

Progress and Prospects of China's Ocean Satellites During the 14th Five-Year Plan Period

QI Ping ZHANG Youguang

National Satellite Ocean Application Service, Beijing, 100081

Abstract

From 2021 to 2025—the "14th Five-Year Plan" period—China established an operational space-based ocean observation system comprising the HY-1, HY-2, and ocean surveillance and monitoring (e.g., GF-3) satellite series. This achievement marks a historic transition from single-satellite missions to an integrated constellation network. This paper systematically reviews the major progress made during this phase.

At the system level, the HY-1C/D/E three-satellite network enabled high-frequency collaborative observations of global ocean color and sea surface temperature. The HY-2B/C/D constellation reduced the revisit time for global sea surface wind fields to within six hours. The HY-4A satellite filled a critical technological gap by achieving, for the first time, active-passive microwave synergistic inversion of sea surface salinity using an indigenously developed Chinese satellite. The GF-3 series enhanced the revisit capability of synthetic aperture radar (SAR) over key areas to an hourly scale. At the technological level, significant improvements in payload performance, coupled with advances in data fusion and calibration, led to systematic breakthroughs in information processing—from algorithms to platforms. Notably, the successful development of AI large models tailored for deep-sea remote sensing has driven a fundamental transformation in space-based ocean observation, shifting from two-dimensional sea surface sensing to three-dimensional stereoscopic perception of the deep ocean. At the application level, the system now fully supports marine environmental monitoring, disaster emergency response, and global ecological assessments. Finally, the paper outlines future directions, including next-generation stereoscopic detection, full-chain intelligent processing, and enhanced international cooperation.

Key words: Ocean satellites; Satellite networking; Remote sensing algorithms; Intelligent processing; Satellite applications

1. Introduction

Ocean satellites are essential for acquiring large-scale, long-term marine environmental parameters. They play a key role in understanding ocean dynamics, monitoring climate change, and managing marine resources. As a vital component of the global Earth observation system, China has developed, through years of sustained effort, a fully operational and synergistic ocean satellite system.

By 2025, this system comprises three major satellite series: the HY-1 series for ocean color remote sensing, the HY-2 series for dynamic environment monitoring, and the ocean surveillance series (e.g., GF-3, 1m-CSAR 01/02) based on Synthetic Aperture Radar (SAR) technology. A total of 11 ocean satellites are currently in orbit, equipped with payloads covering visible, infrared, and microwave spectra, enabling comprehensive multi-band observation capabilities.

This constellation marks a historic transition in China's space-based ocean observation—from experimental single-satellite missions to operational networked applications. It now supports high-frequency, stereoscopic, and near-real-time monitoring of global ocean color, dynamic processes, and maritime targets. The establishment and stable operation of this system not only provide robust data support for China's maritime strategy and sustainable development but also contribute valuable observations to international efforts in ocean governance, disaster reduction, and climate change research..

2. Ocean Satellite Systems and Payload Performance

China's three major ocean satellite series (Figure 1) are equipped with advanced remote sensing payloads spanning the optical, infrared, and microwave spectra. Together, they form a global, multi-parameter collaborative ocean observation system with high measurement accuracy, significantly advancing China's ocean remote sensing capabilities.

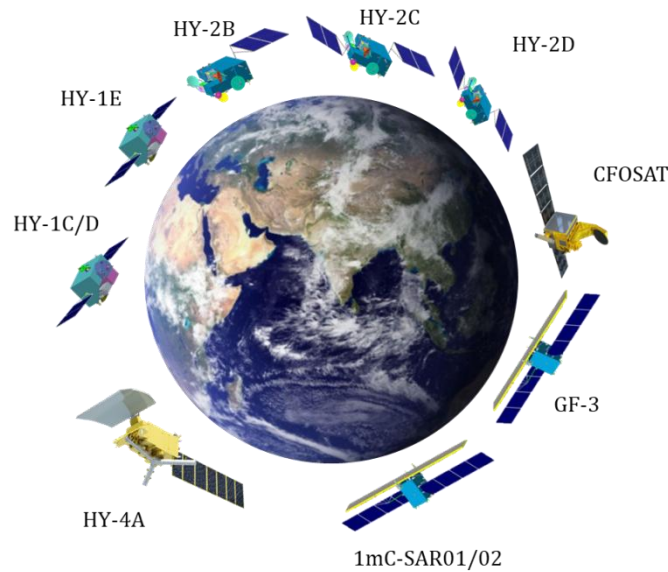


Figure 1 Schematic Diagram of the Ocean Satellite Observation System

2.1 Ocean Color Satellite (HY-1) Series

The HY-1 satellite series serves as critical infrastructure for China's remote sensing monitoring of global ocean color and coastal zone environments. Its primary scientific and application objectives include the quantitative retrieval of key ocean color parameters—such as chlorophyll-a concentration, suspended sediment concentration, and colored dissolved organic matter—as well as sea surface temperature on a global scale. The series also enables high-precision monitoring of phenomena including red tides, green tides, sea ice, sea fog, and dynamic changes in coastal zones.

The HY-1C and HY-1D satellites form an operationally deployed morning–afternoon twin-satellite constellation, significantly improving the temporal resolution of global ocean observations. HY-1E, successfully launched in 2023 as a new-generation ocean color satellite, represents a substantial leap in payload performance. Its Ocean Color and Temperature Scanner (COCTS) features an optimized spatial resolution of 500 m and an increased number of observation bands (18), enhancing its capability for multi-parameter identification. The Medium Resolution Programmable Imaging Spectrometer offers on-orbit programming functionality, allowing flexible configuration of spectral channels to output either 19

bands at 100 m resolution or 106 bands at 200 m resolution, thereby improving customized data acquisition. The Coastal Zone Imager (CZI) achieves a panchromatic resolution of 5 m and a multispectral resolution of 20 m. Coupled with a $\pm 30^\circ$ pointing capability, this significantly strengthens monitoring efficacy for fine-scale coastal geomorphology and ecological processes.

The COCTS is the core payload of the HY-1 satellite series. Data from the HY-1E satellite, with a spatial resolution of 500 m, have been widely used for coastal ecological monitoring. In 2024 alone, these data supported 49 monitoring campaigns for *Ulva prolifera* (green tide) salvage operations in the Yellow Sea, 67 for Sargassum monitoring in the East China Sea, 13 for red tide events, and 6 for offshore oil spill detection. This represents a significant enhancement of China's coastal environmental monitoring capacity.

The series is also equipped with auxiliary payloads, including an Ultraviolet Imager, an Automatic Identification System (AIS) for vessels, and a Data Collection System (DCS), collectively forming an integrated Earth observation platform. The main technical parameters of the HY-1C/D/E satellite payloads are listed in Table 1. As shown in Figure 2, the three-satellite network comprising HY-1C, HY-1D, and HY-1E has markedly enhanced revisit and coverage capabilities for key areas such as the Yellow Sea and Bohai Sea. This enables higher-frequency continuous monitoring and provides robust spatial information support for regional marine environmental management and ecological disaster early warning..

Table 1. Technical Specifications of the Primary Payloads on the HY-1 C/D/E Satellites

Satellite Series	Primary Payload	Spatial Resolution	Swath Width / Coverage Capability	Core Observation Elements
HY-1C/D	Ocean Color and Temperature	1.1 km	>2900 km,	Ocean color
	Scanner (COCTS))		Global coverage	elements, Sea
			in 1 day	surface

Satellite Series	Primary Payload	Spatial Resolution	Swath Width / Coverage Capability	Core Observation Elements
				temperature
HY-1C/D	Coastal Zone Imager (CZI)	50 m	>1000 km, Twice every 3 days for China's coastal waters	Coastal zone environment, Ecological disasters
HY-1E	Ocean Color and Temperature Scanner (COCTS)	500 m	>3000 km	Global ocean color and temperature
HY-1E	Medium-Resolution Programmable Imaging Spectrometer (PMRIS)	100 m / 200 m	>950 km	Coastal hyperspectral ocean color
HY-1E	Coastal Zone Imager (CZI)	5 m (Panchromatic) 20 m (Multispectral)	>1000 km (with side-swing capability)	Fine-scale coastal zone investigation

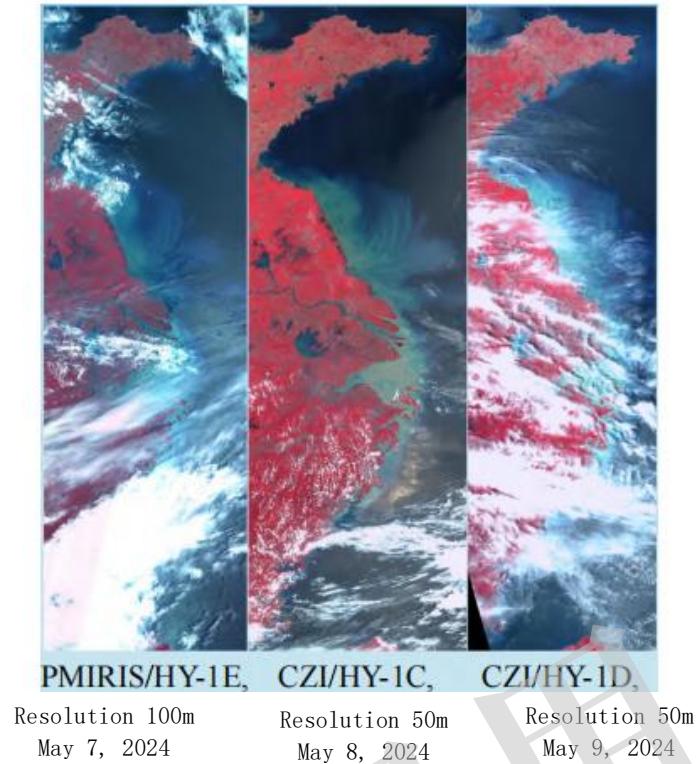


Figure 2 Coverage Map of the Yellow Sea and Bohai Sea, China after HY-1 Three-Satellite Networking

