

Article

An Algorithm to Retrieve Range Ocean Current Speed under Tropical Cyclone Conditions from Sentinel-1 Synthetic Aperture Radar Measurements Based on XGBoost

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Abstract: In this study, a novel algorithm to retrieve the current speed along the range direction under extreme sea states is developed from C-band synthetic aperture radar imagery. To this aim, a Sentinel-1 (S-1) dual-polarized synthetic aperture radar (SAR) dataset consisting of 2300 images is collected during 200 tropical cyclones (TCs). The dataset is complemented with collocated wave simulations from the Wavewatch-III (WW3) model and reanalysis currents from the HYbrid Coordinate Ocean Model (HYCOM). The corresponding TC winds are officially released by IFRMER, while the Stokes drift following the wave propagation direction is estimated from the waves simulated by WW3. In this study, first the dependence of wind, Stokes drift, and range current on the Doppler centroid anomaly is investigated, and then the extreme gradient boosting (XGBoost) machine learning model is trained on 87% of the S-1 dataset for range current retrieval purposes. The rest of the dataset is used for testing the retrieval algorithm, showing a root mean square error (RMSE) and a correlation coefficient (r) of 0.11 m/s and 0.97, respectively, with the HYCOM outputs. A validation against measurements collected from two high-frequency (HF) phased-array radars is also performed, resulting in an RMSE and r of 0.12 m/s and 0.75, respectively. Those validation results are better than the 0.22 m/s RMSE and 0.28 r achieved by the empirical CDOP model. Hence, the experimental results confirm the soundness of the XGBoost, exhibiting a certain improvement over the empirical model.

Keywords: range current speed; tropical cyclone; Sentinel-1



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1. Introduction

Tropical cyclones (TCs) are a serious threat to coastal areas. In recent decades, satellite microwave tools as scatterometers and altimeters have been shown to provide reliable global wind maps daily, thus significantly improving the accuracy of meteorological and oceanic forecasting [1,2]. However, there are differences in wind speed between different wind sources [3]. When small-scale observations are needed, synthetic aperture radar (SAR), calling for a fine spatial resolution down to 1 m and a wide swath width approaching 500 km, has been shown to be a key instrument. Hence, it is commonly used in the field of TC-relevant research [4–6].

In the last two decades, co-polarized SAR wind retrieval algorithms based on geophysical model functions (GMFs) have been proposed to deal with low-to-moderate sea state, i.e., CMOD family for Rardarsat-2, Sentinel-1 (S-1) and Gaofen-3 SAR imagery, and XMOD2 for TerraSAR-X/TanDEM-X and Cosmo-Skymed SAR data [7–12]. Nevertheless, it has been demonstrated that the performance of co-polarized GMF-based wind retrieval algorithms is limited by the saturation issues that affect the co-polarized backscatter signals under strong

wind conditions (i.e., >30 m/s) [5,13]. This is no longer the case of the cross-polarized normalized radar cross section (NRCS), which, therefore, is typically considered to estimate TC winds [4,14,15]. However, the cross-polarized GMF approaches are likely to be affected by low signal-to-noise ratios, resulting in discontinuity of the TC winds using even though ad hoc preprocessing such as thermal noise removal and speckle filtering is undertaken. Hence, to improve the accuracy of GMF-based SAR wind retrieval algorithms during TCs, a combination of both co- and cross-polarized backscattering channels is proposed that provides satisfactory results [16–18]. It is also worth mentioning that non-GMF-based approaches to TC wind estimation from co-polarized SAR imagery have been proposed, i.e., the ones based on the inversion of the polarization-independent azimuthal cutoff wavelength [19].

When dealing with wave retrieval algorithms from SAR measurements, two main categories can be identified: transfer functions that aim at mapping the co-polarized SAR intensity spectrum into a wave spectrum according to the wave mapping mechanism [20–22] and empirical models [23,24], and deep learning-based methods which aim to estimate the integral wave parameters directly from SAR features [25,26]. Nonetheless, even though theoretical algorithms have been implemented for SAR-based wave retrieval under TC conditions [27], their accuracy is not satisfactory due to inaccurate modulation transfer functions and distortion induced by rain cells [28,29].

In the literature, it is shown that the Doppler centroid anomaly (DCA), i.e., the difference in Doppler frequency between SAR measurements and predictions associated with the satellite flight, inherently relates the backscattering roughness pattern with the upper ocean dynamics [30–33]. Moreover, the measured velocity of the Doppler Centroid Technique (DCT) is exactly the magnitude of the sea surface current vector, and it was used to invert the real sea surface vector field's weak background current at about 24°N during Hurricane Sam [34]. In previous studies [35,36], it was demonstrated that wind and current in range/look direction, respectively, can be retrieved from DCA by an empirical model, denoted as CDOP. It has also been shown that radial current velocity can be retrieved from SAR Doppler shift during typhoons, and the results show that the contribution of non-geophysical conditions and sea state to Doppler shift can be accurately estimated and eliminated, so that reliable radial current velocity can be obtained under strong wind conditions [37]. In fact, the Stokes drift induced by huge waves during a TC is supposed to be higher than that during a low-to-moderate sea state. In particular, the empirical model has not been tested during TCs considering the strong wind-induced current and Stokes drift caused by huge waves. Except in the case of typhoons, the studies on the inversion of ocean surface currents are mainly concentrated in coastal areas with land cover. In the vicinity of Kuroshio, a non-geophysical Doppler shift correction algorithm for Kuroshio observation has been proposed [38]. In addition, a direct comparison of the surface radial velocity (RVL) of Sentinel-1 and TanDEM-X satellite SAR systems at different frequencies and imaging modes has been made [39].

In this study, 2300 S-1 SAR images collected during TCs are used to study the dependence of upper ocean dynamics, including wind, Stokes drift, and range current, on DCA. Accordingly, an empirical model based on a machine learning method is developed for range current retrieval purposes from SAR imagery. Furthermore, the extreme gradient boosting (XGBoost) machine learning model trained on such datasets is tested on independent 300 S-1 SAR images. The corresponding results are then contrasted with the ones obtained from actual measurements collected by two high-frequency (HF) phased-array radars [40] under two showcased TCs. Meanwhile, the traditional empirical algorithm is also used to compare with HYCOM and two high-frequency phased-array radars. The contribution of this study is to propose a new algorithm to extract the current speed along the range direction in extreme sea conditions from C-band SAR images, which has certain application value for the study of ocean dynamics and related applications. The rest of this paper is organized as follows: Section 2 describes the datasets including SAR images, hindcasting fields, and HF measurements; the methodology, i.e., the machine learning

method and empirical model, is briefly introduced in Section 3; the validation of SAR retrieval by two approaches is discussed in Section 4; and the conclusion is summarized in Section 5.

2. Datasets

The dataset used in this study is grouped into three categories: S-1 level-1 and level-2 SAR products and CyclObs wind provided by the French Research Institute for Exploitation of the Oceans (IFREMER); sea surface waves simulated by the Wavewatch-III (WW3) model; and sea surface currents simulated by the HYbrid Coordinate Ocean Model (HYCOM) and measured by two HF phased-array radars.

