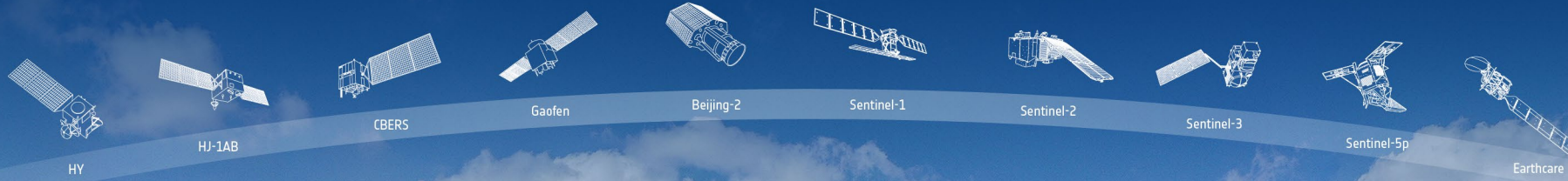




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2025 DRAGON 6 SYMPOSIUM

14-18 JULY 2025

[PROJECT ID. 95315]

[SYNERGISTIC MONITORING AND PREDICTION OF OCEAN DYNAMIC
ENVIRONMENT FROM MULTI-SATELLITE DATA]





<15/JULY/2025, 14:00 - 15:30>

ID. 95315

PROJECT TITLE: SYNERGISTIC MONITORING AND PREDICTION OF OCEAN DYNAMIC ENVIRONMENT FROM MULTI-SATELLITE DATA

PRINCIPAL INVESTIGATORS: [PROF. JINGSONG YANG & DR. BERTRAND CHAPRON]

CO-AUTHORS: [HUIMIN LI; HE WANG; XIAOHUI LI; LIN REN; ROMAIN HUSSON]

PRESENTED BY: [PROF. JINGSONG YANG]

Dragon 6 Project Overview



- To monitor at global scale ocean swell will improve the **wind and wave forecast** for marine meteorology (including extreme events), the ocean dynamics modeling and prediction, our knowledge of climate variability, and fundamental understandings on air-sea surface processes.
- And to monitor and map extreme events during **typhoons (hurricanes) or storm surges** we have to develop the use of multiple satellite wind, wave and sea level data for forecast.
- The Dragon projects have been providing an **excellent opportunity** for Chinese and European ocean research communities to utilize the spaceborne satellite remote sensing data from China, ESA and Third Party Missions (TPM) to actively monitoring ocean swell, wind, storm surge and other relevant parameters.
- It is the purpose of this project to continue **cutting edge research** in synergistic monitoring and prediction of ocean dynamic environment from multi-satellite data at global scale and extreme events in coastal region and gain insight of the physical nature of these phenomena, which will lay a solid foundation as we move to **operational oceanography**.

Dragon 6 Project Overview



- 1. Scientific objectives:

- (1) assimilation studies of **wind, waves and sea level** in the context of hurricanes forecasts;
- (2) the influence of swell on the studies of **coastal extremes**;
- (3) studies of **vortex Rossby waves, asymmetric TC structures, rain bands, and sub-scale circulations** by using high spatial resolution ocean wind data;
- (4) analysis of **relationship between** the above internal dynamical processes and TC intensity changes;
- (5) consistent analysis and prediction of **winds, waves and storm surges** in the context of hurricanes;
- and
- (6) consistent monitoring and prediction of **ocean surface current and internal waves** using multi-source satellite data.

Dragon 6 Project Overview



- The project's schedule, planning and contribution of the partners

The overall progress of this project will be coordinated by the two PIs: Dr. Chapron and Dr. Yang.

The obtained results will be accordingly reported at each annual symposium.

Year 1: Data preparation, methodology development;

Year 2: Data preparation, methodology development, calculation, analysis;

Year 3: Calculation, analysis, prediction, validation;

Year 4: Analysis, prediction, validation, pre-operation and demonstration.

Dragon 6 Project Overview

- Team composition

Principal Investigators information

NAME	INSTITUTION	COUNTRY
Prof. Jingsong Yang	The Second Inst. of Oceanography, MNR	CHINA
Dr. Bertrand Chapron	Institut Francais de Recherche et Exploitation de la MER	FRANCE

This team is a dynamic amalgamation of researchers possessing expertise, knowledge, and skills in **satellite oceanography** and **physical oceanography**, with a special emphasis on **microwave marine remote sensing** and **artificial intelligence techniques** crucial for achieving the project's objectives.

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Ronan	Fablet	France	ronan.fablet@imt-atlantique.fr	IMT-Atlantique	COPI

First Year Results

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Ocean Surface Wind Wave Signatures in
Single-Look Complex SAR Data

Huimin Li^{ID}, Bertrand Chapron^{ID}, Alexis Mouche^{ID}, Chen Wang^{ID},
Wenming Lin^{ID}, *Senior Member, IEEE*, and Yijun He^{ID}, *Member, IEEE*

Abstract—Spaceborne synthetic aperture radar (SAR) provides high-resolution sea surface observations to characterize oceanic and atmospheric variability at submesoscales. Despite significant progress in retrieving wind fields from SAR images, challenges remain particularly for single-antenna measurements where wind speed inversion often requires an external wind direction input. This study introduces and evaluates the use of directional features derived from SAR image sublook cross-spectra to improve wind retrieval. Specifically, we explore the imaginary part of SAR mean cross-spectra (IMACS) and its differential counterpart, Δ IMACS, which capture directional signatures of range-traveling intermediate wind waves. Using systematically collocated Sentinel-1A wave mode SAR images and model winds, we demonstrate that IMACS exhibits a cosine-like dependence on wind direction at given wind speeds at two incidence angles, while Δ IMACS reveals unique sensitivities that complement radar backscattering and can resolve wind direction ambiguities. A novel cost function combining radar backscattering, IMACS, and Δ IMACS is proposed to retrieve wind vectors directly from SAR data without external wind direction inputs. The proposed scheme is evaluated through comparisons with independent model outputs and buoy measurements, showing improved performance. These findings highlight the potential of IMACS and Δ IMACS to enhance self-sufficient wind inversion, offering a promising pathway for single-polarized SAR wind retrieval.

Meteorological Organization [1]. This parameter plays significant roles in meteorology, oceanography, climate, and marine industry, among others. For instance, the sea surface wind vector is a fundamental variable in parameterizing the local air–sea interaction through the surface fluxes of momentum, heat, and moisture exchange [2]. Observations are keys to characterize the spatiotemporal wind patterns across different scales. Though accurate, in situ measurements are typically restricted to fixed and sparse locations over the vast ocean basins [3]. In the meantime, spaceborne remote sensing has become the primary source of global wind observations on a routine basis [4].

Microwave instruments are widely employed sensors for sea surface wind monitoring over the open ocean. Among these, active radars measure the reflected backscatter, known as the normalized radar cross section (NRCS) that is highly related to the wind-induced roughness at sea surface [5]. Wind inversion from radar signal requires first establishing an empirical relation between NRCS and the wind vector, termed the geophysical model function (GMF) [6]. Each GMF is tailored to a specific radar frequency and polarization at various incidence angles that can be applied to different spatial

First Year Results

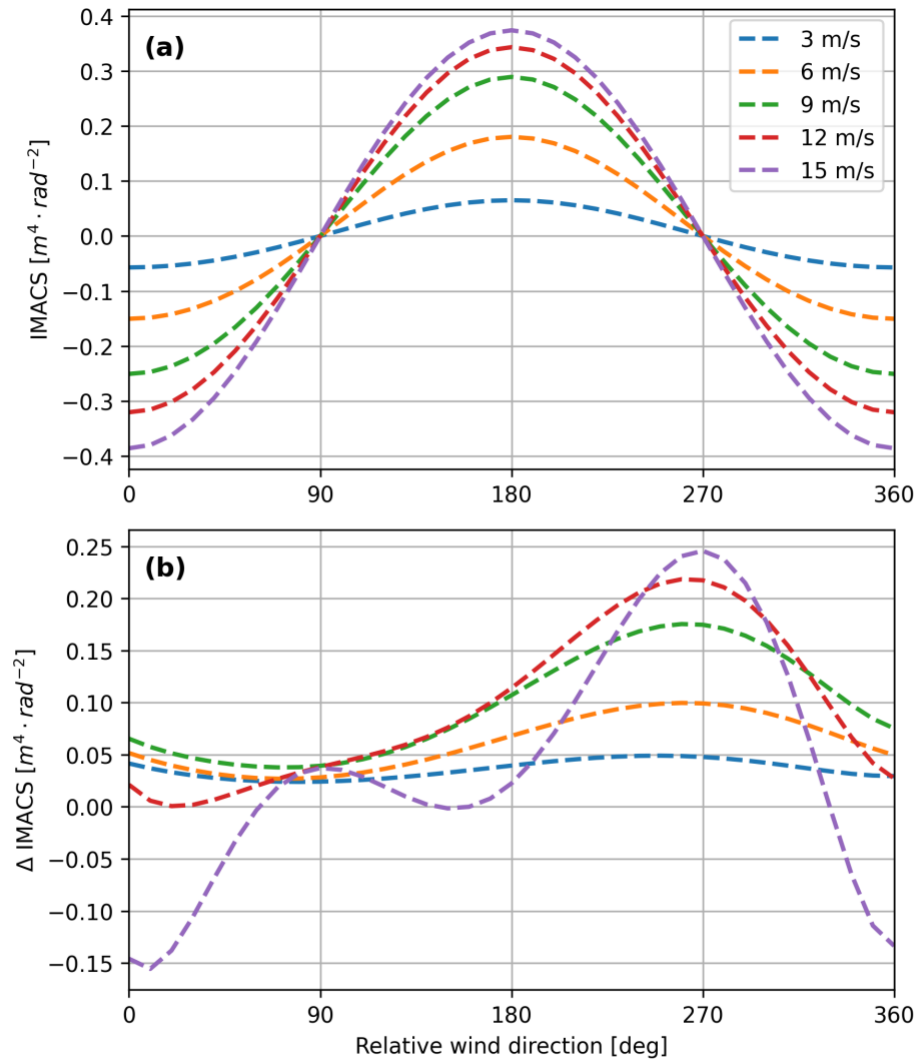


Fig. 4. LUT of (a) IMACS and (b) Δ IMACS versus the relative wind direction at four wind speeds.

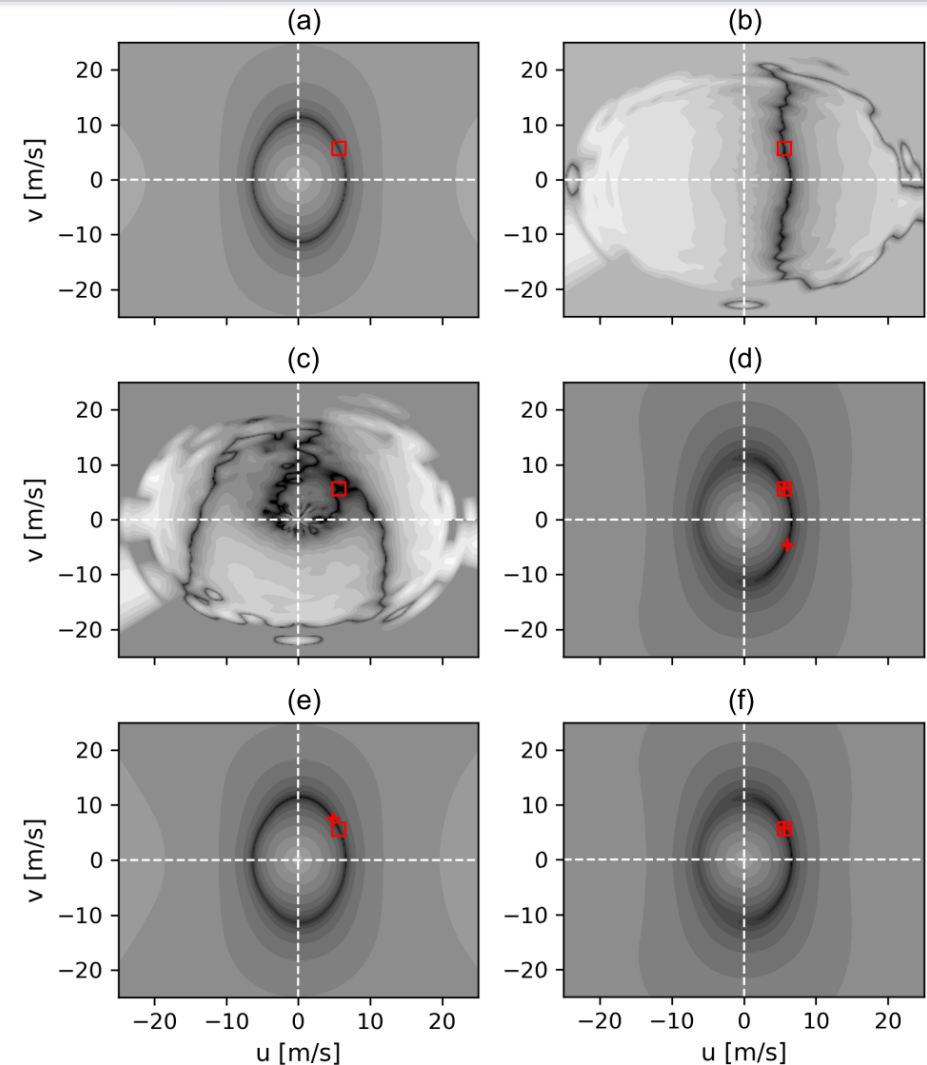


Fig. 5. Demonstration of the individual and combined contribution of the terms in the cost function [see (3)] relative to the wind components for (a) NRCS. (b) IMACS. (c) Δ IMACS. (d) NRCS + IMACS. (e) NRCS + Δ IMACS. (f) NRCS + IMACS + Δ IMACS. A true wind speed of 8 m/s and a relative wind direction of 45° clockwise from the flight azimuth are assumed. The gray shades denote the cost function magnitude with darker corresponding to lower values. The rectangle in red marks the true wind vector, and the “+” denotes the wind solution in terms of the local minimum value of the formulated cost function.