In terms of data quality, the global ocean color and sea surface temperature products from the HY-1E satellite demonstrate high consistency with international standards (linear correlation coefficients ≥ 0.95) and offer higher spatial resolution (500 m) compared to similar products from MODIS and VIIRS. The HY-1E satellite is equipped with the newly added PMRIS payload and an increased number of CZI channels, achieving improved spatial resolution (100 m for PMRIS, 20 m for CZI). Compared to data from HY-1C/D and foreign satellites, the distribution details of ocean color parameters are clearer. Under identical cloud coverage conditions, the amount of valid data exceeds that of comparable products such as MODIS and VIIRS.

2.2 Ocean Dynamic Environment Satellite (HY-2) Series

The HY-2 satellite series is dedicated to observing marine dynamic environment parameters. The currently operational HY-2 series satellites include HY-2B, HY-2C, HY-2D, and HY-4A. This series provides all-weather, all-time, and high-frequency

monitoring capabilities for key parameters including global sea surface height, sea surface wind field, sea surface temperature, significant wave height, wave spectrum, sea surface salinity, and marine gravity field. The satellites are equipped with a range of advanced remote sensing payloads—such as radar altimeters, microwave scatterometers, microwave radiometers, calibration radiometers, synthetic aperture radiometers, active and passive microwave detectors, an Automatic Identification System (AIS), and a Data Collection System (DCS)—forming a comprehensive microwave remote sensing observation system.

The HY-2B, HY-2C, and HY-2D satellites operate as a three-satellite constellation, significantly enhancing China's capability to observe the marine dynamic environment. This system integrates active and passive microwave sensors, features high-precision orbit determination and global coverage, and enables the simultaneous acquisition of multiple parameters, including sea surface wind fields, significant wave height, sea surface height, and sea surface temperature. As shown in Table 2, the primary payloads of the HY-2 series have reached internationally advanced levels in terms of altimetry accuracy, wind speed/direction measurement, and sea surface temperature retrieval. Taking the HY-2B satellite as an example, its sea surface height observation accuracy is 4.58 cm, compared to 4.69 cm for Jason-2 and 4.77 cm for Jason-3. Its sea surface wind field retrieval yields a wind speed error of 1.0 m/s and a wind direction error of 12.9°, versus 0.9 m/s and 16.5° for the ASCAT scatterometer, respectively. Its sea surface temperature observation accuracy is 0.8 K, while the WindSat satellite achieves 0.66 K. These comparisons demonstrate that the HY-2 series satellites are on par with their international counterparts in terms of observation accuracy.

Figure 3 shows that the observational efficiency of the microwave scatterometer improved markedly after the HY-2B/C/D constellation became operational, achieving 80% coverage of the global ocean within six hours—a significant enhancement in the timeliness of sea surface wind field data acquisition. The series has demonstrated outstanding performance in typhoon monitoring. As illustrated in Figure 4, during the passage of Typhoon Chanthu in 2021, the three satellites successfully tracked the

typhoon's path continuously and accurately captured the evolution of its wind field, providing highly timely observational data to support marine disaster prevention and mitigation.

Table 2. Technical Specifications of Core Payloads on the HY-2 Satellite Series

Core Payload	Key Parameters and Performance Indicators	Primary Applications
Radar Altimeter	Altimetry Accuracy: < 5.0 cm Significant Wave Height Accuracy: < 0.45 m or 10%	Sea Surface Height, Mesoscale Eddies, Sea Level Change
Microwave Scatterometer	Wind Speed Accuracy: ± 1.5 m/s Wind Direction Accuracy: < 20° Swath Width: ~ 1350 km	Global Sea Surface Wind Field, Typhoon Monitoring
Scanning Microwave Radiometer	Sea Surface Temperature Accuracy: < 1.0 K Sea Surface Wind Speed Accuracy: < 2.0 m/s	Sea Surface Temperature, Atmospheric Water Vapor Content

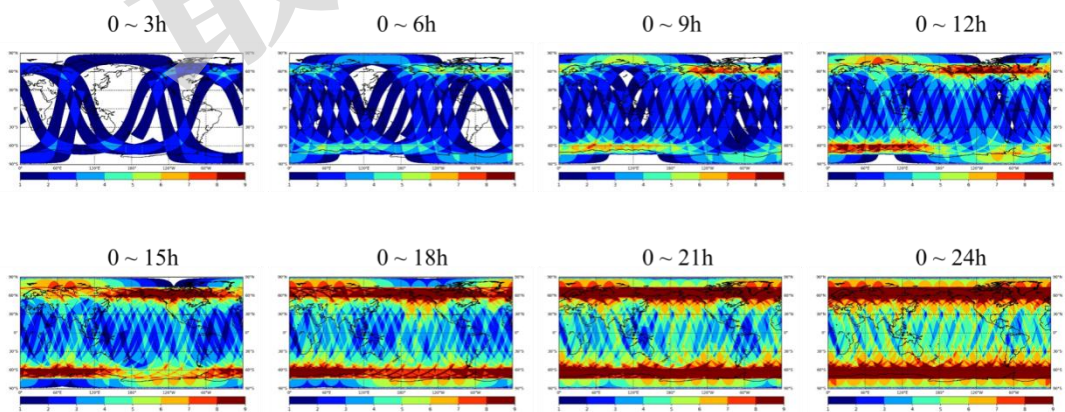


Figure 3. Global Coverage Map of the HY-2 B/C/D Scatterometer Constellation

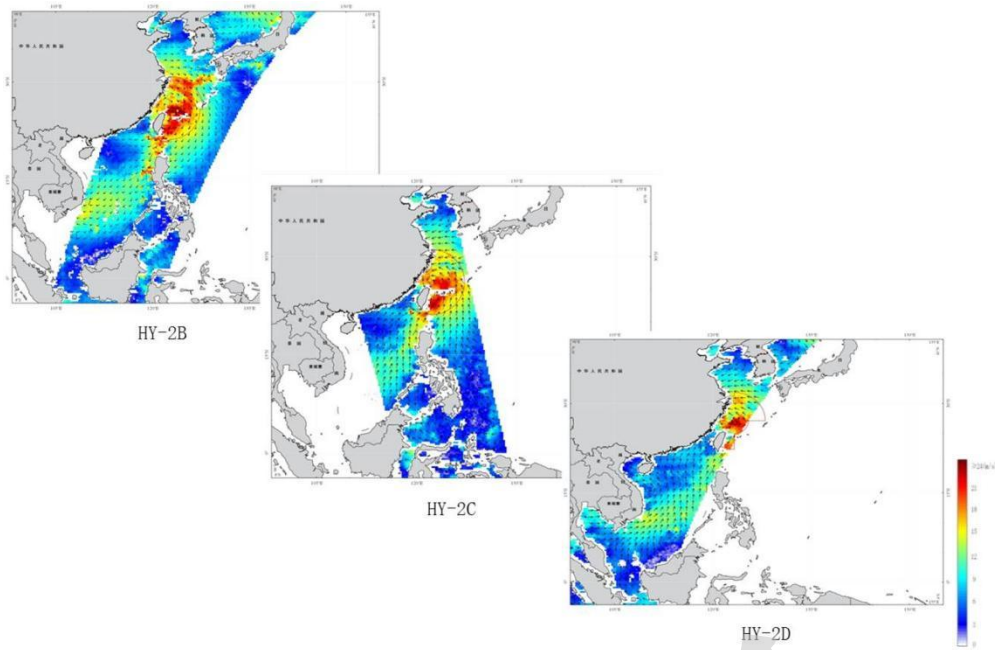


Figure 4. Schematic Diagram of HY-2 B/C/D Observing Typhoon Chanthu from September 11 to 12, 2021.

For wave observation, the HY-2 radar altimeter constellation has significantly increased the daily number of observation passes over coastal regions from 2–3 with a single satellite to 12–15. As shown in Figure 5, which divides a day into three-hour observation intervals, the global coverage characteristics and sampling density of the radar altimeters are visually demonstrated following the establishment of the HY-2B/C/D three-satellite network. This enhanced observation frequency provides critical data support for accurately capturing and tracking dynamic ocean processes such as mesoscale eddies.

