which effectively mitigates the influence of extreme outliers while preserving computational robustness [34]. All of these studies have shown that data assimilation techniques are an effective means to improve the simulation capability of models and provide strong support for storm surge research.

The Bohai Sea is a China's inland sea, with shallow harbor depths and a semi-enclosed topography surrounded by land on three sides [35]. In addition, the Bohai Sea is located in the mid-latitude, where frequent interactions between cold and warm air masses during spring and autumn, combined with winter exposure to intense cold air outbreaks and cold front gales, collectively constitute the primary meteorological triggers for storm surges in the region [36–38]. Once a strong wind process occurs, it can easily lead to drastic changes in water level, increasing the occurrence of marine disasters in the region [38]. Based on this, an optimized adjoint data assimilation model was used in this study with the Bohai Sea as the study area and the temperate storm surge occurring on 18–21 October 2024 as an example. Using the measured wind vector data from seven stations in the northern Bohai Sea during this time, the wind field was constructed by the Kriging interpolation method and introduced into the model to verify its feasibility. Suitable reanalysis product wind fields were then brought into the model and compared with the simulation results of the interpolated wind fields. The effects of different wind fields on the assimilated and non-assimilated results were analyzed and discussed.

2. Materials and Methods

2.1. Data

2.1.1. In Situ Measurements

The region studied in this paper encompasses the entire Bohai Sea (117.5°E–127.5°E, 37.0°N–41.0°N), including its three major bays: Bohai Bay, Liaodong Bay, and Laizhou Bay (Figure 1). In situ measurements were obtained from seven reference tide gauge stations (Ba Yuquan, Dong Gang, Hu Ludao, Lao Hutan, Pi Kou, Xiao Changshan, and Zhi Maowan) within China's coastal monitoring network, with their precise geographic coordinates provided in Table 1.

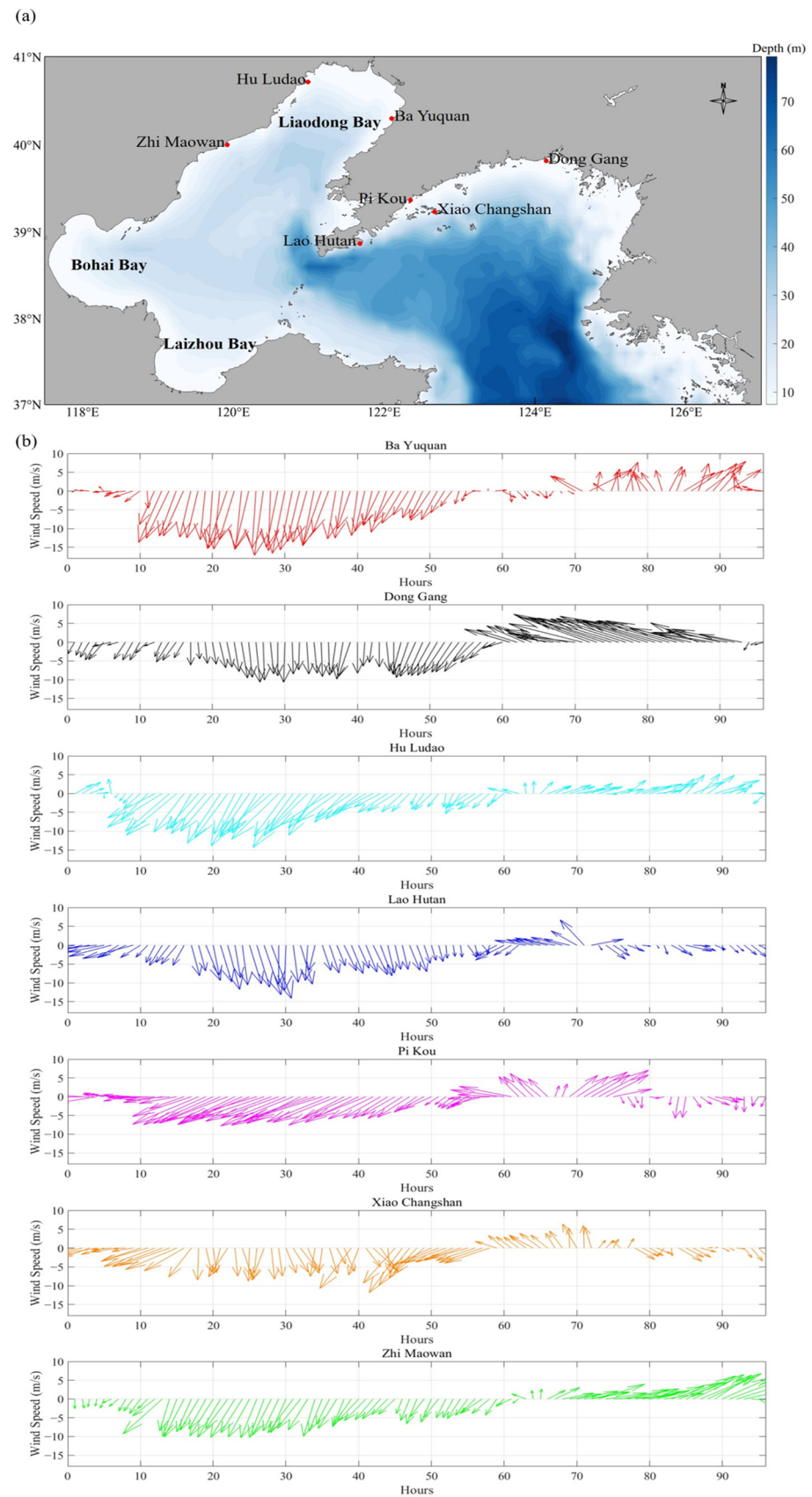


Figure 1. (a) Spatial distribution of water depth and seven tide gauge stations in the Bohai Sea (the gray part represents the land), (b) The time series of wind speeds and wind directions at seven tide gauge stations.

Table 1. Latitude and longitude of the seven tide gauge stations.

	Ba Yuquan	Dong Gang	Hu Ludao	Lao Houtan	Pi Kou	Xiao Changshan	Zhi Maowan
Longitude/°E	122.1	124.15	120.99	121.68	122.35	122.67	119.92
Latitude/°N	40.3	39.817	40.715	38.867	39.367	39.233	40

Figure 1a presents the spatial distribution of the Bohai Sea, with contour lines indicating water depth. As shown by the longitudes and latitudes of the seven stations listed in Table 1, it clearly demonstrates their primary concentration in the coastal region of the northern Bohai Sea. The in situ measurements were conducted from 00:00 on 18 October to 23:00 on 21 October 2024 (UTC+8) with an hourly sampling interval, encompassing water level, wind speed, and wind direction data. Figure 1b illustrates the temporal variations in wind speed and direction across seven tide gauge stations. All stations exhibited a rapid acceleration in wind speed 12 hours after initial observation, reaching peak intensities approximately 27 hours later, accompanied by prevailing northeasterly winds. The maximum wind speed of 17.2 m/s was recorded at Ba Yuquan Station. Initially, the wind direction was predominantly northeasterly, with a notable shift commencing around the 60th hour of the observation period. And tide gauge stations consistently demonstrated bimodal fluctuation patterns. Extreme values revealed a maximum water level (η) of 1.49 m and a minimum of -1.65 m at Ba Yuquan Station.

