



A 1-km weekly dataset of floating *Ulva prolifera* and *Sargassum horneri* blooms in China's marginal seas derived from multi-sensor satellite observations

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Abstract. Floating macroalgae blooms, primarily caused by *Ulva prolifera* and *Sargassum horneri*, frequently occur in the marginal seas around China, posing significant ecological and economic challenges. However, a long-term, high-frequency monitoring dataset capable of capturing bloom seasonality, interannual variability, and rapid transport dynamics across multiple sea regions remains limited. In this study, we derived 1-km weekly mean *U. prolifera* and *S. horneri* dataset covering 2018 to 2025, generated from 85,868 multi-sensor satellite images acquired from the Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), and Ocean and Land Colour Instrument (OLCI). By integrating complementary observations from multiple satellite sensors, the dataset substantially improves temporal continuity and observation availability relative to single-sensor products, enabling more complete characterization of rapidly evolving macroalgal blooms. A two-step deep learning-based approach was employed to detect and distinguish *U. prolifera* and *S. horneri*, achieving >90% accuracy for both bloom extraction and species classification across sensors. Independent validation using hyperspectral Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) Ocean Color Instrument (OCI) and Sentinel-2 MultiSpectral Instrument (MSI) data further supports the reliability of species discrimination. The pair-wise cross-sensor biomass comparisons show strong consistency, with $R^2 > 0.8$ for both species. The dataset reveals distinct spatiotemporal patterns of the two macroalgal species. *U. prolifera* blooms in the Yellow Sea exhibit a relatively consistent seasonal cycle from May to August, with rapid aggregation and dissipation and the highest biomass recorded in 2021, whereas *S. horneri* shows a broader and more variable distribution across the East China Sea, with record-high biomass observed in 2024. Weekly observations further resolve rapid bloom aggregation, transport, and dissipation processes that are difficult to capture using monthly composites. Weekly products provide a balance between temporal resolution and observational completeness, preserving short-term bloom variability while supporting consistent interannual comparisons. Compared with



weekly products, monthly composites underestimated seasonal peak biomass by 24–50% for *S. horneri* and 12–52% for *U. prolifera* during 2018–2025. In contrast, daily products were more sensitive to short-term biomass fluctuations, which could alter the identification of the year with the highest boom intensity, highlighting the importance of temporal aggregation for robust interannual comparisons. Comparisons with previous studies and reported bloom events demonstrate that the dataset reliably reproduces observed spatial distributions and seasonal characteristics. By providing a high-resolution, weekly, and species-resolved dataset of floating macroalgae, this study offers a consistent observational foundation for investigating species-specific bloom dynamics, assessing their responses to environmental variability, and enabling data-driven management and early warning of macroalgal blooms in China’s marginal seas.

1 Introduction

Floating macroalgae are important primary producers in the surface ocean and provide ecological benefits to a wide range of marine organisms (Krause-Jensen and Duarte, 2016; Ortega et al., 2019). However, massive blooms, especially those caused by *Ulva prolifera* and *Sargassum horneri*, have emerged as recurring ecological and socioeconomic challenges in the marginal seas surrounding China. The rapid proliferation of these floating macroalgae blooms, often referred to as “green tides” and “golden tides”, disrupt coastal ecosystems, deteriorate water quality, damage fisheries and aquaculture infrastructure, and impose substantial cleanup costs on local governments (Chen et al., 2022; Liu et al., 2018; Park et al., 2024; Qi et al., 2025; Smetacek and Zingone, 2013; Xiao et al., 2021). In particular, the annual *U. prolifera* bloom in the Yellow Sea has grown to be the world’s largest green tide (Liu et al., 2009, 2013; Xing et al., 2015), while episodic *S. horneri* events in the East China Sea have become more prominent in recent years (Qi et al., 2022, 2017; Z. Wang et al., 2023). The occurrence and intensity of these blooms are strongly influenced by ongoing environmental changes in coastal China, including warming temperatures, eutrophication from aquaculture, and increased riverine nutrient inputs (F. Wang et al., 2023; Wang et al., 2020, 2021). Therefore, long-term observations capable of resolving bloom seasonality, interannual variability, and transport-driven redistribution are essential for understanding bloom dynamics and supporting effective monitoring and management.

Satellite remote sensing provides a powerful tool for long-term large-scale monitoring of floating macroalgae blooms, offering consistent observation across space and time. Most previous studies have relied on single-sensor imagery from sensors such as Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), or Geostationary Ocean Color Imager (GOCI) to map bloom extents and analyse seasonal patterns (Hu et al., 2023a; Jin et al., 2018; Qi et al., 2017, 2016; Wei and Wang, 2024). However, such approaches are limited by frequent cloud and sun glint contamination, resulting in inconsistent temporal coverage (Feng and Hu, 2016; Feng and Wang, 2024; Liu et al., 2024). Moreover, few studies have provided a unified assessment across multiple seas and bloom types, leaving key questions about the long-term dynamics and geographical expansion of these blooms unanswered. In addition, many existing products (Gao et al., 2022; Pan et al., 2024; Qi et al., 2022) rely on daily observations or monthly composites. Daily observations frequently



suffer from substantial data gaps in cloudy coastal regions, whereas monthly composites may smooth short-lived bloom events and fail to capture rapid aggregation, dispersal, and peak biomass development. Integrating multi-sensor satellite observations offers an opportunity to overcome these limitations by improving temporal continuity and enabling weekly mapping of different macroalgal bloom distributions across multiple regions.

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Recent advances in multi-sensor data fusion and deep learning provide new opportunities for high-frequency, long-term monitoring of floating macroalgae blooms. The complementary observation capabilities of ocean color sensors, including MODIS, VIIRS, and the Ocean and Land Colour Instrument (OLCI), enable improved observation availability and cross-sensor consistency compared with individual satellite products (Hu et al., 2023b; Sun et al., 2024; Liu et al., 2026a).

75 Meanwhile, attention-based deep learning approaches have demonstrated increasing capability for extracting floating macroalgal features, estimating biomass, and distinguishing different bloom-forming species. Emerging high-resolution imagery, such as Sentinel-2 MultiSpectral Instrument (MSI) and GaoFen satellites, together with hyperspectral observations from the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) Ocean Color Instrument (OCI) provides independent spectral evidence to validate species identification, increasing confidence in the satellite-derived bloom maps (Feng et al., 2025; Qi et al., 2026; Zhang et al., 2025). An overview of the spatial distribution of floating macroalgae in China's marginal seas, together with representative satellite observations and spectral signatures, is shown in **Figure 1** and **Figure S1**. These developments enable the construction of weekly, 1-km resolution maps, which resolve rapid bloom dynamics and transport pathways previously undetectable in monthly or single-day products.

85 Despite advances in satellite monitoring and deep learning, long-term, high-frequency analyses of *U. prolifera* and *S. horneri* blooms across China's marginal seas remain limited. Existing observations are often constrained by short temporal coverage, dependence on individual sensors, or analyses focused on isolated bloom events and specific regions. Consequently, several important data gaps include: (1) the lack of long-term, high-frequency observations needed to resolve seasonal recurrence and interannual variability across multiple marginal seas; (2) the limited capabilities of existing monthly or single-day products to robustly capture peak biomass events and extreme years; and (3) insufficient observations for resolving rapid bloom aggregations, transport pathways, and dispersal processes that govern bloom evolution at weekly timescales.

90 To address these gaps, we developed a 1-km weekly dataset of floating macroalgae blooms in the Yellow Sea, East China Sea, and South China Sea from 2018 to 2025. This dataset integrates observations from 85,868 satellite images acquired from MODIS, VIIRS, and OLCI sensors, and applies a two-step deep learning-based framework for bloom detection and classification. By combining complementary satellite observations, this dataset improves temporal continuity, reduces cloud-related observation gaps, and enables consistent weekly mean characterization of bloom occurrence, intensity, and spatial extent across diverse oceanographic settings. The objectives of our study are threefold: (1) to assess the seasonal, interannual,



and spatial variability of *U. prolifera* and *S. horneri* blooms in the seas around China; (2) to examine the expansion of bloom
 100 footprints over time; and (3) to explore the large-scale transport processes influencing bloom distributions.

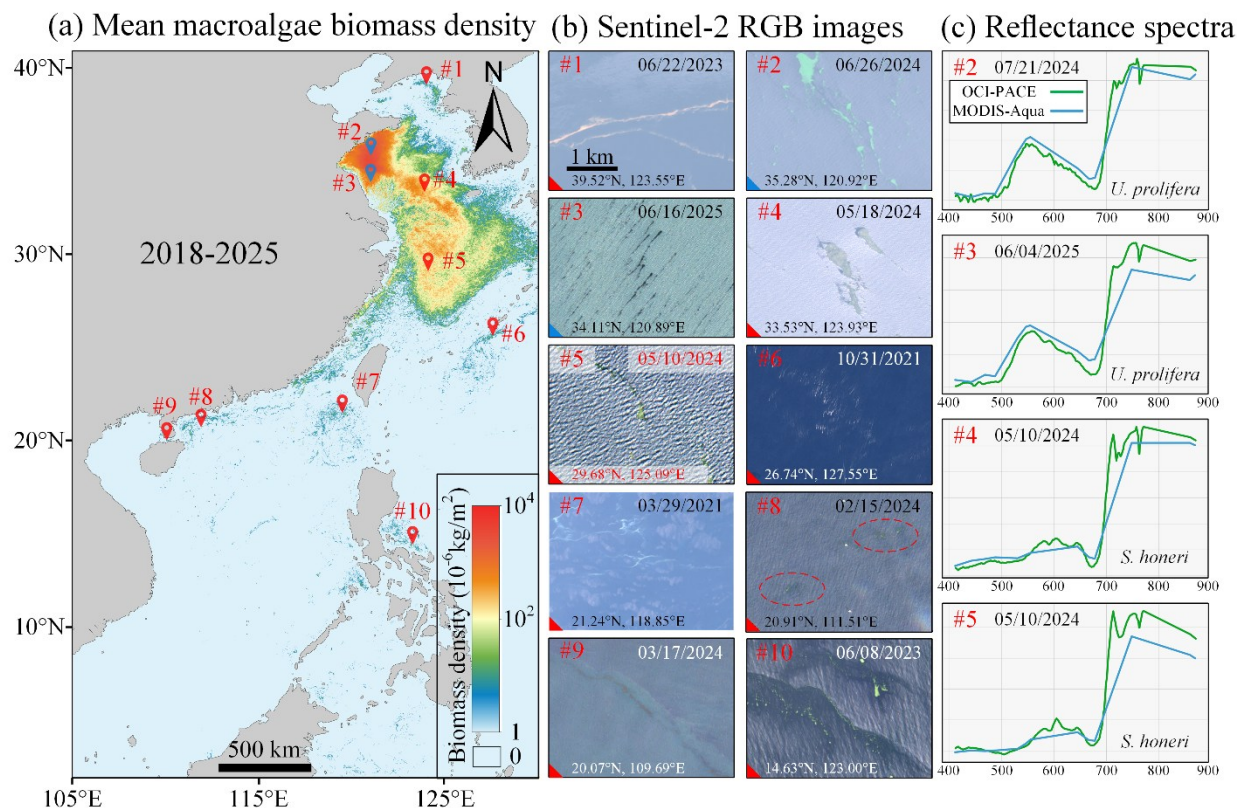


Figure 1. Spatial distribution and representative observations of floating macroalgae in China's marginal seas (2018–2025). (a) Spatial distribution of floating macroalgae. (b) Sentinel-2 RGB images showing macroalgae at ten representative locations (#1–#10). (c) Spectral reflectance of macroalgae observed at locations #2, #3, #4, and #5 from OCI-PACE and MODIS-Aqua.

105 2 Data and methods

2.1 Data preparations

2.1.1 Study region and satellite data

In this study, three types of medium-resolution multispectral sensors, including MODIS, VIIRS, and OLCI, were used to monitor macroalgae dynamics in China's marginal seas (2°–41°N, 105°–130°E). A total of 117,738 Level-0 images were
 110 obtained from the NASA Goddard Space Flight Center Ocean Color website (<http://oceancolor.gsfc.nasa.gov>). The dataset includes images from multiple satellite sensors: MODIS onboard Aqua and Terra, VIIRS onboard Suomi National Polar-orbiting Partnership (SNPP) and NOAA-20, and OLCI onboard Sentinel-3A (S3A) and Sentinel-3B (S3B).



To provide independent spectral evidence for species discrimination, hyperspectral observations from the PACE mission were additionally employed. PACE offers dense spectral sampling with daily global coverage at 1-km resolution, enabling robust differentiation between *U. prolifera* and *S. horneri*. A total of 3,490 PACE images from May 2024 to September 2025 were used to validate the species separation results and to identify and exclude *Trichodesmium* occurrences in the South China Sea.

Additionally, a total of 11,296 high-resolution Sentinel-2 (S2) MSI images were selectively obtained from the Google Earth Engine (GEE) platform to visually identify dominant macroalgal species in representative regions and periods. While Sentinel-2 provides fine spatial detail, its limited revisit frequency, data volume, and spectral coverage constrain its applicability for large-scale, long-term monitoring.

Table 1. The number of multi-sensor satellite images used in this study.