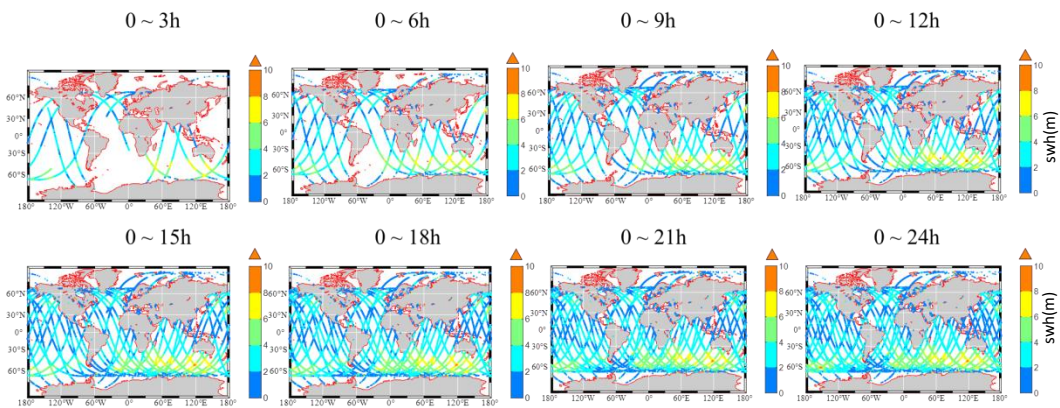


Figure 5. Schematic Diagram of Global Significant Wave Height Observation by the HY-2 B/C/D Radar Altimeter

The Ocean Salinity Detection Satellite (HY-4A), China's first scientific satellite dedicated to global sea surface salinity (SSS) monitoring, represents another significant breakthrough in ocean remote sensing. Employing an internationally advanced active–passive microwave collaborative detection mechanism, the satellite combines a synthetic aperture radiometer (LAMR) with an active–passive microwave detector (MICAP). This configuration effectively overcomes the limitations of single-sensor approaches in terms of signal sensitivity and spatial resolution, providing a unique technological pathway for high-precision, global-scale SSS retrieval.

As listed in Table 3, the core payloads of HY-4A demonstrate excellent performance in L-band radiometry and scatterometry. The synthetic aperture radiometer uses a Y-shaped antenna array, offering high sensitivity and observational stability in the 1.4 GHz frequency band—critical for accurate salinity retrieval under weak signal conditions. The active–passive microwave detector integrates the advantages of both microwave radiometers and scatterometers. Through coordinated observations, it effectively corrects for environmental interference, such as sea surface roughness, in salinity retrieval, thereby enhancing the accuracy and reliability of the data products.

Table 3. Technical Specifications of the Core Payloads on the HY-4A Satellite

Item	Parameter
Operating Frequency	1.4~1.427 GHz
Polarization	V/H/T3
Measurement Sensitivity at FoV	
Center	1.5K (V/H)
Antenna Type	Y-shaped Antenna Array

Item	Parameter
Observational Stability	0.12K
Calibration Accuracy	1.0K
Ground Resolution at FoV Center	Better than 38 km
Observation Swath	Better than 950 km
Active-Passive Microwave Detector (MICAP)	
Microwave Radiometer	
Operating Frequency	1.4~1.427 GHz
Polarization	V/H/T3
Measurement Sensitivity at FoV Center	0.15K
Observational Stability	0.12K
Ground Resolution at FoV Center	75 km × 50 km
Microwave Scatterometer	
Operating Frequency	1.25 GHz
Polarization	HH/VV/HV/VH
Peak Transmit Power	> 200 W

Item	Parameter
Calibration Stability	0.1 dB
Ground Resolution	50 ~ 100 km
Observation Swath (for MICAP)	Better than 950 km

As shown in Figure 6, the HY-4A satellite has successfully acquired China's first global sea surface salinity distribution map, effectively validating its capability to retrieve salinity fields on a global scale using active-passive microwave collaborative technology. This achievement marks a breakthrough in China's mastery of key technologies for spaceborne salinity detection and establishes the country's capacity for operational observation of global sea surface salinity. The mission provides critical data support for related research and operational applications, filling a domestic gap in this specific field of remote sensing.

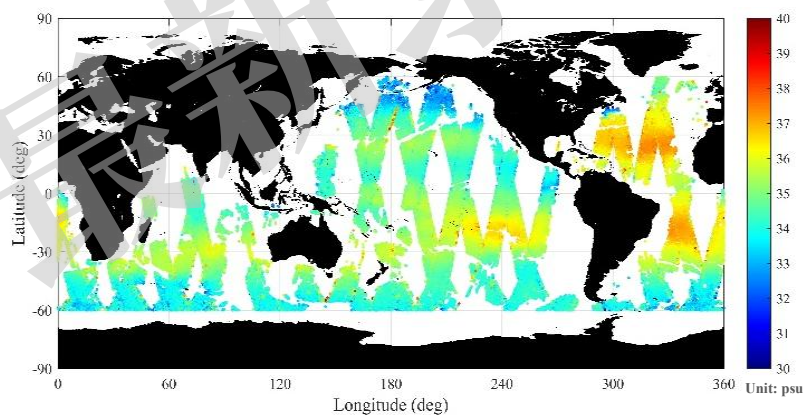


Figure 6. Schematic Diagram of Global Sea Surface Salinity Observation by the HY-4A Satellite

Regarding data product quality, on-orbit test evaluations (Table 4) show that the root mean square error (RMSE) between single-measurement sea surface salinity from HY-4A and Argo buoy observations is 0.225 psu—lower than that of SMOS (1.009 psu) and SMAP (0.543 psu). This demonstrates that HY-4A sea surface salinity observations have reached internationally advanced levels.

Table 4 Comparison of Single-Measurement Salinity Results from HY-4A Satellite
with SMOS and SMAP

Data Source	Data Points	Mean Deviation (psu)	STD(psu)	RMS(psu)	Correlation Coefficient
HY-4A/Argo	4263	-0.001	0.225	0.225	0.964
SMOS/Argo	7754	0.001	1.009	1.009	0.676
SMAP/Argo	5935	-0.001	0.543	0.543	0.842

2.3 Ocean Surveillance and Monitoring Satellite Series

China's marine surveillance and monitoring satellite series—including the GF-3 satellite and the 1-meter C-band Synthetic Aperture Radar (SAR) satellites 01 and 02—is dedicated to high-resolution observation of marine targets and dynamic environmental phenomena. It has the capability to identify typical targets globally, including vessels, reefs, offshore structures, sea ice, and oil spills. In addition, it supports the detection of various marine dynamic and environmental parameters, such as sea surface wind fields, ocean wave directional spectra, internal waves, fronts, mesoscale eddies, and submarine topography.

This series primarily employs Synthetic Aperture Radar (SAR) as its main payload, combined with an Automatic Identification System (AIS), forming an integrated space-ground collaborative surveillance and monitoring system. The GF-3 satellite, China's first C-band multi-polarization SAR satellite, features 12 imaging modes. With the subsequent addition of the 01 and 02 satellites to the constellation, the revisit capability over key areas has been further enhanced to an hourly level, enabling high-frequency dynamic monitoring and rapid response. As shown in Table 5, this satellite series encompasses a range of imaging configurations, from Spotlight

mode (1 m resolution) to Global Observation mode (500 m resolution). Its full-polarization observation capability significantly improves the accuracy of marine target identification and feature classification.

The diverse imaging modes of this satellite series provide high mission adaptability. For instance, the Spotlight mode enables sub-meter detailed observation of key targets (Figure 7); the Wide ScanSAR mode allows for large-area, simultaneous monitoring of marine dynamic phenomena spanning hundreds of kilometers; and the combination of full-polarimetric and wave imaging modes provides rich surface scattering information for the retrieval of sea surface wind fields, ocean wave spectra (Figure 8), and target attribute identification. The collaborative operation of these multiple modes collectively forms an integrated maritime observation system capable of everything from "point" target identification to "area" environmental monitoring, and from "static" observation to capturing "dynamic" processes.