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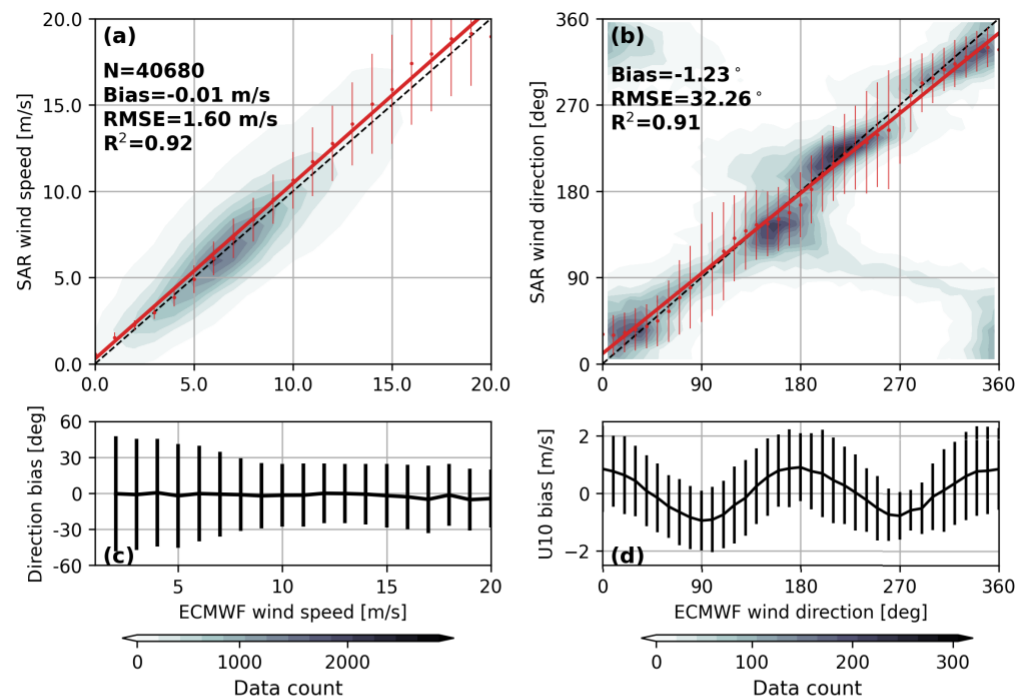


Fig. 7. (Top) Comparison of SAR retrieved (a) wind speed and (b) relative wind direction versus the collocated ECMWF wind field. Color denotes the data count at a wind speed bin of 1 m/s and direction bin of 10° with the binned mean and STD denoted by the error bar. The black dashed curve is the one-to-one line, and solid red is the linear fitting curve. The evaluation metrics of mean bias, root-mean-square-error (RMSE), and correlation coefficient are annotated in each plot. (Bottom) Variation of wind direction bias relative to wind speed in (c) and wind speed bias to wind direction in (d). 0° denotes the upwind, and 180° denotes the downwind direction.

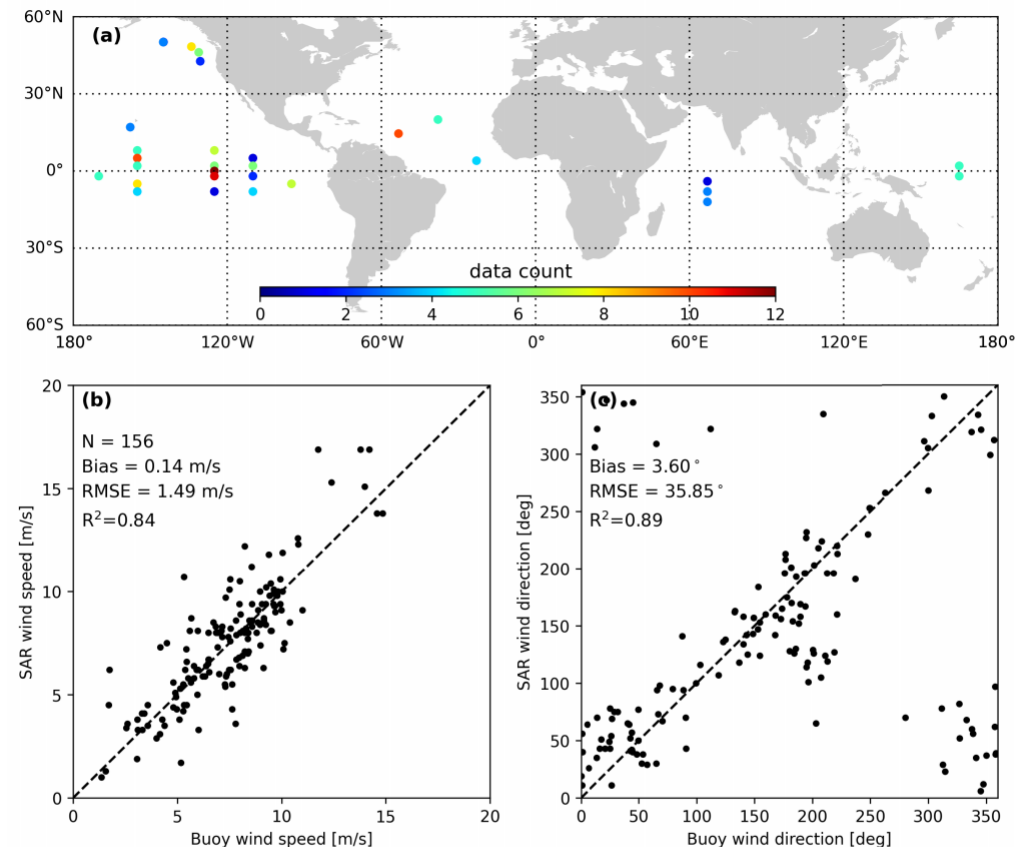


Fig. 9. Validation of the derived wind vectors from SAR images relative to the in situ buoy measurements. (a) Locations of the collocated buoys with the color code as the number of collocated SAR images. (Bottom) Scatter plot of (b) wind speed and (c) wind direction.



Article

NRCS Recalibration and Wind Speed Retrieval for SWOT KaRIn Radar Data

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and Lizhang Zhou ¹

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⁴ National Space Science Center, Chinese Academy of Science

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Abstract: In this study, wind speed sensitivity and calibration bias were first determined for Surface Water and Ocean Topography (SWOT) satellite Ka-band Radar Interferometer (KaRIn) Normalized Radar Backscatter Cross Section (NRCS) data at VV and HH polarizations. Here, the calibration bias was estimated by comparing the KaRIn NRCS with collocated simulations from a model developed using Global Precipitation Measurement (GPM) satellite Dual-frequency Precipitation Radar (DPR) data. To recalibrate the bias, the correlation coefficient between the KaRIn data and the simulations was estimated, and the data with the corresponding top 10% correlation coefficients were used to estimate the recalibration coefficients. After recalibration, a Ka-band NRCS model was developed from the KaRIn data to retrieve ocean surface wind speeds. Finally, wind speed retrievals were evaluated using the collocated European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis winds, Haiyang-2C scatterometer (HY2C-SCAT) winds and National Data Buoy Center (NDBC) and Tropical Atmosphere Ocean (TAO) buoy winds. Evaluation results show that the Root Mean Square Error (RMSE) at both polarizations is less than 1.52 m/s, 1.34 m/s and 1.57 m/s, respectively, when compared to ECMWF, HY2C-SCAT and buoy collocated winds. Moreover, both the bias and RMSE were constant with the incidence angles and polarizations. This indicates that the winds from the SWOT KaRIn data are capable of correcting the sea state bias for sea surface height products.

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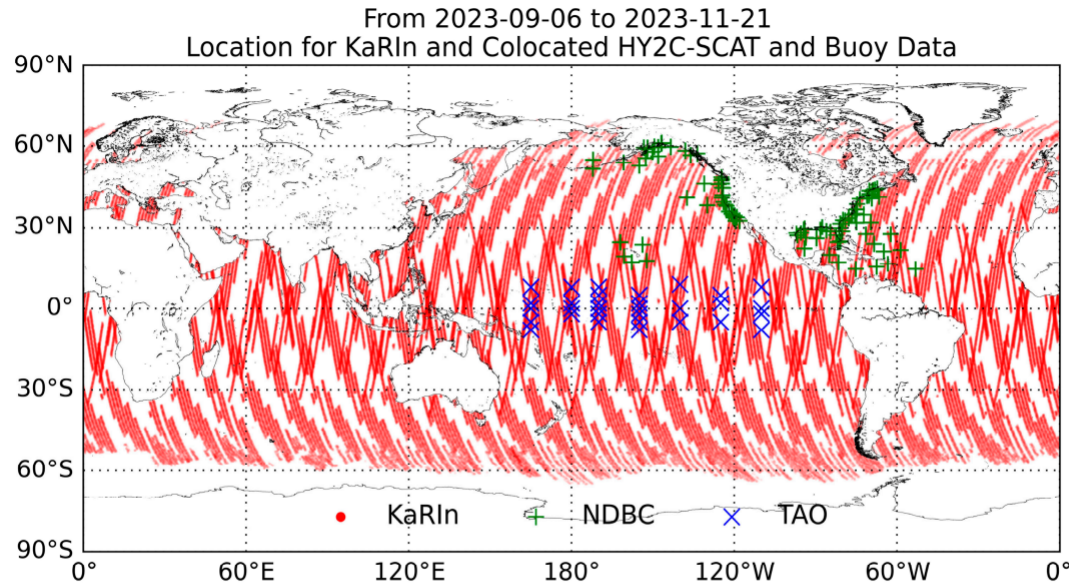


Figure 1. Location map for SWOT KaRIn data and collocated HY2C-SCAT, NDBC buoy and TAO buoy wind data. Here, the red points indicate positions of collocations for KaRIn and HY2C-SCAT data. The green plus signs indicate the NDBC buoy positions. The blue multiple signs indicate the TAO buoy positions. The period for KaRIn data is from 6 September 2023 to 21 November 2023.