Sensor-satellite	Number of images	Spatial resolution	Time period
MODIS Aqua	48,501	1 km	2003/01/01–2025/12/31
MODIS Terra	17,254		2018/01/01–2025/12/31
VIIRS SNPP	12,357		2018/01/01–2025/12/31
VIIRS NOAA-20	12,570		2018/01/01–2025/12/31
OLCI S3A	13,704		2018/01/01–2025/12/31
OLCI S3B	13,352		2018/05/15–2025/12/31
OCI PACE	3,490		2024/05/01–2025/09/30
MSI S2A/B/C	11,296	10 m	2018–2025(05/01–06/30)

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2.1.2 Preprocessing and cloud masking

All satellite imagery from MODIS, VIIRS, OLCI, and OCI were processed into Rayleigh-corrected reflectance (R_{rc}) to partially remove the atmospheric impact before floating macroalgae detection. The SeaWiFS Data Analysis System (SeaDAS, version 9.2.0) software was used with the standard atmospheric correction module (e.g., l2gen). Here partial atmospheric correction accounted for Rayleigh scattering of air molecules was used for the complexity of accurate correction of complex coastal water environments.

For Sentinel-2 MSI imagery, Level-1C top-of-atmosphere reflectance data from the GEE collection ('COPERNICUS/S2') were used directly without Rayleigh correction. This is because Sentinel-2 data in this study were primarily used for high-resolution visual interpretation and species discrimination of floating macroalgae rather than for quantitative biomass retrieval.

The R_{rc} products were projected onto a 1-km spatial grid using an equidistant rectangular coordinate system to ensure spatial consistency across sensors. Based on the corresponding R_{rc} spectral bands, the Floating Algae Index (FAI) and the Alternative Floating Algae Index (AFAI) were subsequently calculated at the pixel level, using the equations detailed below:



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$$FAI = R_{rc,NIR} - R'_{rc,NIR} \quad (1)$$

$$R_{rc,NIR} = R_{rc,RED} + (R_{rc,SWIR} - R_{rc,RED})(\lambda_{NIR} - \lambda_{RED}) / (\lambda_{SWIR} - \lambda_{RED})$$

where the $R_{rc,\lambda}$ represents the R_{rc} data of band λ and the λ_{RED} , λ_{NIR} (NIR, Near-Infrared), and λ_{SWIR} (SWIR, Shortwave-Infrared) correspond to the specific wavelengths of each sensor, as shown in **Table 2**.

$$AFAI = R_{rc,NIR} - R'_{rc,NIR} \quad (2)$$

$$R_{rc,NIR} = R_{rc,RED} + (R_{rc,LNIR} - R_{rc,RED})(\lambda_{NIR} - \lambda_{RED}) / (\lambda_{LNIR} - \lambda_{RED})$$

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where the $R_{rc,\lambda}$ represents the R_{rc} data of band λ and the λ_{RED} , λ_{NIR} , and λ_{LNIR} (LNIR, long NIR) correspond to the specific wavelengths of each sensor, as shown in **Table 3**.

Table 2. Wavelength assignments for λ_{RED} , λ_{NIR} and λ_{SWIR} used for FAI calculation across different sensors.

	MODIS Aqua	MODIS Terra	VIIRS NOAA-20	VIIRS SNPP	OLCI S3A	OLCI S3B
λ_{RED}	645 nm	645 nm	667 nm	671 nm	665 nm	665 nm
λ_{NIR}	859 nm	859 nm	868 nm	862 nm	865 nm	865 nm
λ_{SWIR}	1240 nm	1240 nm	1238 nm	1238 nm	1013 nm	1013 nm

Table 3. Wavelength assignments for λ_{RED} , λ_{NIR} and λ_{LNIR} used for AFAI calculation across different sensors.

	MODIS Aqua	MODIS Terra	VIIRS NOAA-20	VIIRS SNPP	OLCI S3A	OLCI S3B
λ_{RED}	667nm	667 nm	667 nm	671 nm	665 nm	665 nm
λ_{NIR}	748 nm	748 nm	746 nm	745 nm	754 nm	754 nm
λ_{LNIR}	869 nm	869 nm	868 nm	862 nm	865 nm	865 nm

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Cloud and sun glint masking: The threshold-based CLDICE cloud mask product provided by SeaDAS often suffers from omission of cloud edges and shadows, as well as misclassification of valid observations, which may hinder the reliable detection and quantification of macroalgae. Sensor-specific FANet-based models were trained and employed to accurately identify and mask invalid observations, including clouds, cloud shadows, and strong sun glint, thereby ensuring the reliability of subsequent analyses (Liu et al., 2026a).

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2.1.3 Environmental data

To investigate the environmental drivers and transport pathways of macroalgal blooms in China's marginal seas, a monthly ancillary dataset was compiled, including sea surface temperature (SST, °C), photosynthetically active radiation (PAR, $\text{einstein} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$), surface winds (m/s), and surface ocean currents (m/s) during 2018–2025.

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SST fields were sourced from the NOAA Optimum Interpolation Sea Surface Temperature V2 High Resolution dataset (<https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html>), a globally gridded climate data record that blends satellite, ship, buoy, and other in situ measurements into a continuous 0.25° analysis through an optimal interpolation approach. SST



165 anomalies were calculated by subtracting the multi-year monthly climatology from the corresponding monthly SST at each grid cell to highlight departures from typical seasonal conditions.

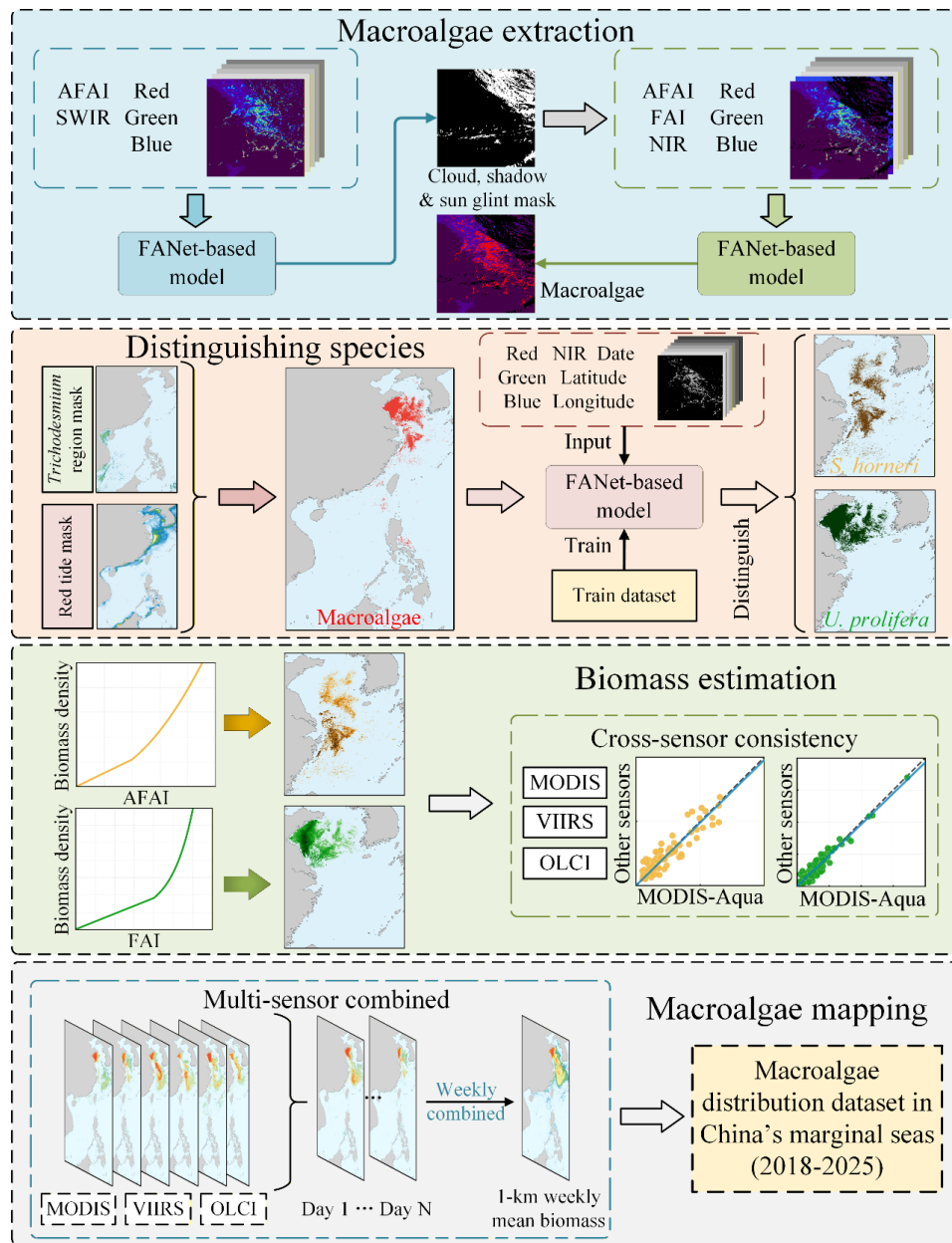
PAR data were obtained from the NASA Ocean Biology Processing Group's Level-3 PAR products, which estimate the photosynthetically active radiation reaching the sea surface in the 400-700 nm spectral range by upscaling satellite-derived
170 radiances from ocean color sensors. These monthly PAR composites (~4 km native resolution) were regridded to a 0.25° grid to ensure spatial consistency with the SST dataset.

Surface ocean currents were obtained from the HYCOM global ocean reanalysis system (<https://www.hycom.org/>). To ensure continuous temporal coverage for the numerical particle tracking experiments, three HYCOM product versions spanning
175 2018–2025 were used (details in **Table S1**). All datasets provide daily global surface currents at a native spatial resolution of ~0.08°. For consistency within the tracking framework, the currents were regridded onto a uniform 0.04° grid. These reprocessed surface currents served as the primary dynamical forcing for simulating macroalgal transport pathways.

Surface wind fields were sourced from the NCEP/NCAR Reanalysis
180 (<https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.html>), which provides monthly global surface winds at 2.5° resolution for 2018–2025. To ensure consistency with the current fields and the particle tracking experiments, the wind data were resampled to a 0.04° spatial grid. The wind forcing was incorporated to assess wind-driven drift and surface dispersion effects on macroalgal transport.

185 2.2 Floating macroalgae detection, classification, and quantification

The overall workflow for floating macroalgae mapping in China's marginal seas is illustrated in **Figure 2**, including macroalgae extraction, species classification, biomass estimation with multi-sensor consistency correction, and macroalgae distribution mapping. Details of each step are described in the following sections.



190 **Figure 2. The workflow for constructing the floating macroalgae distribution dataset in China's marginal seas, including macroalgae extraction, species classification, biomass estimation, and macroalgae mapping.**



2.2.1 Floating macroalgae detection

In this study, floating macroalgae were detected using a deep learning model named Feedback Attention Network (FANet). FANet adopts an encoder-decoder architecture that integrates residual blocks, Squeeze-and-Excitation layers, and attention mechanisms to enhance feature representation and suppress background noise (Tomar et al., 2022). An iterative feedback strategy is implemented, where the predicted mask from the previous epoch is used to refine current features, making it well-suited for detecting morphologically complex and highly dynamic macroalgal features. This network has demonstrated strong generalization capability for *Sargassum* extraction in the Atlantic Ocean and robust performance across multiple sensors (Sun et al., 2024).

To address the severe class imbalance between algae-covered and non-algae pixels, a biomass-weighted loss function was adopted following Liu et al. (2026b). This loss function prioritizes the learning of algal features within specific spectral index ranges and enhances the discrimination against spectrally similar noise, thereby improving detection performance under complex environmental conditions.

MODIS Aqua and Terra, as well as OLCI S3A and S3B, share similar spectral characteristics, so a unified model was trained for each sensor type. In contrast, VIIRS NOAA-20 and SNPP exhibit noticeable differences in spectral response and image quality, and separate models were trained accordingly. For all sensors, model inputs consisted of RGB bands, NIR reflectance, and the FAI and AFAI indices, allowing the network to jointly exploit spectral and index-based information relevant to floating macroalgae detection.

A total of 98 MODIS images, 213 OLCI images, 122 VIIRS NOAA-20 images, and 63 VIIRS SNPP images were used for model training and validation. These macroalgal samples are geographically and ecologically representative, spanning China's marginal seas and covering diverse atmospheric and illumination conditions as well as multiple bloom developmental stages. All images and their corresponding ground truth annotation images were cropped into 256×256 pixel patches. Only patches containing more than 200 valid pixels (water or algae) were included in the datasets. Data augmentation techniques, such as rotation, were applied to algae-containing patches to increase sample diversity and improve model performance. For each model, 85% of the patches were used for training and 15% for validation. Details of datasets used in this study are summarized in Table 4.

Table 4. Number of patches used in training and validation datasets.

Model	Original images	Patch size	Training patches	Validation patches
MODIS	98	256×256	3,806	672
OLCI	213	256×256	5,317	938
VIIRS NOAA-20	122	256×256	5,631	994
VIIRS SNPP	63	256×256	3,574	631



The algae extraction model performance on different sensors was evaluated using 30 independent testing images selected for each model, covering various algal bloom stages and biomass intensities. The extracted floating macroalgae features were compared with the corresponding ground truth annotations. Quantitative assessment was conducted using standard evaluation metrics, including Precision, Recall, F1-score, and Intersection over Union (IoU), defined as follows:

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \quad (4)$$

$$F1 \text{ score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \quad (5)$$

$$IoU = \frac{TP}{TP + FP + FN} \times 100\% \quad (6)$$

where true-positive (TP) indicates the number of correctly detected algae pixels, true-negative (TN) denotes the number of correctly detected water pixels, false-positive (FP) indicates the number of water pixels mistakenly classified as algae, and false-negative (FN) denotes the number of algae pixels mistakenly classified as water.

