

High-Quality Remote Sensing Reflectance Products over China and US Coast

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Abstract Remote sensing reflectance (R_{rs}) is fundamental for deriving bio-optical properties of global surface waters. However, accurate atmospheric correction (AC) to derive R_{rs} in coastal waters remains challenging due to strongly absorbing aerosols and complex water optics. To address this, we developed an improved processing framework that integrates flexible use of global gridded aerosol models better suited for coastal environments and incorporates tailored masking strategies. Based on this framework, we generated a high-quality R_{rs} dataset from Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua observations, spanning 2003–2022 for the coastal waters of China and the United States (US)—two regions where complex water optics and frequent anthropogenic aerosols have long impeded retrieval accuracy and valid data yield. Compared to the NASA standard MODIS Aqua R_{rs} products (~~mean regression slope: 0.90 ± 0.06~~), the improved framework ~~achieves higher accuracy and reduced overcorrection biases (slope: 0.90 ± 0.06)~~ achieved a significant reduction in systematic bias. Multiple validation metrics support this, with the restoration of the mean regression slope to unity (~~$1.00 \pm 0.00 \pm 0.08$ vs. 0.90 ± 0.06~~) across eight bands, ~~especially being the most prominent~~. Performance gains are particularly pronounced in the 488–~~555 nm~~ 555 nm range, ~~which is most relevant to water color applications~~. The new dataset also yields significantly more valid retrievals, with regional mean increases of 56% in the Chinese coastal waters and 18% in the US coastal waters at 443 nm. ~~Regional image analyses confirm its superior capability in preserving valid retrievals and resolving~~ Furthermore, it recovers fine-scale spatial features in turbid ~~nearshore~~ waters. ~~Preliminary spatiotemporal analyses further demonstrate its effectiveness in capturing and captures~~ long-term R_{rs} dynamics ~~and trends. These results highlight the~~, demonstrating its robustness ~~of the improved framework and the practical utility for coastal monitoring~~. As a complementary resource optimized for estuaries, bays, and turbid coastal regions, the new dataset ~~for long term monitoring of coastal water quality and ecosystem variability~~ fills a critical gap in the ocean color data portfolio where standard products are less reliable. The dataset is available at <https://doi.org/10.5281/zenodo.16413443> (Zhao et al., 2025).

1 Introduction

Remote sensing reflectance (R_{rs}), representing the fraction of the top-of-atmosphere (TOA) signal attributable to water-leaving radiance (Gordon, 1997), is fundamental for deriving bio-optical properties of global surface waters, such as inherent optical properties (IOPs) (Lee et al., 2002; Werdell et al., 2013), concentrations of chlorophyll-a (Chl) (O'reilly, 2000; Hu et al., 2019; Tong et al., 2022) and particulate organic carbon (POC) (Stramski et al., 1999; Stramski et al., 2022), among many others. Accurate atmospheric correction (AC)—which removes atmospheric contributions from the total radiance measured by satellite sensors—is critical for retrieving R_{rs} and estimating water quality parameters (Gordon and Wang, 1994; Gordon, 1997). However, a key challenge in AC lies in accurately characterizing aerosol radiative properties, especially in the presence of absorbing aerosols which strongly absorb light at short blue bands (410 or 412 nm and 443 nm) (Bassani et al., 2015; [IEEEgLOCCG](#), 2019). In coastal regions where such aerosols (e.g., dust, smoke, and urban aerosols) are prevalent (Charlson et al., 1992), the aerosol models developed by Ahmad et al. (2010) (hereafter referred to as AF10), which are widely used in current operational AC, fail to account for strong aerosol absorption (Zhao et al., 2023), leading to systematic underestimation and limited reliability of R_{rs} (Wang and Jiang, 2018). In addition to aerosol-related issues, the cloud mask applied in current ocean color data processing pipelines often misclassifies highly reflective turbid waters (e.g., those with high suspended sediment concentrations) as clouds, resulting in the loss of usable R_{rs} data in coastal regions (Wang and Shi, 2006). Together, these issues severely constrain the usability of R_{rs} products in coastal regions and hamper the accurate retrieval of biogeochemical properties in these dynamic environments.

One of the key factors determining the accuracy of R_{rs} retrievals after atmospheric correction is whether the adopted aerosol models can effectively capture the microphysical and optical properties of aerosols, thereby accurately estimating their scattering contributions (Prospero et al., 1983; Gordon et al., 1997; Bassani et al., 2015). To address this, a range of aerosol models has been developed and refined by incorporating observational data and analyzing aerosol sources (Shettle and Fenn, 1979; Gordon and Wang, 1994; Ahmad et al., 2010; Zhao et al., 2023). Early work by Shettle and Fenn (1979) classified aerosols into five types (rural, urban, maritime, tropospheric, and fog) and accounted for humidity effects to produce a set of models (denoted as SF79). Building on this, Gordon and Wang (1994) formulated 12 humidity-dependent aerosol models (denoted as GW94) tailored for marine applications. With improved observational capacity, Ahmad et al. (2010) developed the AF10 models based on long-term data from 11 Aerosol RObotic NETwork (AERONET) sites. The AF10 models parameterize aerosol particle size, refractive index, and fine-mode fraction as functions of relative humidity. Compared to GW94, they significantly reduced the uncertainties in aerosol optical thickness (AOT) and Ångström exponent (He et al., 2011; Mélin et al., 2013). As a result, the AF10 models have become the default aerosol model set in most current operational ocean color data processing systems (Mobley et al., 2016).

However, current operational AC based on AF10 models frequently yield poor R_{rs} retrievals in coastal regions, often resulting in underestimated R_{rs} values, particularly in the blue bands (Wang and Jiang, 2018). This limitation stems from the spatial representativeness of the AERONET sites used to build AF10 models: only three coastal stations (all in Chesapeake Bay) were

included, while the remaining sites were located over open oceans. As a result, AF10 models primarily represent non- or
65 weakly absorbing aerosols over the open ocean, and do not adequately reflect the high AOT and strong absorption features
commonly present in coastal regions (Zhao et al., 2023). Although many studies have proposed aerosol model refinements
(Giles et al., 2012; Hamill et al., 2016; Bru et al., 2017; Zhou et al., 2020; Montes et al., 2022), most focus on specific aerosol
types or lack representation of seasonal variability, limiting their broader applicability for coastal waters.

Recognizing the limitations of the AF10 models, Zhao et al. (2023) developed a set of global gridded aerosol models tailored
70 for inland and coastal waters. Leveraging AERONET observations from 1,475 sites worldwide, they generated 3,207 monthly
aerosol models distributed across 310 $5^\circ \times 5^\circ$ grids, and compiled the models into lookup tables compatible with the Sea-
viewing Wide Field-of-view Sensor (SeaWiFS) Data Analysis System (SeaDAS) to allow seamless integration into operational
AC workflows. Validation using Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua data over six lacustrine or
estuarine regions showed that the gridded models substantially improved R_{rs} retrieval accuracy compared to the AF10 models.
75 Recently, Lv et al. (2024) further demonstrated the robustness of the gridded models through extended validations across
multiple coastal regions and MODIS bands, with notable reductions in aerosol overcorrection errors under complex aerosol
conditions.

Although such global gridded aerosol models have shown promise in characterizing the complex aerosol properties of coastal
regions, several practical challenges hinder their direct application in operational coastal R_{rs} product generation. One key
80 limitation lies in the intrinsic complexity of coastal environments, where both atmospheric and water optical conditions can
exhibit strong spatial heterogeneity within a single satellite scene—from nearshore turbid waters dominated by strongly
absorbing continental aerosols to offshore regions with clearer water and weakly absorbing marine aerosols. Applying either
model type uniformly across such spatial gradients can lead to potential retrieval errors—for instance, using AF10 models
nearshore often results in overestimated aerosol path radiance and underestimated R_{rs} , while applying the gridded models
85 offshore may produce unrealistically high R_{rs} values due to overestimated aerosol absorption. These challenges highlight the
necessity of developing a dynamic and integrated model selection scheme that can adaptively select between gridded and AF10
aerosol models under spatially heterogeneous conditions, to support accurate AC across the full coastal domain and generate
spatially consistent, quality-assured R_{rs} products suitable for large-scale analysis.