2.1.2. Wind Field

Based on the current global product with full spatial and temporal coverage, compatibility, and high usage, the surface wind field data utilized in this study were sourced from internationally recognized datasets, including two four-level product datasets based on scatterometer and model datasets (Global Ocean Hourly Reprocessed Sea Surface Wind and Stress from Scatterometer and Model, post-processed with ERA5 analyses (ASCAT+ERA5) and Global Ocean Hourly Sea Surface Wind and Stress from Scatterometer and Model, post-processed with ECMWF analyses (ASCAT+ECMWF)), ERA5 reanalysis data, CFSv2 data, and MERRA-2 reanalysis data. All five datasets provide hourly 10-meter wind speed data and key characteristics of each dataset are summarized in Table 2.

Table 2. Characteristic of wind field dataset.

Product Name	Spatial Grid Spacing	Time Interval	Website
ASCAT+ERA5	$0.125^{\circ} \times 0.125^{\circ}$	1 h	https://data.marine.copernicus.eu/product/WIND_GLO_PHY_L4_MY_012_006/services (accessed on 23 March 2025)
ASCAT+ECMWF	$0.125^{\circ} \times 0.125^{\circ}$	1 h	https://data.marine.copernicus.eu/product/WIND_GLO_PHY_L4_NRT_012_004/services (accessed on 23 March 2025)
ERA5	$0.25^{\circ} \times 0.25^{\circ}$	1 h	https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download (accessed on 23 March 2025)
CFSv2	$0.5^{\circ} \times 0.5^{\circ}$	1 h	https://www.hycom.org/dataserver/ncp-cfsv2 (accessed on 23 March 2025)
MERRA_2	$0.625^{\circ} \times 0.5^{\circ}$	1 h	https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/ (accessed on 23 March 2025)

In this study, the primary dataset employed is the ERA5 reanalysis data. The selection criteria for wind field are detailed in Section 2.2.2. ECMWF Reanalysis v5 (ERA5), the fifth-generation ECMWF atmospheric reanalysis, provides high grid spacing, consistent, and temporally continuous global climate and weather data spanning 1940 to present. The dataset includes hourly atmospheric, ocean wave, and land surface parameters at a spatial grid spacing of $0.25^\circ \times 0.25^\circ$ (approximately 31 km at mid-latitudes), with vertical grid spacing covering 137 layers from the surface up to 80 km altitude.

2.2. Methods

2.2.1. Numerical Adjoint Model

The numerical model in this research is a two-dimensional mean flow model and the governing equations used are the continuity and momentum vertical integral equations [12]:

$$\begin{aligned} \frac{\partial \zeta}{\partial t} + \frac{\partial[(h + \zeta)u]}{\partial x} + \frac{\partial[(h + \zeta)v]}{\partial y} &= 0 \\ \frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} - fu + \frac{ku\sqrt{u^2+v^2}}{h+\zeta} - A \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) \\ &+ g \frac{\partial \zeta}{\partial x} + \frac{1}{\rho} \frac{\partial P_a}{\partial x} - \frac{\rho_a}{\rho} \frac{\tilde{k} W_x \sqrt{W_x^2 + W_y^2}}{h+\zeta} = 0 \\ \frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} + fu + \frac{kv\sqrt{u^2+v^2}}{h+\zeta} - A \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right) \\ &+ g \frac{\partial \zeta}{\partial y} + \frac{1}{\rho} \frac{\partial P_a}{\partial y} - \frac{\rho_a}{\rho} \frac{\tilde{k} W_y \sqrt{W_x^2 + W_y^2}}{h+\zeta} = 0 \end{aligned} \quad (1)$$

where ζ is the storm surge augmentation level, h is the hydrostatic depth, f is the Coriolis coefficient, g is the gravitational acceleration, u and v are the x-direction (positive east) and y-direction (positive north), respectively, P_a is the air pressure at the sea surface, C_D is the drag coefficient of the wind stress, $\rho_a = 0.0012 \text{ g/cm}^3$ is the density of air, $\rho = 1.025 \text{ g/cm}^3$ is the density of seawater, and W_x and W_y are the speeds of winds in the x and y directions, k is the bottom friction coefficient, and A is the eddy viscosity coefficient.

To construct the adjoint equations, the cost function, which describes the discrepancy between modeling results and measurements, is defined as:

$$J(\zeta) = \frac{1}{2} K_\zeta \int_{\Sigma} (\zeta - \hat{\zeta})^2 dx dy dt \quad (2)$$

where K_ζ is a constant representing the strength of term $(\zeta - \hat{\zeta})$ in Equation (3), which is set to 1 in this model, ζ is the modeled value, $\hat{\zeta}$ is the measured value. Moreover, based on the Lagrangian function, one can obtain Equation (3) accompanying the system of Equation (1) [39]:

$$\begin{aligned} \frac{\partial \zeta_a}{\partial t} + u \frac{\partial \zeta_a}{\partial x} + v \frac{\partial \zeta_a}{\partial y} + \frac{ku\sqrt{u^2+v^2}u_a}{(h+\zeta)^2} + \frac{kv\sqrt{u^2+v^2}v_a}{(h+\zeta)^2} \\ + g \frac{\partial u_a}{\partial x} + g \frac{\partial v_a}{\partial y} = K_\zeta (\zeta - \hat{\zeta}) \\ \frac{\partial u_a}{\partial t} - \left(f + \frac{kuv}{(h+\zeta)\sqrt{u^2+v^2}} \right) v_a - \frac{\partial u}{\partial x} u_a - \frac{\partial v}{\partial x} v_a + \frac{\partial}{\partial x} (uu_a) \\ + \frac{\partial}{\partial y} (vu_a) + (h + \zeta) \frac{\partial \zeta_a}{\partial x} + A \left(\frac{\partial^2 u_a}{\partial x^2} + \frac{\partial^2 u_a}{\partial y^2} \right) \\ - \frac{k(u^2 + 2v^2)v_a}{(h+\zeta)\sqrt{u^2+v^2}} = 0 \\ \frac{\partial v_a}{\partial t} + \left(f - \frac{kuv}{(h+\zeta)\sqrt{u^2+v^2}} \right) u_a - \frac{\partial u}{\partial y} u_a - \frac{\partial v}{\partial y} v_a + \frac{\partial}{\partial x} (uv_a) \\ + \frac{\partial}{\partial y} (vv_a) + (h + \zeta) \frac{\partial \zeta_a}{\partial y} + A \left(\frac{\partial^2 v_a}{\partial x^2} + \frac{\partial^2 v_a}{\partial y^2} \right) \\ - \frac{k(u^2 + 2v^2)u_a}{(h+\zeta)\sqrt{u^2+v^2}} = 0 \end{aligned} \quad (3)$$

where ζ_a , u_a and v_a denote the adjoint variables with respect to ζ , u and v , respectively. For the adjoint Equation (3), the corresponding numerical scheme is similar to that of Lv et al. [40,41].

2.2.2. Model Construction

For model validation, two distinct wind field datasets were adopted as model forcings: reanalysis products and spatially interpolated wind fields (using Kriging interpolation method) generated from in situ measurements at seven coastal stations. By comparing the wind vectors from reanalysis products with measured wind data at seven tide gauge stations, the most suitable reanalysis wind field was selected from five products. The mean absolute error (MAE) is one of the primary validation metrics, which is defined as:

$$\text{MAE} = \frac{1}{N} \sum_i^N (|s_i - \hat{s}_i|) \quad (4)$$

where s_i and $\hat{s}_i$ represent the values of reanalysis products and measurements at the i -th timestep, respectively, and N denotes the total number of samples. The complete comparative results are presented in Table 3.