2.2.2 Classification of *U. prolifera* and *S. horneri* blooms

Distinguishing *U. prolifera* and *S. horneri* in medium-resolution multispectral satellite imagery remains challenging due to their similar spectral responses. In this study, species classification was ultimately performed using a deep learning-based classifier. To ensure reliable training labels, a multi-evidence constrained rule-based strategy was first employed to construct high-confidence species samples by integrating phenological, spatial, morphological, and spectral information. Specifically, these included temporal and spatial distribution patterns reported in the China Marine Ecological Bulletin, previous literature, high-resolution imagery, and hyperspectral reflectance data.

Phenological and spatial constraints were first applied based on long-term observations reported in the China Marine Ecological Bulletin and previous studies. Typically, *U. prolifera* blooms occur from May to August and are concentrated in the Yellow Sea (32°–38°N, 119°–125°E), whereas *S. horneri* blooms generally develop earlier, from February to June, and span a broader region extending from the Yellow Sea to the East China Sea (25°–37°N, 118°–130°E). At the spatial scale of MODIS, VIIRS, and OLCI imagery, the two bloom types are largely separated in both timing and geographic extent, enabling initial species attribution based on bloom seasonality and location.



High-resolution Sentinel-2 MSI imagery was further used to visually examine the morphology of floating macroalgae via RGB composites. In the East China Sea and adjacent waters, macroalgal patches consistently exhibited morphological features characteristic of *S. horneri*, such as elongated streaks or band-like aggregations aligned with surface currents and wind fields. In contrast, *U. prolifera* patches in the Yellow Sea generally appeared as more compact, irregularly shaped, and greenish aggregations, with relatively dense and clustered distributions. These spatial patterns are distinct from the irregular or fragmented shapes of other floating materials (e.g., debris or oil slicks), and in contrast to those materials, macroalgae also exhibit elevated signals in FAI imagery, further supporting reliable species identification.

Hyperspectral data from the PACE OCI provided independent spectral evidence for species discrimination. PACE offers daily global coverage at 1-km resolution with dense spectral sampling, enabling detailed analysis of macroalgal reflectance characteristics. Spectral reflectance curves extracted from representative bloom regions confirmed the presence of *S. horneri* in the East China Sea, while *U. prolifera* dominance in the Yellow Sea was verified through both hyperspectral signatures and phenological consistency.

Based on the above multi-evidence constraints, high-confidence samples of *U. prolifera* and *S. horneri* were constructed to train a deep learning classifier for automated species discrimination. Separate FANet-based models were trained for each sensor (MODIS, VIIRS, and OLCI). Model inputs included RGB and NIR bands, as well as longitude, latitude, and day-of-year to incorporate spatial and temporal constraints. Training samples were generated from previously selected rule-based observations, with 85% used for training and 15% for validation (**Table 5**). Data from 2019, 2021, and 2024, covering the full bloom season, were used for model training, while 2023 observations were reserved for independent testing of classification accuracy. The resulting models integrate spectral, spatial, and temporal information to effectively distinguish the two macroalgal species across different sensors.

Table 5. Number of patches used in training and validation datasets.

Model	Original images	Patch size	Training patches	Validation patches
MODIS	1,290	256 × 256	6,324	1,116
OLCI	1,046	256 × 256	5,236	924
VIIRS	2,036	256 × 256	10,619	1,875

In addition, PACE data also revealed the presence of *Trichodesmium* in the northern South China Sea and western Pacific. As *Trichodesmium* can also have strong NIR reflectance and form elongated algal slicks with strong AFAI and FAI signals, it can also be detected in medium-resolution imagery. These occurrences were identified and excluded based on their distinct hyperspectral reflectance patterns. Representative examples are provided in **Figures S2** and **S3**. In addition, harmful algal bloom (HAB) masks derived from CIE-based indices and deep learning products were applied to exclude nearshore high-AFAI signals associated with small-scale phytoplankton blooms, particularly in the Bohai Sea (Du et al., 2026).



2.2.3 Quantification of bloom intensity – biomass estimation

To quantify bloom intensity, species-specific biomass density models were applied for *S. horneri* and *U. prolifera*. For *S. horneri*, the AFAI-based biomass density model proposed by Wang et al. (2018), derived from field experiments, was employed. After background signal removal, the corrected AFAI values were used to estimate *S. horneri* biomass density (kg/m²) for MODIS Aqua. Multi-sensor biomass estimates were then harmonized by applying the species-specific model from Sun et al. (2024) to the corresponding AFAI values derived from each sensor.

For *U. prolifera*, biomass density was estimated using the FAI-based model developed by Hu et al. (2017), which converts MODIS Aqua FAI values to *U. prolifera* biomass (kg/m²) based on field and laboratory measurements. To extend this approach to other sensors, sensor-specific signal responses were simulated using field-measured data, sensor spectral response functions, and atmospheric radiative transfer modelling. The simulations were conducted under four representative scenarios, combining two aerosol types (maritime aerosols, m90; and coastal aerosols, c50) with two viewing geometries (near satellite nadir and near scan edge). The mean values derived from the four simulation scenarios were used to fit the inter-sensor relationships of FAI, thereby enabling the development of sensor-specific biomass estimation models.

2.2.4 Cross-sensor continuity

To enable consistent long-term and multi-sensor analysis of macroalgal biomass, sensor-specific estimates were harmonized to MODIS Aqua levels. A key prerequisite for cross-sensor comparison is that macroalgal patches remain spatially comparable within the time difference of satellite overpasses on the same day. In this study, the maximum overpass time difference between any two sensors used for regression was less than 5.5 h.

Overlapping observations from different sensors on the same day were identified, and a unified cloud mask derived from the union of both sensors' cloud masks was applied to ensure consistent spatial coverage. Biomass estimates from each sensor were then linearly regressed against those from MODIS Aqua, which served as the reference sensor. To reduce the influence of small-scale or weak bloom events, records with total biomass below 80,000 tons for *U. prolifera* and 50,000 tons for *S. horneri* were excluded prior to regression. Furthermore, to mitigate the impact of anomalous values, observations within the upper decile of absolute residuals were removed, as they exhibited substantial deviations and disproportionately influenced the regression results. The resulting empirical inter-sensor relationships were applied to adjust biomass estimates across sensors, enabling harmonized and consistent long-term datasets for subsequent analysis.



Statistics of surface currents over typical macroalgal distribution regions in the Yellow Sea and East China Sea show a maximum velocity of approximately 2.1 m/s, representing an extreme case observed for *S. horneri* in the East China Sea. In most macroalgal occurrence areas, surface current velocities are substantially lower than this value. Floating macroalgae drift more slowly than surface currents due to drag effects, with drifting speeds estimated at approximately 80% of the surface current velocity (Podlejski et al., 2023). Under this assumption, the maximum drifting speed is about 1.68 m/s, resulting in a potential drifting distance of approximately 33.3 km within 5.5 h. For *U. prolifera*, the drifting speed is typically much lower. For example, blooms originating from the Jiangsu Shoal were reported to drift into the Yellow Sea at an average velocity of approximately 0.28 m/s (Z. Wang et al., 2023b), which would correspond to a displacement of approximately 5.5 km over the same time interval.

However, to assess whether macroalgal drifting between satellite overpasses could influence the inter-sensor regression results, a sensitivity test was conducted by expanding the cloud masks to account for the potential displacement of algal patches during the observation interval. For *S. horneri*, the cloud masks were dilated by 34 km, corresponding to the estimated maximum drifting distance (≈ 33.3 km) within the 5.5 h time window. Similarly, for *U. prolifera*, the cloud masks were expanded by 6 km, consistent with the estimated drifting distance (≈ 5.5 km) over the same period. The expanded cloud masks were applied to both sensors prior to regression to represent a worst-case scenario of macroalgal drifting during the observation interval. The inter-sensor biomass regressions were then repeated using the expanded masks to evaluate whether macroalgal drifting could influence the regression relationships.

2.3 Spatiotemporal analysis

2.3.1 Generation of weekly mean composites

The availability of optical satellite observations is frequently constrained by cloud cover, cloud shadows, sun glint, and other atmospheric or surface interferences, resulting in substantial spatial and temporal data gaps. To mitigate these limitations, valid observations from multiple satellite sensors were combined to generate weekly mean composite products. For each 7-day window, all valid biomass estimates derived from individual sensors (after cross-sensor calibration) were aggregated to produce mean-value composite maps. Mean bloom intensity was calculated using the mean biomass density within the predefined 1-km $\times$ 1-km grid during the 7-day time period. This multi-sensor compositing strategy substantially improves spatial continuity and temporal coverage while reducing random noise associated with single-sensor observations (Hu et al., 2023a). Weekly mean biomass composites of *U. prolifera* and *S. horneri* were generated over China's marginal seas at a spatial resolution of 1-km to provide a consistent dataset for subsequent spatiotemporal analyses of bloom dynamics and transport-driven evolution.



345 2.3.2 Analyses of the bloom dynamics

Based on the weekly composite biomass maps, multiple metrics were derived to characterize the temporal dynamics of floating macroalgae blooms. Bloom extent was quantified as the total area exceeding a predefined biomass threshold. The threshold for each temporal composite was determined separately using the same criterion: the mean biomass plus two standard deviations ($\text{mean} + 2\sigma$) calculated from a non-bloom reference region where macroalgal events rarely occur. Accordingly, the
 350 derived thresholds were 142.05 kg/km², 63.75 kg/km², and 22.95 kg/km² for the weekly, bloom-period, and annual mean composites, respectively. To obtain a stable spatial representation of recurrent bloom presence, the bloom footprint was mapped based on the annual mean biomass distribution. The bloom peak was selected as the maximum total mean biomass intensity in the bloom region. For *U. prolifera* and *S. horneri*, these values were calculated separately and the peak bloom date is determined accordingly.

355 To characterize phenological variability, bloom onset and termination timings were identified for each year as the first and last weeks in which biomass exceeded the detection threshold over contiguous regions. These metrics enabled systematic comparison of interannual variability, seasonal progression, and long-term changes in bloom dynamics for *U. prolifera* and *S. horneri*.

360

2.3.3 Analyses of the bloom evolution pathways

To investigate the spatial evolution and transport pathways of floating macroalgae blooms, latitude-averaged and longitude-averaged biomass distributions were calculated from the weekly composite maps, forming Hovmöller-type diagrams that depict the progression, aggregation, and dispersal of blooms over time.

365

In addition, numerical particle tracking experiments were conducted to examine the transport pathways of *U. prolifera* and *S. horneri* in the Yellow Sea and East China Sea. Particle simulations were driven by daily surface currents from the HYCOM model and 1% of the surface wind fields from the NCEP/NCAR reanalysis. Initial particle distributions were seeded based on satellite-derived weekly mean biomass maps averaged over 2018–2025 peak bloom periods.

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The number of particles released within each grid cell was proportional to the local biomass density. Specifically, biomass density values were divided by a species-dependent scaling factor (0.001 for *U. prolifera* and 0.0001 for *S. horneri*) and rounded to the nearest integer to determine the particle count. Particles were then evenly positioned within each $0.1^\circ \times 0.1^\circ$ grid cell using regularly spaced longitude and latitude coordinates. All particles were initialized at 00:00 local time to ensure
 375 consistent temporal alignment. The current and wind fields used to drive the simulations were resampled to a spatial resolution of 0.04° , and particle trajectories were computed using a fourth-order Runge-Kutta scheme with an hourly time step.



The simulated transport pathways were compared with satellite-observed bloom evolution to assess consistency between physical transport patterns and observed macroalgal distributions. These simulations provided independent physical support for the inferred transport-driven evolution of blooms and helped corroborate species discrimination, particularly in regions where spatial overlap may occur.

Relevant literature and records from the China Marine Disaster Bulletin were also consulted to further support the interpretation of bloom evolution patterns.

3 Results

3.1 Macroalgae bloom extraction and classification accuracy on multi-sensor imagery

We first evaluated the performance of the FANet-based extraction and classification of floating macroalgae. Owing to differences in radiometric characteristics and image quality between VIIRS SNPP and NOAA-20, separate models were trained for the two VIIRS sensors, whereas a unified model was applied to MODIS and OLCI imagery. **Table 6** summarizes the biomass-weighted Precision, Recall, F1 score, and IoU, reflecting accuracy across varying bloom intensities. Overall, the models achieved high detection accuracy (F1 score: >90%), demonstrating its robustness across sensors and bloom conditions. Detailed species-specific extraction accuracies for *U. prolifera* and *S. horneri* are further provided in **Tables S2** and **S3**, respectively.

Table 6. Accuracy of FANet-based macroalgae extraction across MODIS, OLCI, VIIRS SNPP, and VIIRS NOAA-20.

Sensor	Precision	Recall	F1	IoU
MODIS	94.06%	94.96%	94.51%	89.59%
OLCI	90.96%	96.48%	93.64%	88.04%
VIIRS	93.35%	90.22%	91.76%	84.78%
VIIRS	91.16%	92.72%	91.93%	85.07%

Figure 3 illustrates representative samples of extraction results on different sensors and challenging conditions, highlighting the models' ability to accurately extract *U. prolifera* and *S. horneri* bloom pixels. These examples demonstrate that the models can consistently and accurately delineate macroalgae bloom pixels, even under complex conditions such as thin clouds, sun glint, striping noise, and turbid coastal waters, highlighting their robust performance across diverse environmental and observational scenarios. These results confirm that the models can reliably produce weekly high-resolution bloom maps suitable for long-term monitoring and cross-sensor comparisons.