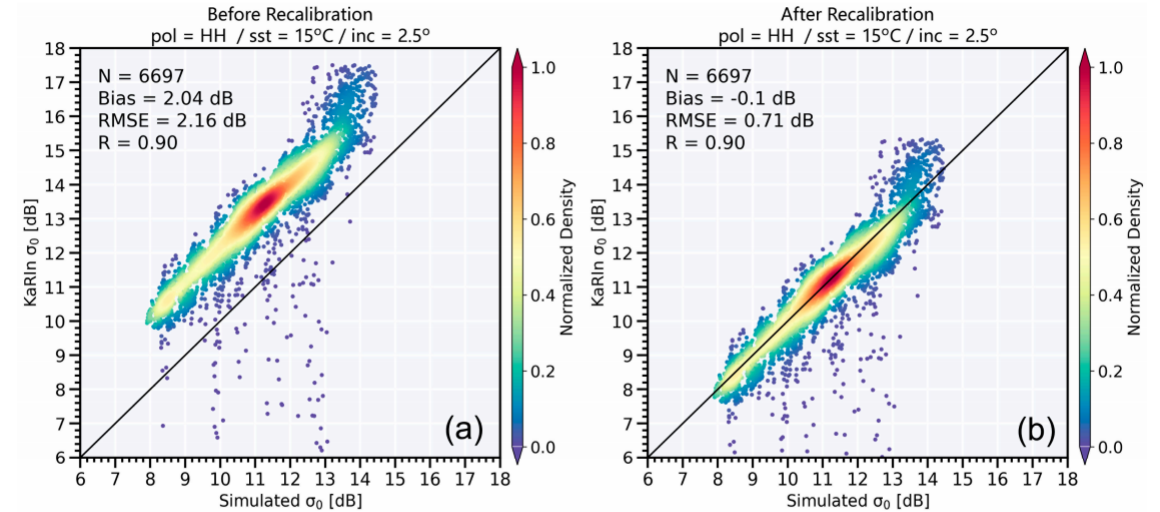


Figure 7. NRCS comparisons between the KaRIn data and the model simulations. (a) Before recalibration and (b) after recalibration.

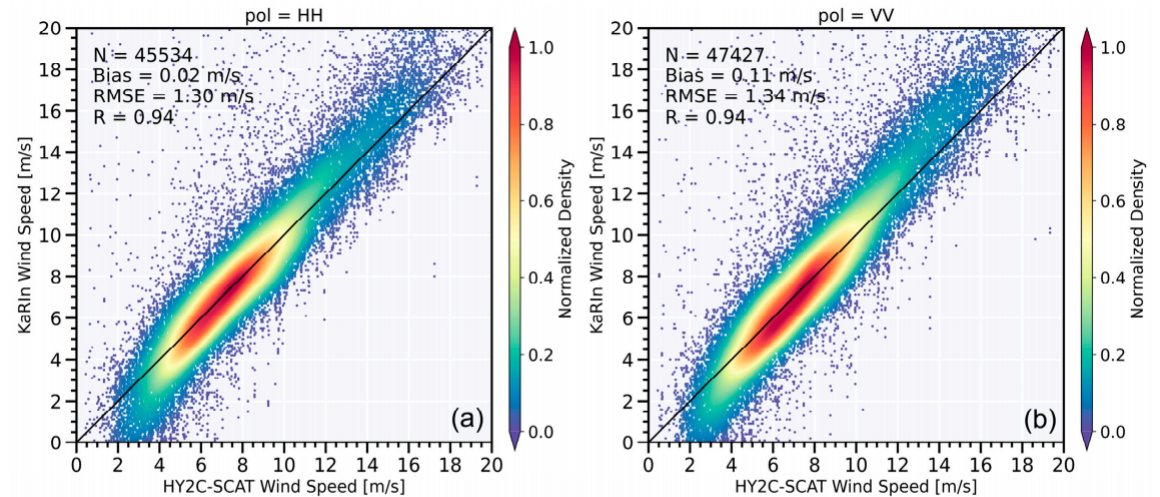


Figure 12. Wind speed comparisons between KaRIn retrievals and collocations from HY2C-SCAT at (a) HH polarization and (b) VV polarization.



Evaluation and deep learning-based calibration of nearshore sea surface wind speeds from FY-3E GNOS-II and TIANMU missions

Xinhai Han^{a,b}, Xiaohui Li^b, Jingsong Yang^{a,b,c}, Wei Tao^d, Guoqi Han^e, Jiuke Wang^f, Yiqi Wang^b, Qinghua Bao^g, Lin Chen^h and Weiqiang Li^{i,j}

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ABSTRACT

This study evaluates and calibrates wind products derived from Global Navigation Satellite System Reflectometry (GNSS-R) using data from the FengYun-3E (FY-3E) global navigation satellite system occultation sounder II (GNOS-II) and TIANMU missions. The research highlights the significance of remote sensing for the accurate measurement of sea surface wind speeds in nearshore areas, which are crucial for environmental monitoring and climate studies. Initial comparisons with National Data Buoy Center (NDBC) measurements revealed root – mean – square errors (RMSE) of 2.49 m/s for FY-3E GNOS-II Beidou navigation satellite system (BDS) signals and 2.13 m/s for global positioning system (GPS) signals. For the TIANMU mission, the RMSE values were 3.21 m/s for BDS, 3.13 m/s for GPS, 2.91 m/s for GLONASS (GLO), and 2.91 m/s for Galileo (GAL) signals. To improve accuracy, especially in the complex nearshore environments, a deep learning calibration model incorporating residual blocks was employed. This model significantly enhanced the performance compared to a basic neural network. An ablation study confirmed that including residual blocks reduced RMSE by over 20% across all signal types. The calibrated model achieved substantial accuracy improvements in the test set, reducing RMSE to 1.03 m/s for FY BDS (improvement of 60%), 0.99 m/s for FY GPS (improvement of 54%), 1.57 m/s (improvement of 51%), 1.36 m/s for TIANMU GPS (57% improvement), 1.26 m/s for TIANMU GLO (improvement of 56%), and 1.50 m/s for TIANMU GAL (improvement 47%).

ARTICLE HISTORY

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Accepted 6 December 2024

KEYWORDS

FengYun-3E (FY-3E);
TIANMU; Global Navigation
Satellite System
Reflectometry (GNSS-R); sea
surface wind speed;
nearshore; deep learning

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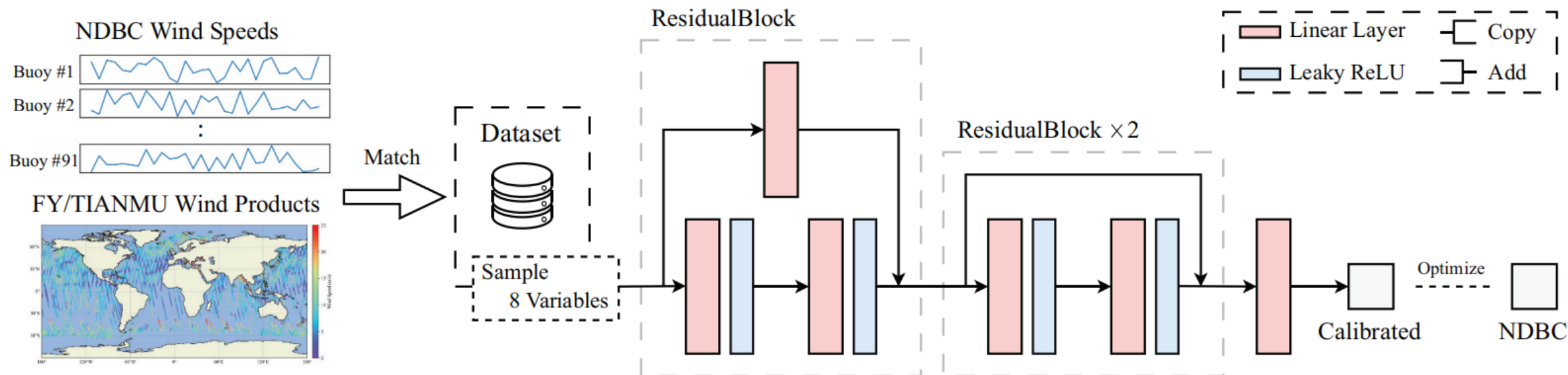


Figure 3. Overview of proposed deep learning model. By matching NDBC and GNSS-R wind speeds, a calibration dataset comprising 8 variables is formed. All residual blocks facilitate residual connections, with the first residual block performing dimension matching via a linear layer. The calibrated output is optimized through gradient iterations that minimize discrepancies between GNSS-R and NDBC wind speeds.

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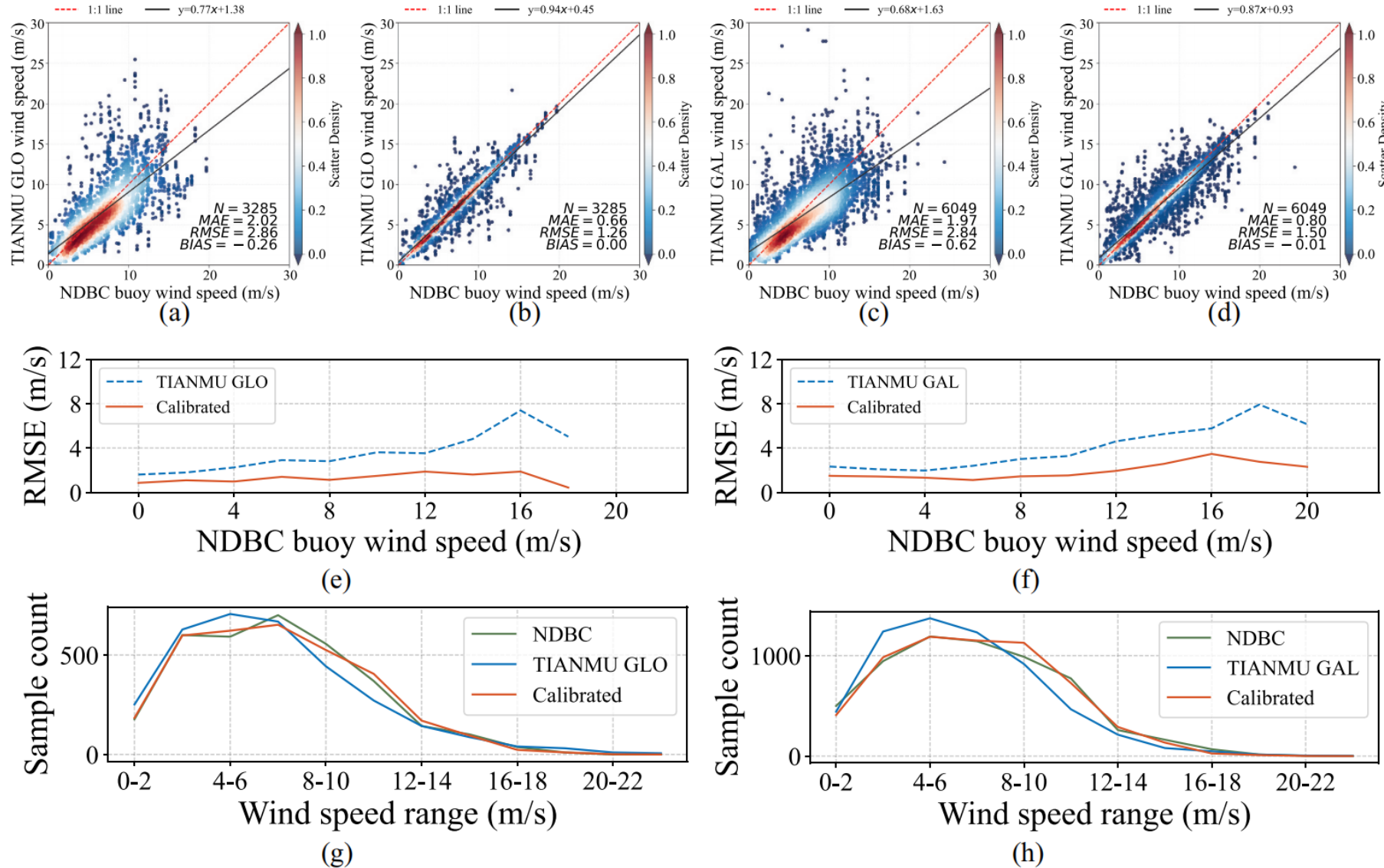


Figure 9. Wind speed comparison (September 1, 2023, to December 16, 2023): TIANMU GNSS-R vs. NDBC buoys, based on test set. Pre- and post-calibration for (a)–(b) GLO and (c)–(d) GAL; error statistics for (e) GLO and (f) GAL, calculated within ± 2 m/s wind speed bins; distribution of pre- and post-calibration (g) GLO and (h) GAL samples.