In addition to aerosol model selection issues, a more suitable cloud masking strategy is also essential for improving the usability
90 of coastal R_{rs} data. The default cloud mask employed in current operational processing workflows—originally designed for
open-ocean applications—relies on a Rayleigh reflectance threshold at 869 nm ($R_{rc,869} = 0.027$) to identify cloudy pixels
(Robinson et al., 2003). However, in turbid coastal waters, this threshold can easily be exceeded due to high water-leaving
radiance, leading to misclassification of valid pixels as cloudy (Wang and Shi, 2006). As a result, a substantial portion of valid
data was incorrectly discarded, limiting the spatial coverage and continuity of the standard R_{rs} products. To address this,
95 previous studies have proposed using alternative thresholds at 1240 or 2130 nm, as these relaxed cloud masking thresholds

help retain more turbid water pixels. However, the relaxation of the cloud masking criteria may increase the risk of residual contamination from thin clouds. Therefore, targeted masking approaches must be incorporated during data processing to complement the modified cloud masking threshold, thereby ensuring data reliability.

In summary, while prior studies have addressed two major limitations of standard R_{rs} products in coastal waters—namely, the inadequacy of aerosol models and the excessive cloud masking—these improvements ~~haveare not~~ yet ~~to be~~ fully integrated into operational data production. ~~To bridge this~~ This study bridges the gap, we developed by developing an improved processing framework that integrates refined aerosol model assignment and targeted masking strategies. ~~To evaluate its performance, we conducted MODIS satellite in situ matchup validation on a global scale and compared with the standard R_{rs} products. We further applied the improved framework to generate a consistent and high-quality MODIS R_{rs} dataset for two representative coastal regions—the coastal waters of China and the United States (US)—both of which are characterized by optically complex waters, strong anthropogenic influences, and insufficient data availability (Charlson et al., 1992; Wang et al., 2017). Evaluation of data coverage and spatiotemporal analyses were conducted using the new dataset to assess its utility to provide a consistent and high-quality basis for long-term coastal monitoring and regional change detection.~~

The framework is applied to generate a consistent, high-quality MODIS R_{rs} dataset (2003-2022) for two strategically selected regions: the coastal waters of China and the United States (US). These regions together provide representative cases for the optical challenges in coastal zones—from the highly turbid waters and frequent absorbing aerosols of China’s coast to the diverse optical environments and significant anthropogenic influences along the US coast (Charlson et al., 1992; Wang et al., 2017), and serve as a rigorous testbed to validate the framework’s robustness under the most demanding conditions.

The performance of the resulting dataset is comprehensively evaluated, with analyses presented on its radiometric accuracy, data coverage, and ability to resolve fine-scale and long-term spatiotemporal patterns. These results are then discussed to critically position the new framework within the current landscape of coastal ocean color research and outline its potential for future development.

2 Data and Methods

2.1 Datasets

2.1.1 Satellite Imagery

This study utilized two types of MODIS Aqua satellite data acquired from the NASA Ocean Biology Processing Group (<https://oceancolor.gsfc.nasa.gov/>): Level-1A (L1A) and Level-2 (L2) ocean color products. L1A products contain unprocessed full-resolution data, supplemented with radiometric and geometric calibration coefficients and georeferencing parameters. L2 products provide derived geophysical variables (e.g., R_{rs} , Chl) at the same spatial resolution and geolocation as L1A data.

A total of 136,544 L1A images acquired between 2002 and 2022 (data beyond 2022 were excluded here due to satellite orbital changes beginning in 2023 (Twedt et al., 2023; Nasa Ocean Biology Processing Group, 2024)) were used in this study for two main purposes:

- (1) Matchup validation: A subset of 4,961 L1A images (2002-2022) was used to generate satellite R_{rs} for validation against *in situ* measurements, with temporal coverage aligned to field campaigns.
- (2) New coastal R_{rs} dataset generation: Most of the images (128,226 scenes, from 2003 to 2022) were used to generate the new R_{rs} dataset for two regions: the coastal waters of Chinese mainland (106°E–127°E, 17°N–41°N) and the US (128°W–65°W, 18°N–51°N).

NASA standard Level-2 R_{rs} products generated using the operational AC algorithm developed by NASA OBPG (Nasa Ocean Biology Processing Group, 2022) were also obtained. This dataset was used for:

- (1) Comparative validation with R_{rs} data generated in this study using a common set of *in situ* measurements.
- (2) Evaluation of improvements in valid data yield by comparing valid observations counts (see Sect. 2.3.2) and assessing single-scene retrievals.

Both the new dataset and standard products include R_{rs} at 10 spectral bands: 412, 443, 469, 488, 531, 547, 555, 645, 667, and 678 nm, all at 1 km spatial resolution.

2.1.2 Ancillary Environmental Data

To support accurate AC, this study also incorporated ancillary data (Nasa Ocean Biology Processing Group, 2019) during the processing of MODIS imagery. These inputs—automatically acquired via the SeaDAS processing environment—include meteorological variables (e.g., wind speed, surface pressure, relative humidity) and concentrations of atmospheric gases (e.g., water vapor, ozone, nitrogen dioxide). These parameters are essential for calculating Rayleigh scattering, atmospheric transmittance, and gaseous absorption, and thus directly influence the quality of retrieved R_{rs} values. The best available ancillary data at the time of processing were used, consistent with standard SeaDAS ancillary data usage practices. This approach helps minimize the influence of auxiliary input differences when comparing with the standard R_{rs} products and improves the reliability of R_{rs} values derived with our improved processing framework.

2.1.3 In Situ Data

To evaluate the performance of the improved processing framework and compare its outputs with the standard products, we used *in situ* R_{rs} measurements archived in the SeaWiFS Bio-optical Archive and Storage System (SeaBASS, <http://seabass.gsfc.nasa.gov/>) (Werdell et al., 2003; Bailey and Werdell, 2006). SeaBASS provides precompiled satellite-*in situ* matchup records, each containing metadata such as geographic coordinates, sampling time, cruise ID, measured R_{rs} values, corresponding MODIS Aqua filenames, and validation flags. In this study, the metadata was used to extract satellite-derived R_{rs} from outputs of our improved processing framework and standard products, rather than using the satellite R_{rs} values directly

included in the SeaBASS records. This allowed us to apply a unified and more stringent quality control (QC) strategy (see Sect. 2.2.2) to both data, ensuring consistency and reliability of the accuracy assessment.

The *in situ* measurements cover eight MODIS bands: 412, 443, 488, 531, 547, 555, 667, and 678 nm. Due to a lack of *in situ* records at 469 and 645 nm, these two bands were excluded from all accuracy assessments (see Sect. 2.3.1).

To focus on coastal conditions and To ensure compatibility with the coverage of the global gridded aerosol models and focus on coastal conditions, observations located outside the spatial domain of the global gridded aerosol models or over open ocean or inland waters were excluded. A total of 6,362 *in situ* records were retained for validation, distributed across a wide range of coastal environments (see Figure 1).

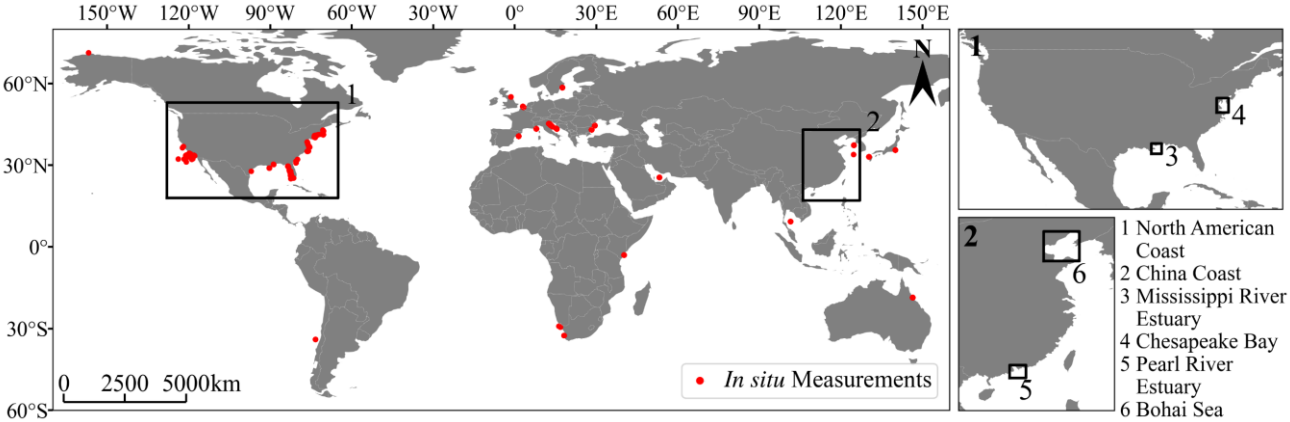


Figure 1: Distribution of *in situ* measurements. Also shown are the study areas—the coastal waters of China and the United States—as well as four specific regions of interest: the Mississippi River Estuary, Chesapeake Bay, Pearl River Estuary, and Bohai Sea.