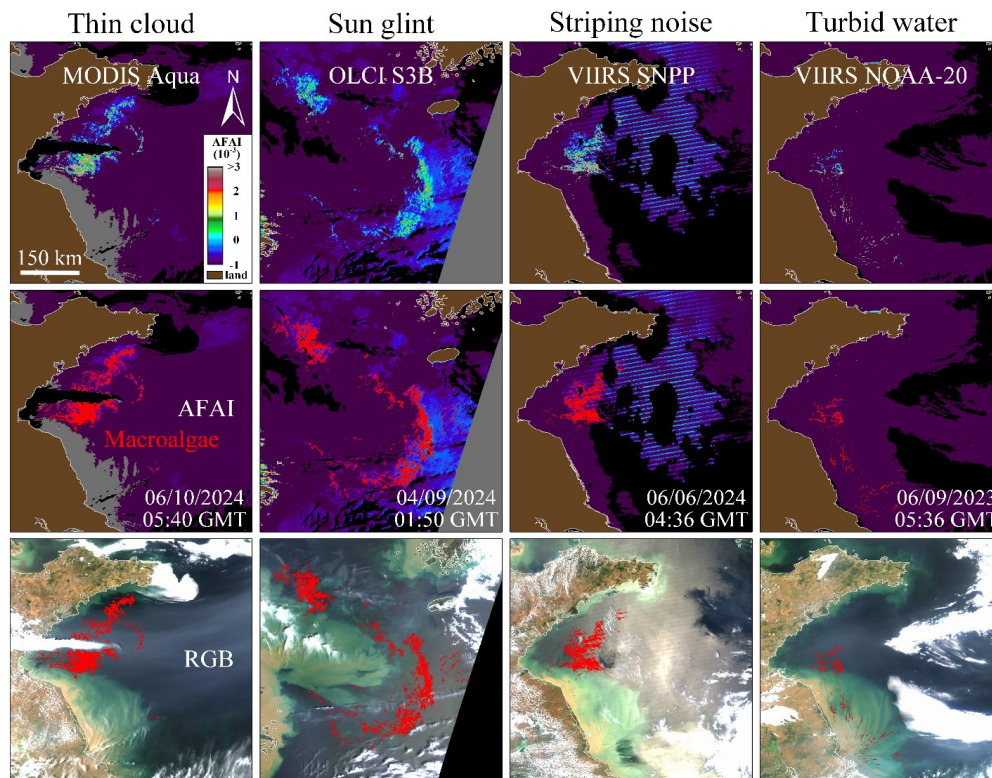


Figure 3. Performance of macroalgae extraction across different sensors. For MODIS, OLCI, VIIRS SNPP, and VIIRS NOAA-20, results under various environmental conditions, including thin clouds, sun glint, turbid waters, and striping noise, are shown. The first row displays AFAI images, the second and third rows show extraction results overlaid on AFAI and RGB images, respectively.

The *U. prolifera* and *S. horneri* classifier achieved high and balanced performance across sensors, with F1 scores exceeding 90% for both species (Tables 7 and 8), demonstrating stable discrimination capability under varying observational conditions in China’s marginal seas. Figure 4 further illustrates representative examples of species classification across different satellite sensors.

When applied to bloom pixels identified in the weekly composites, the deep learning–based classification showed high consistency with the rule-based species attribution derived from phenology, spatial distribution, high-resolution RGB morphology, and hyperspectral validation. More than 90% of bloom pixels exhibited consistent species labels between the two approaches, with discrepancies mainly occurring in transitional regions and under low-biomass conditions where spectral signals become weak and mixed.



420 These results provide independent quantitative support for the reliability of the species-resolved bloom maps. The agreement between the data-driven classifier and the multi-evidence rule-based attribution confirms that the identified *U. prolifera* and *S. horneri* distributions are physically and ecologically consistent, thereby ensuring the robustness of the subsequent analyses of regional bloom dynamics and transport pathways.

425 **Table 7. Classification accuracy of *U. prolifera* across MODIS, OLCI, and VIIRS sensors using the deep learning-based species classifier.**

Sensor	Precision	Recall	F1	IoU
MODIS	98.31%	96.19%	97.23%	94.62%
OLCI	97.63%	95.86%	96.74%	93.68%
VIIRS	99.52%	96.66%	98.07%	96.22%

Table 8. Classification accuracy of *S. horneri* across MODIS, OLCI, and VIIRS sensors using the deep learning-based species classifier.

Sensor	Precision	Recall	F1	IoU
MODIS	87.91%	94.39%	91.04%	83.55%
OLCI	92.38%	95.58%	93.95%	88.59%
VIIRS	85.71%	97.73%	91.32%	84.03%

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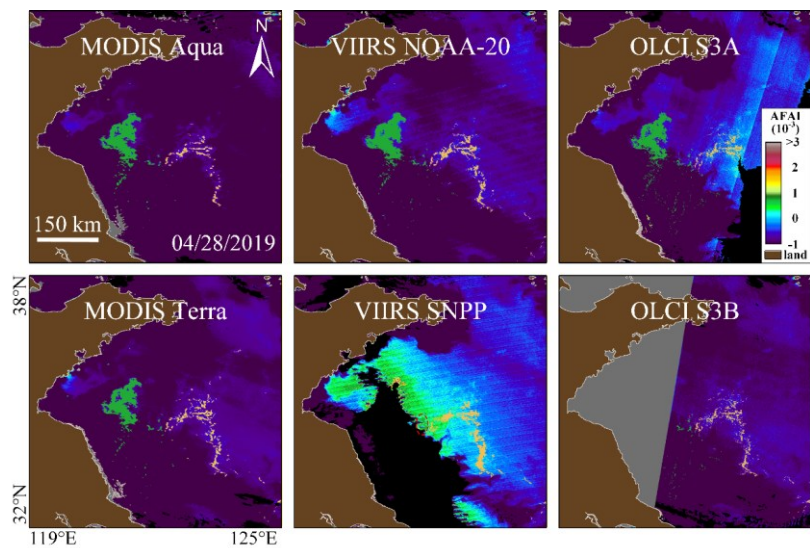


Figure 4. Performance of macroalgae species classification across different sensors. Green indicates *U. prolifera*, and yellow represents *S. horneri*.



3.2 Cross-sensor consistency of biomass estimates

To ensure comparability of multi-sensor observations, we compared daily biomass estimates among MODIS Aqua, MODIS Terra, VIIRS NOAA-20, VIIRS SNPP, OLCI S3A, and OLCI S3B (Figures 5 and 6). Scatter plots show strong agreement along the 1:1 line for both *U. prolifera* and *S. horneri* blooms, indicating that the extracted biomass is consistent across sensors. Figures S4 and S5 show the results of inter-sensor regressions after expanding cloud masks to account for potential macroalgal drifting. The slopes of the regressions changed minimally, indicating that drifting has negligible impact on sensor harmonization. This cross-sensor reliability allows the integration of multi-platform observations to produce continuous, high-frequency bloom maps from 2018 to 2025, overcoming individual sensor gaps due to cloud cover or low temporal resolution.

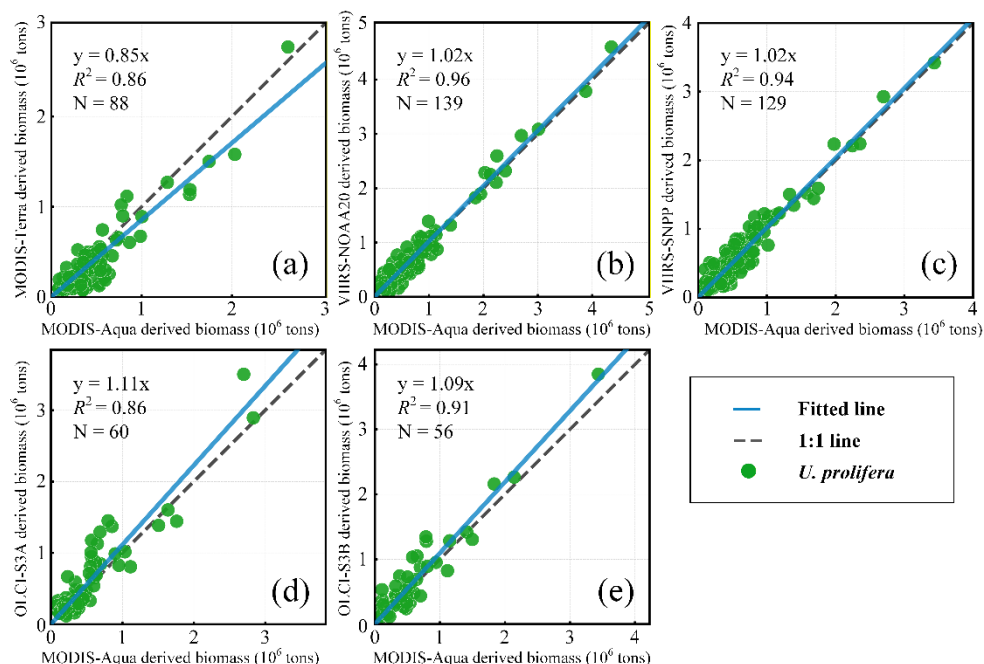
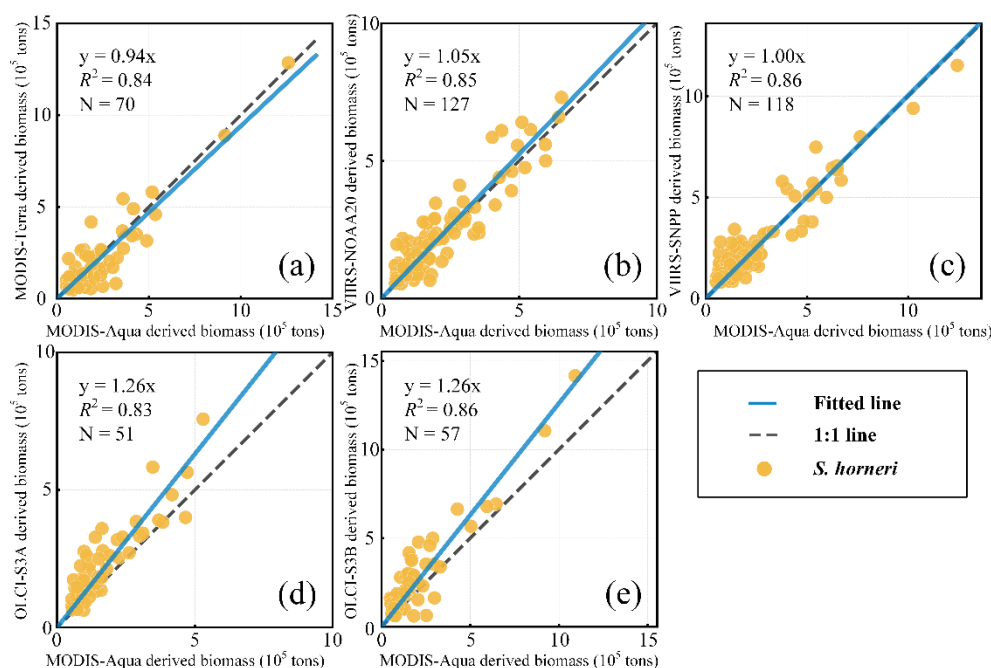


Figure 5. Scatter plots of daily satellite-derived *U. prolifera* biomass in Yellow Sea from MODIS-Aqua compared with MODIS Terra (a), VIIRS NOAA-20 (b), VIIRS SNPP (c), OLCI S3A (d), OLCI S3B (e). The dash lines represent 1:1 lines.



450 **Figure 6. Scatter plots of daily satellite-derived *S. horneri* biomass in Yellow Sea and East China Sea from MODIS-Aqua compared with MODIS Terra (a), VIIRS NOAA-20 (b), VIIRS SNPP (c), OLCI S3A (d), OLCI S3B (e). The dash lines represent 1:1 lines.**

3.3 Weekly mean macroalgal bloom distributions during 2018–2025

Using the validated macroalgae detection, species discrimination, and cross-sensor consistent biomass estimates, we generated 1-km weekly mean composite maps of floating macroalgae across China's marginal seas from 2018 to 2025. These products
 455 provide a spatially continuous and temporally consistent view of bloom occurrence, extent, and intensity, enabling systematic analysis of basin-scale distributions, regional characteristics, and interannual variability. Weekly compositing was selected as an effective temporal scale for characterizing macroalgal blooms by balancing short-term variability and interannual comparability. Monthly composites capture the overall seasonal progression of blooms but smooth transient biomass maxima, leading to reduced seasonal peak biomass estimates compared with weekly products (**Tables S4 and S5**). Conversely, daily
 460 observations preserve high-frequency variability but are more susceptible to short-lived biomass fluctuations, which may influence interannual comparisons of bloom intensity; for example, daily and weekly composites identified different peak years for *U. prolifera* during 2018–2025 (**Fig. S6**). Thus, weekly composites provide a consistent representation of bloom intensity and temporal evolution for long-term macroalgal bloom monitoring.

465 **Figure 7** compares the spatial footprints of floating macroalgal blooms in China's marginal seas during two periods (2003–2014 and 2015–2025), based on MODIS Aqua annual composite maps. The comparison is designed to assess decadal changes



in the distribution and spatial extent of macroalgal blooms. Regions highlighted in purple indicate areas where floating macroalgae were detected during 2015–2025 but were absent in the earlier period, representing newly expanded bloom footprints in the past decade.