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Transfer Learning-Based Generative Adversarial Network Model for Tropical Cyclone Wind Speed Reconstruction From SAR Images

 Xiaohui Li^{ID}, Xinhai Han^{ID}, Jingsong Yang^{ID}, Jiuke Wang, and Guoqi Han^{ID}

Abstract—Synthetic aperture radar (SAR) plays a crucial role in monitoring the fine structure of tropical cyclones, but its effectiveness is constrained by limitations such as signal degradation and saturation. To address this challenge, we proposed a transfer learning-based generative adversarial network (GAN) framework with a dilated convolution and attention mechanism for reconstructing inner-core high winds from SAR images. We have employed the principles of transfer learning to adapt pretrained models developed by the Hurricane Weather Research and Forecasting (HWRF) model winds to SAR images during tropical cyclone events for reconstruction. The proposed model can effectively capture the relationship between features in the low-precision areas and global features from SAR images, facilitating tropical cyclone wind speed reconstruction. The utilization of Global Precipitation Measurement (GPM) Level 3 rainfall data facilitates the identification of rainfall regions in 89 SAR images obtained from Radarsat-2 and Sentinel-1A/B missions. Comparison with stepped frequency microwave radiometer (SFMR) data reveals that the model exhibits a bias of -0.69 m/s, a root-mean-square error (RMSE) of 4.08 m/s, and an R value of 0.91 under heavy rainfall conditions (>7.62 mm/h). Remarkably, the GAN model exhibits excellent performance compared with measurements from the soil moisture active passive (SMAP) L-band radiometer, achieving an RMSE of 3.78 m/s. Our findings indicate that deep learning (DL) technology holds significant promise for the reconstruction and monitoring of tropical cyclones through the utilization of SAR imagery.

Index Terms—Generative adversarial network (GAN), machine learning, synthetic aperture radar (SAR), transfer learning, tropical cyclone, winds reconstruction.

I. INTRODUCTION

TROPICAL cyclones, also known as warm-core cyclones, are considered one of the most dangerous natural disasters on Earth due to their potential for widespread damage through strong winds, heavy rainfall, and storm surges, leading to loss of life, property damage, and economic disruption [1], [2], [3], [4]. The structure of a tropical cyclone includes the peripheral area, the maximum wind speed area, and the cyclone eye. Understanding the inner-core structure might lead to a better prediction of tropical cyclone intensity. Detailed knowledge of wind speeds within tropical cyclones is indispensable for accurately predicting the cyclone's potential strength.

Satellite radar imaging from synthetic aperture radar (SAR) is a remote sensing technology that can capture the fine structures of tropical cyclones due to its high resolution [5], [6]. To date, the spaceborne SAR satellites that have been launched include the first generation of ERS1/2, ENVISAT-ASAR, and

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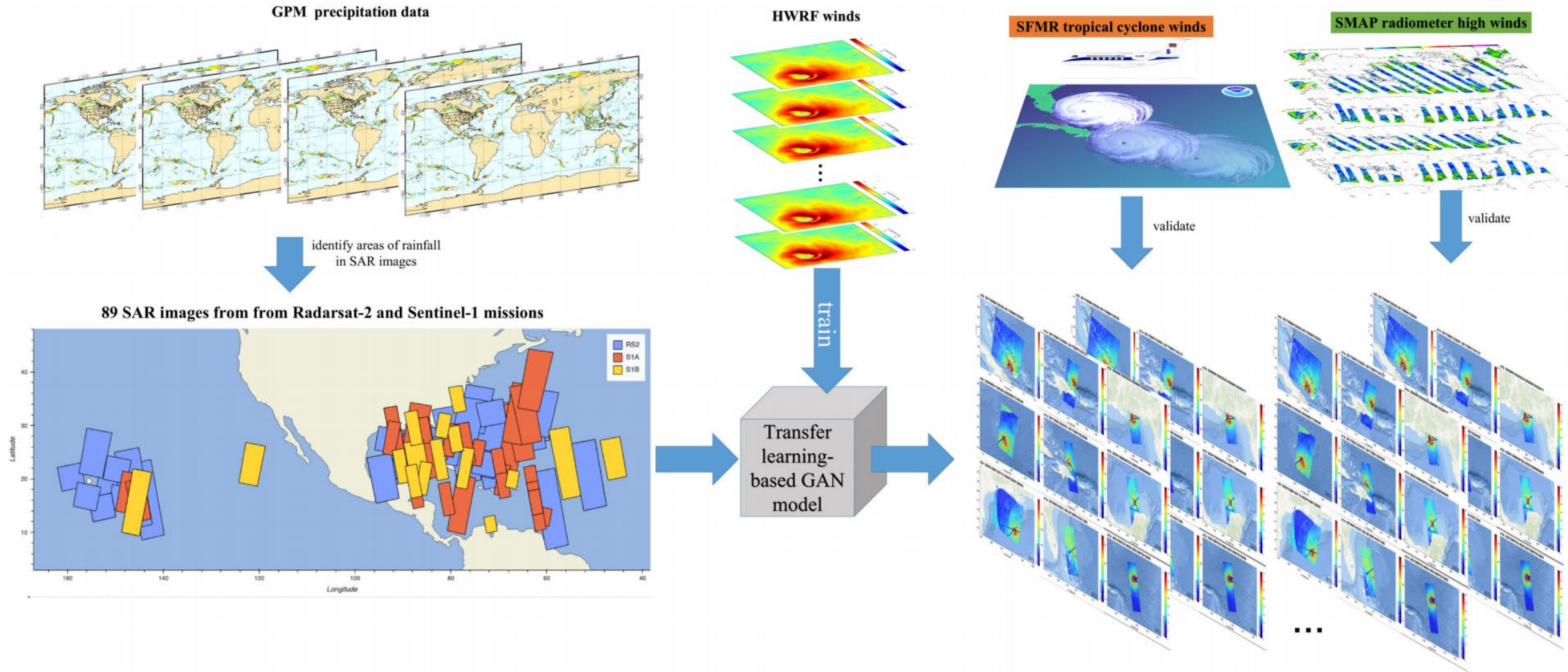


Fig. 2. Implementation and data flow framework of transfer learning-based GAN model.

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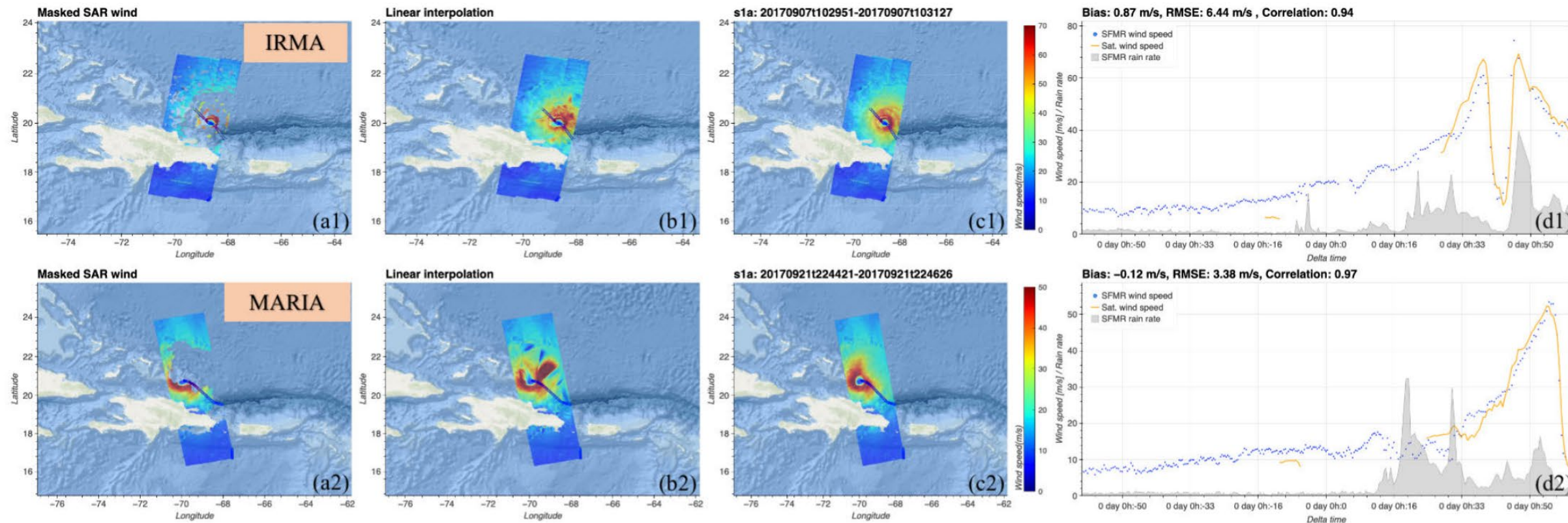


Fig. 14. Evaluating the performance of the ReTC-GAN model on Sentinel-1A SAR image, demonstrated for two hurricanes. (a1)–(d1) Hurricane Irma. (a2)–(d2) Hurricane Maria.



A Generative Adversarial Network with an Attention Spatiotemporal Mechanism for Tropical Cyclone Forecasts[✱]

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(Received 28 September 2023; revised 4 June 2024;

ABSTRACT

Tropical cyclones (TCs) are complex and powerful weather systems, and accurately forecasting their path, structure, and intensity remains a critical focus and challenge in meteorological research. In this paper, we propose an Attention Spatio-Temporal predictive Generative Adversarial Network (AST-GAN) model for predicting the temporal and spatial distribution of TCs. The model forecasts the spatial distribution of TC wind speeds for the next 15 hours at 3-hour intervals, emphasizing the cyclone's center, high wind-speed areas, and its asymmetric structure. To effectively capture spatiotemporal feature transfer at different time steps, we employ a channel attention mechanism for feature selection, enhancing model performance and reducing parameter redundancy. We utilized High-Resolution Weather Research and Forecasting (HWRF) data to train our model, allowing it to assimilate a wide range of TC motion patterns. The model is versatile and can be applied to various complex scenarios, such as multiple TCs moving simultaneously or TCs approaching landfall. Our proposed model demonstrates superior forecasting performance, achieving a root-mean-square error (RMSE) of 0.71 m s^{-1} for overall wind speed and 2.74 m s^{-1} for maximum wind speed when benchmarked against ground truth data from HWRF. Furthermore, the model underwent optimization and independent testing using ERA5 reanalysis data, showcasing its stability and scalability. After fine-tuning on the ERA5 dataset, the model achieved an RMSE of 1.33 m s^{-1} for wind speed and 1.75 m s^{-1} for maximum wind speed. The AST-GAN model outperforms other state-of-the-art models in RMSE on both the HWRF and ERA5 datasets, maintaining its superior performance and demonstrating its effectiveness for spatiotemporal prediction of TCs.

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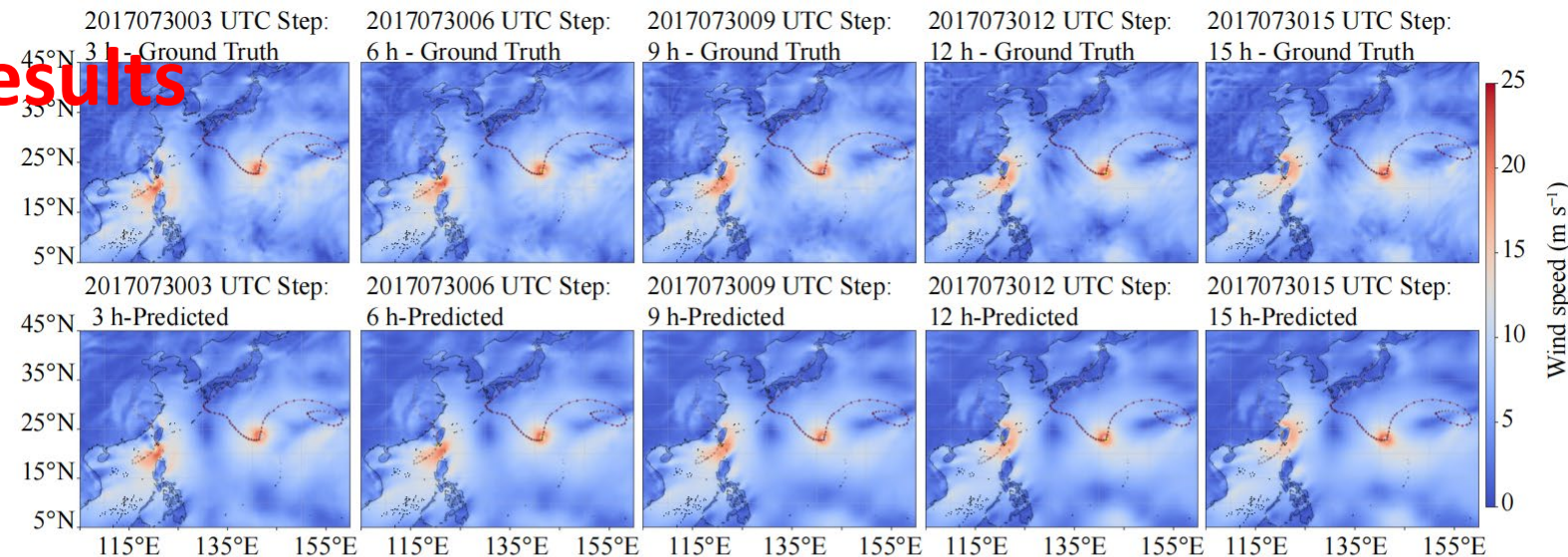


Fig. 7. The 15-hour forecast at 3-hour intervals (2017073003 UTC–2017073015 UTC; 5°–45°N, 105°–160°E) for TC Haitang (circular scatter points) and TC Noru (triangle scatter points).