170 **2.2 Processing Framework**

Accurate AC is essential for deriving reliable R_{rs} in optically complex coastal waters, where high turbidity and variable aerosol properties present persistent challenges. In this study, we refined current operational ocean color AC algorithm (Mobley et al., 2016) to enhance its performance in such environments. All processing was conducted using SeaDAS software (version 8.3.0).

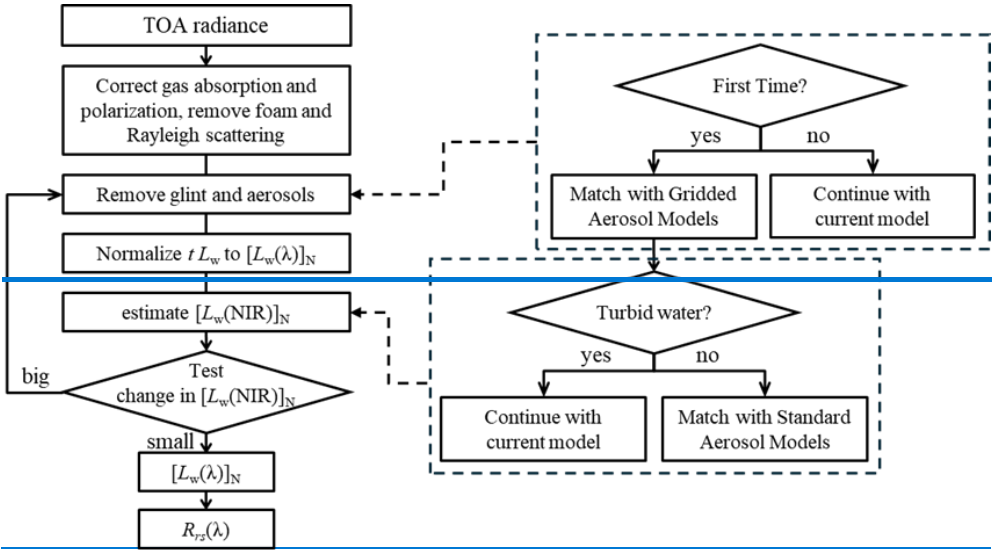
Our modifications build upon the standard near-infrared (NIR) iterative approach, which estimates aerosol contributions by assuming negligible water-leaving radiance in the NIR bands and minimizing residual signals through iteration (Gordon and Wang, 1994; Mobley et al., 2016). While effective over open ocean, this method could produce biased results in coastal waters due to sharp gradients in both water optical properties and aerosol characteristics. To address these limitations, we introduced a more flexible AC approach tailored to spatially heterogeneous coastal conditions. The full procedure is detailed in Sect. 2.2.1.

180 Additionally, a unified set of QC strategies was applied to both the newly generated data in this study and standard R_{rs} products to ensure consistency in evaluation. These procedures are described in Sect. 2.2.2.

2.2.1 Improved Atmospheric Correction

Building upon the standard NIR iterative approach, we further enhanced AC performance in coastal waters by incorporating the global gridded aerosol models (Zhao et al., 2023) and introducing a spatially adaptive aerosol model selection strategy. The overall process is illustrated in Figure 2.

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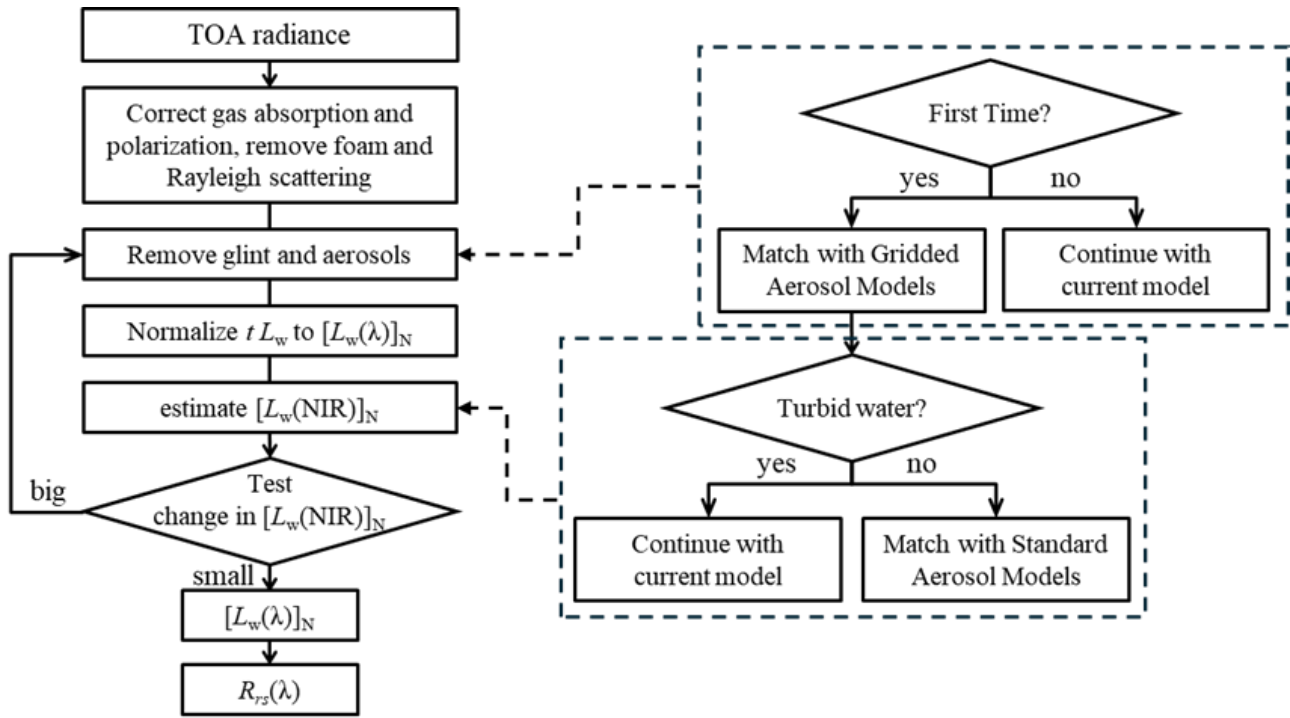


Figure 2: Improved atmospheric correction (AC) workflow. Notation: t (diffuse transmittance), L_w (water-leaving radiance), λ (wavelengths), NIR (near-infrared), N (normalization).

After preprocessing steps such as Rayleigh scattering and sun glint removal, the initial aerosol contribution was estimated using a gridded aerosol model selected based on the pixel’s geographic location and date (Zhao et al., 2023), since the gridded models offer improved representation of the diverse and potentially absorbing aerosols common in coastal regions.

To account for spatial heterogeneity in coastal conditions, each pixel was preliminarily classified based on its normalized NIR water-leaving radiance (denoted as $[L_w(NIR)]_N$). Specifically, a pixel was classified as “turbid” if $[L_w(NIR)]_N$ exceeded the empirical threshold defined by the TURBIDW flag in NASA Standard Level-2 Ocean Color Flags. Although this classification nominally distinguishes between clear and turbid waters, it served here primarily as a proxy for proximity to land. Turbid waters—characterized by elevated NIR reflectance due to high concentrations of suspended sediments or phytoplankton—are typically concentrated in nearshore zones, where riverine input and absorbing aerosols from anthropogenic sources are most pronounced (Husar et al., 1997). For these pixels, the gridded aerosol model originally assigned to the location was retained throughout iteration to better represent local aerosol properties. In contrast, pixels classified as “clear” were generally located offshore, where continental aerosol influence is weaker and water clarity is higher. For these pixels, an AF10 aerosol model was selected following the conventional open-ocean AC algorithm and used in subsequent iterations, as continued use of the gridded model in such areas could lead to underestimation of aerosol path radiance and overestimation of water-leaving

205 radiance. This spatially adaptive model selection approach—guided by an indirect indicator of coastal influence—was key to improving retrieval performance across diverse coastal environments.

The iteration proceeded until the change in $[L_w(NIR)]_N$ between successive steps fell below a set threshold, after which the final $[L_w(\lambda)]_N$ was converted to $R_{rs}(\lambda)$.