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Overall, the spatial extent and intensity of macroalgal blooms during 2015–2025 are markedly greater than those observed in 2003–2014. In the Yellow Sea, *U. prolifera* blooms exhibit increased biomass density and broader spatial coverage, indicating intensified bloom activity in recent years. In contrast, *S. horneri* blooms in the East China Sea show pronounced spatial expansion, extending southward and offshore compared with the earlier period, suggesting a substantial escalation in bloom occurrence and persistence.

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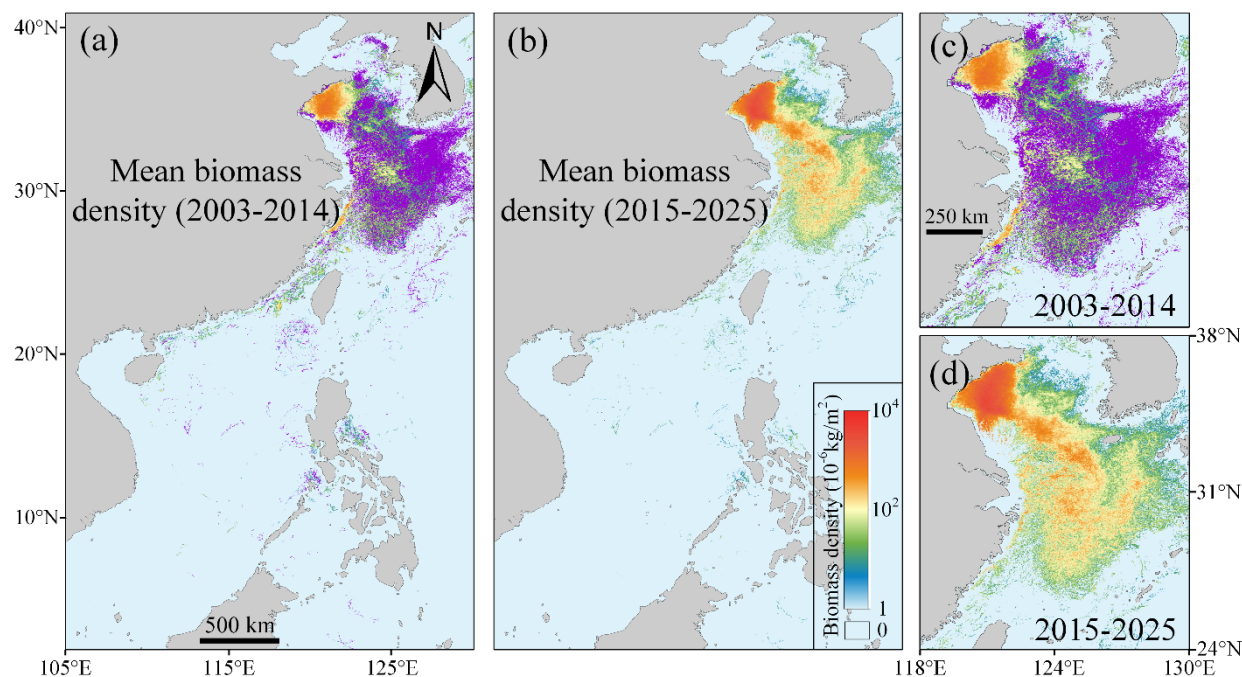


Figure 7. Mean biomass density distribution of floating macroalgae in China's marginal seas during (a) 2003–2014 and (b) 2015–2025, derived from MODIS Aqua observations. In subfigure (a) and (c), the purple areas denote regions where macroalgae were detected in 2015–2025 but not in 2003–2014.

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3.3.1 Weekly 1-km composite distributions of *U. prolifera* blooms in the Yellow Sea

In the Yellow Sea, *U. prolifera* blooms exhibit a pronounced seasonal cycle from mid-May to August, characterized by rapid growth, northward expansion, and subsequent dissipation. The multi-year weekly composites (**Figure 8**) reveal a consistent development pattern, with blooms initiating in the southern Yellow Sea in mid-May, followed by rapid growth, northward

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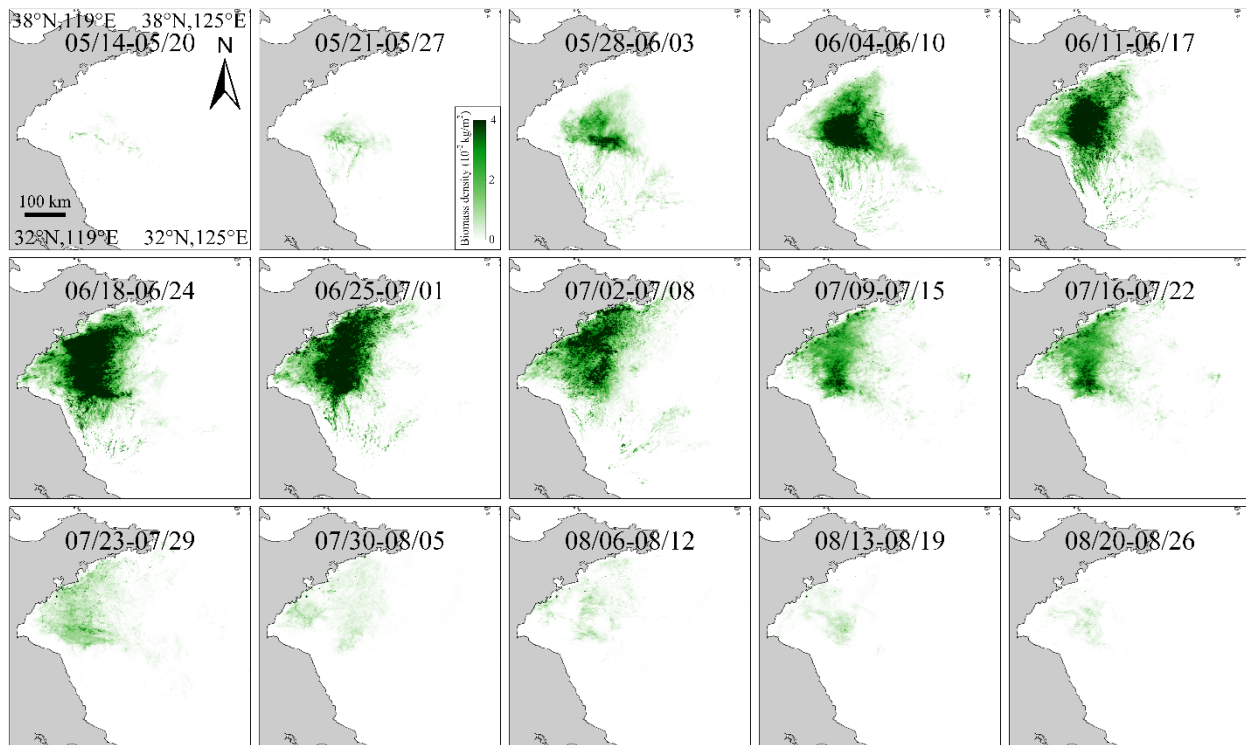


expansion, and spatial aggregation in June, and then transitioning to gradual decay in July and eventual dissipation by August. Weekly changes in *U. prolifera* distribution for each year from 2018 to 2025 are shown in **Figures S7–S14**.

490 The spatial distributions during the peak bloom week of each year (**Figure 9**) demonstrate substantial interannual variability in both extent and intensity, with particularly strong bloom conditions observed in 2021. Despite these differences, the timing of peak blooms remains relatively consistent, occurring predominantly in mid-June across most years. Notably, a slight delay in peak timing is evident in recent years, with peak weeks shifting toward late June. Year-to-year variations in peak-week biomass generally reflect the overall bloom season patterns, with higher peak-week biomass corresponding to larger cumulative extent and intensity (**Figure S15**).

495 Weekly biomass variations further highlight the temporal dynamics of bloom development (**Figure 10**), with a consistent rapid increase during the growth phase across all years. However, anomalous fluctuations are observed during peak bloom periods. These fluctuations correspond closely to reductions in the number of valid satellite observations, indicating that they are primarily caused by insufficient data coverage rather than actual biomass changes. As illustrated in **Figure S16**, persistent cloud coverage during these periods can substantially limit valid observations across all sensors, leading to biased biomass estimates. Although the integration of multi-sensor observations effectively mitigates the impacts of clouds and sun glint, extreme cases of widespread cloud cover can still introduce uncertainties in the weekly composites.

500 Overall, these results indicate that *U. prolifera* blooms in the Yellow Sea are highly dynamic, with consistent seasonal evolution but significant interannual variability, driven by the combined effects of environmental conditions and transport processes.



510 **Figure 8. Weekly mean distribution of *U. prolifera* in the Yellow Sea from mid-May to August.** Each weekly map represents the average biomass density over the corresponding week across 2018–2025.

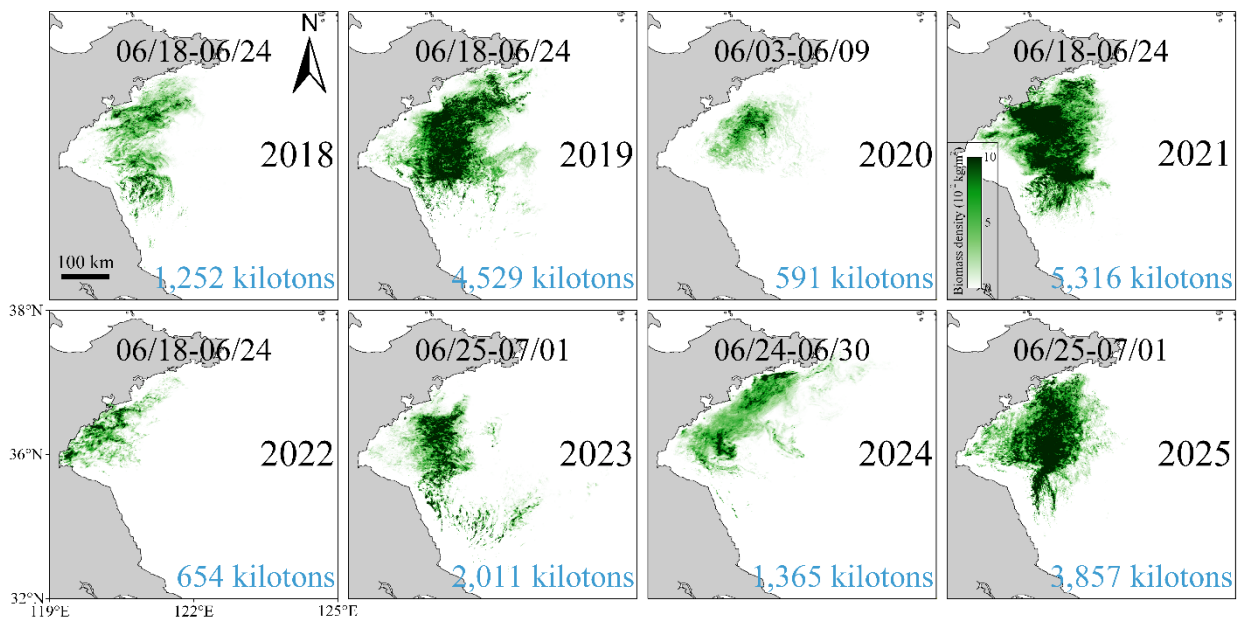




Figure 9. Weekly mean biomass density distribution of *U. prolifera* during the peak bloom week each year from 2018 to 2025 in the Yellow Sea. Black labels indicate the timing of the peak bloom, and blue labels denote the weekly mean biomass.

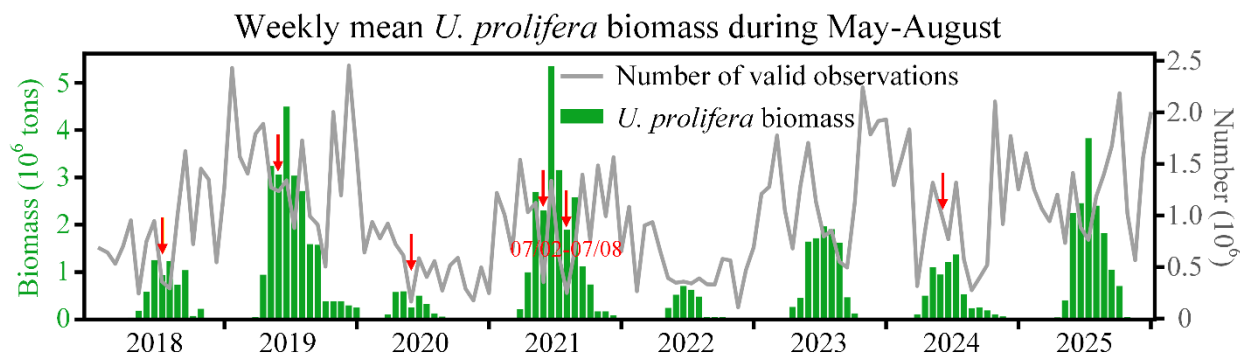


Figure 10. Weekly mean biomass of *U. prolifera* in the Yellow Sea from May to August and the number of valid satellite observations over the macroalgal footprints from 2018 to 2025. Bars represent the estimated macroalgal biomass, while lines denote the weekly count of valid observations within the detected bloom areas. Red arrows indicate anomalous biomass fluctuations during peak bloom periods.

3.3.2 Weekly 1-km composite distributions of *S. horneri* blooms in the East China Sea

In the East China Sea and Yellow Sea, *S. horneri* blooms display a longer and more spatially extensive seasonal cycle than *U. prolifera*, spanning February to June and covering broader areas across the East China Sea and southern Yellow Sea (Figure 11). Blooms typically initiate in early February, with biomass gradually increasing through February and March, reaching peak bloom conditions during April and May, and gradually declining in June. The week-to-week progression for each year from 2018 to 2025 is shown in Figures S17–S24.