Table 3. The MAE of the product wind field data relative to the measured wind vectors.

Product Name	MAE (m/s)
ERA5	3.79
CFSv2	5.75
ASCAT+ERA5	5.86
ASCAT+ECMWF	5.86
MERRA_2	6.10

As quantitatively demonstrated in Table 3, the ERA5 reanalysis dataset outperforms other products with the lowest mean absolute error (MAE = 3.79 m/s) across all seven stations, showing significant agreement with in situ wind speed measurements. Therefore, the ERA5 reanalysis product was selected for numerical simulation.

Although wind speed and direction measurements were collected from seven tide gauge stations, their spatial coverage proved insufficient to represent the entire Bohai Sea region. To generate a spatially continuous wind field dataset, we implemented ordinary Kriging interpolation with a linear variogram model, upscaling discrete station data to a $5' \times 5'$ spatial grid spacing. This method establishes optimal predictions by statistically fitting known data points within a defined search radius or a fixed number of neighboring points [42]. As a best linear unbiased estimator, it leverages regionalized variables and variogram modeling to minimize estimation variance in spatial interpolation [43]. In terms of the point s_0 to be interpolated, the estimated value of its attribute value $\hat{z}_0$ is the linear weighted sum of the same attribute value z_i at the known sample points in the neighborhood, and its estimation formula is [44]:

$$\hat{z}(s_0) = \sum_i^n \lambda_i z(s_i) \quad (5)$$

where $\hat{z}(s_0)$ is the estimate at location s_0 , $z(s_i)$ is the measured value in the i th observation point, λ_i ($i = 1, \dots, n$) are the weights assumed at the basis of variogram.

Figure 2 illustrates the ERA5 reanalysis wind field (EWF) and the Kriging interpolated wind field (IWF) (at the 24th hour for example).

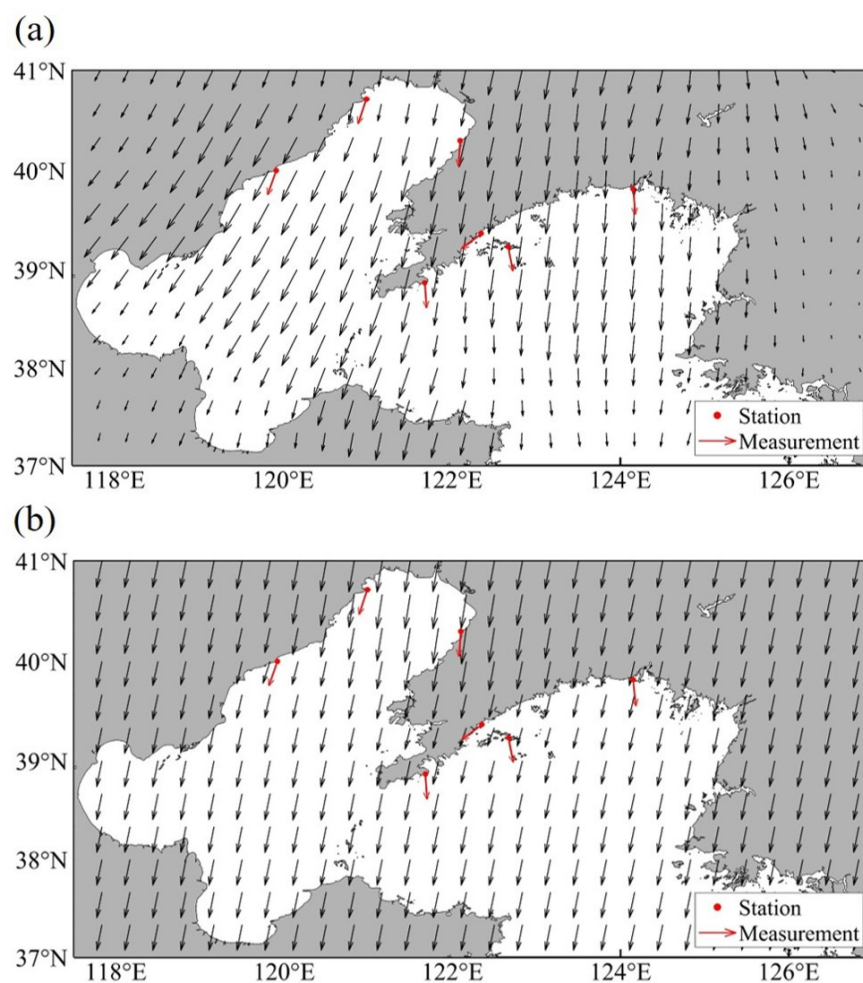


Figure 2. The 24th hour wind field vectors: (a) EWF, (b) IWF (The red dots denote the locations of the measurement stations, while the red arrows represent the measured wind vectors at those stations).

Figure 2 illustrates the wind field at the time when the wind speed reached its maximum (at the 24th hour), with all seven stations registering predominantly northeasterly winds. This wind pattern was consistently reproduced in both the interpolated wind field and reanalysis wind products, as clearly shown by their vector fields. However, we focused only on offshore wind speed data and consequently did not adequately account for the land–sea interface differences. Additionally, due to the limited number and spatially uneven distribution of interpolation points, the interpolated wind field exhibited notable certain errors across the entire domain and thus served primarily as a reference for comparison with ERA5 reanalysis wind fields.

To enhance computational efficiency and facilitate a detailed analysis of the spatiotemporal evolution of storm surges, the entire simulation period (96 h) was divided into 12 consecutive 8-hour sub-processes. The model adopted a time step of 60 s to accurately capture the dynamic processes of storm surges. In terms of spatial grid spacing, the model employed a uniform grid system with a grid spacing of $5' \times 5'$.

Regarding model parameter settings, the bottom friction coefficient (k) was uniformly set to 0.001, and the seawater density was set to 1025 kg/m^3 . For the parameterization of the sea surface wind stress drag coefficient (C_D), three comparative experiments were designed:

E1 scheme: A constant drag coefficient was adopted, with C_D uniformly set to 0.0026 across the entire domain.

E2 scheme: A wind-speed-dependent linear parameterization was employed based on Wujin's formula, expressed as [14]:

$$C_D = (a + b * U_{10}) * 10^{-3}, 0 < U_{10} < 50 \quad (6)$$

where a , b are empirical coefficients with values of 0.8 and 0.065, respectively, and U_{10} is the wind speed at 10 m above the sea surface.

E2 (a) scheme: To evaluate the impact of empirical formulas on model accuracy, another wind-speed-dependent linear parameterization was employed as an additional experiment based on Smith's formula, expressed as [45]:

$$C_D = \begin{cases} (a + b * 6) * 10^{-3}, & U_{10} \leq 6 \\ (a + b * U_{10}) * 10^{-3}, & 6 < U_{10} < 22 \\ (a + b * 22) * 10^{-3}, & U_{10} \geq 22 \end{cases} \quad (7)$$

where the values of a , b are 0.61 and 0.063, respectively.

E3 scheme: Based on E2 scheme (Equation (6)), the model computes the simulated storm surge water levels through numerical calculations. The discrepancy between the simulated and measured water levels is used as the forcing term to drive the adjoint equations, and backward integration of these equations iteratively optimizes coefficients a and b . This process is repeated until the average error between the simulated and measured water levels is reduced to an acceptable threshold, at which point the inversion is terminated, yielding the optimized coefficients a and b within the C_D field.