210 While the NIR-SWIR switching method is considered more robust for highly turbid waters—leveraging the near-zero water-leaving radiance assumption in the shortwave infrared (SWIR) bands—it is constrained by the low signal-to-noise ratios (SNR) of MODIS Aqua SWIR bands (Wang et al., 2009; Werdell et al., 2010). As demonstrated in previous studies (Shi and Wang, 2007; Wang et al., 2009) and confirmed by our tests, excessive noise in these bands can significantly compromise retrieval accuracy. Therefore, we retained the NIR iterative approach, with enhanced reliability achieved through spatially adaptive aerosol model selection.

215 2.2.2 Quality Control Strategies

To ensure reliability and comparability of R_{rs} retrievals, a unified set of QC strategies was applied to both the newly generated data in this study and standard products prior to subsequent analysis. These procedures aimed to eliminate contaminated or highly uncertain retrievals and to support robust evaluation of data accuracy and comparison of valid data yield.

220 NASA Standard Level-2 Ocean Color Flags (l2_flags) were used to mask pixels affected by clouds, ice, sun glint, stray light, and extreme solar or sensor viewing angles. In addition, pixels flagged as MAXAERITER, indicating that the maximum number of aerosol iterations was reached without convergence, were also excluded to minimize the influence of potential AC failure under complex water or aerosol conditions.

Among these flags, the CLDICE mask was customized ~~to improve cloud detection performance overfor~~ turbid coastal waters. ~~A by applying a revised threshold of $(R_{rc,2130} = -0.037$ was applied to reduce). This adjustment reduces~~ excessive cloud masking over areas with high AOT and turbid waters (Zhao et al., 2023; Zhang et al., 2014). ~~and serves as the targeted first step to recover valid turbid-water pixels that are frequently misclassified.~~ In contrast, the standard R_{rs} products used for comparison was originally generated with the conventional $R_{rc,869} = 0.027$ threshold.

To ~~further suppress residual~~ ~~mitigate the potential inclusion of non-water features resulting from the relaxed~~ cloud ~~contamination that may result in abnormally elevated R_{rs} values~~mask, a secondary spectral filter was applied. Specifically, any 230 TURBIDW-flagged pixel with R_{rs} in any of the four blue bands (412–488 nm) exceeding the value at 531 nm was excluded. This criterion effectively identifies cloud-contaminated water pixels whose spectral shapes deviate from typical turbid water profiles—characterized by a reflectance peak near the green wavelengths and decreasing reflectance toward the blue, due to strong absorption by colored dissolved organic matter (CDOM) and Chl (Kirk, 2010). In contrast, cloud-contaminated pixels often exhibit spuriously enhanced blue-band reflectance, resulting in anomalous spectral peaks uncharacteristic of true turbid 235 waters. This filter is hereafter referred to as the “Wrong Turbid Water Mask”.

Extremely turbid waters were also excluded to reduce uncertainty in AC performance. Specifically, pixels exhibiting saturated R_{rs} signals in the 667 nm band—typically associated with very high suspended sediment concentrations—were filtered out, as such conditions compromise the reliability of both aerosol estimation and water-leaving radiance retrievals (Hu et al., 2012). This step is referred to as the “Saturated $R_{rs}(667)$ Mask”.

240 ~~By applying these QC strategies consistently across both datasets, we~~ By implementing this multi-step QC framework—comprising initial flagging, targeted cloud mask relaxation with subsequent spectral filtering, and exclusion of unreliable water signals—we prioritize data recovery in challenging coastal regions while proactively controlling for quality, thereby achieving a balance between coverage and reliability. Applying these QC strategies consistently across both datasets ensured that subsequent analyses were based on equivalently screened, quality-assured R_{rs} products.

245 2.3 Data Usability Assessment

2.3.1 Accuracy Evaluation

To assess the accuracy of the R_{rs} data derived with our processing framework and compare it with standard products, satellite–*in situ* matchups were compiled following NASA OBPB protocols (Bailey and Werdell, 2006). As mentioned in Sect. 2.1.3, both two kinds of satellite R_{rs} values were re-extracted based on the SeaBASS-provided metadata (e.g., geographic coordinates, acquisition time), with the same stricter QC strategy (Sect. 2.2.2) applied to ensure comparability.

255 Matchups were identified based on a ± 3 -hour temporal window between satellite overpass and *in situ* measurement. To ensure spatial representativeness and minimize the impact of pixel-level variability, a 5×5 pixel window centered on the *in situ* location was extracted from each satellite image. Within each window, only non-land pixels were considered. A matchup was deemed valid only if more than 50% of the pixels in the window passed QC screening and the coefficient of variation (standard deviation divided by the mean) was below 0.15—ensuring spatial homogeneity and consistency with *in situ* conditions.

R_{rs} accuracy was evaluated using four metrics: regression slope, coefficient of determination (R^2), median absolute percentage error (MdAPE), and normalized root mean square error (NRMSE). Among them, MdAPE serves as a robust indicator of relative error, being less sensitive to outliers than MAPE (mean absolute percentage error). NRMSE provides a scale-independent measure suitable for cross-band error comparison. These metrics were calculated as follows:

$$260 \quad MdAPE = median\left(\left|\frac{Y_i - X_i}{X_i}\right| \times 100\%\right)$$

$$NRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - X_i)^2}}{(X_{max} - X_{min})} \times 100\%$$

where X_i and Y_i denote the *in situ* and satellite-derived R_{rs} values respectively, and N is the number of valid matchups.

2.3.2 Valid Data Yield Comparison

Because valid R_{rs} retrievals are often restricted by atmospheric conditions and QC thresholds (Wang and Shi, 2006; [Lee et al., 2010](#)), the frequency with which a dataset provides usable values serves as a practical indicator of its spatiotemporal utility. To quantify differences in data availability between the new dataset for coastal waters of China and US and the standard products, we computed a pixel-level metric representing the number of days with valid R_{rs} retrievals throughout the analysis period. For each pixel and spectral band, the number of days with valid retrievals was counted and denoted as VO (Valid Observation). A retrieval was considered valid if the R_{rs} value was non-negative and passed all QC filters described in Sect. 2.2.2.

The difference in valid observation counts between the two datasets was defined as:

$$VOD = VO_{New} - VO_{Standard}$$

Here, VOD (Valid Observation Difference) captures the pixel-wise and band-wise difference in the number of valid retrieval days between the new and standard datasets. A positive VOD indicates that the new dataset provided valid R_{rs} values on more days than the standard dataset at the specific pixel and spectral band.

2.4 Analysis of Spatiotemporal Dynamics

To demonstrate the practical utility of the new R_{rs} dataset for long-term monitoring, we conducted a preliminary spatiotemporal analysis over the study regions. For each pixel and spectral band, a monthly time series of mean R_{rs} was first constructed by averaging all valid retrievals within each calendar month over the 20-year period (i.e., 240 monthly averages per pixel). The overall mean of this time series was then calculated and used to visualize the typical spatial patterns of R_{rs} across the study region.

To detect long-term trends, we applied the seasonal Mann–Kendall test—a non-parametric method that accounts for intra-annual variability and is robust to missing or abnormally distributed data (Mann, 1945; Kendall, 1970)—to the 240-month R_{rs} time series of each pixel. To ensure reliable trend estimation, only pixels with valid data in at least 50% of the months were retained. The rate of change ($\% \text{ yr}^{-1}$) was then calculated by dividing the Mann–Kendall slope by the corresponding long-term mean R_{rs} for each pixel.

3 Results and Discussion

3.1 In Situ Validation

The comprehensive validation (shown in Figure 3) ~~suggested~~ demonstrates that R_{rs} products generated with ~~the our~~ improved processing framework ~~demonstrate~~ achieve strong agreement with field observations ~~across eight MODIS Aqua bands, with data points closely clustered along the 1:1 line. Overall, The most significant improvement is the correction of the pervasive systematic low bias present in the standard product, as evidenced by~~ the average regression slope ~~reaches 1.00 ± 0.08~~

significantly improved across the eight MODIS Aqua bands increasing from 0.90 ± 0.06 of the standard products—indicating to 1.00 ± 0.08 . This indicates that the aerosol overcorrection problem ~~is inherent to~~ the standard AC ~~was~~ algorithm in coastal waters has been substantially mitigated.