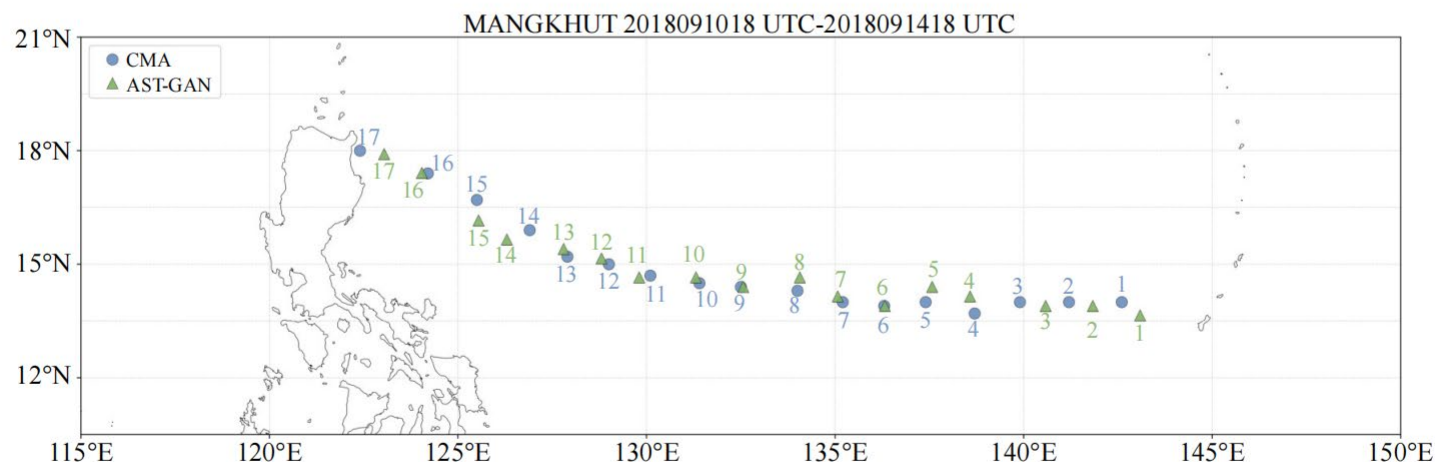


Fig. 8. The 99-hour trajectory forecast for TC Mangkhut, at 6-hour intervals (2018091018 UTC–2018091418). The circles or triangles represent the position of the TC center, where the blue color and the green color denote the CMA data and the AST-GAN prediction result, corresponding to the color of the annotation. “1” represents the position of the TC center at the start time (2018091018 UTC), and “17” represents the position of the TC center at the end time (2018091418 UTC).



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Multi-station water level forecasting using advanced graph convolutional networks with adversarial learning

Xinhai Han^{a,b}, Xiaohui Li^b, Jingsong Yang^{a,b,c}, Jiuke Wang^d, Guoqi Han^e, Jun Ding^f, Hui Shen^f, Jun Yan^f and Dake Chen^{a,b,c}

^aSchool of Oceanography, Shanghai Jiao Tong University, Shanghai, China; ^bState Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, Ministry of Natural Resources, Hangzhou, China; ^cSouthern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai, China; ^dSchool of Artificial Intelligence, Sun Yat-sen University, Zhuhai, China; ^eFisheries and Oceans Canada, Institute of Ocean Sciences, Sidney, Canada; ^fZhejiang Marine Monitoring and Forecasting Center, Hangzhou, China

ABSTRACT

This paper presents an advanced graph convolutional network model, enhanced with Wasserstein distance-based adversarial learning (WD-ACGN), addressing the limitations of existing single-station and less explored multi-station water level forecasting approaches. The model features a novel coupled module for effectively capturing short and long-term dependencies, and a hybrid distance-based adaptive graph learning approach for spatial dependencies. This spatial dependency analysis enables rapid deployment in different coastal settings. Adversarial learning with gradient penalty further refines the model's performance. Our model, applied to datasets from China's Zhejiang coast and Daya Bay, outperforms baselines with a notable 12-h average root mean square error of 6.77 cm at 16 Zhejiang stations, proving its efficacy in varied maritime environments. Ablation studies validate the contribution of each model component, highlighting their collective impact on overall efficacy. Notably, the model showcases robustness in tropical cyclone scenarios and reliable results when tested with real-world observational data, underlining its potential for versatile applications in ocean engineering.

ARTICLE HISTORY

Received 23 May 2024

Accepted 22 January 2025

KEYWORDS

Water level; multi-station forecast; deep learning; graph convolutional networks

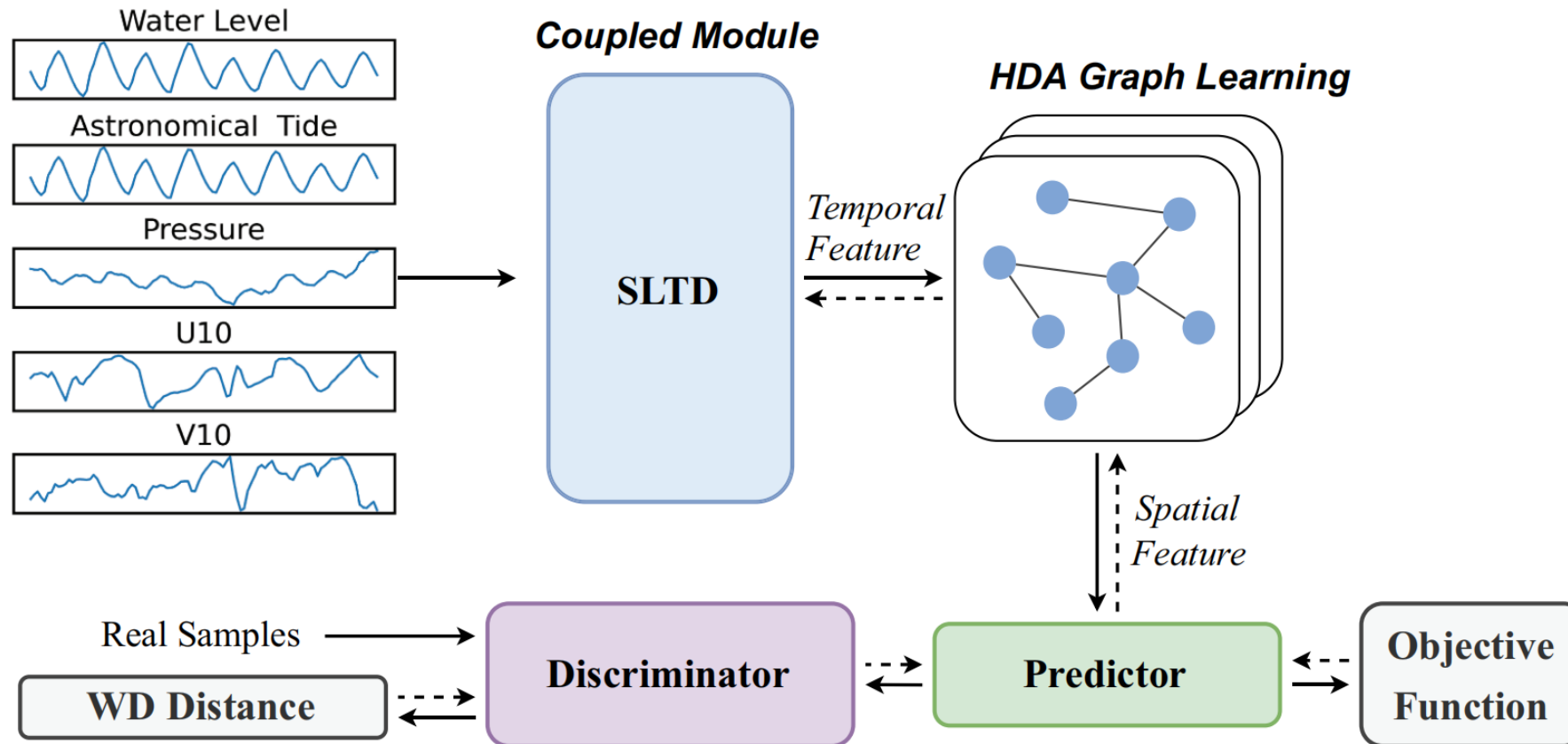


Figure 1. Diagram of the WD-ACGN architecture. Within the coupled module, multi-parameter input data undergoes SLTD extraction. Spatial dependencies are then ascertained through HDA graph learning. Subsequent results are optimized by the discriminator to minimize the WD distance relative to associated labels. Dashed lines indicate the direction of gradient flow.

First Year Results

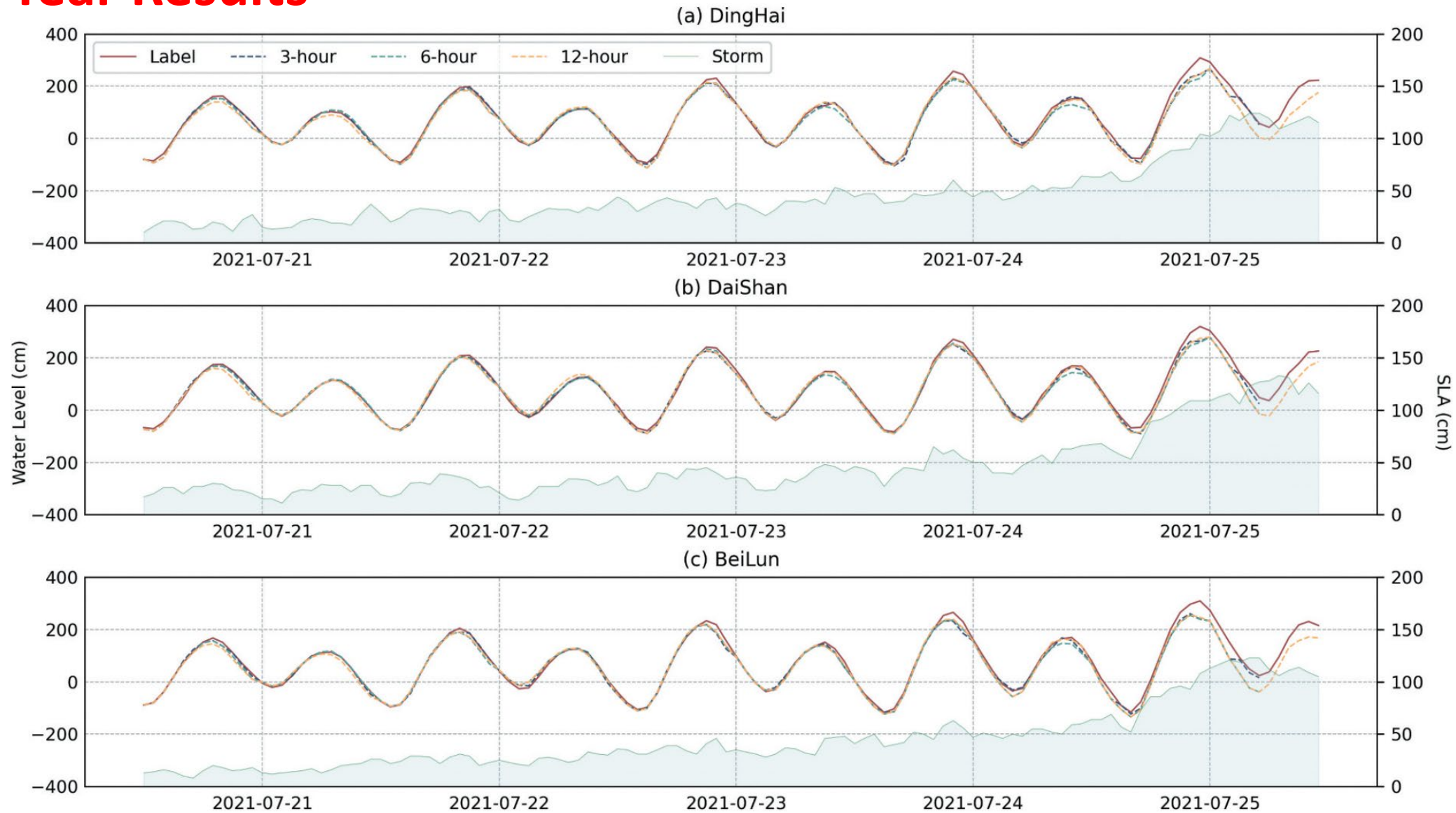


Figure 10. The proposed model's water level forecast results at 3, 6, and 12 hours using real-world observations during TC In-fa (from 12:00 on July 20, 2021 to 14:00 on July 25, 2021).