The spatial distributions during the peak bloom week of each year (Figure 12) reveal substantial interannual variability in both biomass magnitude and timing. Record-high biomass was observed in 2024, representing a pronounced increase relative to previous years. Peak-week biomass varies markedly between years, with the smallest value in 2025, highlighting the episodic nature of *S. horneri* blooms. The timing of the peak bloom week is less consistent than for *U. prolifera*, with peak occurrences spread across February to May, reflecting the more variable phenology of *S. horneri*. Overall, year-to-year variations in peak-week biomass are generally consistent with the full bloom-season patterns, with years exhibiting higher peak-week biomass also showing larger cumulative extent and intensity (Figure S25).

Weekly biomass variations further highlight the temporal dynamics of *S. horneri* development (Figure 13), showing substantial interannual differences in the timing and progression of growth phases. Anomalous fluctuations frequently occur during bloom periods, generally coinciding with reductions in the number of valid satellite observations (Figure S26).



Compared with *U. prolifera*, *S. horneri* is more affected by these observational limitations due to its broader spatial distribution,
 540 resulting in anomalous biomass fluctuations almost every year despite multi-sensor integration.

Overall, these results indicate that *S. horneri* blooms are highly dynamic, with less predictable seasonal timing, greater spatial
 variability, and pronounced interannual differences in both biomass and distribution, driven by complex interactions of
 environmental conditions, transport processes, and observational limitations.

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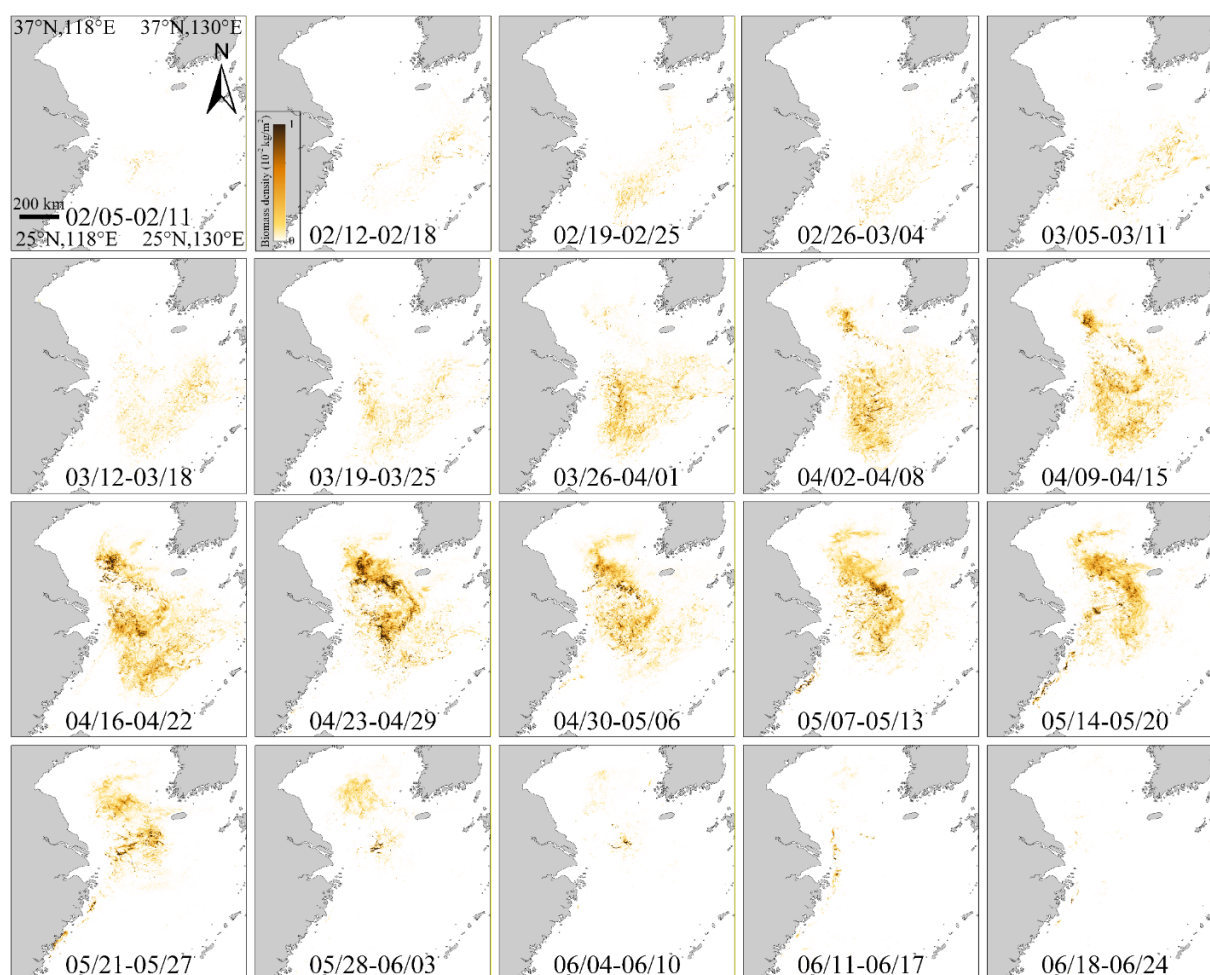


Figure 11. Weekly mean distribution of *S. horneri* in the East China Sea and Yellow Sea from February to June. Each weekly map represents the average biomass density over the corresponding week across 2018–2025.

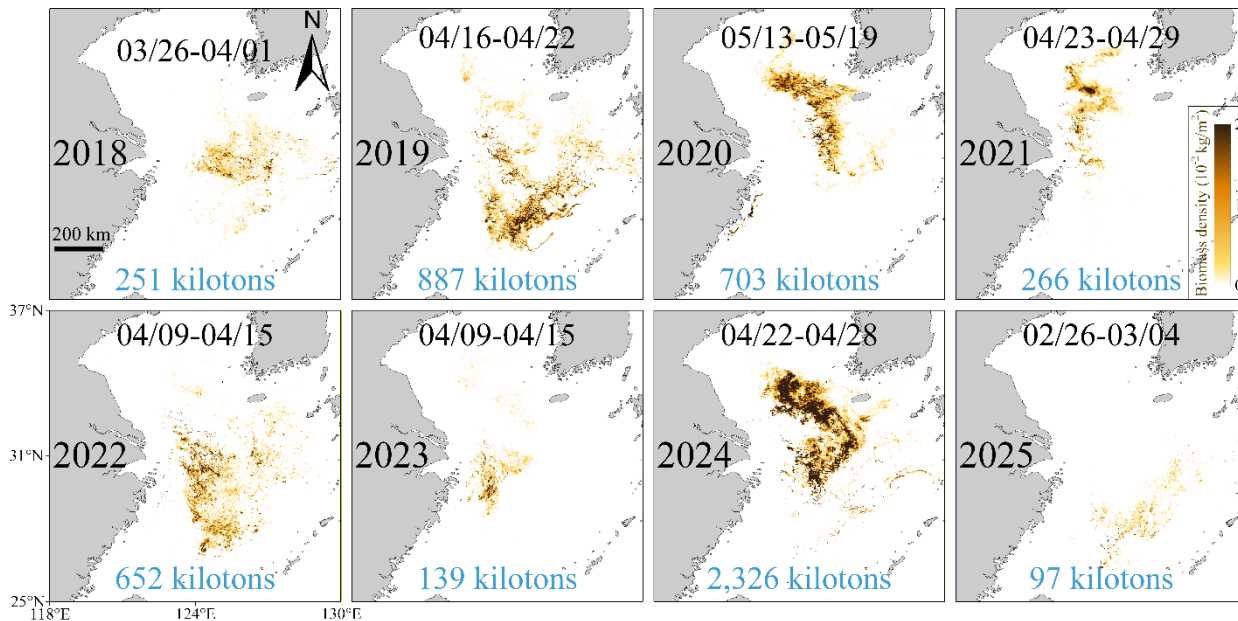


Figure 12. Weekly mean biomass density distribution of *S. horneri* during the peak bloom week each year from 2018 to 2025 in the East China Sea and Yellow Sea. Black labels indicate the timing of the peak bloom, and blue labels denote the weekly mean biomass.

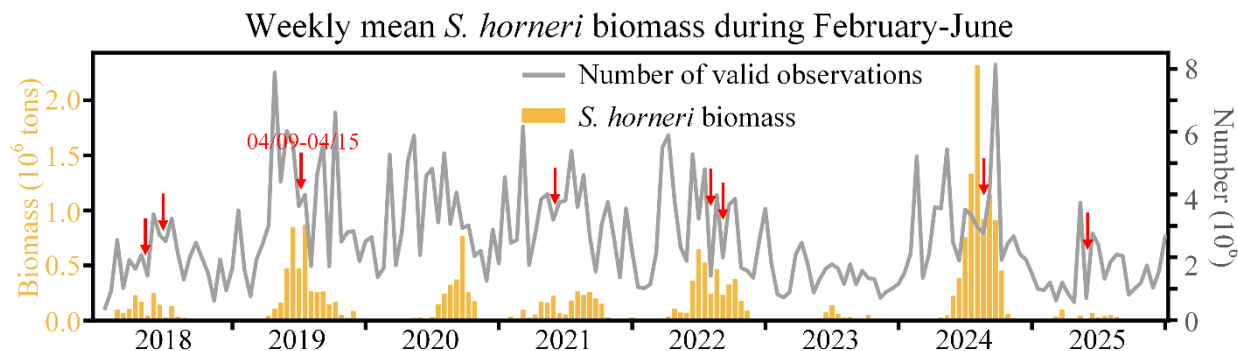


Figure 13. Weekly mean biomass of *S. horneri* biomass in the Yellow Sea and East China Sea from February to June and the number of valid satellite observations over the macroalgal footprints from 2018 to 2025. Bars represent the estimated macroalgal biomass, while lines denote the weekly count of valid observations within the detected bloom areas. Red arrows indicate anomalous biomass fluctuations during peak bloom periods.

3.3.3 Seasonal timing and peak-week dynamics of *U. prolifera* and *S. horneri*

The seasonal timing and peak-week dynamics of *U. prolifera* and *S. horneri* during 2018–2025 are illustrated in **Figure 14**. The growth period of *U. prolifera* typically begins in mid-to-late May and lasts until late July or early August, showing



relatively small interannual variations in start and end dates. In contrast, *S. horneri* starts its growth period earlier, usually in February, and extends until June, with greater year-to-year variability. Peak-week timing also differs between the two species: *U. prolifera* reaches its peak biomass predominantly in June, reflecting a stable and predictable maximum bloom period. *S. horneri* peak weeks are more dispersed between March and May, with the 2024 peak markedly higher than other years and the 2025 peak notably lower. Overall, *U. prolifera* exhibits a relatively consistent seasonal pattern in both growth period and peak timing, whereas *S. horneri* displays stronger interannual variability, likely influenced by environmental conditions and transport processes. Comparatively, *S. horneri* blooms occur earlier and last longer, while *U. prolifera* shows more concentrated and regular peak weeks.

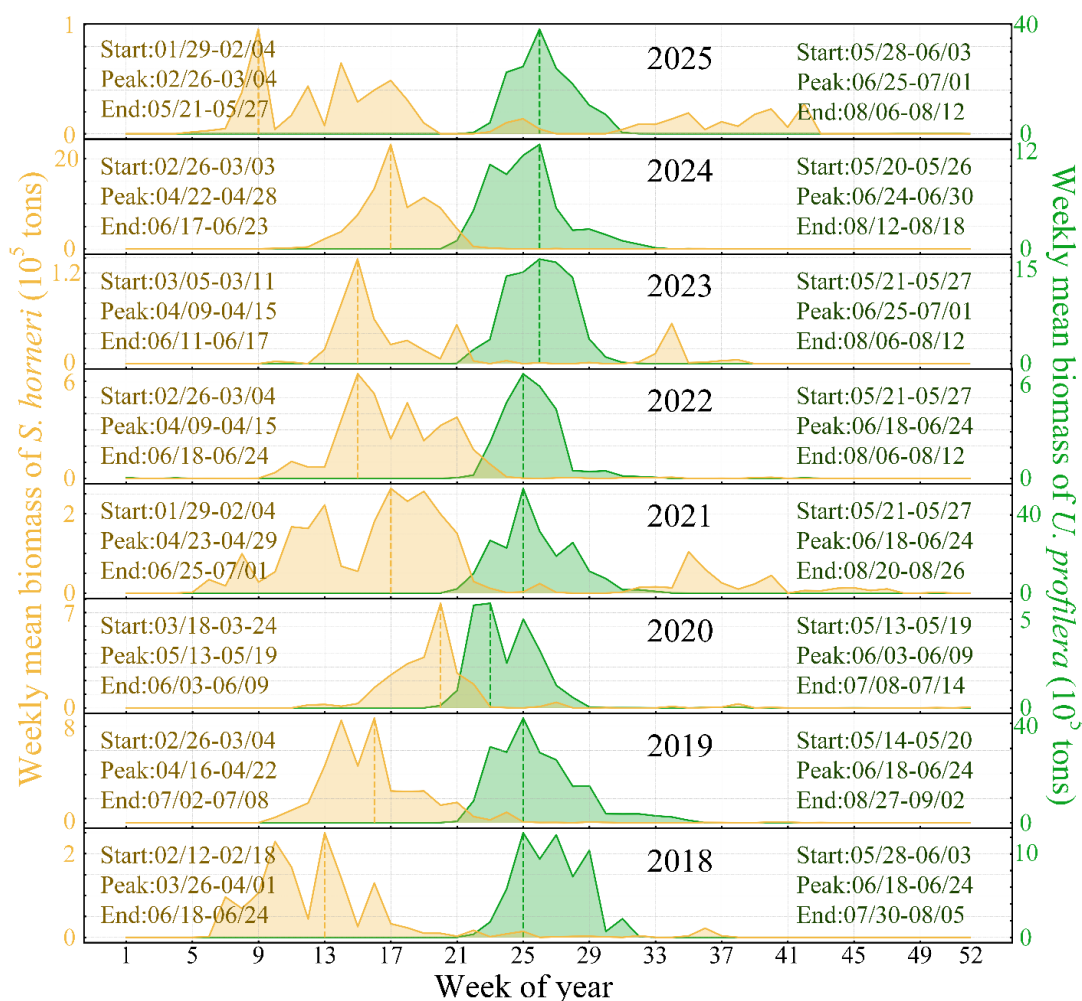


Figure 14. Weekly biomass variations of *U. prolifera* in the Yellow Sea and *S. horneri* in the Yellow Sea and East China Sea from 2018 to 2025. Green shaded areas indicate the annual growth periods of *U. prolifera*, and green dashed lines mark the peak bloom weeks. Yellow shaded areas indicate the annual growth periods of *S. horneri*, and yellow dashed lines represent the weeks of peak biomass.