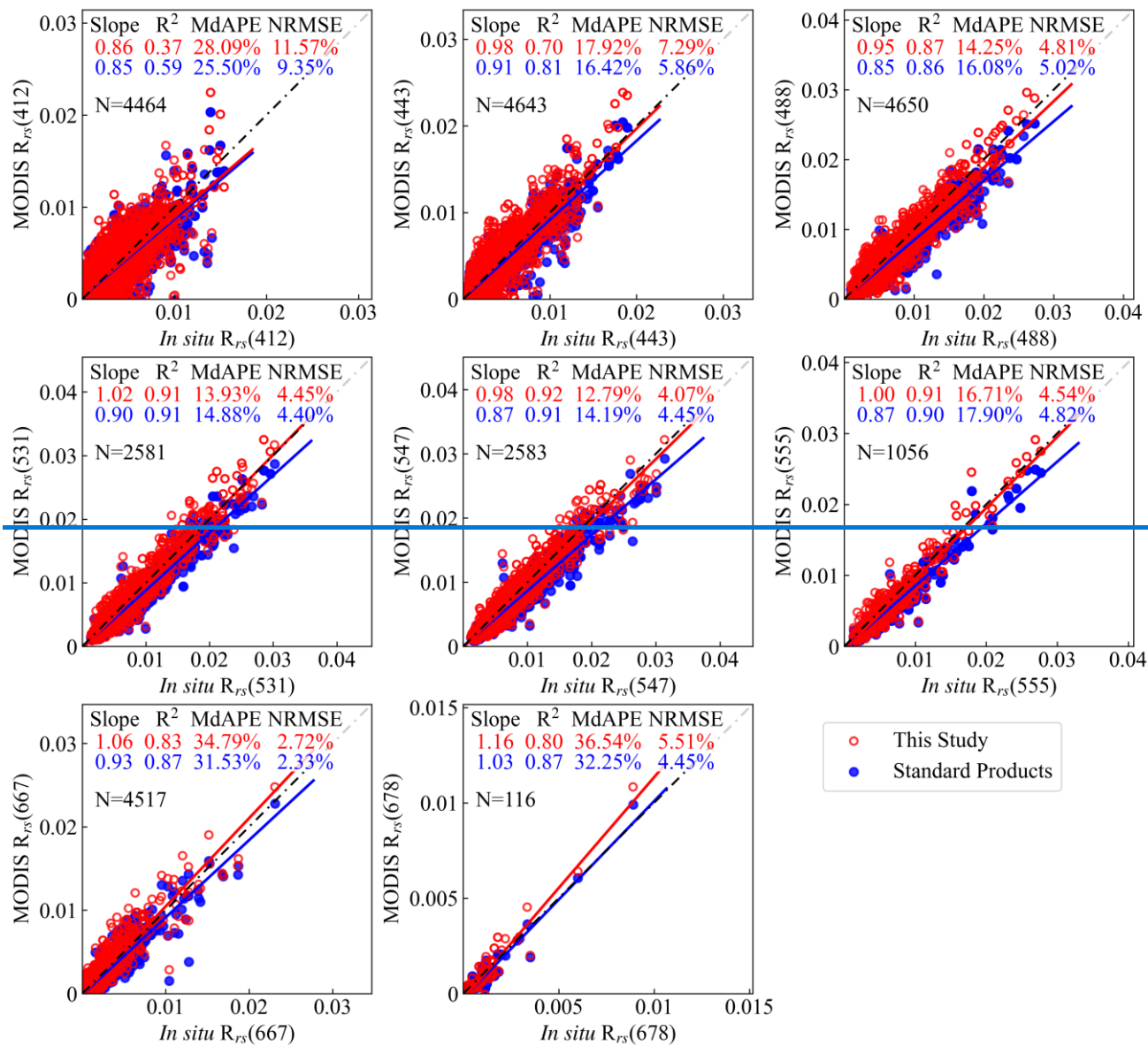
The improvement is particularly pronounced in the 488–555 nm range, where ~~our~~ the new R_{rs} data consistently outperform the standard products, achieving R^2 values of 0.90 ± 0.02 , MdAPE as low as $14.42 \pm 1.7\%$, and NRMSE below 5%, across all metrics. These results confirm that ~~incorporating the use of~~ global gridded aerosol models ~~greatly improves, providing a regionally informed prior, is highly effective in enhancing~~ retrieval accuracy ~~in the visible spectrum, which is most relevant to for~~ water color applications.

Despite these improvements, some challenges remain in the blue bands (412 and 443 nm), where strong absorption and high aerosol sensitivity complicate AC (IoCCG, 2014; Kirk, 2010). While the regression slopes improve relative to the standard products, other metrics show slightly reduced performance, likely due to the limited temporal resolution of monthly aerosol models in highly dynamic coastal regions. Nevertheless, the use of geographically informed aerosol priors still helps reduce the overcorrection tendencies typical of the standard products.

~~In the red bands (667 and 678 nm), a slight overestimation is observed (slopes = 1.06–1.16), possibly due to uncertainties in aerosol absorption assumptions or the inherently low magnitude of R_{rs} signals at these wavelengths (IoCCG, 2019). Even so, our new data better preserves high R_{rs} values in turbid waters, which are often underestimated in the standard product due to conservative assumptions about aerosol absorption.~~

In the red bands (667 and 678 nm), the retrievals exhibit a slight overestimation (slopes = 1.06–1.16), attributable to the combined effects of aerosol model uncertainty and the very low water-leaving signal (IoCCG, 2019). Crucially, even with this residual uncertainty, our new data better preserve high R_{rs} values in turbid waters that are systematically underestimated by the standard product, demonstrating an effective correction of this bias.

In summary, the improved processing framework ~~substantially enhances the~~ delivers a substantial advance in coastal R_{rs} accuracy ~~of satellite derived R_{rs} , particularly by improving aerosol correction in optically complex coastal waters through the flexible use of by using~~ global gridded aerosol models ~~to achieve a major reduction in systematic bias~~. This ~~improvement ensures~~ establishes a more reliable R_{rs} ~~inputs~~ radiometric foundation for coastal monitoring, long-term change detection, and ~~ecological modeling downstream biogeochemical applications~~.