3. Results

For better result analysis, a systematic comparison between simulated water levels and measured water levels under three different schemes should be conducted for this model. Due to the inaccuracy of the bathymetric data input into the model, the coarse grid spacing, and the excessive proximity of the Pi Kou Station and Zhi Maowan Station to the land, it was difficult to accurately simulate the water level variations at these two stations. Therefore, Pi Kou Station and Zhi Maowan Station were designated as land points in the model, with only the water level data from the remaining five stations retained for numerical simulations and subsequent analyses. Furthermore, since the simulation accuracies of the two schemes E2 and E2 (a) are nearly identical (Table 4), we directly excluded the supplementary scheme E2 (a) and retained schemes E1, E2, and E3 for subsequent analysis. Figure 3a,b shows the simulated water levels at five stations driven by the ERA5 reanalysis wind field and the interpolated wind field under the three schemes, respectively. In addition, the residuals (ϵ) between the simulated and measured water levels for three schemes was calculated, as shown in Figure 4a,b.

Table 4. Average values of MAE, RMSE, and R of water levels at five stations for two wind fields under four schemes.

	E1		E2		E2(a)		E3	
	EWF	IWF	EWF	IWF	EWF	IWF	EWF	IWF
MAE (m)	0.46	0.54	0.50	0.57	0.51	0.57	0.28	0.15
RMSE (m)	0.55	0.63	0.59	0.66	0.60	0.66	0.38	0.23
R	0.62	0.51	0.57	0.48	0.57	0.48	0.89	0.91

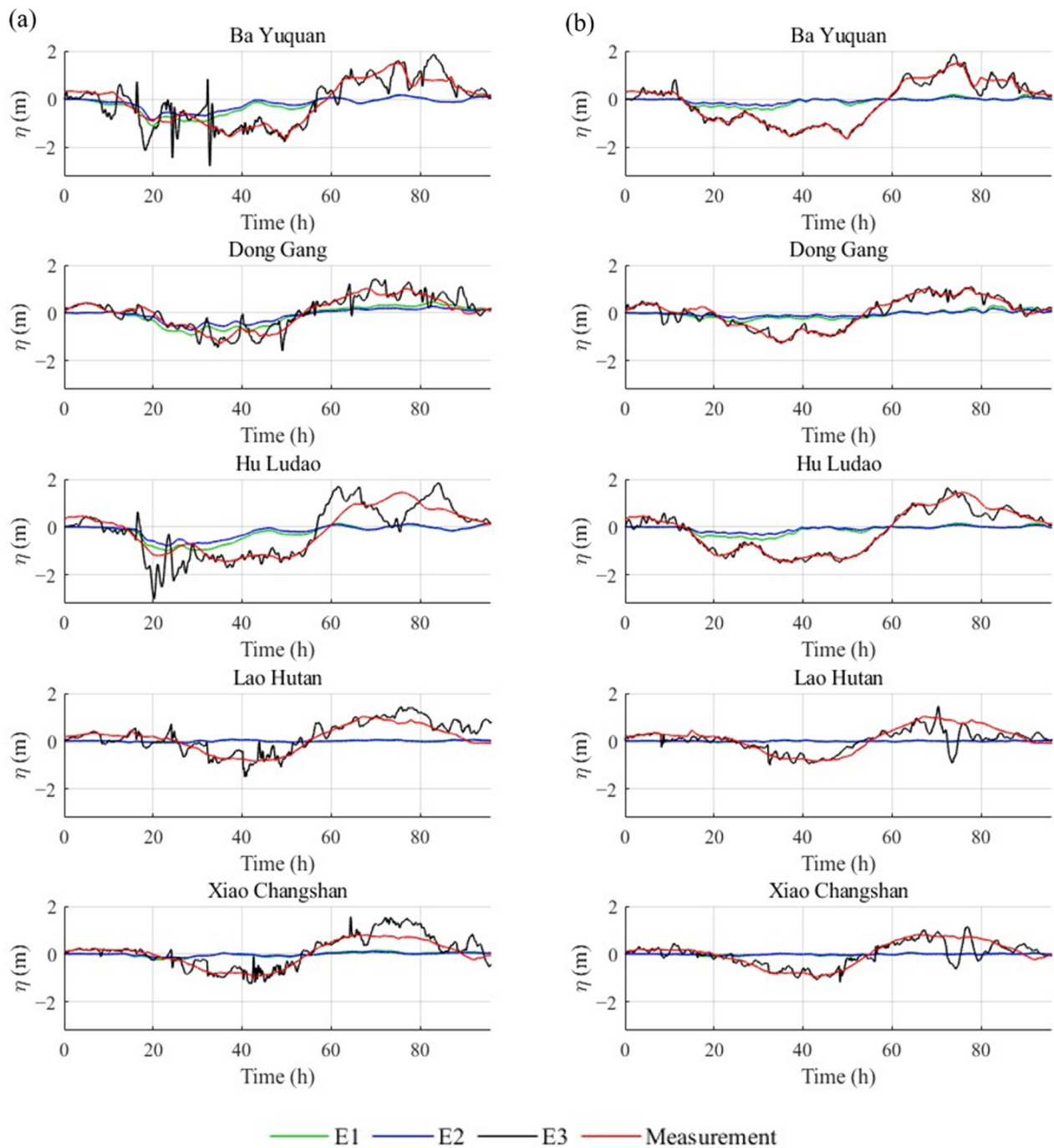


Figure 3. (a). The simulated water levels at five stations driven by the EWF under E1, E2, and E3 schemes; (b) The simulated water levels at five stations driven by the IWF under E1, E2, and E3 schemes.

As shown in Figure 3, both the water level simulations driven by ERA5 reanalysis wind fields and the interpolated wind fields demonstrate that the temporal trend of E3 scheme's simulated water levels aligns closely with the measured water level. And the occurrence times of peak values under E3 scheme show excellent agreement with the actual measurements. However, the simulated water levels of both E1 and E2 schemes exhibited notable discrepancies compared with the measured water levels. Furthermore, Figure 4 indicates that while residuals of the E3 scheme under both wind field configurations display higher frequency oscillations, their amplitudes are notably smaller compared to those of E1 and E2 schemes, with fluctuations primarily centered around zero. The residual curves of

the E3 scheme exhibit less smoothness compared to those of the E1 and E2 schemes. This is attributed to the spatiotemporally varying empirical coefficients a and b in the E3 scheme, whereas a and b in E2 scheme are fixed constants, and the C_D in E1 scheme remains constant. The residuals of the E1 and E2 schemes are similar and relatively large. This strongly suggests that the implementation of the adjoint data assimilation significantly enhances the consistency between simulated and measured water levels, achieving markedly higher simulation accuracy than the other two experimental schemes. Consequently, the adjoint data assimilation method effectively reduces simulation errors.