Table 5. Main Technical Indicators for the 01 and 02 Satellites

No.	Imaging Mode	Resolution (m)	Imaging Swath (km)	Incidence Angle Range (°)	Polarization Mode
1	Spotlight	1	10×10	20~50	Selectable Single-polarization
2	Ultra-fine Strip	>3	30	20~50	Selectable Single-polarization
3	Fine Strip 1	5	50	19~50	Selectable Dual-polarization
4	Fine Strip2	10	100	19~50	Selectable Dual-polarization

No.	Imaging Mode	Resolution (m)	Imaging Swath (km)	Incidence Angle Range (°)	Polarization Mode
					Selectable
	Standard Strip	25	130	17~50	Dual-polarization
	Narrow				Selectable
6	ScanSAR	50	300	17~50	Dual-polarization
					Selectable
7	Wide ScanSAR	100	500	17~50	Dual-polarization
	Full-polarimetric				
8	Strip 1	8	30	20~41	Full-polarization
	Full-polarimetric				
9	Strip 2	25	40	20~38	Full-polarization
	Wave Imaging				
10	Mode	8	20×20	20~41	Full-polarization
	Global				Selectable
11	ScanSAR	500	650	17~53	Dual-polarization
		Low			
		Incidence			Selectable
		Angle	130	10-20	Dual-polarization
12	Extended				
	Incidence Angle	Large			
		Incidence			Selectable
		Angle	80	50-60	Dual-polarization

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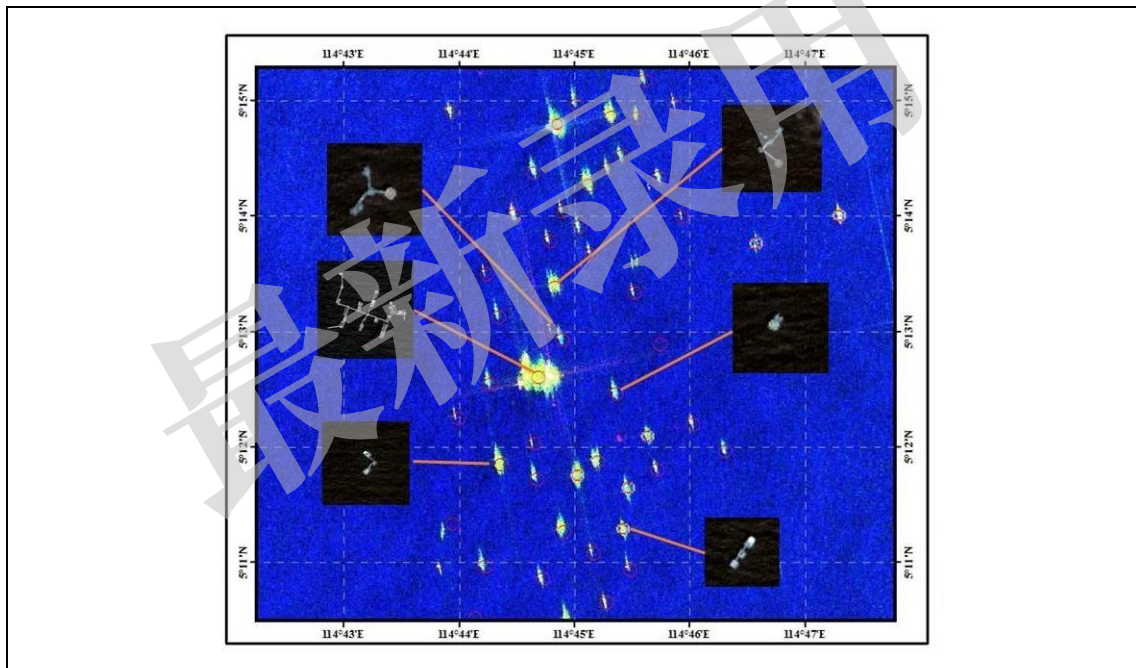


Figure 7. Monitoring of oil and gas platforms in the South China Sea

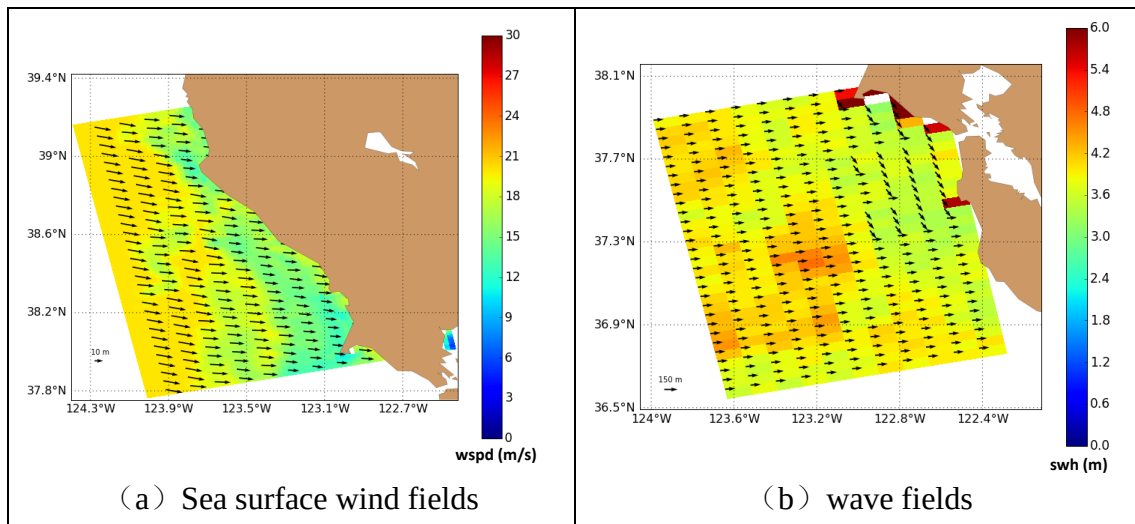


Figure 8. Sea surface wind fields and wave fields observed by the GF-3 satellite.

3. Advances in Ocean Remote Sensing Research

During the 14th Five-Year Plan period, the enhanced performance of China's ocean satellite payloads, coupled with the growing demand for high-precision marine environmental information, drove systematic breakthroughs in ocean remote sensing across fundamental mechanisms, algorithm innovation, intelligent processing, and data calibration. Research focused on key challenges in optical and microwave remote sensing, including signal extraction, parameter inversion, target identification, and data validation. By integrating physical models with artificial intelligence technologies, technical bottlenecks—such as atmospheric correction under complex conditions, parameter retrieval in extreme sea states, and nonlinear error correction in SAR observations—were overcome. A complete technical system was established, spanning from signal processing to product generation. The development and application of domain-specific AI large models for ocean remote sensing have facilitated the transition from two-dimensional surface perception to three-dimensional stereoscopic cognition. This has laid a solid theoretical and technical foundation for the effective application of satellite data in environmental monitoring, disaster warning, and global ecological assessment. This section systematically reviews the latest progress in China in the areas of optical and microwave remote sensing mechanisms and algorithms, intelligent information processing, and data calibration and validation.

3.1 Optical Remote Sensing Mechanisms and Algorithms

3.1.1 Resolution of Atmospheric Correction Error Problems

Signal distortion caused by atmospheric interference is a fundamental bottleneck in optical remote sensing, especially the correction challenges brought by the vertical distribution of absorbing aerosols and the complexity of coastal water bodies. Targeting this issue, research has evolved from traditional algorithms to intelligent optimization solutions: the Intelligent Polarized Atmospheric Correction (IPAC) algorithm proposed by He et al. [8] extracts polarized water-leaving radiance information and aerosol characteristics by processing multi-angle, multi-spectral and polarized satellite data, which can accurately retrieve the Stokes vectors of water-leaving radiance and hydro-optical parameters, providing key algorithm support for polarized ocean color remote sensing. Aiming at the correction deviation induced by absorbing aerosols (AA), Song et al. [23] constructed the OC-XGBRT algorithm based on radiative transfer simulation and machine learning, which significantly improved the retrieval accuracy of remote sensing reflectance $R_{rs}(\lambda)$ in the blue/ultraviolet bands. In coastal and inland waters, the Average Percentage Deviation (APD) and Root Mean Square Error (RMSE) of $R_{rs}(412/443\text{ nm})$ were below 36.9% and 5.5×10^{-4} , respectively. Meanwhile, to address the high computational cost of traditional aerosol retrieval methods relying on Look-Up Tables (LUTs), Mei et al. [18] developed the Fast Semi-Analytical Model for Aerosol Retrieval (FASMAR) based on the successive scattering technique. The error of top-of-atmosphere reflectance was $\leq \pm 3\%$ under typical satellite geometric conditions (zenith angle $< 70^\circ$), making it suitable for the near-real-time generation of global aerosol products for non-polarized sensors.

3.1.2 Accurate Retrieval of Multi-Parameters in Ocean Color

Quantitatively extracting key ecological parameters of the ocean from satellite signals is the core application goal of optical remote sensing, with technological evolution showing a trend from single-parameter to multi-parameter retrieval and from simple models to intelligent fusion. For phytoplankton pigment monitoring, Li et al. [10] integrated multi-source satellite data to build a deep learning model, realizing

the simultaneous global retrieval of 17 pigments, which was successfully applied to analyze the dynamic impact of El Niño events on the phytoplankton community structure in the western equatorial Pacific. For the uncertainty in phytoplankton Primary Production (PP) estimation, Li et al. [11] combined an enhanced Random Forest regression algorithm with a theoretical productivity model to achieve global PP retrieval from clear to turbid waters, showing significant advantages in polar and coastal complex areas. Song et al. [22] identified chlorophyll-a concentration (Chl) as the main error source in the Carbon-based Production Model (CbPM08), providing a clear direction for model optimization. For the retrieval of Particulate Organic Carbon (POC) concentration, Liu et al. [14] verified that machine learning models such as XGBoost outperformed traditional blue-green band ratio algorithms, offering a reliable tool for the dynamic monitoring of POC in the global ocean and high-productivity marginal seas.