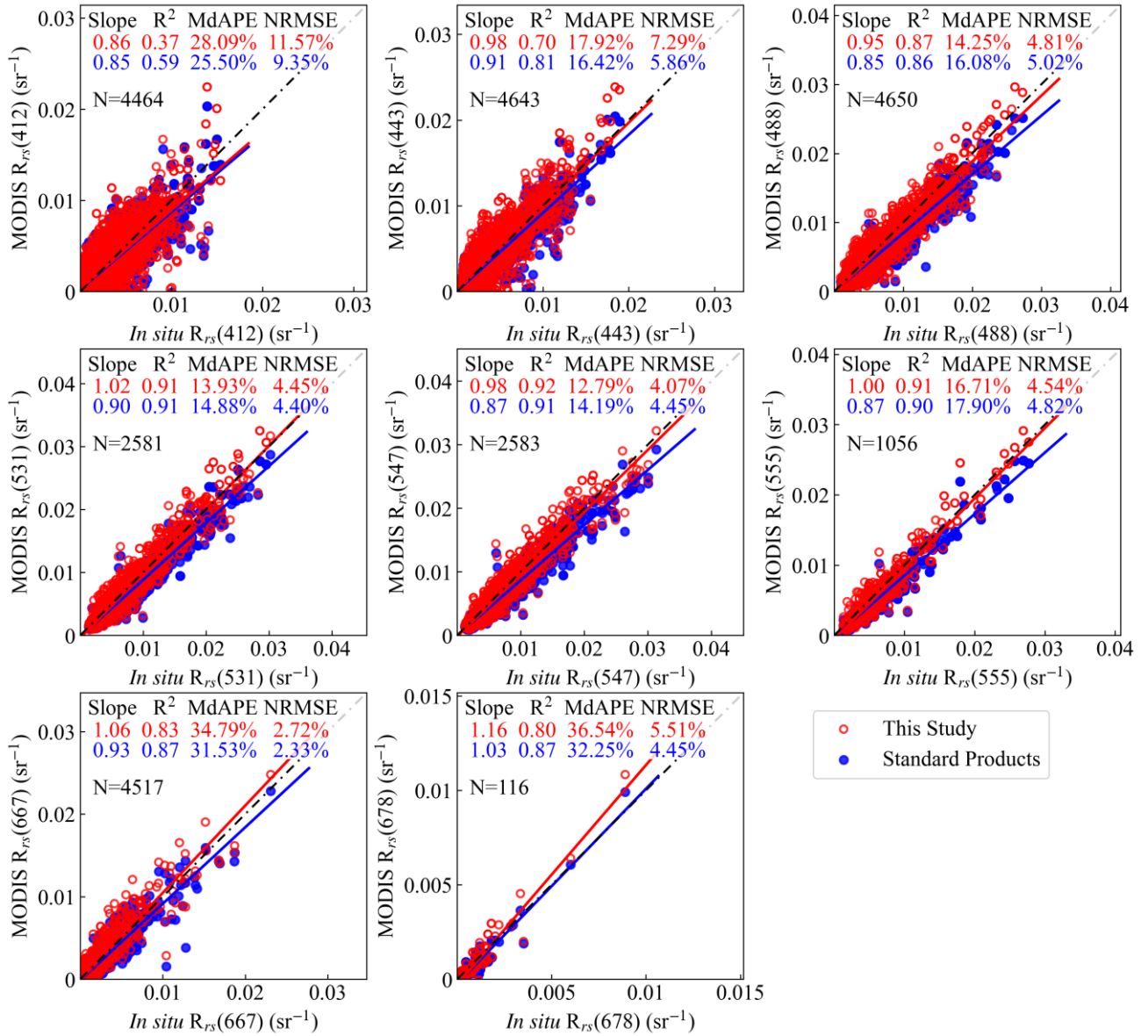


Figure 3: Scatter plots showing the validation of R_{rs} (unit: sr^{-1}) from this study and from NASA standard MODIS Aqua products against *in situ* measurements across eight spectral bands. Accuracy metrics and the number of match-ups (N) are annotated.

325 3.2 Valid Data Yield Comparison Analysis

Figure 4 presents the spatial distribution of valid observations (VO) at 443 nm for both the new R_{rs} dataset and standard products, along with their difference (VOD), over the coastal waters of China and the US in 2007 (region locations shown in

Figure 1). The year 2007 was selected as a reference due to its high data availability and broad spatial coverage in both study regions, providing a practical basis for consistent comparison.

330 In the Chinese coastal waters, the new dataset consistently yields more valid retrievals than the standard products, with notable improvements in the Bohai Sea, the Yellow Sea, and along the broader coastline. On average, the new dataset provides 51 VO per pixel per year, with local maxima reaching 140 days in the Bohai Sea—a region where semi-enclosed geography and sediment-laden river inflows result in persistently turbid conditions that challenge conventional AC (Xu et al., 2018). In contrast, the standard products yield an average of 32 VO, with a maximum of ~110 days observed off the northern coast of
335 the Philippines. The resulting VOD indicates an average increase of 18 days per year in the Chinese coastal waters, reaching up to 94 days in some areas. These improvements reflect the enhanced retrieval capacity of the new processing framework in optically complex coastal regions where the standard operational processing tends to underperform.

In the US coastal waters, the difference between the two datasets is generally smaller but still appreciable. The new dataset achieves an average of 80 VO per year, compared to 68 ~~from~~of the standard products. Both datasets report their highest VO in
340 the Gulf of California, with values of 232 (new) and 225 (standard). The average VOD in this region is 12 days per year, with localized peaks up to 115 days, particularly around Chesapeake Bay, the western Gulf of Mexico, and Cuba.

Overall, the new dataset delivers a regional average increase of 18 days per year in the Chinese coastal waters and 12 days per year in the US coastal waters for $R_{rs}(443)$, corresponding to relative gains of approximately 56% and 18%, respectively. Similar improvements are observed at other visible wavelengths, as illustrated in Figures 5 and 6 for 547 nm and 667 nm, further
345 confirming the broader enhancement in valid data yield provided by the new dataset across the visible spectrum.

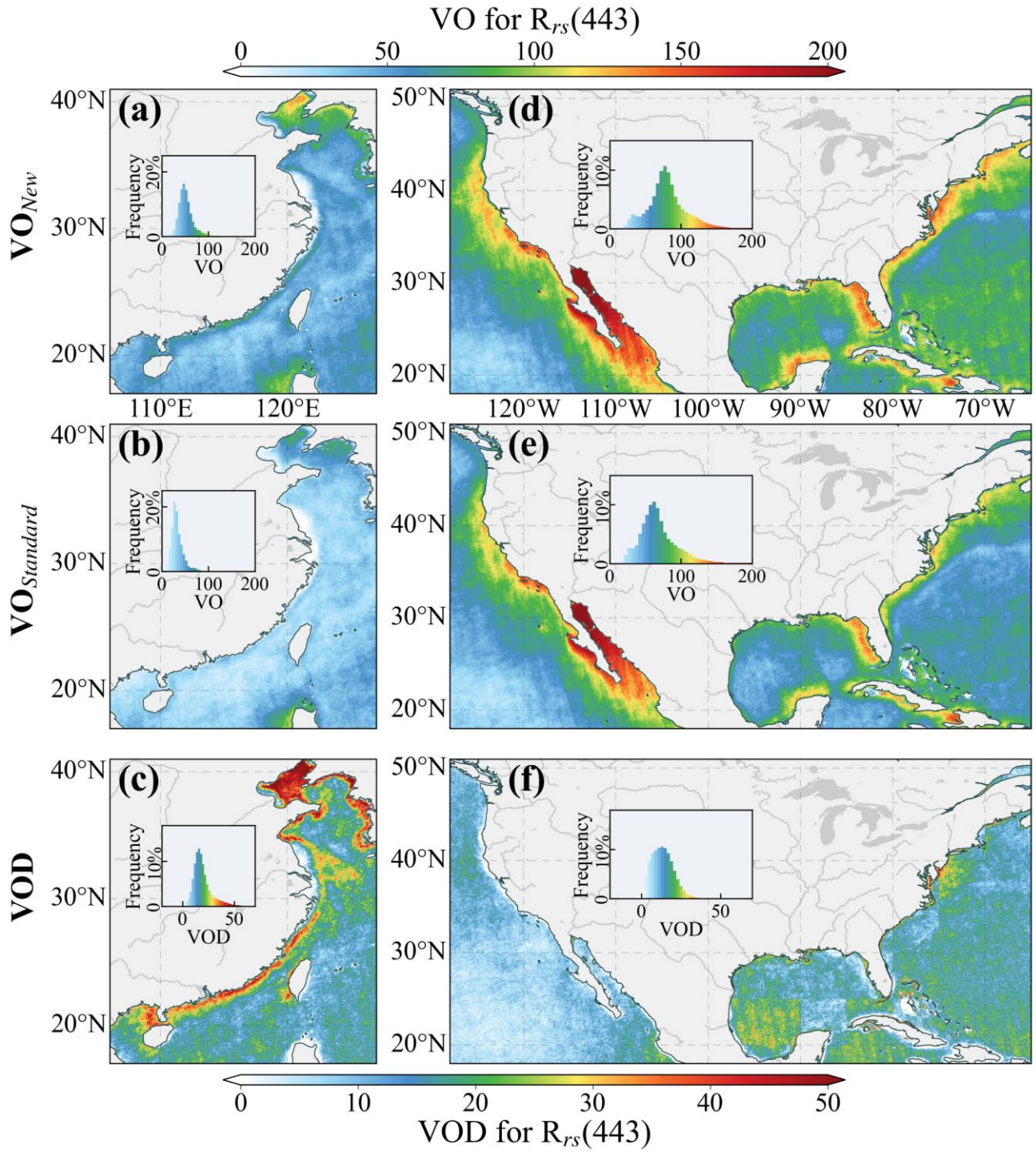


Figure 4: Spatial distribution of valid observations for the new dataset (VO_{New}), the standard products (VO_{Standard}) and their difference (VOD, valid observation difference) for $R_{rs}(443)$ in the coastal waters of China and the United States (US) in 2007.