2.1. S-1 SAR Data and CyclObs Wind

As the TC data after 2016 are relatively complete, we chose to collect SAR images within 500 km of the central eye of the TC at the same TC time from 2016 to build our dataset. Thus, the SAR dataset consists of 2300 dual-polarized (VV and VH) S-1 images collected during 200 different TCs from 2016 to 2023. They are acquired in interferometric and extra-wide swath modes with a pixel size of 10 m and 40 m, respectively. The corresponding S-1 level-2 products (OCN) are also considered, which provide the information on DCA. The frames of the S-1 SAR images overlaid on the TC track and maximum wind speeds are shown as boxes in Figure 1, in which the red boxes indicate the training set and the black boxes indicate the test set. The wind information is obtained from the IFREMER CyclObs winds generated according to [17]. The aim was to develop a unique database of satellite and field data related to TC, estimating new sea surface wind speeds using L-band radiometer and C-band SAR (i.e., S-1A/B and RADARSAT-2). We match the wind field information with other parameter information to form the training dataset used in this paper. As a showcase, the VV- and VH-polarized NRCS graytone image relevant to the S-1 SAR acquisition, collected during the TC Infa on 24 July 2021 at 09:55 UTC, is shown, in decibel scale, in Figure 2a,b, while the corresponding CyclObs wind map is depicted in Figure 2c.

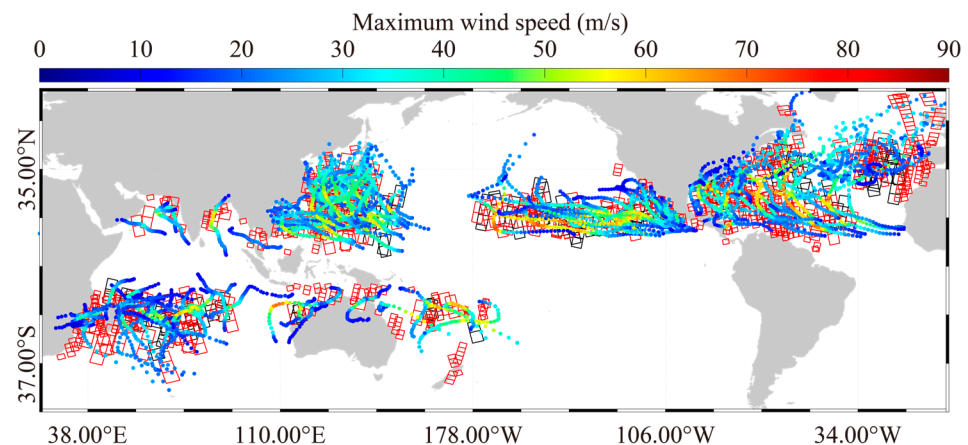


Figure 1. The frames of the 2300 S-1 SAR images overlaid on the TC tracks and maximum wind speeds, in which the red boxes indicate the training set and the black boxes indicate the test set.

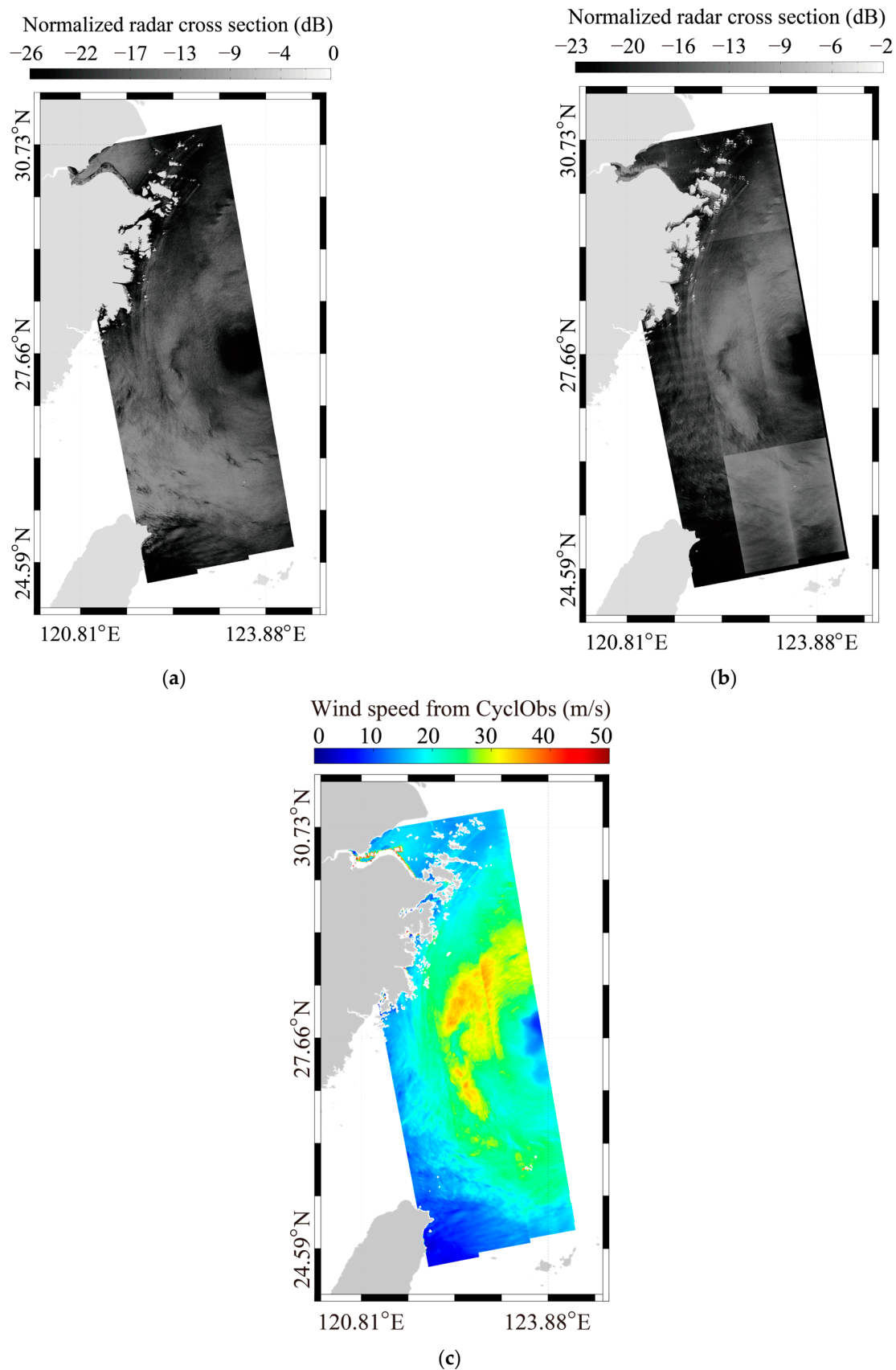


Figure 2. (a) S-1 VV-polarized NRCS image collected during the TC Infa (24 July 2021, 09:55 UTC); (b) S-1 VH-polarized NRCS image collected during the TC Infa (24 July 2021, 09:55 UTC); (c) corresponding CyclObs wind map.

2.2. WW3-Simulated Wave

WW3 is a mature numeric wave model commonly used for hindcasting waves [41,42]. It was already successfully adopted to deal with wave analysis during TCs [43,44]. Nowadays, the wave parameters from the altimeter and Surface Wave Investigation and Monitoring (SWIM) instruments onboard the Chinese-French Oceanography Satellite was used to validate the accuracy of the WW3-simulated result [45,46]. As a showcase, the significant wave height (SWH) map relevant to the TC Infa (24 July 2021, 10:00 UTC) overlaid on the Haiyang-2B (HY-2B) altimeter footprint is shown in Figure 3a, with a time difference of one hour. The reliability of WW3-simulated SWHs is confirmed by the results depicted in Figure 3b, where they are compared with HY-2B SWHs. These results refer to the 15°N–45°N and 110°E–135°E observed in the China seas between June and August 2022, showing a root mean squared error (RMSE) of 0.41 m and a correlation coefficient (r) of 0.88. Substantially, the WW3-simulated wave result is suitable for this study. Considering the varying influences of sea conditions, during the data matching process, the range of significant wave heights in the effective dataset exceeds 100,000 entries, with the significant wave height ranging from 0 to 8 m. As the SWHs are below 2.5 m, they can be classified as normal sea conditions; when the SWHs exceed 2.5 m, they can be considered as extreme sea conditions. As depicted in Figure 3b, there is a high degree of conformity when the SWHs are less than 6 m.