3.1.3 Fine Identification of Typical Marine Ecological Phenomena

To meet the monitoring needs of typical ecological and environmental phenomena such as red tides, green tides, oil spills and whitecaps, research has broken through the limitations of traditional visual interpretation and spectral analysis, and developed deep learning fusion technologies. Jiao et al.[9] constructed an integrated optical remote sensing framework of deep learning and spectral analysis, realizing the comprehensive quantification of the type, concentration and thickness of marine oil spills, and accurately revealing the distribution and attributes of oil spills in the satellite images of China's marginal seas. Qi et al.[20] established a spectral characteristic analysis and identification method for floating algal blooms (*Ulva prolifera*, *Sargassum*, *Noctiluca scintillans*, etc.) based on the high-resolution Coastal Zone Imager (CZI) data of HY-1C/D, supporting the fine monitoring of "concurrent algal blooms" in coastal waters. Zhao et al. [38] utilized the high reflectivity of the near-infrared band, combined with a radiative transfer model and a window filtering method to retrieve ocean whitecap coverage, confirming its positive correlation with wind speed (the coverage was about 0.65% at a wind speed of 10.4 m/s), and the deviation between the retrieved sea surface wind speed and ERA5 reanalysis data was

≤ 1.6 m/s. In addition, Yang et al.[35]built a sea surface background noise model for the ICESat-2 photon-counting lidar, and realized the direct retrieval of Aerosol Optical Depth (AOD) in daytime ocean areas using satellite data only, with the results showing a correlation of 0.95 with MODIS products.

3.2 Microwave Remote Sensing Mechanisms and Algorithms

3.2.1 Parameter Retrieval Accuracy under Extreme Sea Conditions

Extreme sea conditions such as tropical cyclones and strong winds result in complex sea surface states, making it difficult for traditional microwave remote sensing models to accurately retrieve parameters such as wave height and wind speed. To address this challenge, machine learning-driven optimization schemes have been developed: Hu [42]built an XGBoost model based on SMAP radiometer data by integrating cyclone structure parameters and wind speed data, realizing the high-precision retrieval of Significant Wave Height (SWH) under tropical cyclone conditions, with an RMSE of 0.50–0.71 m and a correlation coefficient of 0.92–0.96, which was significantly superior to traditional empirical models. Aiming at the wind field retrieval challenge of the Ku-band fan-beam scatterometer on the China-France Oceanography Satellite (CFOSAT) under rainfall conditions, Zhao et al. [39] revealed the error characteristics under different rainfall intensities: the underestimation of backscatter measurements at low incidence angles under heavy rainfall led to a significant low retrieval of wind speed, while there was a compensation effect between measurements at different incidence angles under low to moderate rainfall, providing a key basis for the optimization of high wind speed retrieval algorithms.

3.2.2 Correction of Nonlinear Errors in SAR Observations

Although Synthetic Aperture Radar (SAR) altimeters and imaging satellites have the advantage of high resolution, their measurements are susceptible to nonlinear errors caused by factors such as wave direction and Doppler shift. For this reason, multi-dimensional correction technologies have been developed: Wang et al.[30]used a neural network algorithm to correct the interference of ocean waves on SAR altimeter-derived sea surface height and SWH data, and the in-situ measurement verification showed that the SWH measurement error was reduced by 29%. Wang et

al.[28] proposed a non-geophysical correction scheme integrating sea state parameters for the sea surface current velocity retrieval error of Sentinel-1 SAR images, which improved the current velocity accuracy by more than 60%. Yang et al.[34]corrected the electromagnetic pointing error of Sentinel-1A, quantified the impact of wind waves on Doppler shift, and constructed four Geophysical Model Functions (GMFs). The optimal model improved the current velocity retrieval accuracy to an RMSE of 0.19 m/s, realizing the accurate detection of hundred-meter scale submesoscale eddies in the Gulf Stream region. Facing the nonlinear challenge of SAR ocean wave spectrum retrieval, Wu et al. [31] constructed the Wave-Spec-CNN model integrating physical mechanisms, realizing the separate retrieval of swell and wind wave components for the first time (SWH-RMSE were 0.46 m and 0.42 m, respectively).

3.2.3 Optimization of Microwave Key Parameter Retrieval

Centering on the microwave remote sensing retrieval needs of key parameters such as sea ice, salinity and atmospheric precipitable water, research has broken through the limitations of single sensors and developed multi-source fusion and model improvement technologies. Qu et al. [21]optimized the passive microwave retrieval algorithm for the Arctic sea ice freeze-up period by introducing sea ice concentration screening and ice type change correction, significantly improving the retrieval accuracy of the Early Freeze-up Onset (EFO), and revealing a delay trend of 6.4 days per decade in the Arctic sea ice freeze-up period from 2003 to 2021. Sun et al. [25] fused microwave and near-infrared remote sensing data to propose a new parameter of polarized brightness temperature difference ratio and a two-step fusion strategy, generating an all-weather atmospheric Total Precipitable Water (TPW) product with a high spatial resolution of 0.05° , and the accuracy was improved by 20–27% compared with the original MODIS and AMSR2 products. Q. W. Xing et al.[32]constructed an automated ocean mesoscale front detection algorithm fusing inverse distance weighting and mathematical morphology operators, solving the problems of missed detection of coastal fronts, fragmented frontal lines and repeated identification in traditional methods, and systematically identifying 59 persistent fronts in China's offshore waters for the first time. W. T. Ma et al. [16]developed a semi-theoretical

L-band fully polarized sea surface emissivity model, which revealed the variation patterns of the third and fourth Stokes parameters with wind speed and observation angle, with an error of <0.2 K compared with satellite observations within a wind speed range of 35 m/s.

3.3 Intelligent Information Processing Technology

3.3.1 High-Precision Intelligent Identification of Marine Targets

To meet the automatic identification needs of marine targets such as waterlines, aquaculture areas, algal blooms, ocean fronts and eddies, research has broken through the limitations of traditional threshold methods and single models, and developed multi-source data fusion and deep learning algorithms. B. Ai et al.[1] proposed the RTDL model integrating radiative transfer theory and deep learning, using multi-source data from ICESat-2 and Sentinel-2 to realize the high-precision classification of coral reef geomorphology, and the classification accuracy in key areas such as fore-reef slopes, sand cays and lagoons was improved by 9%–26%. G. Zheng et al. [40] constructed a difference-focusing fusion decision framework with multi-resolution deep neural networks, and the SRUNet model proposed by J. Liu et al. [15]fusing Sentinel-1 and Sentinel-2 images achieved an F1-score of 86.52%, enhancing the robustness of waterline extraction in complex tidal flat environments[13]. W. T. Chen and X. F. Li[4] developed the MAZ-Net model to realize the long-term monitoring of nori aquaculture areas on the North Jiangsu Shoal based on Sentinel-1 VH polarization images, with an F1-score of 94.77%. For green tide monitoring, L. Gao et al.[6] proposed the AlgaeNet model adapted to the characteristics of optical and SAR images, and combined the ConvLSTM network with multi-source data to reconstruct the missing daily green tide distribution, with a time series monitoring accuracy of 95.92%. Y. Li et al.[12] realized the automatic detection of ocean fronts in sea surface temperature images based on the U-Net model, and X. Sun et al.[26] constructed the SCSE-Eddy benchmark dataset based on the CNN framework to realize the accurate extraction and dynamic tracking of ocean eddies.

3.3.2 Inversion and Reconstruction of Marine 3D Structure

Breaking through the bottleneck of traditional microwave and optical remote sensing limited to 2D sea surface observation, multi-source data fusion technologies for marine 3D structure inversion have been developed. L. J. Zhang et al. [37] constructed a Deep Neural Network (DNN) retrieval model for sea surface salinity (SSS) in the 0–200 km coastal zone, trained and optimized based on Aquarius satellite data and HYCOM reanalysis data, and the RMSE between the retrieved SSS and in-situ measurements was 0.35, which was significantly better than official products. J. Qi et al. [19] fused sea surface height, temperature, salinity, wind field and geographical location data to build an ensemble machine learning model, successfully retrieving the subsurface thermal structure of the upper 1000 meters in the South China Sea, with accuracy superior to single machine learning algorithms and better performance in winter. Combined with the domestic "Skyocean" AI large model, the end-to-end reconstruction and prediction from remote sensing data to 3D salinity field, temperature field and current velocity field have been realized, driving the transformation of ocean observation from 2D sea surface perception to 3D deep sea cognition.

3.4 Data Calibration and Validation

3.4.1 Improvement of Cross-Sensor and On-Orbit Calibration Accuracy

Aiming at the problems of on-orbit performance attenuation of satellite payloads and poor data consistency of multi-sensors, a multi-dimensional calibration technology system has been established. J. W. Wang et al. [27] developed a cross-sensor calibration method for the ultraviolet imager of HY-1C satellite based on co-orbital platform sensors, reducing the post-calibration error of remote sensing reflectance in the 355 nm/385 nm bands to 15.7%/8.4%. S. Wang et al. [24] used the GPM GMI radiometer as a reference to perform on-orbit brightness temperature calibration for seven channels of the HY-2B scanning microwave radiometer by the double difference method, clarifying the key technical requirements such as ascending/descending orbit distinction and first-order fitting. X. Ma et al. [17] established an on-orbit radiometric calibration method for the calibration microwave radiometer of the HY-2 satellite constellation with HY-2B as the

benchmark, unifying the brightness temperature baseline, and reducing the bias of wet path delay products among different satellites in the constellation by more than 20%, with accuracy comparable to the Jason-3 satellite ($\text{RMSE} < 1 \text{ cm}$). X. Zheng et al. [41] proposed an on-orbit calibration method for the HY-2C calibration microwave radiometer combining antenna pattern correction and neural network, significantly reducing the zonal bias of brightness temperature data. In addition, Wang et al. [29] achieved the intercalibration of Ku-band scatterometers across the HY-2 satellite constellation using three distinct methods. Their results demonstrated a high degree of consistency, with discrepancies remaining within 0.1 dB, thereby ensuring the uniformity of the derived sea surface wind field products.