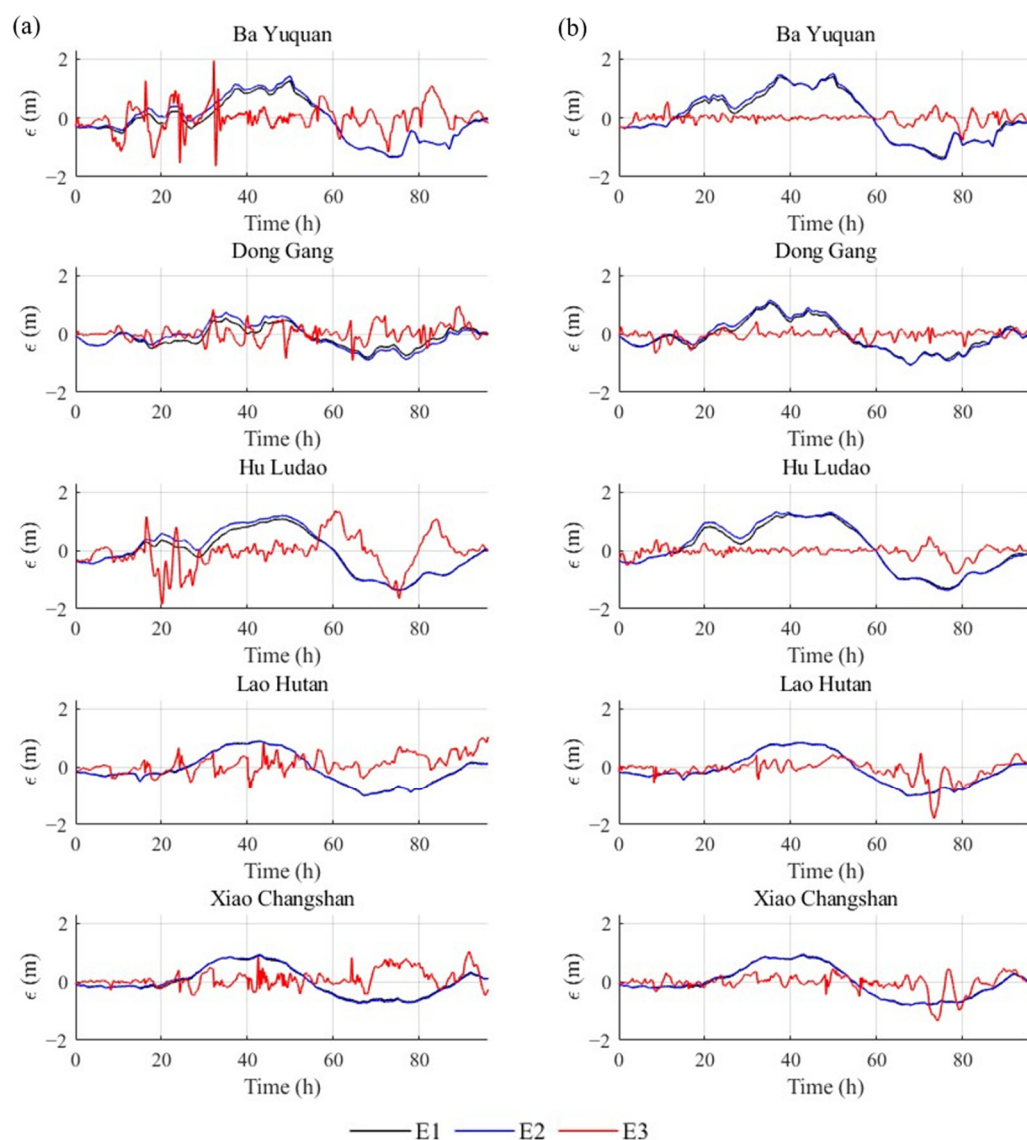


Figure 4. (a) The residuals between the simulated and measured water levels by the EWF simulations under E1, E2, and E3 schemes. (b) The residuals between the simulated and measured water levels by the IWF simulations under the E1, E2, and E3 schemes.

To further validate the accuracy of the four schemes, we also calculated the MAE, root mean square error (RMSE), and correlation coefficient (R). The MAE is defined as in Equation (4) of Section 2.2.2, while the formulas for RMSE and R are provided below:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (s_i - \hat{s}_i)^2} \quad (8)$$

$$R = \frac{\sum_{i=1}^N (s_i - \bar{s}_i)(\hat{s}_i - \bar{\hat{s}}_i)}{\sqrt{\sum_{i=1}^N (s_i - \bar{s}_i)^2 \sum_{i=1}^N (\hat{s}_i - \bar{\hat{s}}_i)^2}} \quad (9)$$

where s_i and $\hat{s}_i$ represent the values of simulations and measurements at the i th timestep, respectively, and N denotes the total number of samples.

Figure 5 illustrates the spatially averaged MAE values derived from Equation (4) for 12 processes, with the last column summarizing their overall mean. Table 4 lists the average values of MAE, RMSE, and R of water levels at five stations for two wind fields under four schemes.

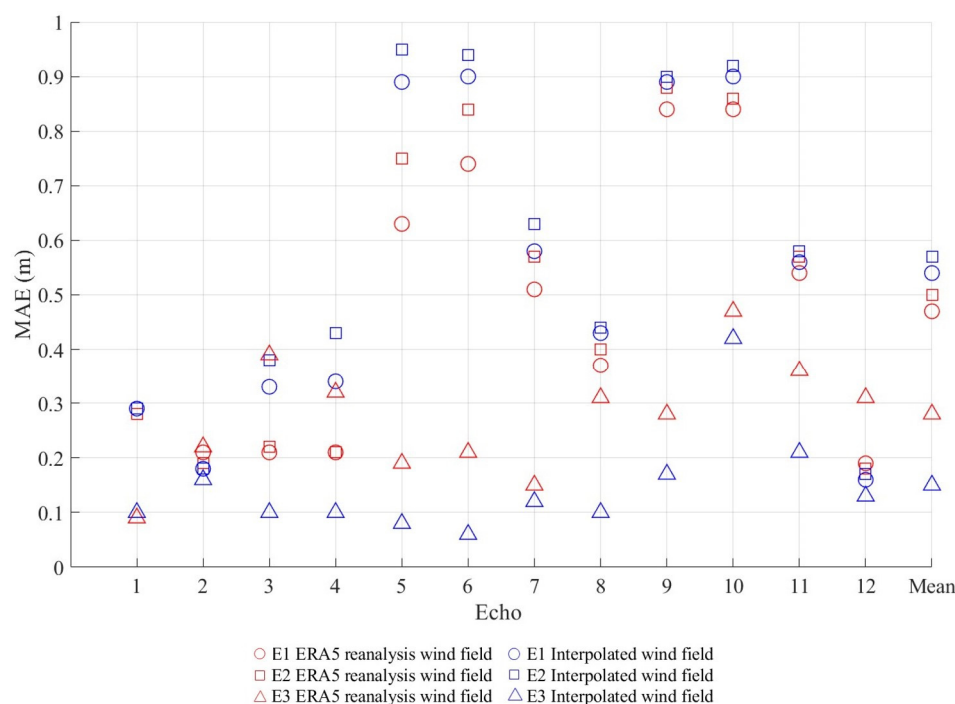


Figure 5. The water level spatially averaged MAEs in 12 processes driven by two wind fields under E1, E2, and E3 schemes.

As indicated by the three metrics (MAE, RMSE, and R) in Table 4, the E2 and E2 (a) schemes exhibited minimal differences in all performance indicators, suggesting that the choice of empirical formula has a negligible impact on the model's accuracy. Table 4 also demonstrated the overall MAE values for the E1 scheme were 0.46 m (EWF) and 0.54 m (IWF), while those for E2 scheme were 0.5 m (EWF) and 0.57 m (IWF). The E3 scheme, leveraging the adjoint data assimilation, reduced these MAEs to 0.28 m and 0.15 m, respectively. Notably, the error reduction rate (ε) was calculated by

$$\varepsilon = \frac{z_1 - z_0}{z_0} \times 100\% \quad (10)$$

where z_0 denotes the value of the non-assimilation scheme, and z_1 represents the value of the adjoint data assimilation scheme.