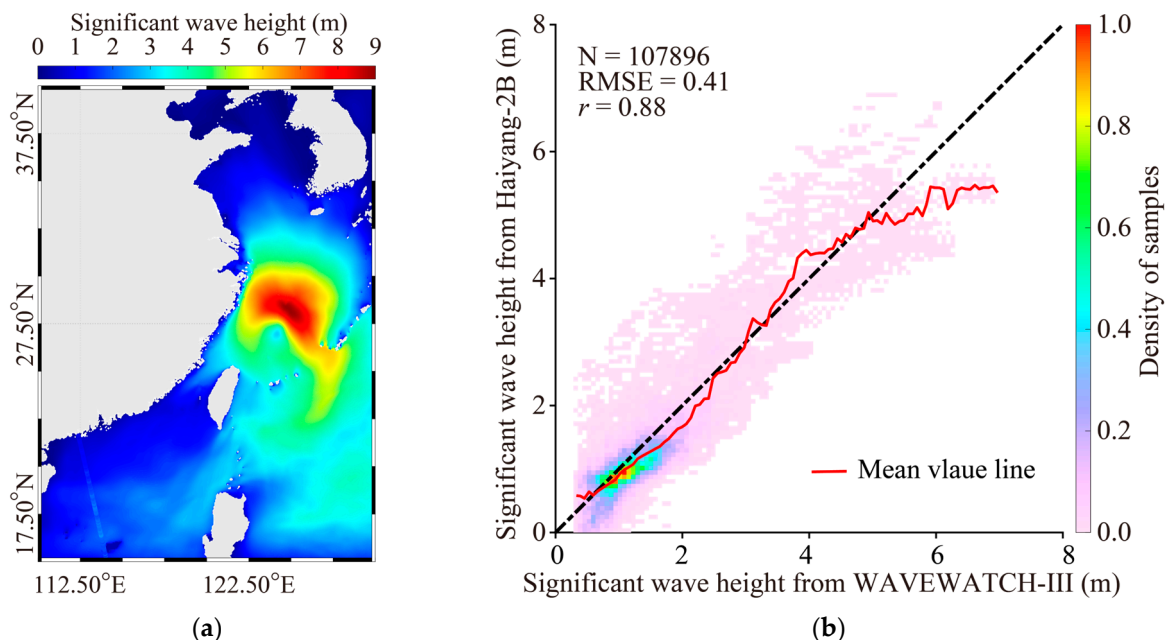


Figure 3. (a) SWH map simulated by WW3 at 10:00 UTC on 24 July 2021 relevant to the TC Infa, where the footprint of the HY-2B altimeter track is highlighted. (b) Validation of WW3-simulated SWH against the HY-2B products during the period of June–August 2022 in China seas.

2.3. Ocean Current Data

The current dataset in this study consists of HYCOM reanalysis currents and HF radar measurements. The spatial resolution of HYCOM data is a $\sim 0.08^\circ$ grid at 3 h intervals [47]. An example of the reanalysis current map (24 July 2021, 09:00 UTC) produced using HYCOM is shown in Figure 4, where the S-1 SAR image footprint of Figure 2a is annotated as a black box. The resolution of the HF phased-array ground radar measurements data is 0.03° . A showcase of the HF phased-array ground radar measurements that refer to the TC Infa is shown in Figure 5, where the current maps measured on 24 July 2021 at 09:55 UTC and on 25 July 2021 at 21:51 UTC are displayed in panels (a) and (b), respectively. In Figure 5, the red circle is the typhoon eye position at different times, while the red triangle corresponds to the typhoon eye position at the corresponding time of the HF phased-array ground radar, and the black line is the typhoon track. HYCOM data are used as the real values of the training dataset, and

they are matched with other parameter data in time and space to build the training set, while HF data are matched with a single TC in time and space to build the dataset, so that it can be used for the prediction and result verification of the proposed model.

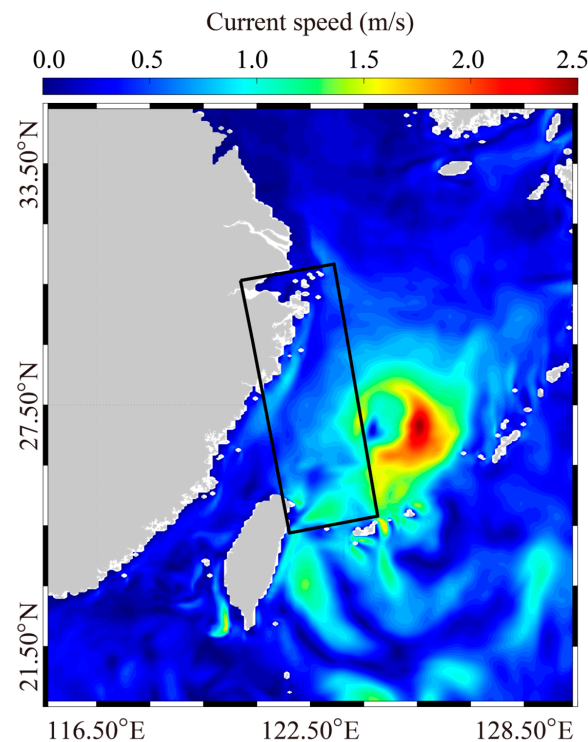


Figure 4. Current speed map simulated for 24 July 2021, 09:00 UTC, using HYCOM. The black box represents the footprint of the S-1 SAR image shown in Figure 2a.

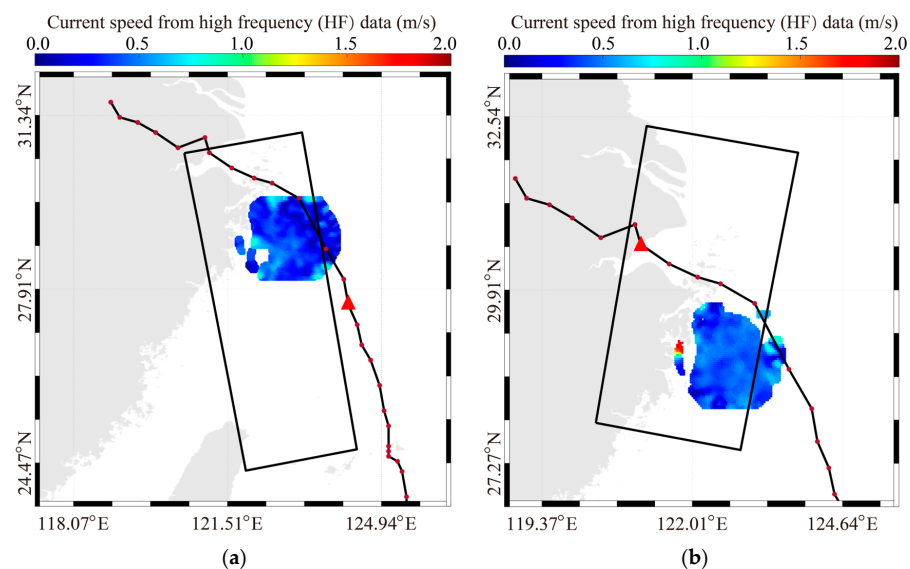


Figure 5. Current speed maps measured by the HF phased-array radars over the TC Infa on (a) 24 July 2021, 09:55 UTC, and (b) 25 July 2021, 21:51 UTC. The black line and red dot are the typhoon track, and the red triangle is the current typhoon time position.