3.4.2 Product Validation and Long-Term Dataset Construction

To ensure the reliability and application value of satellite remote sensing products, a complete validation system from single-point verification to global dataset fusion has been established. B. Guan et al. [7] carried out a synchronous observation experiment of multi-antenna GNSS buoys and mooring arrays in the Qianliyan area of the Yellow Sea, verifying the feasibility of the ground calibration site for ocean altimeter satellites, and the standard deviation of the filtered sea surface height difference was only 2.76 cm. R. Chen et al. [2] used VIIRS as the reference sensor to perform cross-calibration for the thermal infrared bands of HY-1D satellite COCTS in the South China Sea, reducing the brightness temperature bias of the $11 \mu\text{m}/12 \mu\text{m}$ bands to about 0.01 K and improving the retrieval accuracy of sea surface temperature in the South China Sea. J. Xu et al. [33] integrated multi-source altimeter data from the HY-2 series, CFOSAT and international satellites to construct a long-term and high-resolution SWH climate dataset for China's offshore waters. After buoy verification and linear correction, the temporal correlation coefficient of the 10-day average data was increased from 0.87 to 0.90, and the bias was reduced from 0.28 m to 0.03 m. R. Chen et al. [3] proposed an automatic standardization method for yaw data for the image distortion caused by the large field of view of the HY-1D satellite CZI, reducing the striping coefficients of land/ocean scenes to below 0.04%/0.07%. F.

Yu et al. [36] evaluated the mesoscale eddy detection capability of the HY-2 satellite constellation, confirming that the fused product improved the eddy identification accuracy by 23%, and was superior to international reference satellite combinations in presenting spatial details such as eddy radius and amplitude. S. Chen et al. [5] evaluated the performance of the HY-1C satellite COCTS, showing that the uncertainty of remote sensing reflectance in the blue band was below 5%, and the data reliability reached the level of international mainstream sensors.

4. Major Application Areas of Ocean Satellites

4.1 Marine Environment Monitoring

Ocean satellites provide high-precision, continuous global marine environment data, supporting applications in climate research, resource surveys, and ocean forecasting. Utilizing the HY-1 satellite series, operational production of daily, decadal, and monthly mean sea surface temperature (SST) fusion products for both global oceans and China's coastal waters is conducted. In 2022, these products were applied to typhoon forecasting and fishery analysis. The product resolution was optimized in 2023. With the commissioning of the new-generation HY-1E ocean color satellite in 2024, observations with higher spatiotemporal resolution were achieved, improving data accuracy by approximately 40%. These data serve international climate research. Figure 9 shows the global monthly mean SST distribution map for November 2024. These data provide foundational remote sensing support for key natural resource management functions, including the formulation of marine ecological early-warning monitoring plans and marine disaster emergency response plans, national marine functional zoning, and the delineation of offshore aquaculture areas.

Parameters such as chlorophyll-a concentration and suspended matter distribution are acquired via the HY-1C/D satellites. Global monthly mean products were released in 2022, with applications extended to coastal ecological assessment in 2023. The enhanced spectral detection capabilities of the HY-1E satellite in 2024 support the analysis of ecological events like red tides and algal blooms. Data are shared with

international organizations. Figure 10 shows the global monthly mean chlorophyll-a concentration distribution map for November 2024. The chlorophyll-a concentration data from the HY-1C/D/E satellite series has provided regular support for fishery condition forecasting in fishing grounds, improving the fishing efficiency of surrounding fishery production areas and driving the growth of the fishery economy.

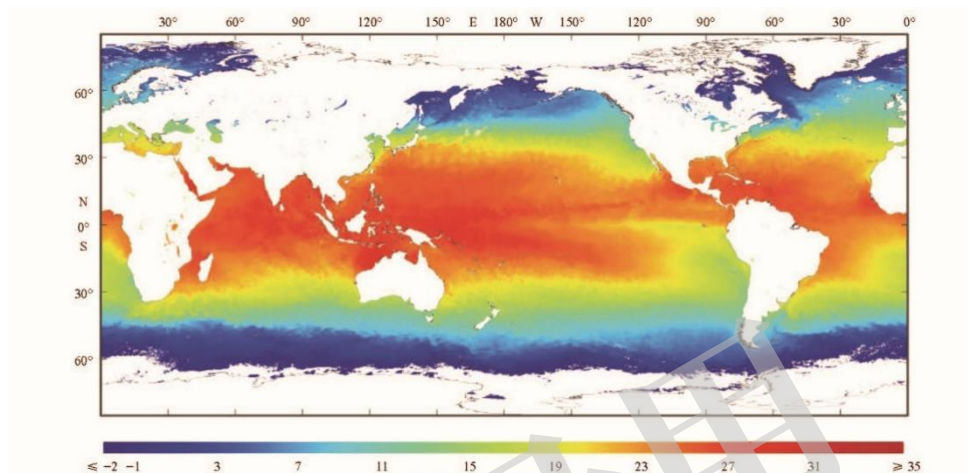


Figure 9. Global Monthly Mean Sea Surface Temperature Distribution Map
November 2024

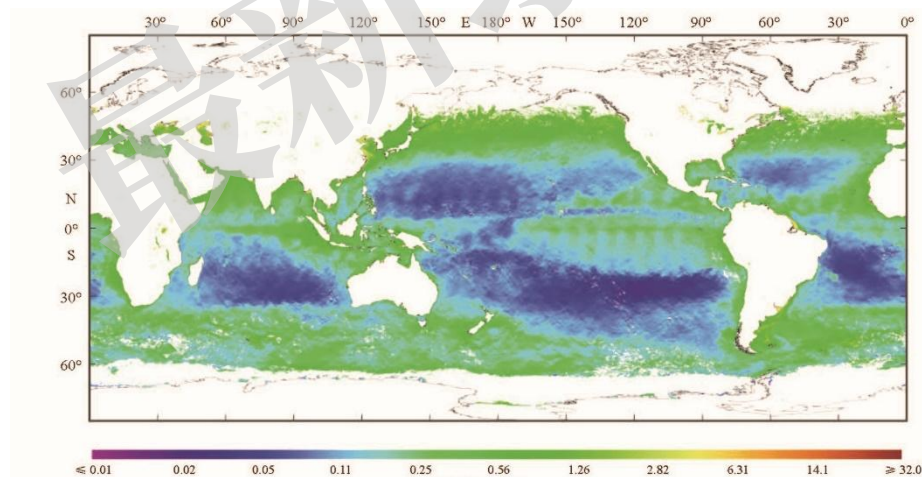


Figure 10 Global Monthly Mean Chlorophyll-a Concentration Distribution Map,
November 2024

The HY-2 satellite constellation has achieved operational monitoring of sea surface wind fields, sea level anomalies, and geostrophic currents. In 2022, it began producing 6-hourly wind field products, as shown in Figure 11. In 2023, it released global 1/4° resolution fused sea level anomaly products (Figure 12) and sea surface temperature fused data products (Figure 13). A breakthrough in multi-source data

fusion technology was achieved in 2024 and applied to global ocean reanalysis.