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RESEARCH ARTICLE

Transformer-Based Hierarchical Multiscale Feature Fusion Internal Wave Detection and Dataset

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Ocean internal waves (IWs) are widespread submesoscale dynamical phenomena in oceans, and they have important impacts on energy transfer, nutrient transport, and human activities. In this study, Sentinel-1 synthetic aperture radar (SAR) images from 2014 to 2023 were collected to construct a global IW dataset (S1-IW-2023) through a series of optimized data processing. S1-IW-2023 was constructed to address the issue of insufficient data and lack of variation in the deep learning IW datasets; it can be used in IW studies using deep learning methods to enhance model generalizability and robustness. Moreover, considering the limitations of existing convolutional neural network (CNN)-based IW detection models in handling complex interferences in SAR images, resulting in frequent false positives, false negatives, or inaccurate bounding box positioning, we employed transfer learning to train a Transformer-based hierarchical IW detector, IWD-Net, that extracts features via Swin Transformer and fuses the visual, semantic, and contextual features of IWs via a multiscale feature fusion network. Experimental results demonstrated the effectiveness of applying Transformer concepts to IW detection for addressing complex interferences. This study provides an efficient and stable new method for extracting IW features from massive SAR data and lays the foundation for applying Transformer concepts to detect IWs in SAR images.

Ma Z, Yang J. (2024). S1-IW-2023 dataset (ocean internal wave dataset) [dataset]. Zenodo. <https://doi.org/10.5281/zenodo.11090328>.

First Year Results

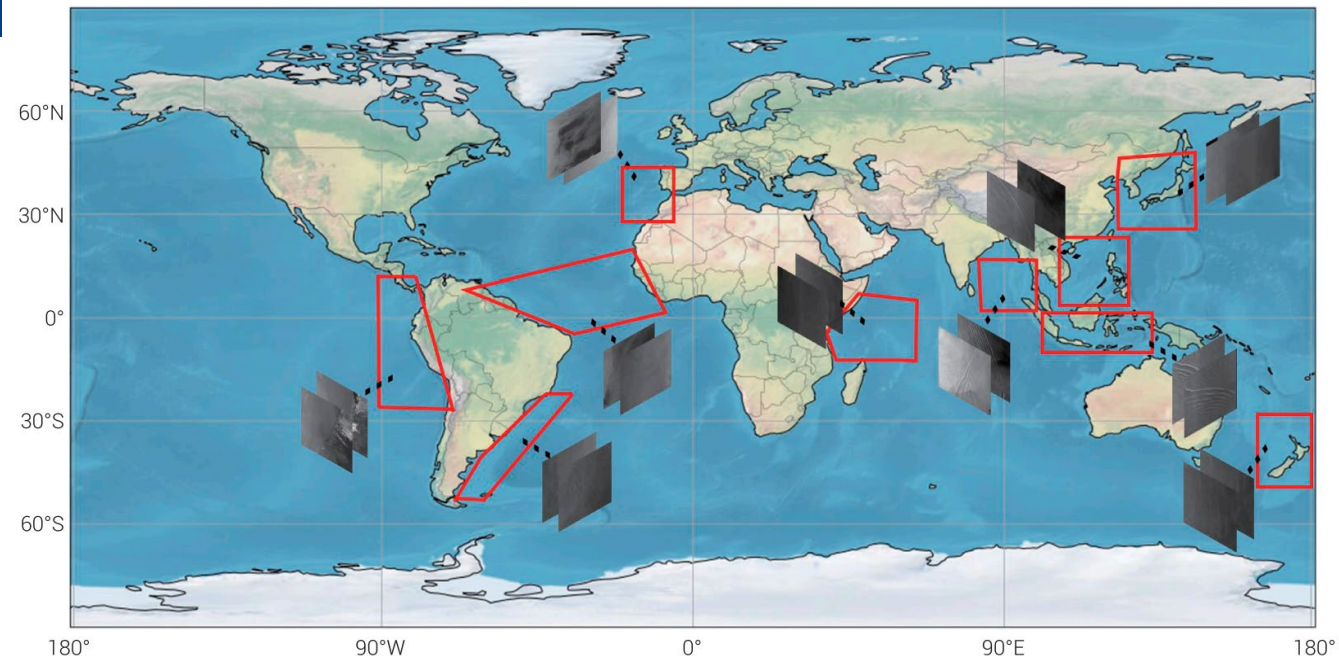


Fig.1 IW data of Sentinel-1 collection areas. This figure shows multiple sea areas where IWs were searched, along with a demonstration of some data.

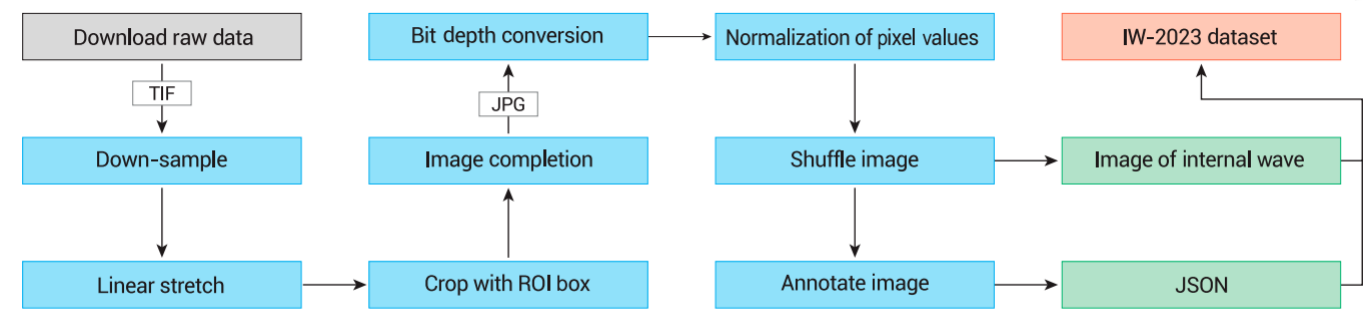


Fig. 2. Flowchart of S1-IW-2023 creation.

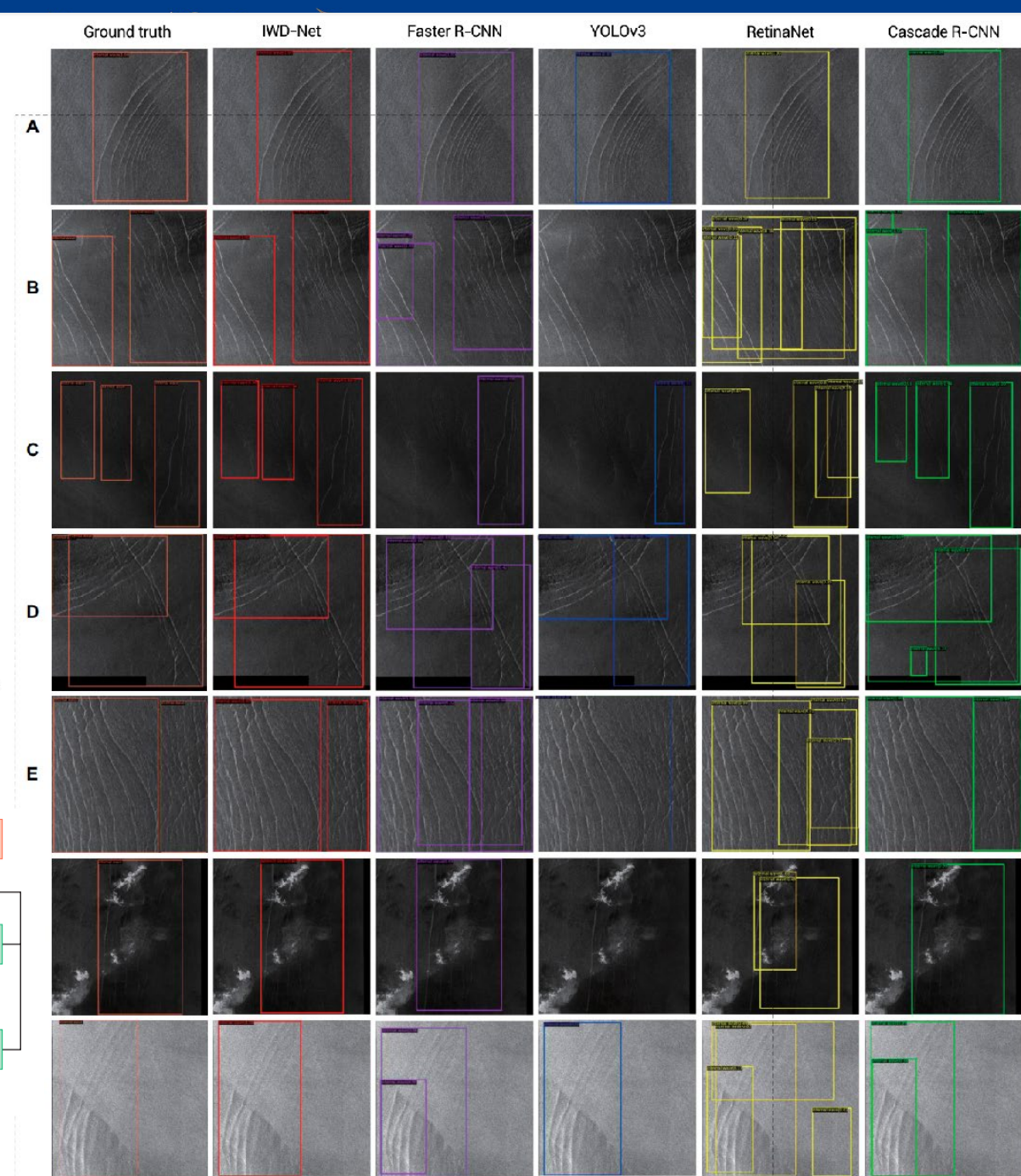


Fig. 9. Visualization of multiple network detection results. (A-G) show the detection results of different IW samples respectively.

Generation of diurnal internal solitary waves (ISW-D) in the Sulu Sea: From geostationary orbit satellites and numerical simulations

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ABSTRACT

Our recent study reported the existence of internal solitary waves with the diurnal tidal cycle (ISW-D) in the Sulu Sea, however, the three-dimensional characteristics and generation mechanism of ISW-D are still unclear (Huang et al., 2023). In this work, the spatial-temporal characteristics, generation mechanism and propagating process of ISW-D in the Sulu Sea are first preliminary investigated based on high-temporal-resolution Geostationary Orbiting Satellite (GOS) images and high-spatial-resolution two-dimensional numerical model (MITgcm). GOS images from 2018-2022 are retrieved and a total of 13 pairs of ISW-D packets are found. ISW-D occur at spring tide during May–August, with an average interpacket distance of 198 km and a phase speed of 2.30 m/s. To further knowledge of the generation mechanism and propagation process of ISW-D, the non-linear and non-hydrostatic numerical simulations are conducted. The comparison of ISW-D parameters with GOS images proves the validity of numerical simulations. The results of numerical simulations and theoretical parameters indicate that ISW-D are generated at the sill near Pearl Bank by internal tide release mechanism. Moreover, three sensitivity experiments are designed to investigate the effects of tidal force and seawater stratification on the generation and propagation of ISW-D. The results reveal that the ISW-D is generated by diurnal tides with stronger intensity than semidiurnal tides. Seawater stratification does not influence the generation of ISW-D but modulates the propagation process. Phase speeds from GOS images and theoretical model show a positive correlation between the phase speeds of ISW-D and the intensity of seawater stratification.