3. Methodology

In this section, an analysis of the relationship between upper oceanic dynamics and DCA is undertaken, and then, the machine learning-based XGBoost model and empirical algorithm of range current retrieval, denoted as the CDOP model, are briefly presented.

3.1. Relationship between Upper Oceanic Dynamics and DCA

According to the microwave scattering theory, the DCA in the range direction is given by

$$f_{DC} = f_{DR} - f_{DP} + \Delta \quad (1)$$

where f_{DC} is the DCA, f_{DR} and f_{DP} are the SAR and predicted Doppler shift, and Δ is the error in the estimation process of f_{DR} and f_{DP} . All those parameters are provided by the S-1 level-2 (OCN) product. The Stokes drift in the range direction can be estimated as a function of SWH and mean wave period as follows:

$$u_0 = \frac{2\pi^3 H_s^2}{g T^3} \quad (2)$$

where u_0 is the Stokes drift, H_s is the SWH, T is the mean wave period, and g is the gravitational acceleration. Those parameters can be obtained from WW3 model simulations. The behavior of the DCA with respect to the range wind vector component (U_{10}), the Stokes drift, and the current speed (V), projected onto the range direction, is depicted in Figure 6a–c, respectively, where black lines represent the linear regression results. It can be observed that f_{DC} calls for a linear trend with the range-oriented components of U_{10} , u_0 and V . This matter lies at the basis of the proposed approach for the range component of ocean current retrieval during TC conditions.

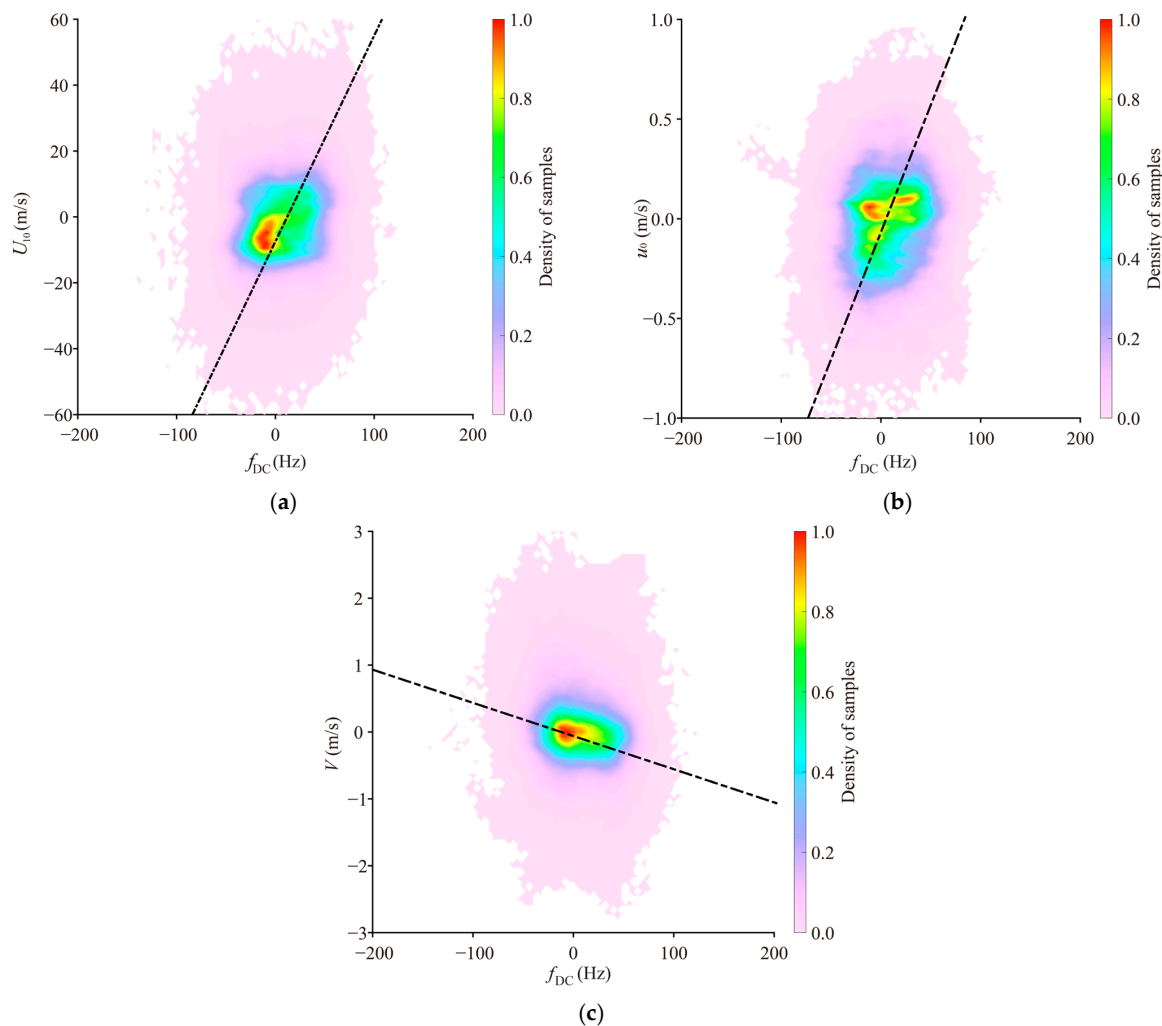


Figure 6. DCA versus (a) wind speed, (b) Stokes drift, and (c) current speed, projected onto the range direction. Black lines stand for the linear regression results.

3.2. XGBoost

The XGBoost machine learning model is an ensemble learning algorithm with high computational efficiency and precision. It is an iterative algorithm based on Gradient Boosted Decision Trees (GBDTs) that minimizes the loss function by gradually adding new weak prediction models (usually decision trees). However, it also requires careful hyperparameter tuning and feature engineering to achieve optimal performance [18]. Through continuous adjustment and optimization of hyperparameters, the specific parameters of the XGBoost model used in this study are shown in Table 1. The 2300 S-1 SAR imagery used in this study is divided into 2000 images (>200 million samples) for training and 300 images for testing. The XGBoost algorithm flow chart is presented in Figure 7. In the training process, the XGBoost model is fed with the DCA f_{DC} , the range wind vector component U_{10} , the range component of the Stokes drift u_0 , the radar incidence angle θ , and the azimuth direction from SAR ϕ to obtain the range component of the ocean current V as output. The behavior of the XGBoost training process with three wave parameters is illustrated in Figure 8a. As the model training process iterates, the XGBoost training processes converge eventually, and the RMSE between the achieved predicted value and the true value is less than 0.1 m/s of range current speed. SHAP (Shapley Additive exPlanations) is a method of explaining machine learning model predictions, and the SHAP value is used to measure the importance of each feature to the model. Details can be found in the relevant literature, as described in [48]. Figure 8b shows the SHAP values highlighted by the feature value relative to the characteristic of the input parameter (f_{DC} , U_{10} , ϕ , u_0 , θ). Each row in Figure 8b represents a feature, and the horizontal coordinate is the SHAP value. The features are ranked according to the average absolute value of the SHAP, which is the most important feature to the model. Wide areas indicate a large number of sample clusters. A dot represents a sample; the redder the color, the larger the value of the feature itself, and the bluer the color, the smaller the value of the feature itself. It is found that U_{10} and ϕ have the greatest impact on the XGBoost model, while θ is the least important factor. It can be seen from the results of the SHAP values in this paper that the relationship between wind speed and azimuth direction angle is obvious, which can indirectly prove that these two parameters have a strong correlation with the velocity, and it can also be understood that these two parameters have a high contribution to the final results in model training and prediction.