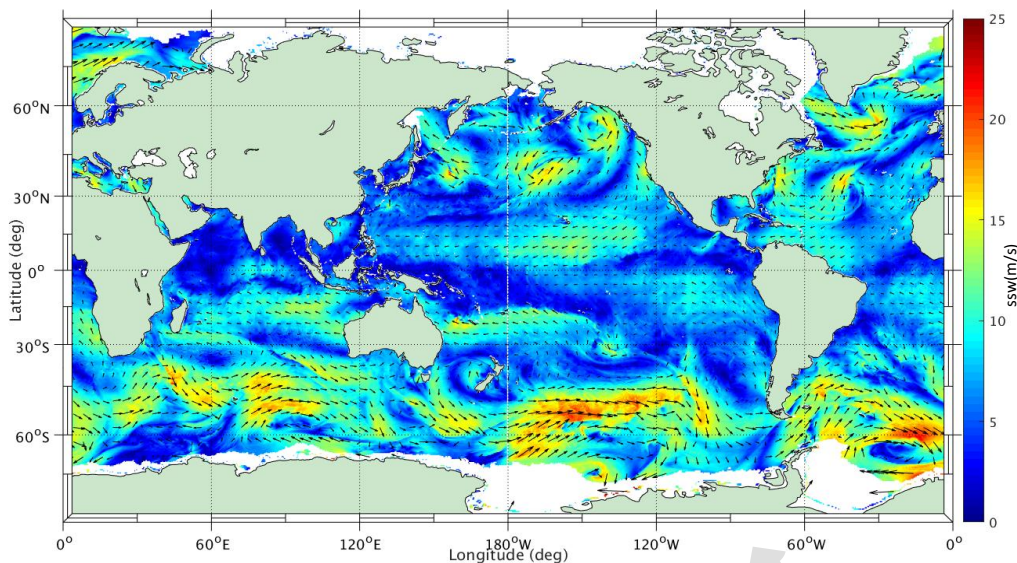


Figure 11 Schematic Diagram of the Global Sea Surface Wind Field Merged Product

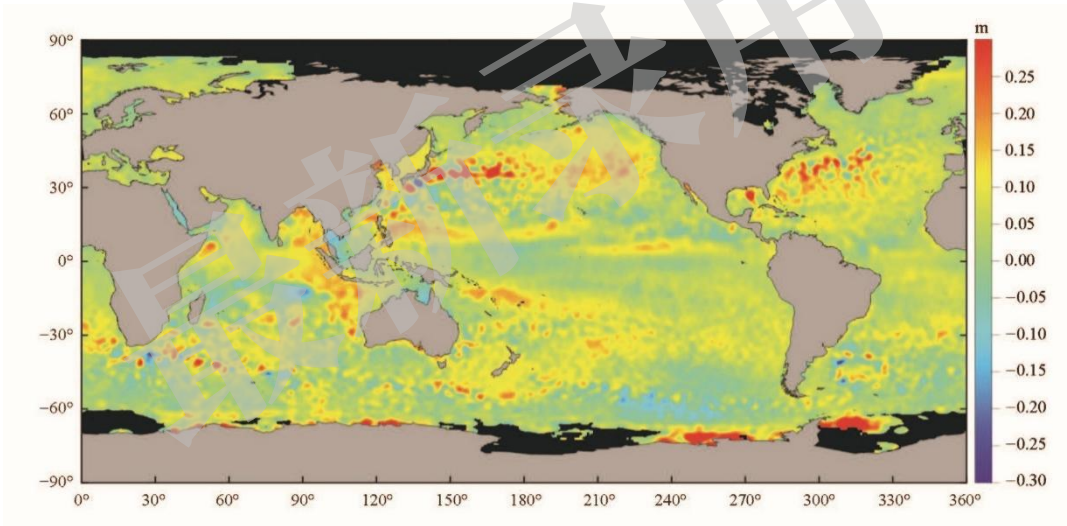


Figure 12 Schematic Diagram of the Global Sea Surface Height Anomaly Merged Product

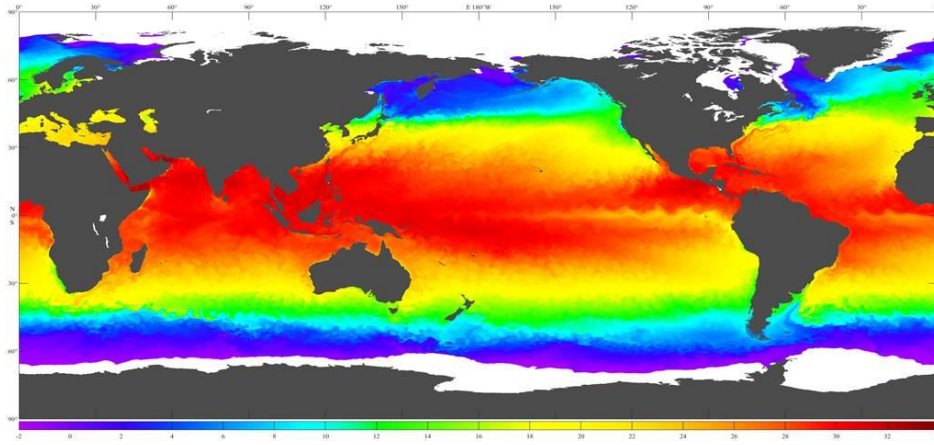


Figure 13 Schematic Diagram of the Global Sea Surface Temperature Merged Product

4.2 Marine Disaster Monitoring and Early Warning

The application of ocean satellite data enables early identification, dynamic tracking, and damage assessment of marine disasters, thereby enhancing global maritime navigation safety. Operational monitoring of sea ice in the Bohai Sea and the northern Yellow Sea is conducted every winter. The number of monitoring bulletins issued increased from 78 in 2022 to 99 in 2024. Since 2024, operational monitoring of Arctic sea ice concentration and abnormal changes has been carried out using data from the HY-2B satellite's microwave radiometer. The resolution of the operational product has been improved to 12.5 kilometers (Figure 14), providing support for polar navigation.

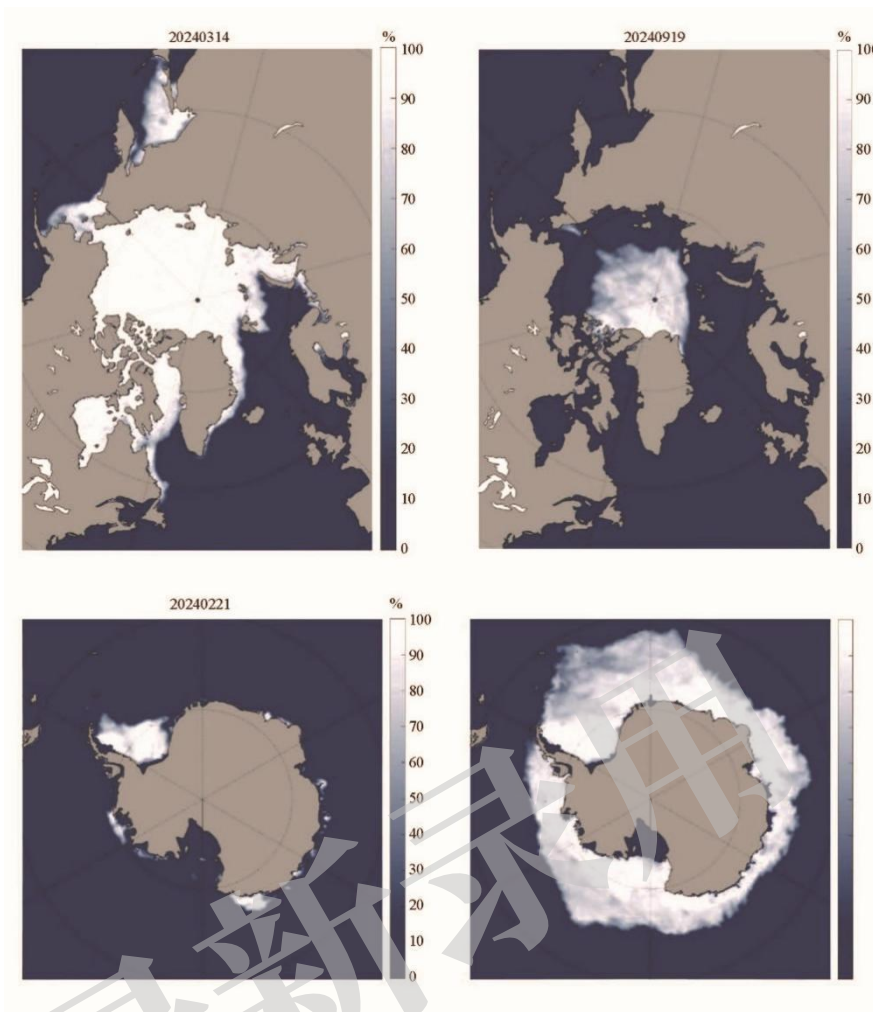


Figure 14 Schematic Diagram of Sea Ice Concentration Distribution in the Arctic and Antarctic

Regarding the green tides caused by *Ulva prolifera* in the Yellow Sea, based on observations from the HY-1C/D satellites, a cumulative total of 539 monitoring reports were issued from 2022 to 2024, achieving whole-process tracking from discovery to extinction. Operational monitoring of *Sargassum* was initiated in 2023, with 259 reports issued in 2024 to analyze its bloom patterns. The frequency of red tide monitoring (Figure 15) decreased from 48 instances in 2022 to 32 in 2024, reflecting the effectiveness of control measures. Routine oil spill monitoring (Figure 16), conducted jointly by the HY-1C/D/E and GF-3 satellites, has been implemented to support marine ecological protection.