First Year Results



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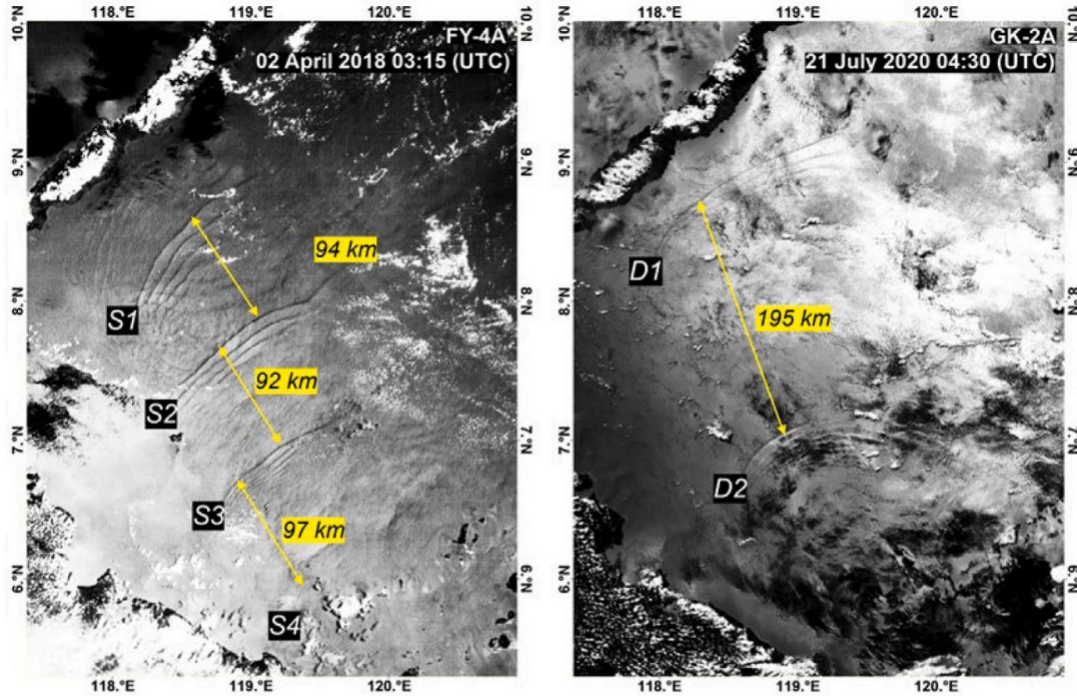


Fig. 2. (a) ISW-S with semidiurnal tidal cycle. (b) ISW-D with diurnal tidal cycle.

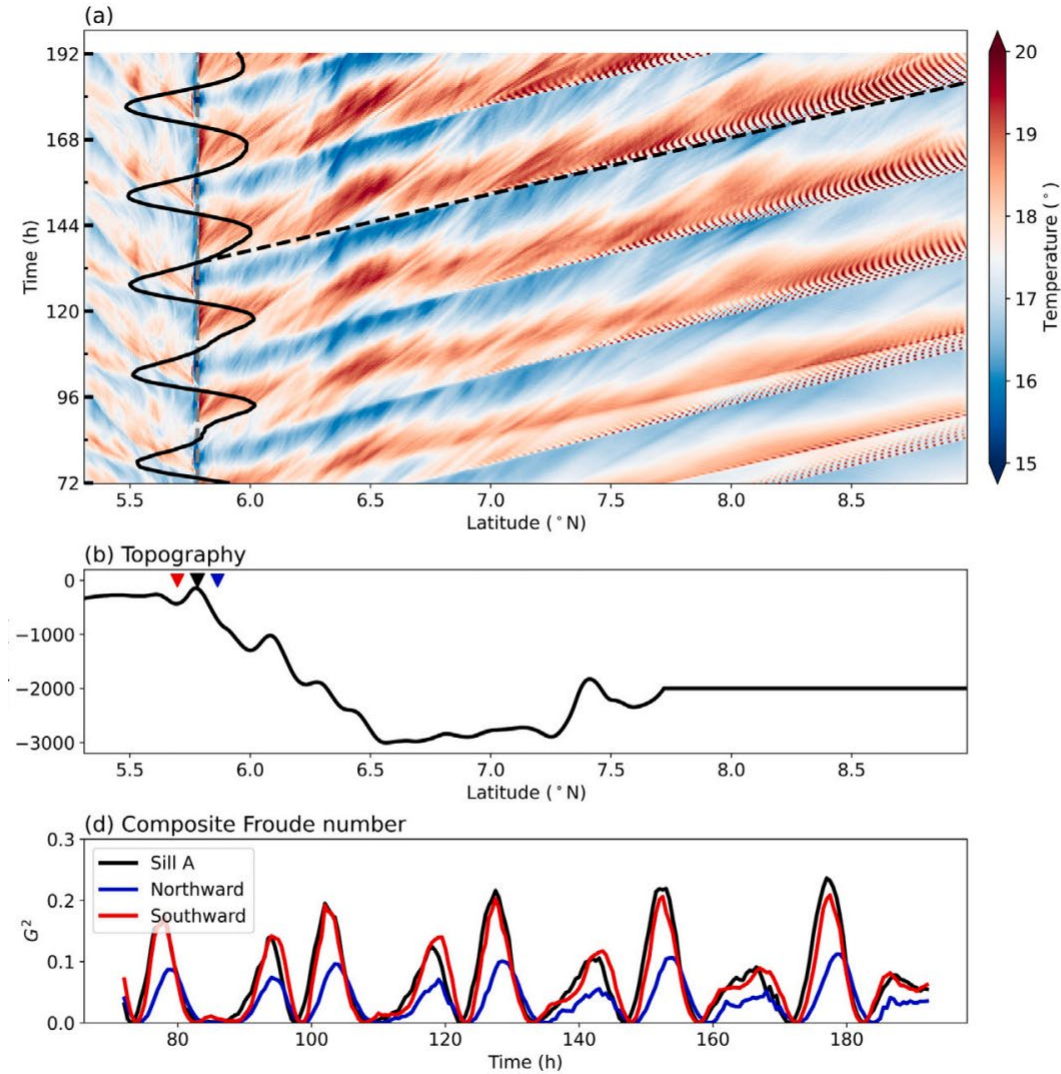


Fig. 9. (a) Hovmöller diagram of the temperature at 140 m depth. The solid black curve indicates the tidal current amplitude at sill A (rightward positive), and the dashed gray line represents the tidal current velocity of 0. The black dashed line depicts the propagation of IW in Fig. 8. (b) The bottom topography input in E-STD. (c) Values of G^2 . The colors correspond to the locations labeled by triangles in (b).



Research paper

Real and long-time predicting the trajectories of internal solitary waves: Case studies in the Sulu Sea

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Keywords:

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ABSTRACT

The propagation of internal solitary waves (ISWs) carries the tremendous amounts of energy threatening the human ocean engineering activities. Thus, it is necessary to develop an effective model to predict the trajectories of ISWs. In this study, a real and long-time prediction scheme for ISWs trajectory is proposed based on satellite remote sensing and deep learning technologies. First, we develop a purely data-driven model based on recurrent neural network for predicting the trajectories of ISWs (ISW-PRED). Only the location information of the initial ISWs is required to achieve the precise prediction of ISWs. Then, the ISWs trajectories in the Sulu Sea are continuously 4-h tracked every 10 min by two tandem satellites to train the deep learning model. Compared to satellite observations, the mean absolute position error (MAPE) of the model is 1.87 km for single-iteration prediction (30 min). For the long-term prediction, the MAPE are 4.43, 6.40, 7.23 and 5.18 km for the propagation after one semidiurnal tidal cycle, two semidiurnal tidal cycles, one diurnal tidal cycle and 24 h, respectively. When compared with numerical model, our model shows the better performance and robustness, which further proves the ability to predict the ISWs trajectories in long-term propagation. Overall, our scheme combining continuous observed ISWs data from GOS with deep learning techniques is demonstrated promising in the trajectory prediction of ISWs.

Huang L, Yang J (2025). Four-hour satellite-observation data for internal solitary waves (ISWs) in the Sulu Sea [Data set]. Ocean Engineering. Zenodo.
<https://doi.org/10.5281/zenodo.15400378>

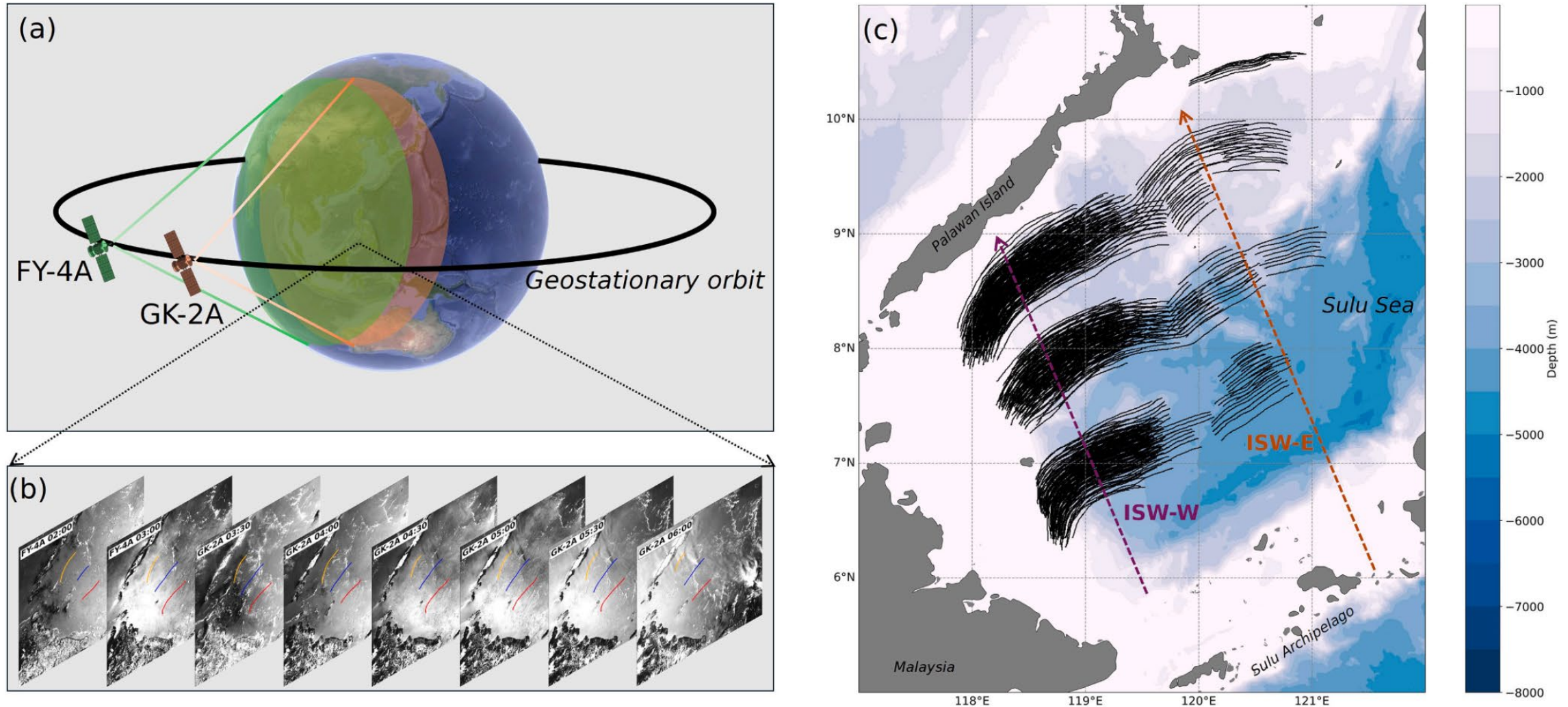


Fig. 2. (a) The schematics of full-disk imaging mode of FY-4A (green) and GK-2A (orange). (b) The GOS images during 02:00–06:00, April 17, 2022 (UTC), and the colorful curves show the ISWs of three packets. (c) The water depth distribution in the Sulu Sea, with the superimposed black curves showing the ISWs that meet the conditions for continuous 4 h observations, totalling 64 wave packets. The purple and brown dashed lines show the propagating directions of ISW-W and ISW-E, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