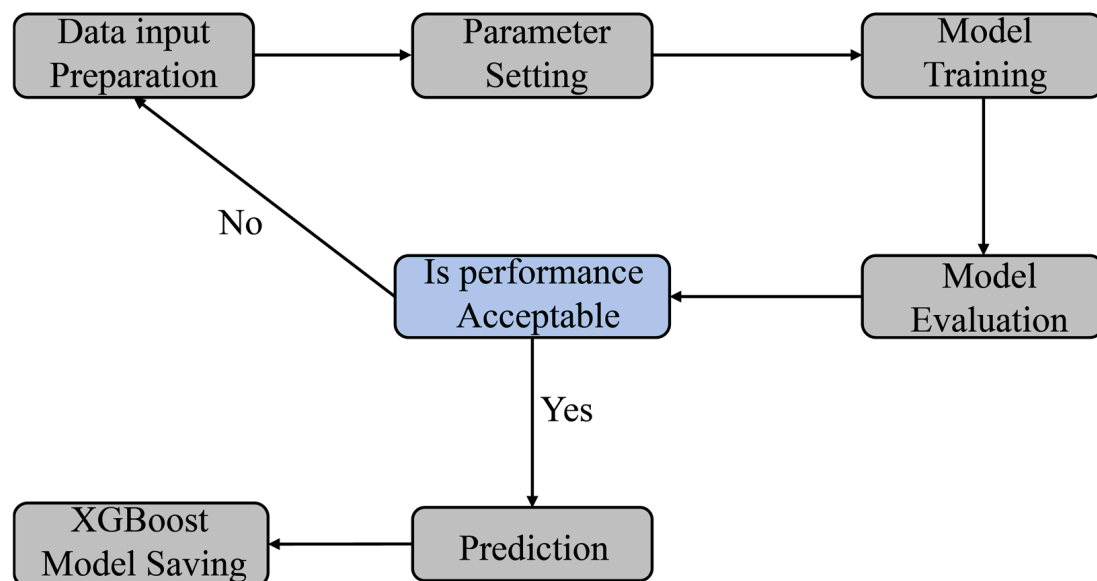
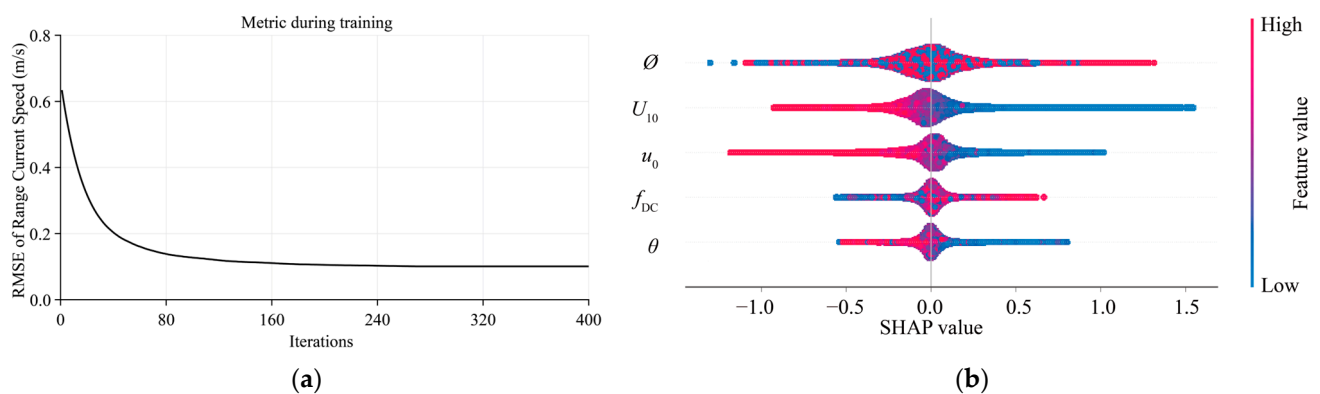


Figure 7. The flow chart of the eXtreme gradient boosting (XGBoost).

Table 1. The hyperparameters used in XGBoost.

Hyperparameter	Value
max_depth	15
learning_rate	0.05
n_estimators	400
objective	reg: linear
booster	gbtree
gamma	0.3
min_child_weight	1
subsample	1
colsample_bytree	1
reg_alpha	0
reg_lambda	1
eval_metric	rmse

**Figure 8.** (a) The behavior of the XGBoost training process and (b) the SHAP value map.

3.3. Empirical Algorithm

The principle of the estimation of sea surface current speed based on SAR Doppler centroid frequency was first proposed by Advanced Synthetic Aperture Radar (ASAR) wave mode images [31]. Utilizing data from the Envisat ASAR images, the measured velocity by Doppler centroid frequency encompassed the combined effects of sea surface wind, waves, and ocean currents [31]. In this study, the f_{DC} mentioned in Section 3.1 is obtained after effective correction of the SAR Doppler shift. And the f_{DC} here can be considered as a combination of sea state and current, and the influence of the sea state needs to be further removed to obtain more accurate sea surface current. In the previous study, the existing CDOP model was used to obtain the Doppler shift caused by sea surface wind [35], and the specific formula is as follows:

$$f_w = \text{CDOP}(U_{10}, \theta, \varphi_w, \text{pol}) \quad (3)$$

in which U_{10} and φ_w are the wind speed and direction relative to the radar look direction at a height of 10 m; θ is the incidence angle and pol is the polarization mode of radar.

In addition, the remaining Doppler anomalies expected to be associated with sea surface currents are obtained by subtraction [49]:

$$f_{cur} = f_{DC} - f_w \quad (4)$$

in which f_{cur} represents the residual Doppler shift associated with the surface radial current velocity and f_w contributes to the sea state that needs to be removed from the corrected geophysical Doppler.

Surface current velocity is related to the residual Doppler shift following the equation below [33,50]:

$$V_D = -\frac{\pi f_{cur}}{k_e \sin \theta} \quad (5)$$

where k_e is the incident radar wavenumber and V_D is assumed to be the line-of-sight velocity of the ocean surface current. In this study, the CyclObs wind provided by the IFREMER was used in the CDOP model to remove the wind-induced Doppler shift.

In this study, two methods were used to derive the current speed from SAR images in TCs. The major difference is the parameters, and the parameter pairs of XGBoost and empirical algorithms are shown in Table 1.

4. Results and Discussion

In this section, the comparisons of the range current speeds between SAR retrievals by XGBoost and the CDOP model against the HF measurement are presented. Moreover, the error of SAR retrievals is measured.

4.1. Validation

The trained XGBoost model and the empirical algorithm are applied to the test dataset to retrieve the range component of the ocean current. A showcased result by XGBoost relevant to the TC Infa is depicted in Figure 9a. Similarly, the example of the empirical algorithm is shown in Figure 9b, and the HYCOM range current speed map on 24 July 2021, 09:00, is presented in Figure 9c. It was found that the range current speed result by the XGBoost model is consistent with the HYCOM range current speed map, which is better than the inversion result by the empirical algorithm. A comparison between the XGBoost result, the empirical algorithm result, and the HYCOM output along the 123° longitude (see the dashed red line in panel (a)) is shown in Figure 10. It can be noted that the range component of the ocean current pattern inverted from S-1 SAR imagery by the XGBoost model is generally consistent with that from HYCOM simulations. However, the inversion result by the empirical algorithm has a huge error with the HYCOM simulations.