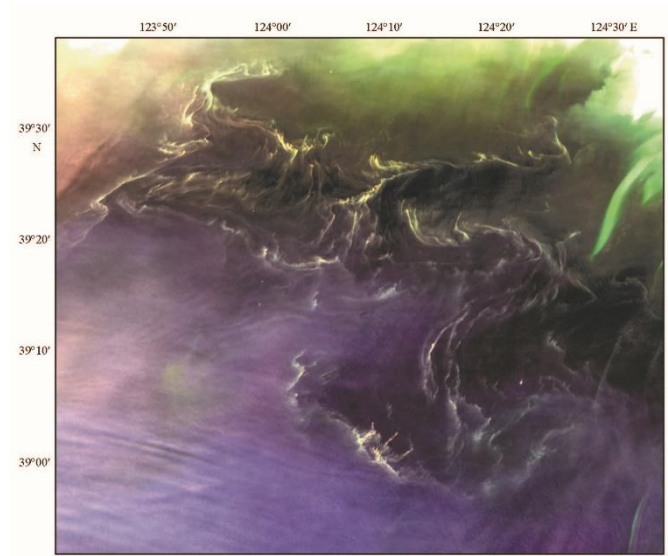


Figure 15 Remote Sensing Image of Red Tide in the Yellow Sea Area



Figure 16 Remote Sensing Image of Oil Spill in the Yellow Sea Area

The ocean satellite constellation possesses high-frequency observation capabilities for global oceanic cyclones (see Figures 3 and 4), enabling annual monitoring of typhoons in the Western Pacific. This included 23 events in 2022 and 26 events in 2024, with over 300 thematic maps produced annually. The satellite data is integrated into global forecasting systems, providing near-real-time wind field and path information for the Asia-Pacific region.

4.3 Global Ecological Monitoring

Through the China-ASEAN Satellite Remote Sensing Application Center and the China-Africa Satellite Remote Sensing Application Cooperation Center, international cooperation on mangrove monitoring has been carried out. In 2024, a marine satellite remote sensing dataset for mangrove monitoring along the eastern and western coasts of Africa was established, providing data support for global mangrove conservation. Since 2023, operational production of global coral reef bleaching hotspot and weekly thermal stress products has been achieved using HY-1C/D satellites. In 2024, with the inclusion of HY-1E satellite data, the global coral reef bleaching monitoring capability was further enhanced (Figure 17), offering a China-specific solution for global coral reef protection.

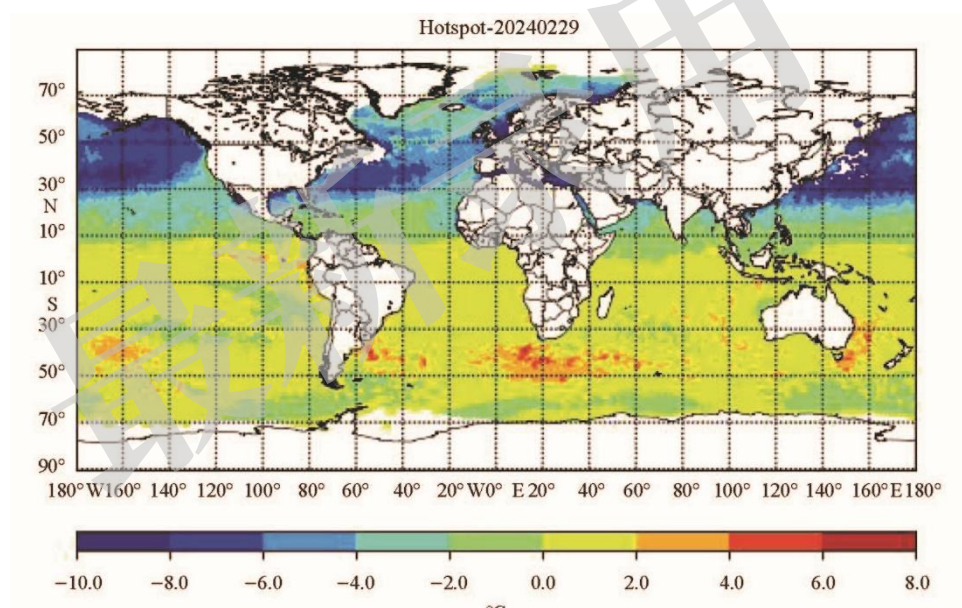


Figure 17 Global Hotspot Product of Coral Reef Bleaching

4.4 AI Large Model for Deep-Sea-Oriented Remote Sensing

With the exponential growth of ocean satellite data and its deep integration with artificial intelligence technology, China has successfully developed "Skyocean," an AI large model specifically for the ocean remote sensing domain. This represents a regional ocean AI large model that covers the entire chain from "remote sensing - reconstruction - prediction - digital twin," transforming ocean satellite observations from a "two-dimensional" perspective to a cognitive "three-dimensional" prediction.

It constitutes an "end-to-end" artificial intelligence ocean application platform (Figure18).

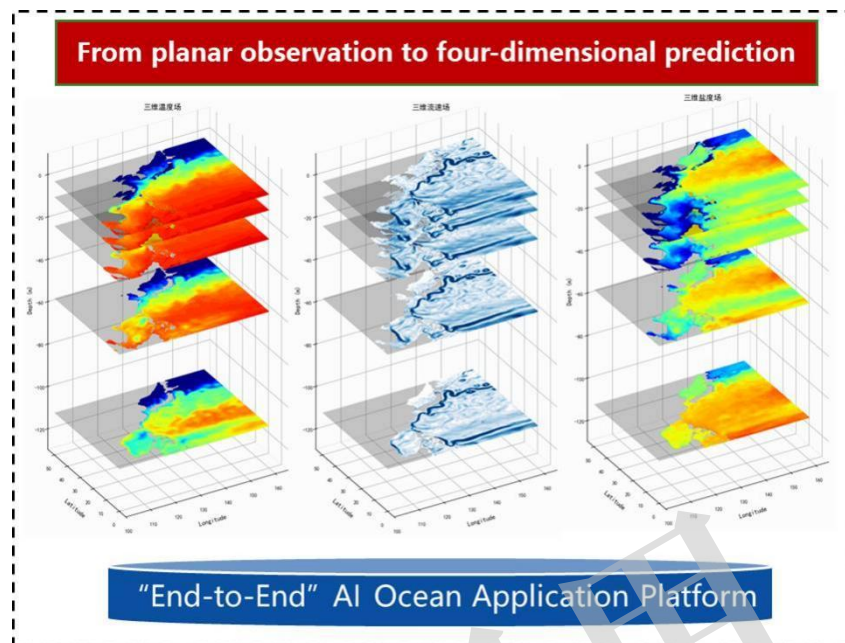


Figure 18 End-to-End AI Ocean Application Platform

5. Summary and Outlook

During the 14th Five-Year Plan period (2021–2025), China established an operational ocean satellite observation system comprising three major series: ocean color, marine dynamic environment, and marine surveillance and monitoring satellites. This achievement marks a historic transition for China's ocean satellites—from single-satellite experimentation to operational constellation networking. The constellations, consisting of the HY-1C/D/E, HY-2B/C/D, and GF-3 series, have respectively enabled high-frequency observation of ocean color and sea surface temperature, six-hour global coverage of dynamic environmental parameters (e.g., wind fields), and hourly revisits by Synthetic Aperture Radar (SAR) over key areas. The successful launch of the HY-4A satellite filled a critical technological gap by achieving, for the first time, active–passive microwave coordinated detection of sea surface salinity using an indigenously developed Chinese satellite. At the international level, continuous progress has been made in cooperation and applications based on ocean satellite data. China maintains operational data exchange with the European

Organisation for the Exploitation of Meteorological Satellites (EUMETSAT). Ocean color and dynamic environment data—including chlorophyll concentration, sea surface height, and wind fields—are now routinely assimilated into several European operational numerical prediction systems, demonstrating their international recognition and impact.

Technologically, a high-precision spaceborne sensing system covering the full spectrum was established, achieving a significant advance in payload performance. Breakthroughs were made in information extraction technology, progressing from algorithm development to integrated platforms. Notably, the successful development of the "Skyocean" AI large model for deep-sea remote sensing has fundamentally expanded space-based ocean observation from two-dimensional sea surface sensing to three-dimensional perception of the deep ocean, forming a complete technological chain from data acquisition to intelligent cognition. In terms of application, the system has comprehensively supported marine environmental monitoring, disaster prevention and mitigation, and global change research, playing a key role in emergency response to disasters such as green tides and typhoons. Through cooperation mechanisms such as the China-ASEAN and China-Africa initiatives, it continues to provide "China's solutions" and data support for global ocean governance.

However, gaps remain in China's ocean satellite system and its technological applications. The observation system remains predominantly focused on two-dimensional sea surface parameters, with a notable lack of capability for three-dimensional vertical profiling of the water column. The performance of certain core payload indicators still requires improvement. Remote sensing inversion algorithms show limited adaptability in complex marine environments—such as coastal turbid waters and extreme sea states—and the engineering application of advanced algorithms needs to be strengthened. The integration of AI technologies with ocean remote sensing is still in its early stages, with insufficient capacity for intelligent processing of massive satellite data and an incomplete chain for transforming data into intelligent decision-making. Furthermore, the standardization and systematic nature of the data calibration and validation system need to be

enhanced.

Looking ahead, the development of ocean satellites will focus on breakthroughs in novel detection technologies, including space–ground collaboration and lidar, aiming to acquire information on extreme marine environments and achieve stereoscopic observation of the ocean's vertical profile. Efforts will be directed toward deepening full-chain intelligent applications to build integrated capabilities from perception to decision-making. The next-generation satellite constellation system will be optimized to enhance observation efficiency for specific processes and targets. In addition, the international standardization and sharing of data products will be strengthened to provide critical data and scientific support for global climate research, ocean forecasting, and sustainable development.

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