After applying the calculation based on Equation (10), the MAE of the adjoint data assimilation method (E3) in simulations driven by the EWF was reduced by approximately 39% and 44%, respectively, compared to the E1 and E2 schemes. For the IWF, the improvements were even more pronounced, with reductions of approximately 72% (E1) and 74% (E2). From the perspective of the RMSE, which reflects the distribution characteristics of prediction errors, the E3 scheme demonstrated significantly lower prediction errors in both wind fields compared to the E1 and E2 schemes. Specifically, for the EWF, the RMSE

of the E3 scheme was reduced by approximately 31% and 36%, respectively, relative to the E1 and E2 schemes; for the IWF, the RMSE of the E3 scheme was reduced by approximately 63% (E1) and 65% (E2), respectively. The correlation coefficient (R) results reveal that the R values for both wind fields under the E1 and E2 schemes ranged between 0.4 and 0.7, indicating moderate correlation. In contrast, the E3 scheme applying the adjoint data assimilation significantly enhanced the correlation: the R values reached 0.8 for the EWF and 0.9 for the IWF, both demonstrating strong linear correlation. Furthermore, the comparable MAE, RMSE, and R values of E1 and E2 schemes indicate that their simulation accuracies are similar. These results indicate that the empirically derived wind stress drag coefficients are at the same level as the constant coefficients in terms of simulation accuracy.

And as shown in Figure 5, the water level errors of the E3 scheme exhibit a marked overall reduction compared to the E1 and E2 schemes. Specifically, the MAEs in Processes 5–11 driven by both wind fields decreased significantly. For the EWF, the E3 scheme achieved the largest error reduction of 0.56 m compared to E1 scheme in Process 9 and 0.63 m compared to E2 scheme in Process 5. Under the IWF, the E3 scheme reduced errors by 0.84 m and 0.88 m relative to E1 and E2 schemes, respectively, in Process 6. Therefore, the above results indicated that the wind stress drag coefficients inverted through the adjoint data assimilation in the E3 scheme are more physically plausible, thereby significantly enhancing simulation accuracy. The spatial distribution of the C_D values is illustrated in Figure 6.

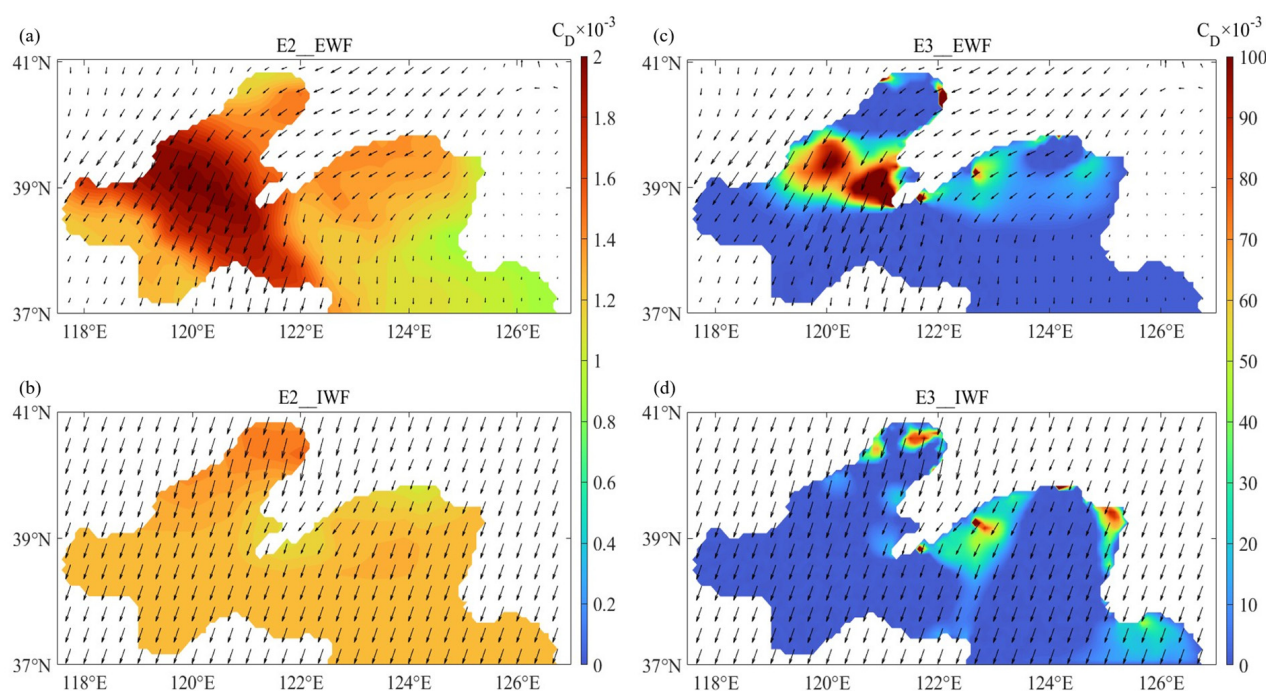


Figure 6. The spatial distribution of C_D values at 15:00 October 18 driven by EWF and IWF under the E2 and E3 scheme ((a) driven by EWF under E2 scheme, (b) driven by IWF under E2 scheme, (c) driven by EWF under E3 scheme, (d) driven by IWF under E3 scheme).

In Figure 6, taking 15:00 on October 18 as an example, under the E3 scheme, the C_D values exhibited a more complex spatial pattern compared to the E2 scheme. Following data assimilation, the C_D values in both wind fields under the E3 scheme remained predominantly within 2×10^{-3} , which the C_D values were generally reasonable, according to previous studies [12,28,46–48]. And abrupt changes were observed in certain regions, with magnitudes reaching two orders of magnitude higher than those without the adjoint data assimilation. Additionally, these extreme values occur both in the offshore regions

and in certain nearshore regions under high wind speeds. This also suggests potential differences in C_D between close to shore and well offshore. And in the EWF, the proportion following temporal averaging of C_D values exceeding 0.01 was 24%, while those exceeding 0.1 accounted for approximately 4%. In the IWF, the corresponding proportions were 22% and 2%, respectively. Consequently, the E3 scheme using the adjoint data assimilation demonstrated better alignment with actual conditions.

It is noteworthy that the ERA5 reanalysis wind field driven water level simulations under E3 scheme exhibited noticeable deviations at Station 1 (Ba Yuquan) during the 12–35 h period and Station 3 (Hu Ludao) during the 16–29 h period, as illustrated in Figures 3a and 4a. These discrepancies may be attributed to the stations' location in the northern Bohai Sea, which features shallow water depths, as well as the extremely high wind speeds during these periods that led to model instability. And persistent deviations at Station 3 during hours 57–87 may relate to directional errors in the wind field products. Additionally, the interpolated wind fields at five stations outperformed the ERA5 reanalysis wind fields across all three evaluation metrics under E3 scheme. This discrepancy arises because the interpolated wind speeds near the stations closely align with measured values. However, the limited number of measurement stations (seven in total) leads to a spatial degradation of wind vector accuracy with increasing distance from the stations, thereby reducing the overall simulation precision. Future studies could enhance the regional applicability of the Bohai Sea temperate storm surge numerical model by implementing targeted wind field corrections in specific spatiotemporal domains.

4. Discussion

Based on the effectiveness of the E3 scheme applied to the adjoint data assimilation, the spatial distribution of a and b values at 15:00 October 18 is demonstrated in Figure 7 and the validation results of E3 scheme are demonstrated in Figures 8 and 9, which present the simulated water level fields driven by ERA5 reanalysis and interpolated wind fields, respectively.