In addition, the statistical results of the range current wind speeds based on the XGBoost result, the empirical algorithm, and the HYCOM data are presented in Figure 11. The composition of the validation data is made up of 300 random pieces of data in 2300 images. The analysis revealed that the accuracy assessment of the XGBoost SAR retrievals with respect to HYCOM data results in an RMSE = 0.11 m/s and $r = 0.97$, which is better than the empirical algorithm result with an RMSE of 0.68 m/s and $r = 0.22$. Similarly, the verification results of the two high-frequency radar measurements in Figure 5 are shown in Figure 12a and Figure 12b, respectively. The comparison of the inversion result by the XGBoost model shows an RMSE = 0.12 m/s and $r = 0.75$, which is better than the RMSE = 0.22 m/s and $r = 0.28$ in the empirical algorithm. Nonetheless, it is worth noting that even though the use of a machine learning approach results in remarkable improvements, prior information on the sea waves and wind speed is needed. A Taylor diagram with respect to the current speed up to 3 m/s at intervals of 1 m/s is shown in Figure 13, in which the blue and red symbols represent the result using XGBoost and the empirical algorithm. In total, the inversion result by the XGBoost method is better than the empirical algorithm under the difference current speed ranges. Therefore, the XGBoost method is an optional way to retrieve range current speed from SAR typhoon images.

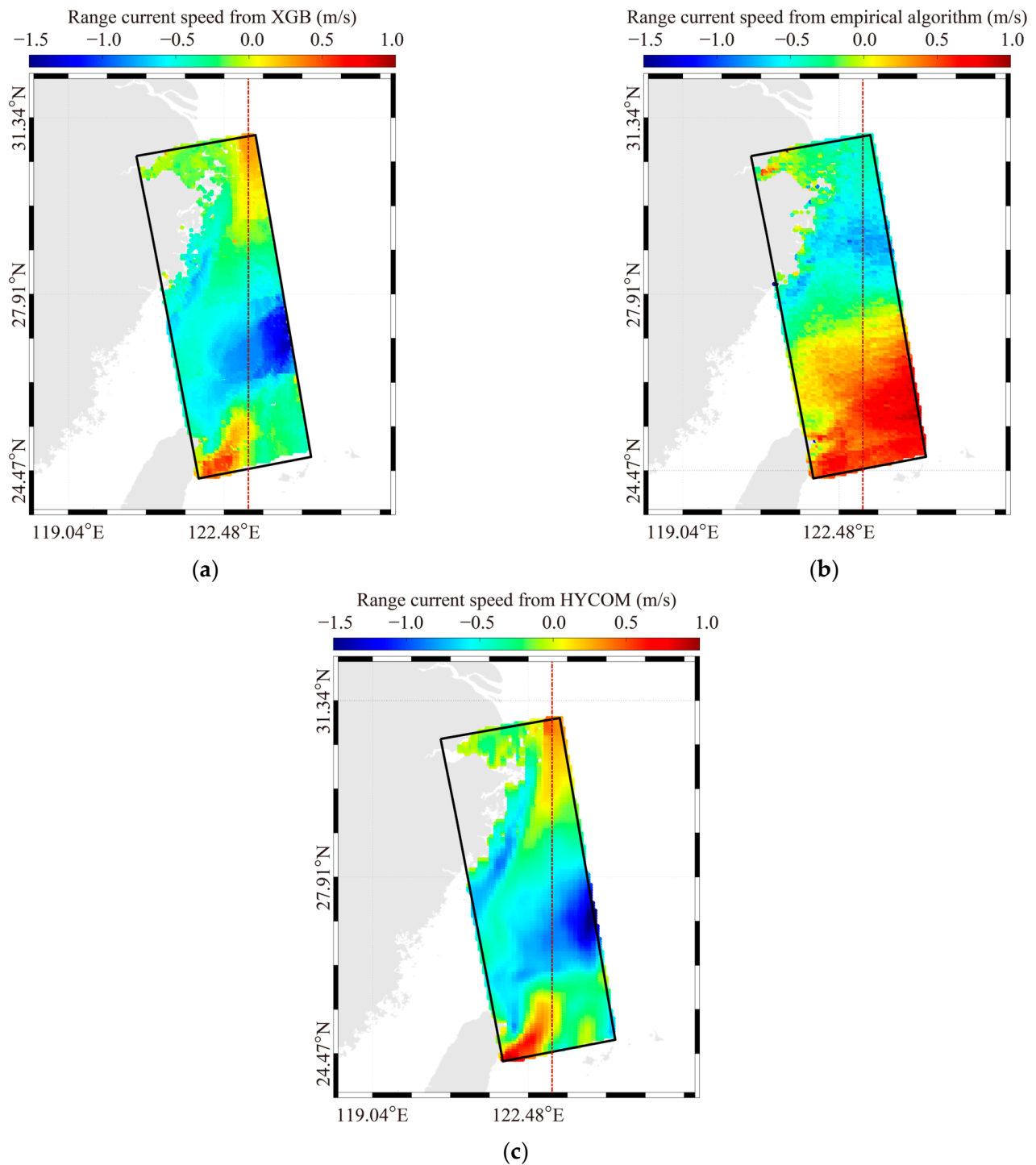


Figure 9. (a) Range current speed map by XGBoost method and (b) the empirical algorithm obtained from the S-1 SAR scene collected over TC Infa on 24 July 2021, 09:55 UTC; (c) the HYCOM range current speed map on 24 July 2021, 09:00.

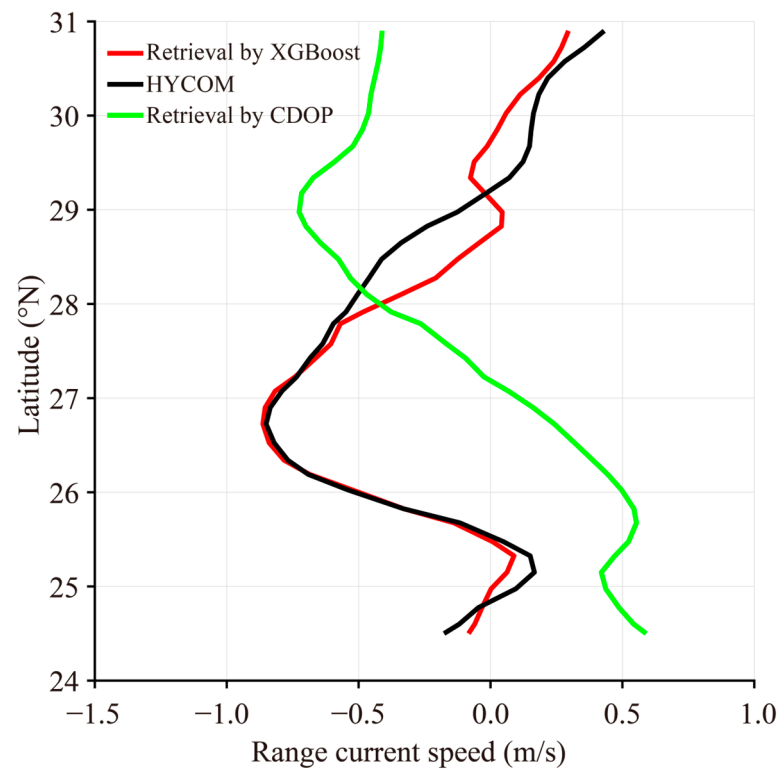


Figure 10. Latitude variation given the longitude—see the dashed red line in (Figure 9a)—of the range current speed retrieved by XGBoost (red line), by CDOP model (green line), and simulated with HYCOM (black line).