3.4 Drifting patterns of the floating macroalgae blooms

Weekly mean biomass maps provide a unique opportunity to examine the short-term aggregation, dispersion, and transport behaviour of floating macroalgae at sub-seasonal time scales. Distinct drifting patterns are observed for *U. prolifera* in the Yellow Sea and *S. horneri* in the East China Sea, reflecting differences in bloom morphology, spatial extent, and dominant transport regimes. Overall, *U. prolifera* in the Yellow Sea exhibits rapid north–south aggregation and dispersion within the bloom season, whereas *S. horneri* in the East China Sea shows broader longitudinal transport patterns with episodic high-density patches.

Numerical particle tracking experiments based on HYCOM surface currents and NCEP/NCAR wind forcing (Figure S27) confirm that ocean circulation and wind play key roles in shaping *S. horneri* distributions. Forward and backward tracking simulations align with observed satellite distributions, validating that transport pathways drive short-lived bloom peaks and interannual variability. The tracking results further show that *U. prolifera* primarily originates from the Subei Shoal, consistent with previous understanding, while *S. horneri* is mainly sourced from the Zhejiang coastal waters (Figure 15).

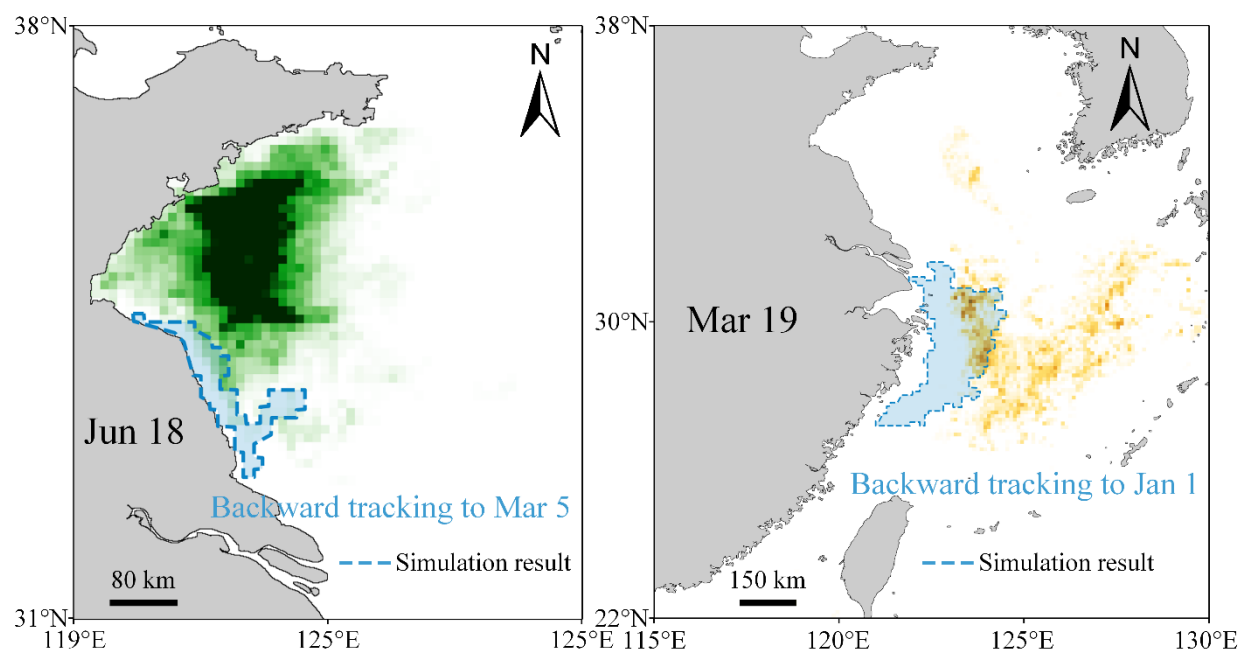


Figure 15. Backward tracking of *U. prolifera* and *S. horneri* in the Yellow Sea and East China Sea, based on HYCOM daily surface currents and NCEP/NCAR wind forcing. For *U. prolifera*, the backward tracking was conducted from 18 June to 5 March. For *S. horneri*, the tracking was implemented from 19 March to 1 January. The initial conditions were derived from the multi-sensor weekly mean biomass of the two species, respectively, composited across the 2018–2025 bloom seasons. The blue dashed area indicates the simulated distribution of *U. prolifera* and *S. horneri* particles traced backward.



3.4.1 Transport patterns of *U. prolifera* blooms in the Yellow Sea

Weekly mean biomass maps (**Figure 8**) reveal that *U. prolifera* in the Yellow Sea undergoes pronounced north-south redistribution within the bloom season (May–August). High-biomass patches repeatedly emerge within confined latitudinal bands and subsequently disperse over time scales of one to several weeks, indicating strong aggregation-dispersion dynamics rather than gradual in situ biomass accumulation.

Longitude-averaged weekly biomass time series (**Figure 16**) reveal sharp latitudinal shifts of biomass centers, characterized by intermittent intensification and rapid displacement of high-biomass zones. These patterns are consistent with episodic convergence features that migrate within the Yellow Sea, rather than representing stationary growth hotspots.

Particle tracking simulations driven by HYCOM surface currents and NCEP/NCAR wind fields suggest that these spatial and temporal patterns are largely controlled by ocean circulation and wind forcing. Simulated particle trajectories reproduce the observed short-term aggregation and dispersion behaviour, supporting the interpretation that physical transport processes dominate bloom redistribution on weekly time scales.

Together, satellite observations and numerical simulations indicate that *U. prolifera* blooms in the Yellow Sea are primarily regulated by short-range transport and convergence processes, which govern the formation, migration, and dissipation of high-biomass patches throughout the bloom season.

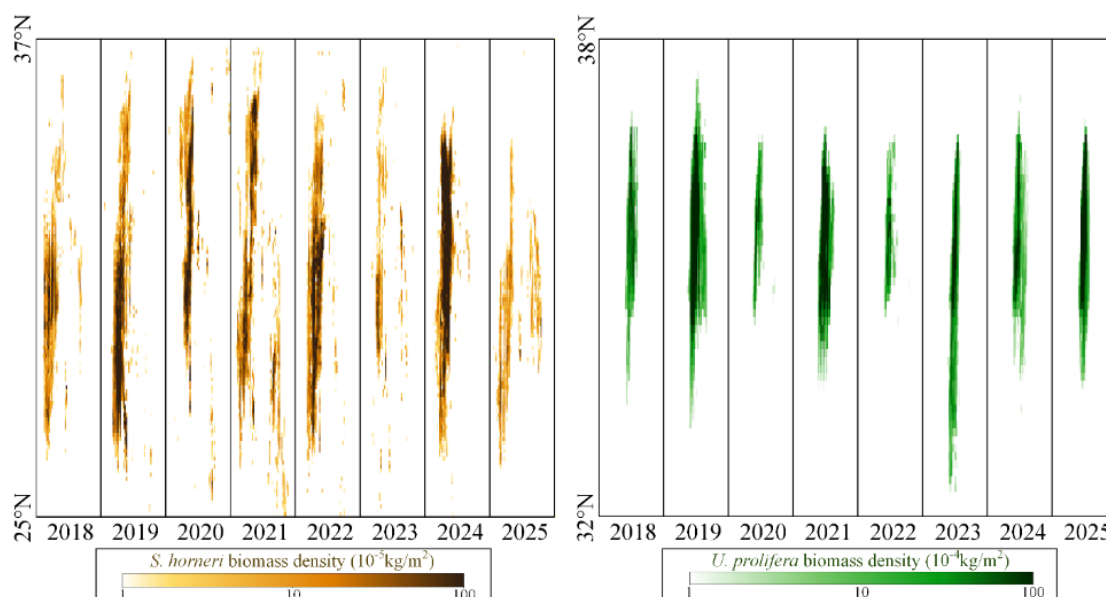


Figure 16. Longitude-averaged (from 105°E to 130°E) *S. horneri* and *U. prolifera* weekly mean biomass density from 2018–2025.



3.4.2 Transport patterns of *S. horneri* blooms in the East China Sea

620 In contrast to *U. prolifera*, *S. horneri* exhibits broad longitudinal and latitudinal transport pathways across the East China Sea. Weekly biomass maps (**Figure 11**) show episodic eastward and north-eastward displacement of high-biomass patches, often spanning several degrees of longitude within a few weeks.

625 The spatial evolution indicates a transport-dominated regime characterized by long-range advection and intermittent accumulation, rather than localized convergence (**Figure 17**).

Particle tracking simulations reveal coherent transport pathways consistent with the satellite-observed displacement of *S. horneri* biomass. Forward trajectories initiated from high-biomass regions in the East China Sea reproduce downstream spreading patterns, while backward simulations trace likely source regions to the Zhejiang coastal region, supporting the
 630 inferred transport connectivity.

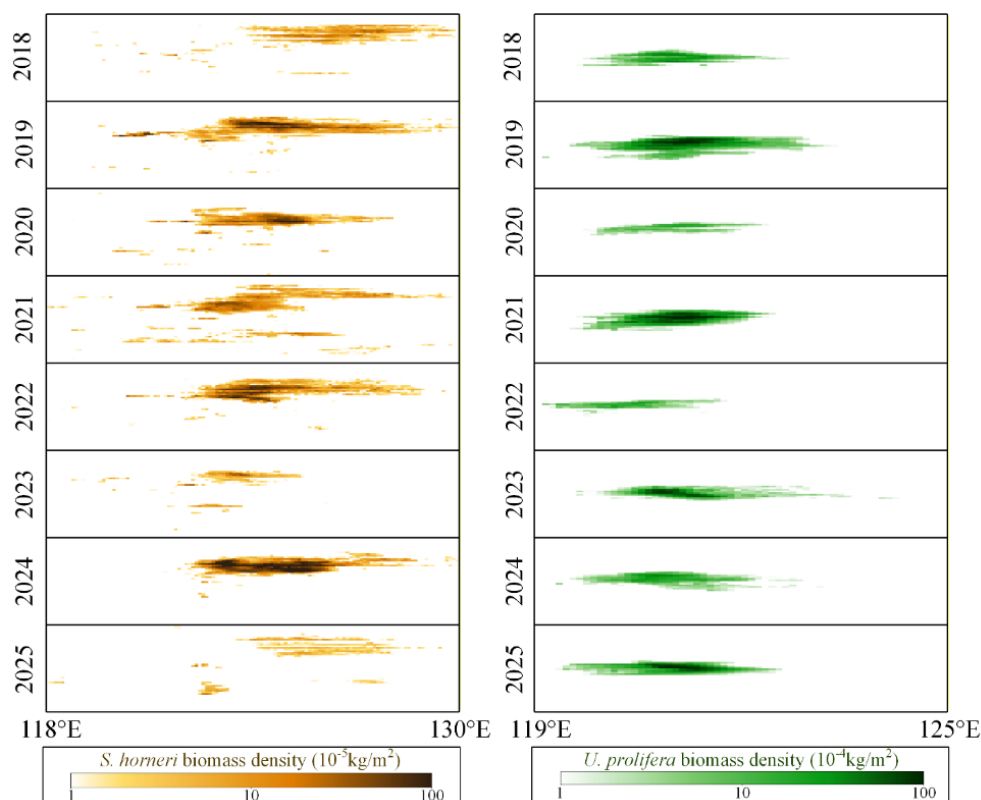


Figure 17. Latitude-averaged (from 2°N to 41°N) *S. horneri* and *U. prolifera* weekly mean biomass density from 2018–2025.



635 4 Discussion and Conclusion

4.1 Weekly-scale dynamics and transport-driven evolution of floating macroalgae

By integrating multi-sensor satellite observations into consistent 1-km weekly composites, this study enables the characterization of floating macroalgal bloom dynamics at an intermediate temporal scale bridging daily observations and monthly products. Compared with monthly products, the weekly observations reduce temporal smoothing and better capture
640 rapid changes in bloom extent, aggregation, and dissipation that are otherwise obscured in coarser datasets. This capability is particularly important for highly dynamic coastal bloom systems, where short-lived transport and redistribution processes can substantially modify observed bloom patterns.