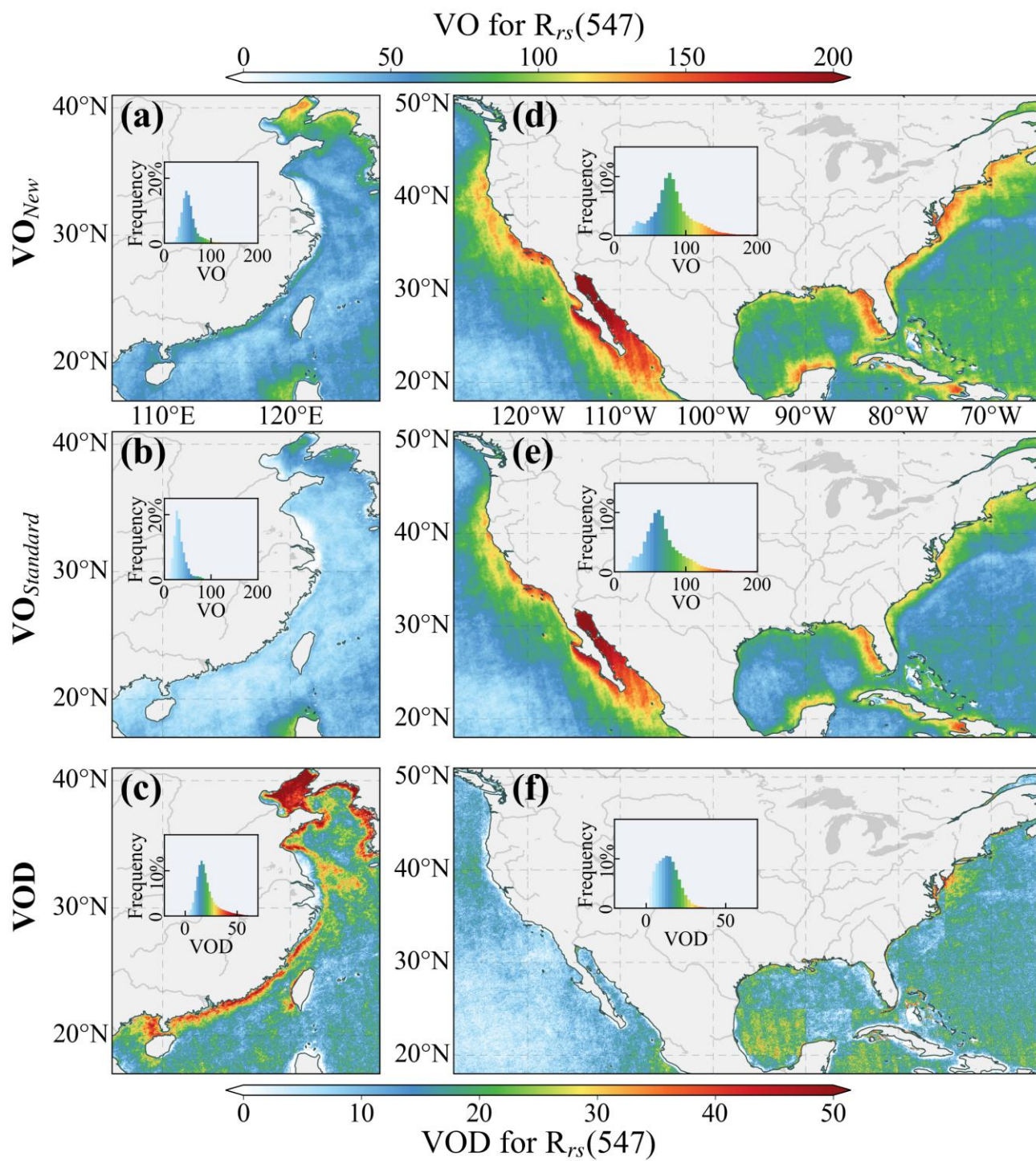


Figure 5: Spatial distribution of V_{ONew} , $V_{OStandard}$, and V_{OD} for $R_{rs}(547)$ in the coastal waters of China and the US in 2007.

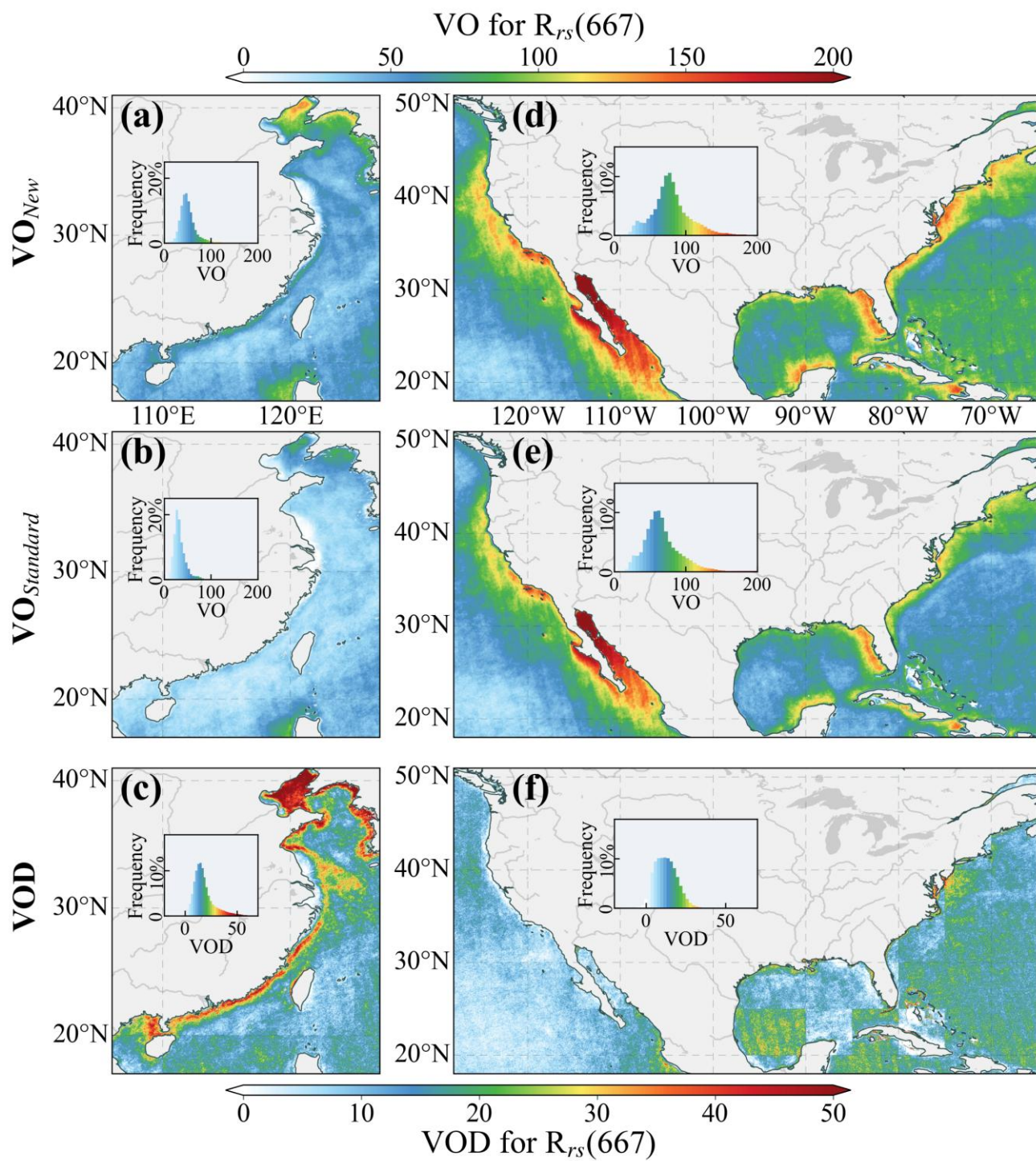


Figure 6: Spatial distribution of $VONew$, $VOStandard$, and VOD for $R_{rs}(667)$ in the coastal waters of China and the US in 2007.

355 Since cloud masking significantly affects the availability of valid satellite ocean color retrievals (Zhao et al., 2023; Zhang et al., 2014), a sensitivity analysis was conducted to isolate the effect of the updated cloud-masking strategy on data availability. Specifically, we reprocessed the 2007 MODIS data for both study regions using the standard NIR iterative AC algorithm and the AF10 aerosol models, but replaced the default cloud-masking threshold ($R_{rc,869} = 0.027$) with the revised threshold ($R_{rc,2130} = 0.037$) adopted in our processing framework. All other processing steps, including the QC procedures described in Sect. 2.2.2, were kept consistent. ~~The resulting VO under this~~ This configuration is denoted as AF10&2130, and its $VO_{AF10\&2130}$, ~~which~~ was then compared to the new dataset's VO_{New} . Their difference, defined as $VOD_{AF10\&2130} = VO_{New} - VO_{AF10\&2130}$, quantifies the change of VO when using the full improved framework beyond the cloud-masking update alone.

Results show that adjusting the cloud-masking threshold alone leads to substantial increases in VO relative to the standard products ($VO_{AF10\&2130} > VO_{Standard}$ in Figure 4), particularly along the Chinese coast. This confirms that the updated threshold more effectively preserves valid water pixels in highly turbid areas that would otherwise be incorrectly excluded.