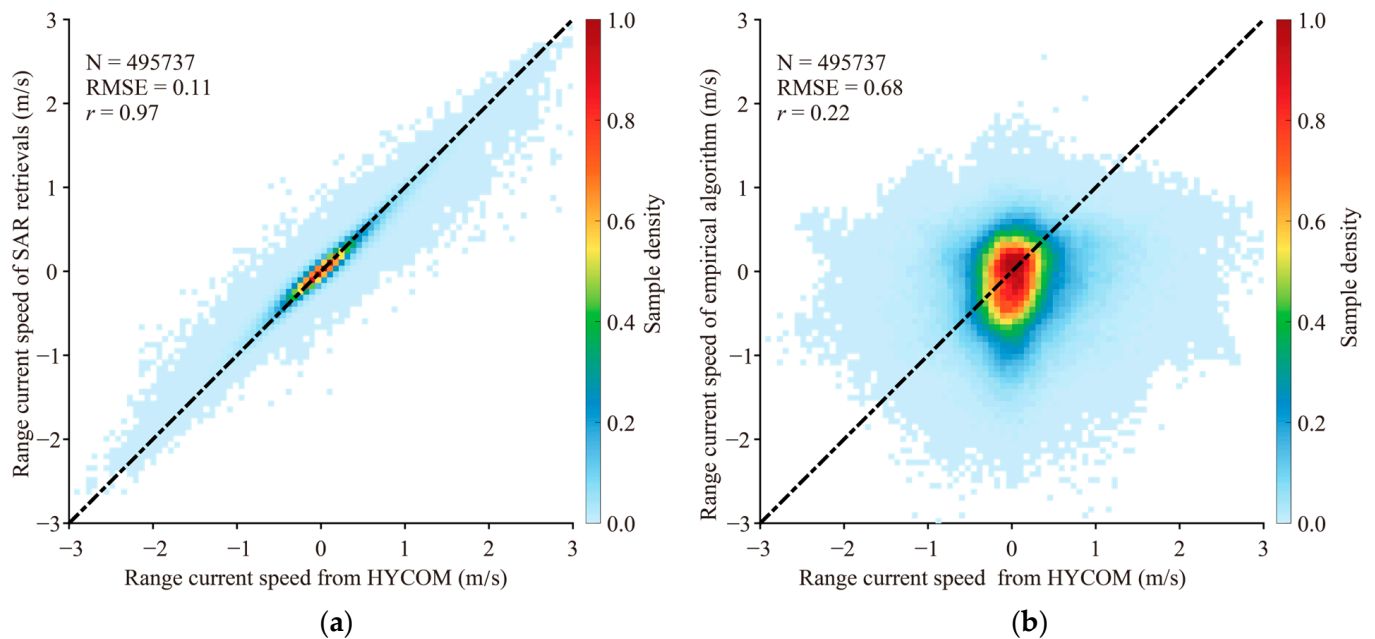


Figure 11. Validation of SAR-derived range current wind speeds by (a) XGBoost and (b) the CDOP model against HYCOM data.

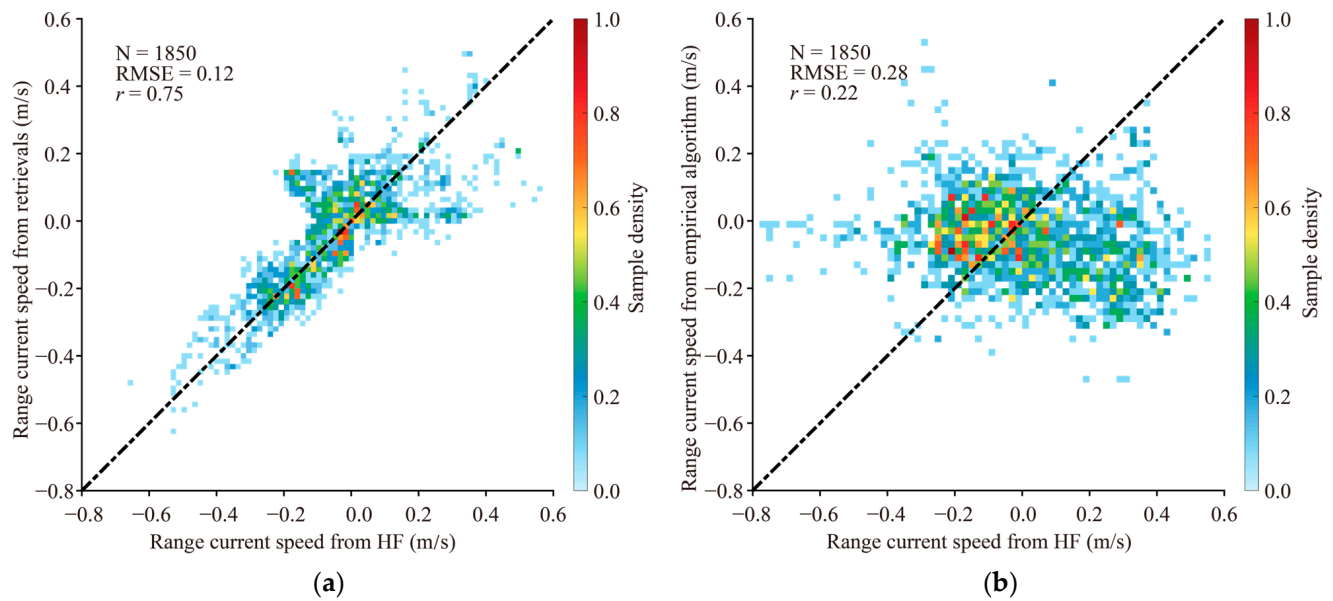


Figure 12. Validation of SAR-derived range current wind speeds by (a) XGBoost and (b) CDOP model against HF radar measurements.

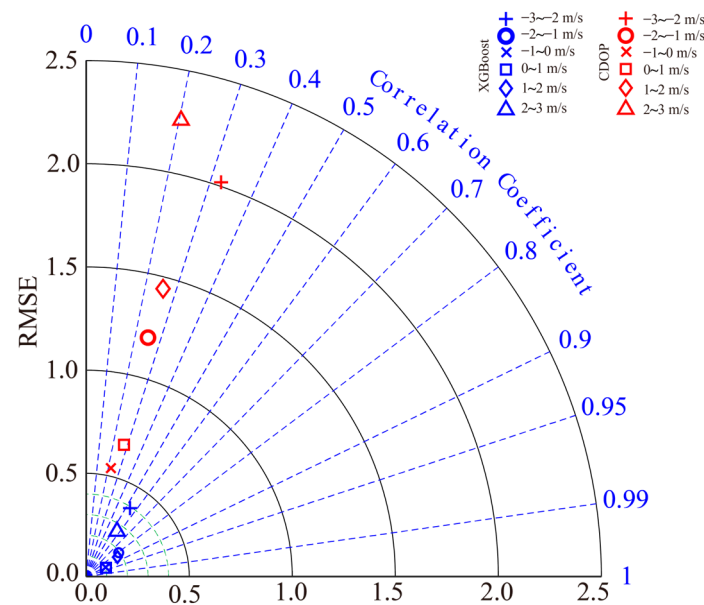


Figure 13. Taylor diagram with respect to current speed up to 3 m/s at intervals of 1 m/s, in which the red and blue symbols represent the result using XGBoost and the CDOP model.