In the Yellow Sea, weekly observations reveal that *U. prolifera* bloom evolution involves not only a gradual accumulation,
645 but also rapid changes in spatial distribution during the growth period. These short-term variations reflect the influence of surface transport and aggregation processes, which can rapidly concentrate or disperse floating biomass. Such transient dynamics are often obscured in monthly products, potentially leading to misinterpretation of bloom development and intensity changes. In contrast, *S. horneri* in the East China Sea exhibits more episodic and spatially variable evolution, with pronounced changes in bloom extent and distribution over the weekly timescales. The observed patterns suggest stronger modulation by
650 ocean circulation and wind-driven transport, resulting in complex pathways of aggregation and dispersion. These differences between *U. prolifera* and *S. horneri* highlight the importance of high-frequency observations for accurately characterizing bloom dynamics in regions with complex and rapidly changing environmental conditions.

The consistency between satellite-derived weekly patterns and particle tracking simulations further demonstrates the capability
655 of the dataset to capture transport-related changes in floating macroalgal distributions. By resolving bloom evolution at weekly intervals, this dataset provides improved observational constraints for quantifying short-term aggregation, dispersion, and transport processes that are difficult to characterize using lower-frequency products. These results highlight the value of weekly multi-sensor observations for advancing the monitoring and understanding of floating macroalgal dynamics across China's marginal seas.

660

4.2 Intercomparison with previous macroalgae datasets

Our dataset demonstrates strong consistency with existing macroalgal bloom products while providing improved temporal continuity through multi-sensor integration. For a consistent comparison with previous MODIS-based products, we generated a MODIS-only version of the present dataset using the same processing framework. Comparisons with previous MODIS-



665 based datasets show that the **major spatial distributions, seasonal cycles, and interannual variability** of both *U. prolifera* and *S. horneri* blooms are consistently reproduced across different temporal and spatial scales. The remaining differences primarily reflect variations in cloud screening strategies, spatial resolution, and retrieval algorithms, highlighting the methodological uncertainties that influence satellite-based macroalgae mapping.

670 Comparison with the monthly products of Qi et al. (2022) indicates strong agreement in both spatial patterns and bloom magnitude during 2018–2021 (**Figures S28–S31**). The developed dataset captures similar seasonal progression and bloom distributions, with pixel-level comparisons yielding R^2 values of 0.90 and 0.78 for *U. prolifera* and *S. horneri*, respectively, and biomass comparisons showing R^2 values of 0.84 and 0.96. Differences between the two products could be mainly associated with cloud masking strategies. Threshold-based cloud detection methods may incorrectly remove high-reflectance
 675 macroalgal pixels, particularly in optically complex coastal environments characterized by dense blooms, turbid waters, or strong solar illumination. Such over-masking is evident in regions such as the Subei Shoal, where reduced valid observations can lead to underestimation of bloom extent and biomass.

The consistency of the developed dataset is further supported by comparisons with daily MODIS-based products developed
 680 using different retrieval strategies. The comparison with the daily MODIS-derived bloom area product of Gao et al. (2024) shows strong agreement, with R^2 values exceeding 0.85 for both MODIS Aqua and Terra (**Figure S32**), while biomass comparisons with Pan et al. (2026) also reveal a strong relationship ($R^2 = 0.81$; **Figure S33**). These differences among these products may primarily reflect variations in retrieval frameworks, including spatial resolution, spectral information, cloud screening, and biomass estimation approaches. Such differences are expected given the challenges of detecting floating
 685 macroalgae in heterogeneous coastal environments, where mixed macroalgae–water pixels and variable atmospheric conditions can influence satellite-derived estimates. Nevertheless, the consistent spatial and temporal patterns among independent datasets demonstrate the robustness of the developed dataset for long-term monitoring of floating macroalgae blooms.

690 **4.3 Importance of spectral indices for reliable macroalgal bloom mapping**

Reliable macroalgal bloom datasets require accurate representation of the spatial extent of floating algae blooms. Incomplete detection, particularly in regions with mixed macroalgae–water pixels, can lead to systematic underestimation of bloom coverage and reduce the overall reliability of the dataset. However, uncertainties associated with the choice of spectral indices and their sensitivity to different bloom conditions are often overlooked in satellite-based macroalgal mapping.

695 As shown in **Figures 18 and 19**, different spectral representations provide substantially different depictions of *U. prolifera* and *S. horneri* distributions. Conventional RGB composites (FRGB) often fail to resolve weak, fragmented, or low-density



macroalgal signals, particularly in optically complex coastal waters. In contrast, macroalgal indices (FAI and AFAI) enhance the spectral contrast between floating algae and surrounding seawater, allowing improved identification of mixed pixels and more complete characterization of bloom boundaries.

The comparison between FAI and AFAI further demonstrates that spectral index selection can strongly influence the spatial completeness of derived macroalgal products. Although both indices improve bloom detectability relative to RGB imagery, AFAI shows greater sensitivity to weak and marginal signals, enabling the detection of more dispersed or early-stage bloom features. These differences highlight that spectral indices represent an important source of uncertainty in multi-sensor macroalgal datasets, particularly when generating long-term records across diverse coastal environments.

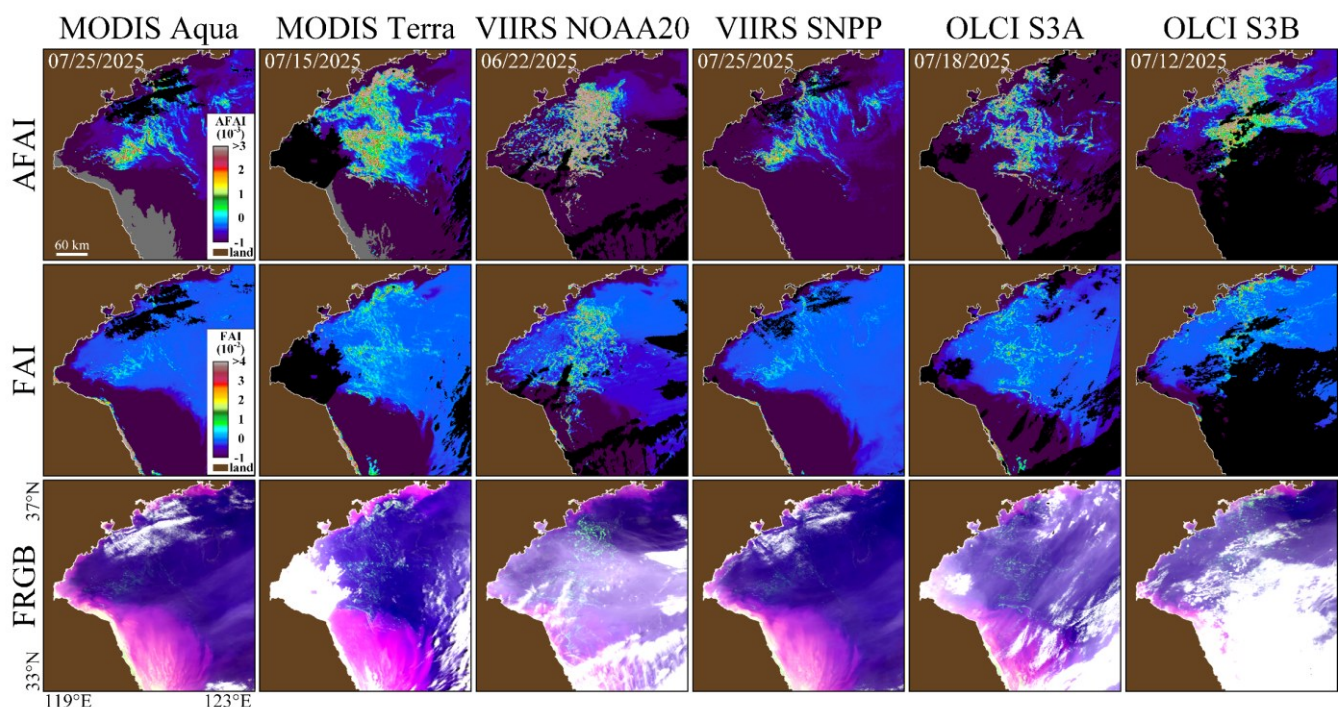


Figure 18. Comparison of *U. prolifera* appearance from multi-sensor observations. The first, second, and third rows show AFAI, FAI, and FRGB, respectively. Brown areas indicate land, and black areas in the AFAI and FAI panels represent cloud cover.

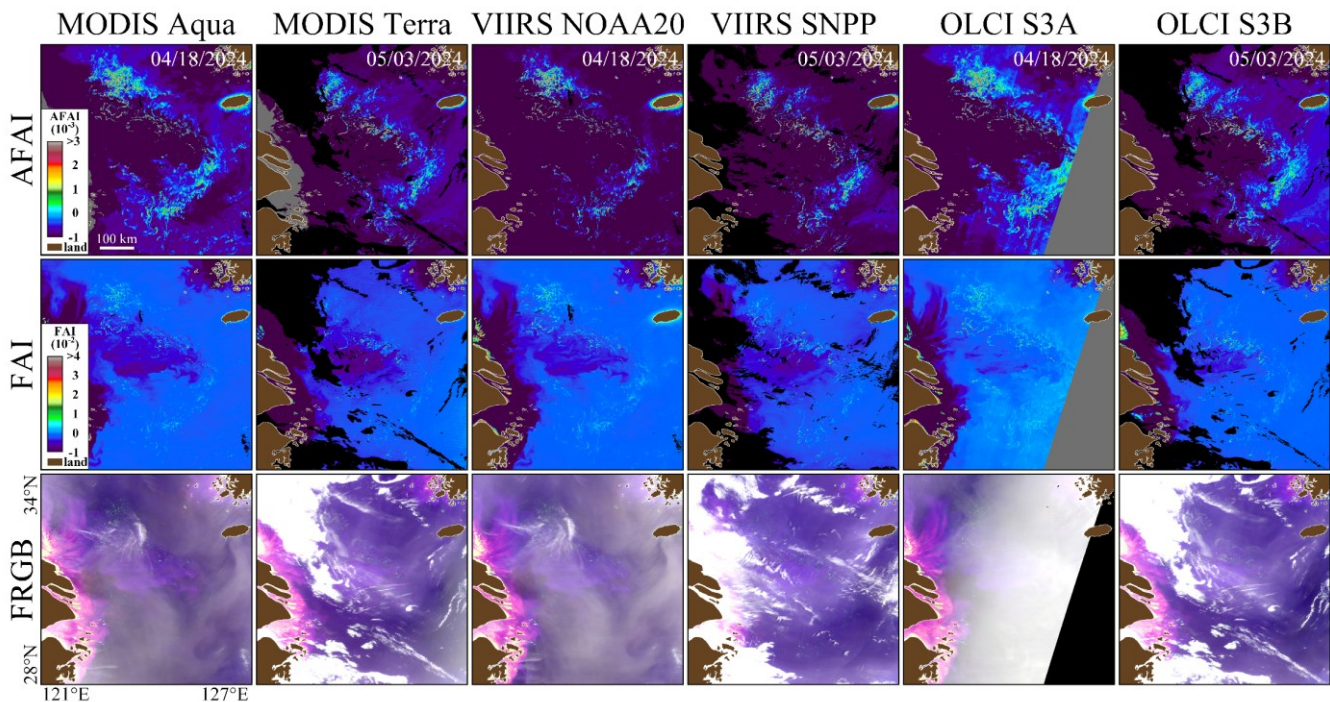


Figure 19. Comparison of *S. horneri* appearance from multi-sensor observations. The first, second, and third rows show AFAI, FAI, and FRGB, respectively. Brown areas indicate land, and black areas in the AFAI and FAI panels represent cloud cover.

4.4 Limitations and future studies

Despite these advantages of the multi-sensor weekly dataset, several limitations remain. First, uncertainties associated with sensor differences, cloud contamination, and retrieval algorithms may affect biomass estimation, particularly during extreme bloom events with highly heterogeneous spatial distributions. Although multi-sensor integration improves observation continuity, residual cross-sensor inconsistencies cannot be completely eliminated. In addition, quantitative validation remains challenging due to the limited availability of field observations coincident with satellite acquisitions, especially for offshore and rapidly evolving bloom events. Second, the weekly composite framework represents a balance between temporal continuity and spatial coverage, but it may still smooth short-lived bloom events or rapid changes in bloom structure occurring at finer temporal scales. Future improvements in sensor availability and data fusion approaches may enable higher-frequency monitoring while maintaining sufficient spatial coverage. Third, while satellite observations and particle tracking simulations provide valuable constraints on bloom transport and redistribution, the current framework does not explicitly resolve biological processes such as growth, mortality, fragmentation, and physiological states. Future studies integrating satellite observations with coupled physical–biological models will be essential for better understanding the mechanisms controlling bloom initiation, persistence, and decline. Beyond improving temporal and spatial observations, recent advances in hyperspectral observations,



730 such as those provided by the PACE OCI, offer new opportunities to improve species discrimination, quantify physiological conditions, and characterize bloom development beyond spectral detection alone. These developments will further improve species-resolved monitoring of macroalgal blooms and enhance the capability to detect emerging bloom events under changing environmental conditions

Data availability

735 The dataset supporting this study, titled “A 1-km weekly dataset of floating *Ulva prolifera* and *Sargassum horneri* blooms in China’s marginal seas derived from multi-sensor satellite observations” (Liu and Wang, 2026), is publicly available from the Science Data Bank at <https://doi.org/10.57760/sciencedb.38784>.

Supplement link

Author contributions

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Competing interests

The contact author has declared that none of the authors has any competing interests.



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Review statement

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