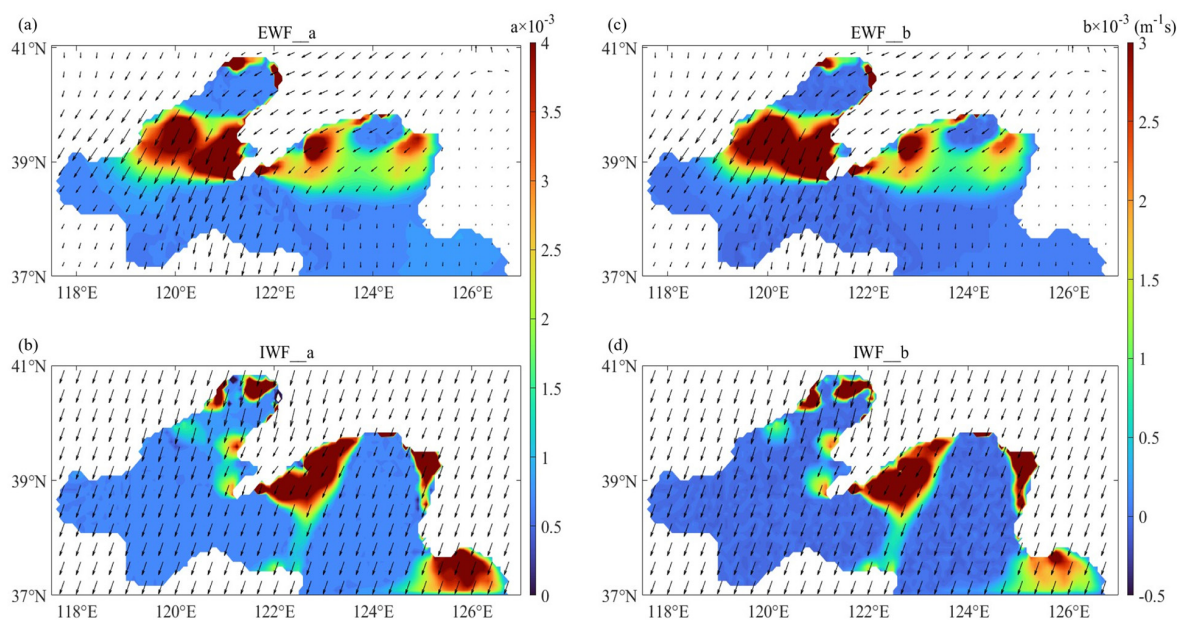


Figure 7. The spatial distribution of a and b values at 15:00 October 18 driven by ERA5 reanalysis wind field and interpolated wind field in under the E3 scheme ((a) a values driven by EWF, (b) a values driven by IWF, (c) b values driven by EWF, (d) b values driven by IWF).

As shown in Figure 7, the locations where the values of a and b increase are generally consistent with those of C_D . The occurrence of this phenomenon may be attributed to two main factors: on the one hand, the C_D increases with increasing wind speed for wind speeds below 30 m/s; on the other hand, the increase in the C_D near the shore is due to processes such as steepening of waves and reduction in the wave phase speed during the shoaling as water depth decreases [49–51].

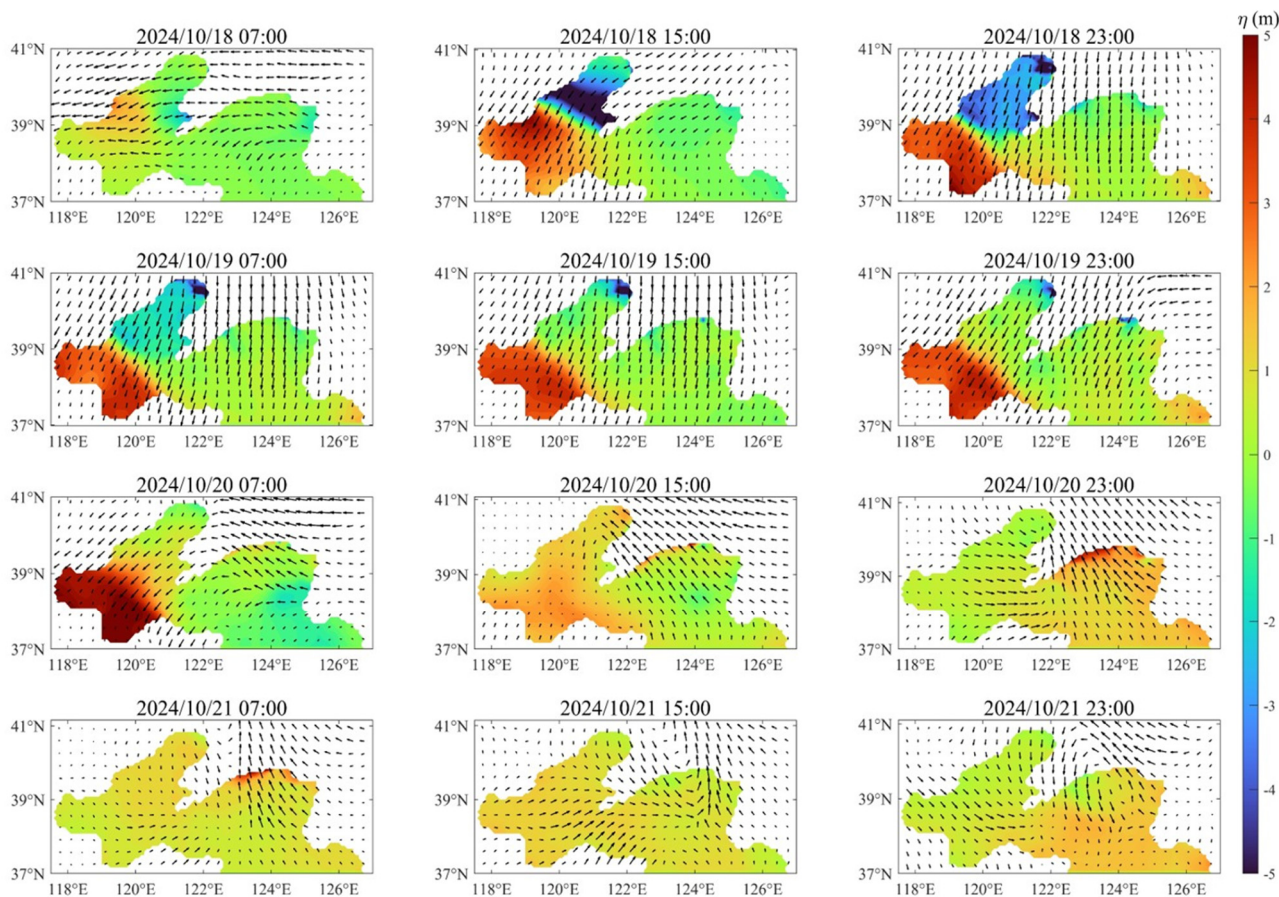


Figure 8. The spatial distribution of simulated water level driven by ERA5 reanalysis wind field under the E3 scheme.