First Year Results

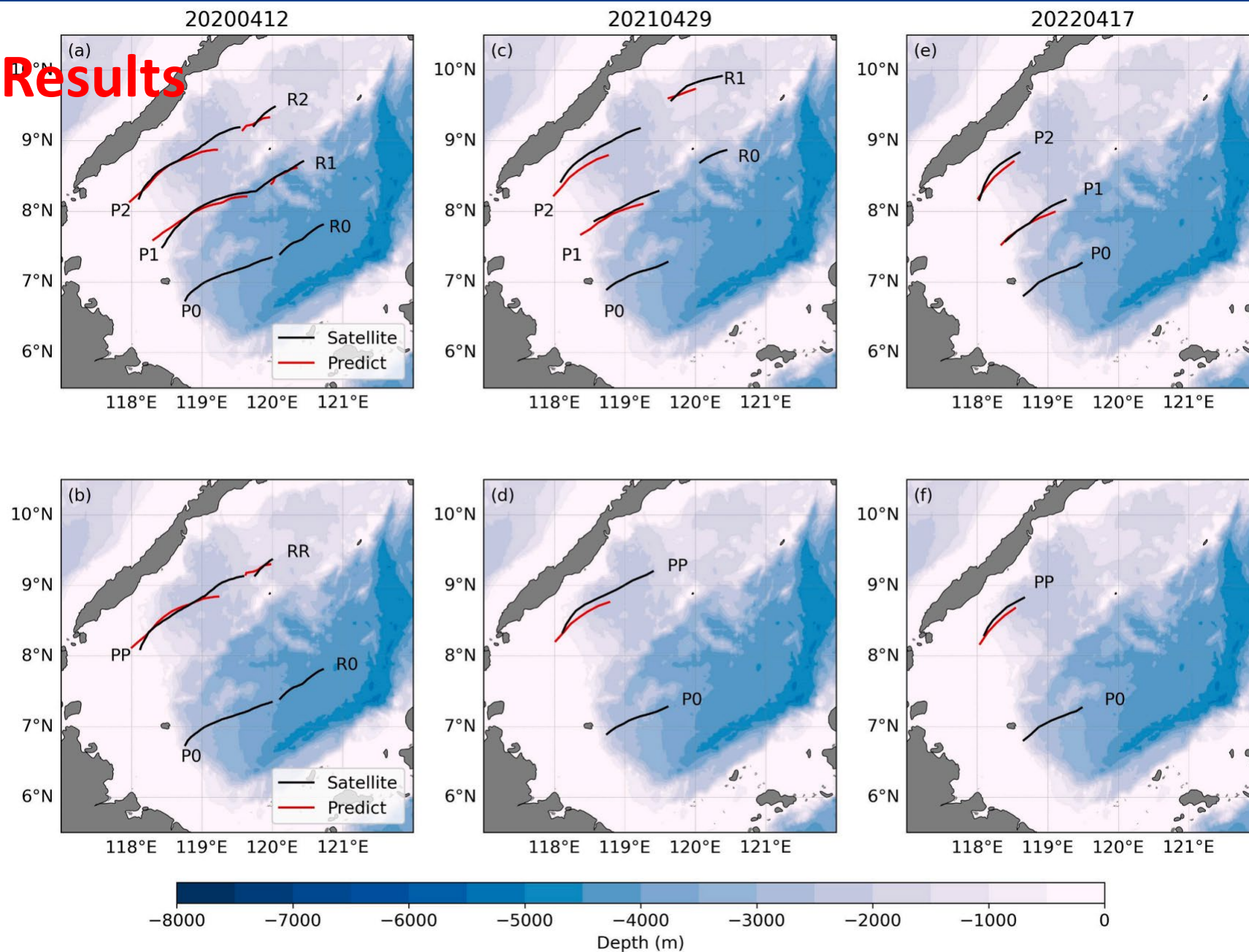


Fig. 11. Long-term prediction results of ISW-PRED, with the red and black curves indicating the model-predicted and satellite-observed ISWs, respectively. P0 is the initial ISW-W, and P1/P2/PP are the ISW-W of P0 after propagating one tidal cycle, two tidal cycles and 24 h, respectively (like Fig. 10). R0/R1/R2/RR are the predicted results of ISW-E. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

First Year Results

Poster in this symposium

Evaluating and comparing ASCAT and Sentinel-1 SAR winds against NDBC buoys

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Abstract

This study assesses and compares the accuracy of the widely used ocean wind vector products from two European C-band spaceborne radars: MetOp-A/B Advanced Scatterometer (ASCAT) and Sentinel-1A/B synthetic aperture radar (SAR) in Interferometric Wide (IW) mode. Two years (2019 – 2020) SAR/ASCAT winds are validated against the ground truth from the offshore/coastal meteorological buoys of National Data Buoy Center. Winds from radars and buoys are considered spatially matched if the buoy is located within the satellite wind cell, with a time difference limited to 30 min. To evaluate SAR/ASCAT winds against buoys in the same framework, we use 43 offshore buoy stations as common reference, and then validate them at comparable spatial resolution (25 km). Intercomparison results show that ASCAT winds exhibit higher accuracy level with root mean square error (RMSE) of 0.92 m/s (21.71°) in terms of the wind speed (direction). Regarding the Sentinel-1 SAR, offshore wind speed (direction) data downsampled to 25 km present an RMSE of 1.03 m/s (27.48°), showing very little change compared to 1 km products originally provided by ESA. Furthermore, wind accuracy degrades for Sentinel-1 SAR at both 1 km and 25 km resolutions when validated against coastal buoys, where ASCAT winds are usually unavailable. In general, our results demonstrate that the Sentinel-1 winds are as accurate as ASCAT in open ocean, while the performance of coastal SAR winds could be further improved. This finding could be helpful for better exploiting synergies in the ocean wind datasets from these two spaceborne radars.

Introduction

Ocean surface winds monitoring relies on remote sensing technology for global coverage, where ASCAT and SAR complement each other in offshore and coastal wind measurements, making them ideal for data fusion. However, the consistency of accuracy between ASCAT and Sentinel-1 has not been systematically compared.

This study addresses this critical gap through a unified validation framework using NDBC buoy networks. Our findings establish fundamental understanding for synergistic use of these datasets in both offshore and coastal regimes.

Objective & Study areas

The objective of this study is to compare the accuracy of ASCAT and Sentinel-1 SAR wind measurements, using buoy data as a benchmark.

• SAR collocated buoys (n=106)

• ASCAT collocated buoys (n=43)

Validation results

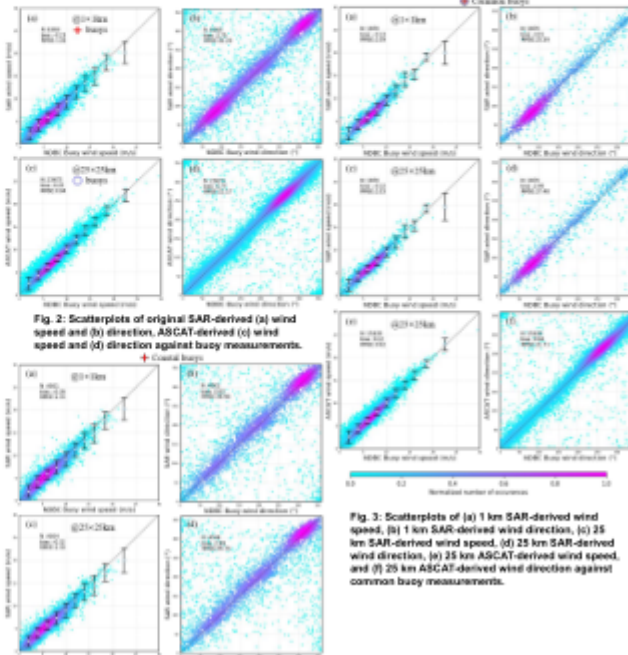


Fig. 2: Scatterplots of original SAR-derived (a) wind speed and (b) direction, ASCAT-derived (c) wind speed and (d) direction against buoy measurements.

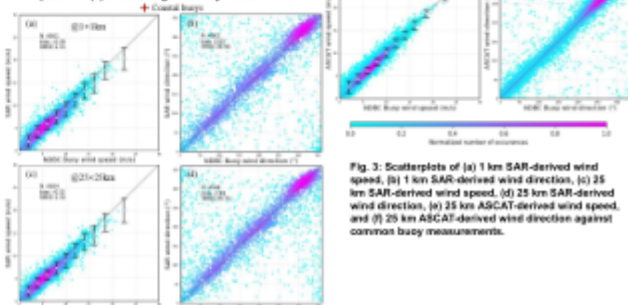
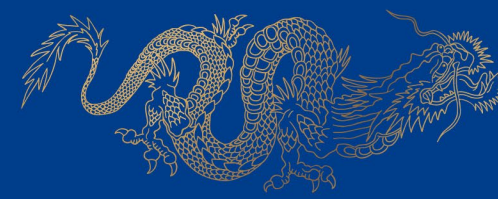


Fig. 3: Scatterplots of (a) 1 km SAR-derived wind speed, (b) 1 km SAR-derived wind direction, (c) 25 km SAR-derived wind speed, (d) 25 km SAR-derived wind direction, (e) 25 km ASCAT-derived wind speed, and (f) 25 km ASCAT-derived wind direction against common buoy measurements.

Fig. 4: Scatterplots of 1 km/25 km SAR-derived wind speed (a)(c) and direction (b)(d) against coastal buoys.



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Conclusions

➤ Comparison results show ASCAT wind products exhibit higher accuracy than Sentinel-1 SAR, regardless of whether the resolution of SAR is 1 km or 25 km.

➤ The evaluation results indicate that reducing the resolution of SAR wind data has an insignificant effect on the accuracy.

➤ These findings indicate that ASCAT wind products generally exhibit higher accuracy. However, comparisons with coastal buoys highlight that SAR has the potential to offer detailed inshore observations, particularly in wind direction, requires refinement.

➤ Moving forward, future work will focus on developing algorithms for the joint use of ASCAT and Sentinel-1 SAR wind products to further enhance their observational capabilities and precision.

Major reference

- [1] H. Wang, J. Yang, A. Mouche et al., "GF-3 SAR ocean wind retrieval: The first view and preliminary assessment," Remote Sensing, vol. 9, no. 7, pp. 694, 2017.
- [2] R. Kumar, A. Chakraborty, A. Parekh et al., "Evaluation of Oceansat-2-Derived Ocean Surface Winds Using Observations From Global Buoys and Other Scatterometers," IEEE Transactions on Geoscience and Remote Sensing, vol. 51, no. 5, pp. 2571-2576, 2013.
- [3] J. Xing, J. Shi, Y. Lei et al., "Evaluation of HY-2A Scatterometer Wind Vectors Using Data from Buoys, ERA-Interim and ASCAT during 2012–2014," Remote Sensing, 8, 2016.
- [4] H. Wang, J. Zhu, M. Lin et al., "Evaluating Chinese HY-2B HSCAT Ocean Wind Products Using Buoys and Other Scatterometers," IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 6, pp. 923-927, 2020.
- [5] C. W. Fairall, E. F. Bradley, J. E. Hare et al., "Bulk Parameterization of Air–Sea Fluxes: Updates and Verification for the COARE Algorithm," Journal of Climate, vol. 16, no. 4, pp. 571-591, Feb. 2003.

Methodology

(1) 10 m equivalent neutral winds conversion

To facilitate comparison with ASCAT and Sentinel-1 SAR wind data, buoy wind speeds are converted to equivalent neutral winds at a height of 10 meters, accounting for variations in the anemometer heights across different buoys. In this work, the conversion were performed using the Coupled Ocean-Atmosphere Response Experiment (COARE) bulk algorithm (version 3.0) developed by Fairall et al. (2003).

(2) Evaluation index

In the intercomparison of ASCAT and SAR with buoy wind field data, we calculate bias and Root Mean Square Error (RMSE) as follows:

$$Bias = \frac{\sum_{i=1}^N (y_i - x_i)}{N}$$
$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - x_i)^2}{N}}$$

where y_i represents the satellite-derived wind estimates and x_i represents the in situ wind records.

Chinese Young Scientists contributions in Dragon 6



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Name	Institution	Poster title	Contribution including period of research
Yihong Chen	National Ocean Technology Center, MNR	Evaluating and comparing ASCAT and Sentinel-1 SAR winds against NDBC buoys	Data analysis
Lizhang Zhou	State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, MNR		Winds & waves
Xinhai Han	Shanghai Jiao Tong University State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, MNR		Typhoon & water level
Longyu Huang	Zhejiang University State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, MNR		Internal waves
Zetai Ma	Zhejiang University State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, MNR		Internal wave detection



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