4.2. Discussion

Error analysis of the SAR retrieval using the XGBoost method and the HYCOM data was conducted. The relationships between the bias (SAR-derived minus HYCOM data) of the range current speed and the range HYCOM current speed for a 0.375 m/s bin, the range wind speed for a 10 m/s bin, the range Stokes drift for a 0.125 m/s bin, and the DCA for a 12.5 Hz bin are shown in Figure 14. The analysis revealed that the range wind speed, the range Stokes drift, and the DCA created less distortion in the performance of XGBoost at a range wind speed between -60 m/s and 40 m/s, a range Stokes drift between -0.75 m/s and 0.6 m/s, and a DCA between -75 Hz and <75 Hz. At a range wind speed > 40 m/s and < -60 m/s, higher wind speed has a sensitive effect on the performance of XGBoost. In other cases, the range Stokes drift has a symmetric effect on the performance of XGBoost, while there is no special relationship for the DCA as a whole. However, it is

found that the bias was decreased as the range HYCOM current speed increased. Thus, the XGBoost model is recommended for the SAR range component of ocean current retrieval under extreme sea states, although prior wave information is necessary.

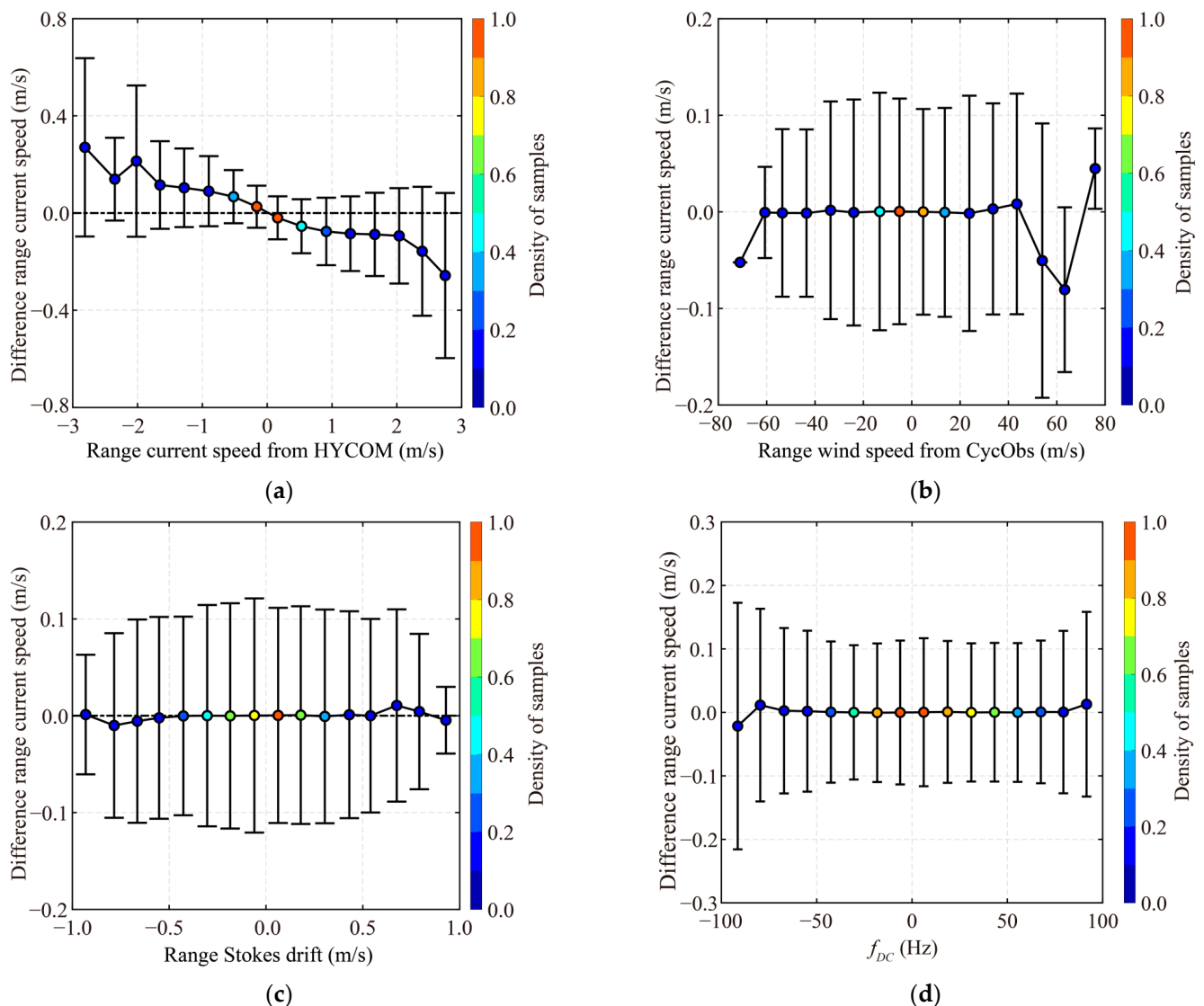


Figure 14. Variation in the bias (SAR-derived minus HYCOM data) of the range current speed with respect to (a) the HYCOM current speed for 0.375 m/s, (b) the wind speed for 10 m/s, (c) the Stokes drift for a 0.125 m/s bin, and (d) the DCA for a 12.5 Hz bin.

5. Conclusions

In this study, a novel algorithm to retrieve the range component of the ocean current during a TC from SAR measurements is proposed. To this aim, 2300 S-1 SAR images collocated with waves simulated by WW3 and reanalysis currents from HYCOM are considered. The comparison of WW3-simulated SWHs with HY-2B products collected in China seas in the period of June–August 2022 demonstrates their effectiveness, since $RMSE = 0.41$ m and $r = 0.88$ are obtained. Stokes drift is estimated by the SWH, and the mean wave period is simulated using the WW3 model. The CycObs winds provided by IFREMER by inverting co- and cross-polarized backscattering signals are also considered, while the DCA information, expressed as the difference between the radar return Doppler frequency and the predicted Doppler shift, is provided by S-1 level-2 OCN products. The main conclusions can be summarized as follows:

- (1) Under TC conditions, both wind and current speeds call for a linear relationship with the DCA. This agrees with the findings reported in [35,40]. In addition, we also found that the Stokes drift is linearly correlated with the DCA.
- (2) The range component of the ocean current obtained as output of the trained XGBoost machine learning model is compared with HYCOM data and two collocated HF phased-array radar measurements. It results in RMSE = 0.11 m/s and $r = 0.97$, and RMSE = 0.12 m/s and $r = 0.75$, respectively. The above result is better than the empirical CDOP model with an RMSE = 0.68 m/s and $r = 0.22$ for HYCOM and an RMSE = 0.22 m/s and $r = 0.28$ for HF data.
- (3) The error analysis confirms the steady performance of XGBoost at a range wind speed between -60 m/s and 40 m/s, a range Stokes drift between -0.75 m/s and 0.6 m/s, and a DCs between -75 Hz and 75 Hz. However, the accuracy is gradually reduced by XGBoost with increasing current speed.

Hence, the XGBoost model is recommended for the SAR range component of ocean current retrieval under extreme sea states, although prior wave information is necessary. Future work will include the use of SAR imagery as the unique source of wave information, without the need to use the simulations from a numeric model. In the future, more validation data will be collected to verify the model, analyze the dataset according to different regions and different latitudes, and perform regionalization simulation of the data under various conditions.

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