As shown in Figure 8, persistent northeasterly winds starting from 00:00 on October 18 induced a marked decline in water levels within the Liaodong Bay. Meanwhile, water masses converged towards the Bohai Bay and Laizhou Bay along wind-driven transport pathways, giving rise to a rising water level trend constrained by the trilateral terrestrial topography, while the Liaodong Bay exhibited a decreasing water level trend. This trend reached its peak during the 7th 8-hour sub-process (approximately around the 50th hour), aligning well with the observed measurements in Figure 3. From 15:00 on October 20 onwards, as wind velocities gradually diminished and the wind direction shifted, water masses in the Bohai Bay and Laizhou Bay diffused outward, leading to a rebound in water levels within the Liaodong Bay. Notably, due to the lower average wind speed in the interpolated wind field compared to the product wind field, the water level fluctuations depicted in Figure 9 are less pronounced than those in Figure 8. Additionally, around 23:00 on the 20th (during the 9th sub-process), the interpolated wind field drove a notable water level rise in the Liaodong Bay, whereas the reanalysis wind field exhibited only a marginal response. Concurrently, the simulation error of the reanalysis wind field for this sub-process in Figure 5 exceeded that of the interpolated wind field. This discrepancy

arises from wind field differences within this specific sub-process and region. It is reiterated that while the reanalysis wind field demonstrates superior overall accuracy, its localized precision in certain subdomains falls short of that of in situ observational data. Despite local discrepancies in water level distributions between Figures 8 and 9 arising from differences between the reanalysis wind field and the interpolated wind field, the overall variation trends remained consistent. Although the numerical model does not take into account the tidal mechanisms, it successfully replicated this phenomenon. In Figure 8, localized water level oscillations exceeding 5 m are primarily attributed to two factors: (1) the persistent intense wind forcing, and (2) a potential overestimation of C_D . This elevated C_D value may amplify the wind-driven aspect, making the effect of the wind stronger. Furthermore, the adopted parameterization scheme, which employs constant bottom friction coefficients, might introduce errors in the inversion of C_D , thereby propagating inaccuracies into the simulation results.

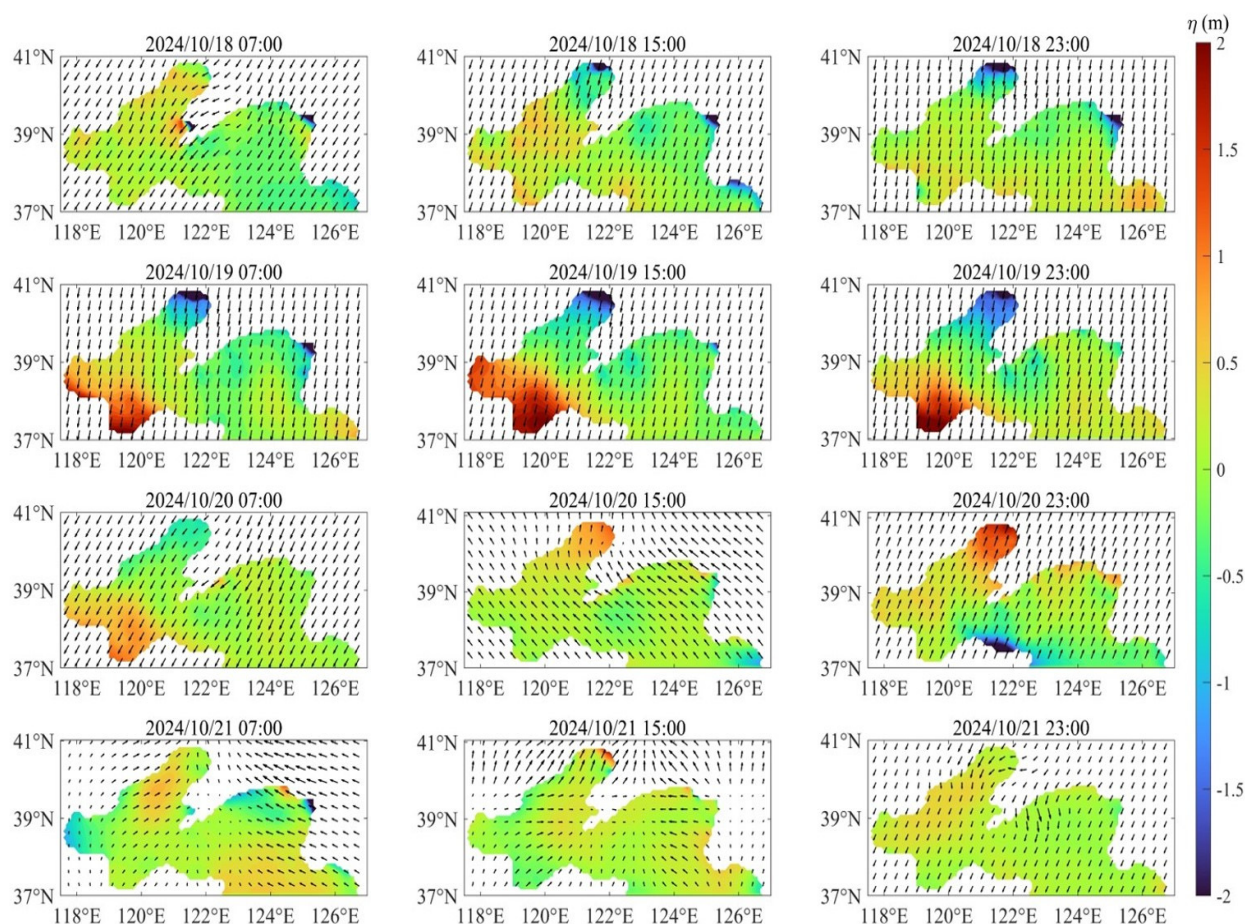


Figure 9. The spatial distribution of simulated water level driven by interpolated wind field under the E3 scheme.

5. Conclusions

This study conducted numerical simulations of the Bohai Sea temperate storm surge event occurring from 18–21 October 2024, applying an optimized storm surge numerical model. The input wind fields consist of an ERA5 reanalysis product and an interpolated wind field constructed using the Kriging interpolation method. Regarding the treatment of the C_D , this study implemented three processing schemes and introduced the adjoint data assimilation method to derive a more physically plausible C_D field. Hence, the generated simulation results exhibited consistency with the measured data.

(1) The E3 scheme utilized the adjoint data assimilation driven parameter optimization, reducing ERA5 wind field errors by 39% (compared to E1 scheme) and 44% (compared to E2 scheme), and interpolated field errors by 72% (compared to E1 scheme) and 74% (compared to E2 scheme). This improvement significantly strengthened the alignment between simulations and measurements, validating the model's reliability in optimizing the C_D through the adjoint data assimilation.

(2) Under the E1 scheme, the spatial and temporal mean MAE values for water levels driven by the ERA5 reanalysis wind field and the interpolated wind field were 0.46 m and 0.54 m, while the corresponding RMSE values were 0.55 m and 0.63 m, respectively. For the E2 scheme, the corresponding MAE values for the ERA5 and interpolated wind fields were 0.50 m and 0.57 m and the RMSE values were 0.59 m and 0.66 m, respectively. Additionally, the correlation coefficients for both schemes fell within the range from 0.4 to 0.6, indicating comparable performance levels. These indicated that this the empirically derived wind stress drag coefficients are at the same level as the constant coefficients in terms of simulation accuracy, and both approaches exhibit relatively low overall accuracy.

(3) The numerical simulation results in this study demonstrated localized deviations in specific regions and periods. Future research should prioritize the correction and optimization of the wind field in these biased spatial and temporal domains, as well as model improvements to address the current exclusion of tidal dynamics and seafloor friction effects. These improvements will increase the usefulness of simulations of temperate storm surges in the Bohai Sea region.

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

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