365 Interestingly, Figure 7 shows that $VOD_{AF10\&2130}$ is negative in many regions, suggesting that the AF10&2130 configuration can sometimes produce more VO than our full processing framework. However, the added retrievals may not be of comparable quality. Although these additional pixels passed the same QC filters, these filters—especially those based on spectral shape and signal saturation—were optimized for the improved processing framework. Consequently, they may not fully capture retrieval errors specific to the AF10&2130 configuration, especially the known R_{rs} underestimation issue associated with AF10 models in coastal waters (see Figure 3).

370 Overall, the new dataset achieves a more balanced outcome by integrating a spatially adaptive aerosol model selection strategy, an improved cloud mask, and tailored QC criteria. These components jointly enhance not only the data yield but also the reliability of R_{rs} retrievals in challenging coastal environments.

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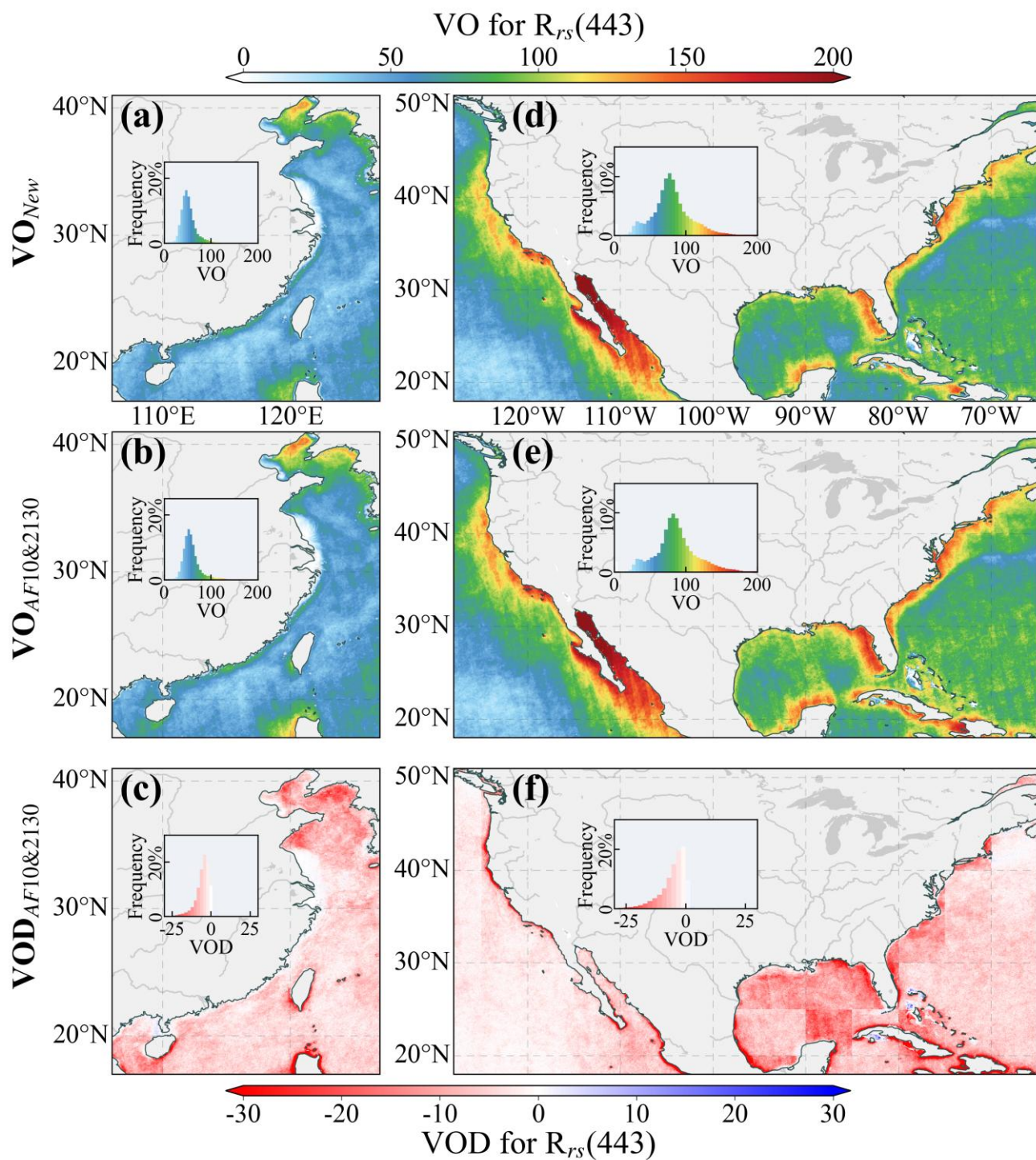


Figure 7: Spatial distribution of valid observations for the new dataset (VO_{New}), the AF10&2130 configuration ($VO_{AF10\&2130}$) and their difference ($VOD_{AF10\&2130} = VO_{New} - VO_{AF10\&2130}$) for $R_{rs}(443)$ in the coastal waters of China and the US in 2007.

380 3.3 Single-Scene Imagery Comparison

To further assess the utility of the new R_{rs} dataset, we conducted single-scene comparisons across four representative coastal regions: the Pearl River Estuary, the Bohai Sea, the Chesapeake Bay, and the Mississippi River Estuary (see Figure 1 for their locations). This analysis aimed to evaluate the dataset's ability to capture regional R_{rs} features under diverse optical conditions, and to delineate the respective contributions of the updated cloud mask and improved aerosol model. To this end, the comparisons include not only our new dataset and the standard product, but also the AF10&2130 configuration (defined in Section 3.2) that applies the standard AF10 aerosol models with our updated cloud mask ($R_{re,2130}=0.037$).

Figure 8 presents the and Figure 9 present the comparative results for the Pearl River Estuary and the Bohai Sea, both of which are characterized by turbid nearshore waters (Liu et al., 2012; Xu et al., 2018). While both datasets broadly reproduce the spatial patterns of R_{rs} . In these regions, the new dataset provides a markedly more extensive coverage of valid data coverage than the standard product. For instance, while the standard products yield few to no valid pixels within the Pearl River Estuary and large portions of the Bohai Sea, whereas the new dataset successfully retrieves recovers these missing observations. This enables the capture of fine-scale coastal structures—such as the distinct high-reflectance band along the Pearl River Estuary's western coast—that are otherwise lost. Critically, the AF10&2130 configuration achieves near-identical spatial coverage of valid pixels, confirming that the relaxed cloud mask is the primary driver for the increased data availability in our new dataset.

However, among the restored turbid water pixels, critical differences exist in the retrieved R_{rs} values. In specific regions characterized by intense sediment plumes, such as the western coast of the Pearl River Estuary and the central Bohai Sea, the R_{rs} values in these retrieved by the AF10&2130 configuration are systematically and significantly lower than those in our new dataset. This pattern is consistent with the known limitation of the standard AF10 models, which tend to overestimate aerosol path radiance in the presence of absorbing aerosols, thereby over-correcting the water-leaving signal and leading to a pervasive low bias. The regionally informed aerosol models integrated into our framework effectively mitigate this issue. Previously validated for strongly absorbing coastal regions like the Bohai Sea (Lv et al., 2024; Zhao et al., 2023), these models provide a more accurate representation of local aerosol properties. Consequently, within the sample windows (marked by black rectangles in Figures 8 and 9), our new dataset yields higher and physically more plausible R_{rs} values. For example, the mean $R_{rs}(547)$ in the Pearl River Estuary window increases from approximately 0.0233 sr^{-1} (AF10&2130) to 0.0270 sr^{-1} , representing a more realistic spectral magnitude for these turbid waters.

We further examined two representative regions in the US coastal waters: the Chesapeake Bay and the Mississippi River Estuary. The same three-way comparisons presented in Figures 10 and 11 (new dataset, standard product, AF10&2130) corroborate the findings from the Chinese seas. The relaxed cloud mask remains the primary driver for increased data coverage, recovering valid pixels in areas— (e.g., the northern Chesapeake Bay and western Mississippi River Delta) that are typically flagged in the standard product. Meanwhile, the improved aerosol model ensures the radiometric fidelity of these recovered

pixels. Within the highlighted sample windows, the new dataset yields R_{rs} values that are consistently higher than the AF10&2130 baseline—for example, approximately 0.0242 sr^{-1} versus 0.0199 sr^{-1} in the Chesapeake Bay at 547 nm—further evidencing the mitigation of systematic underestimation. These consistent results across geographically and optically diverse waters confirm that the observed improvements are not region-specific.

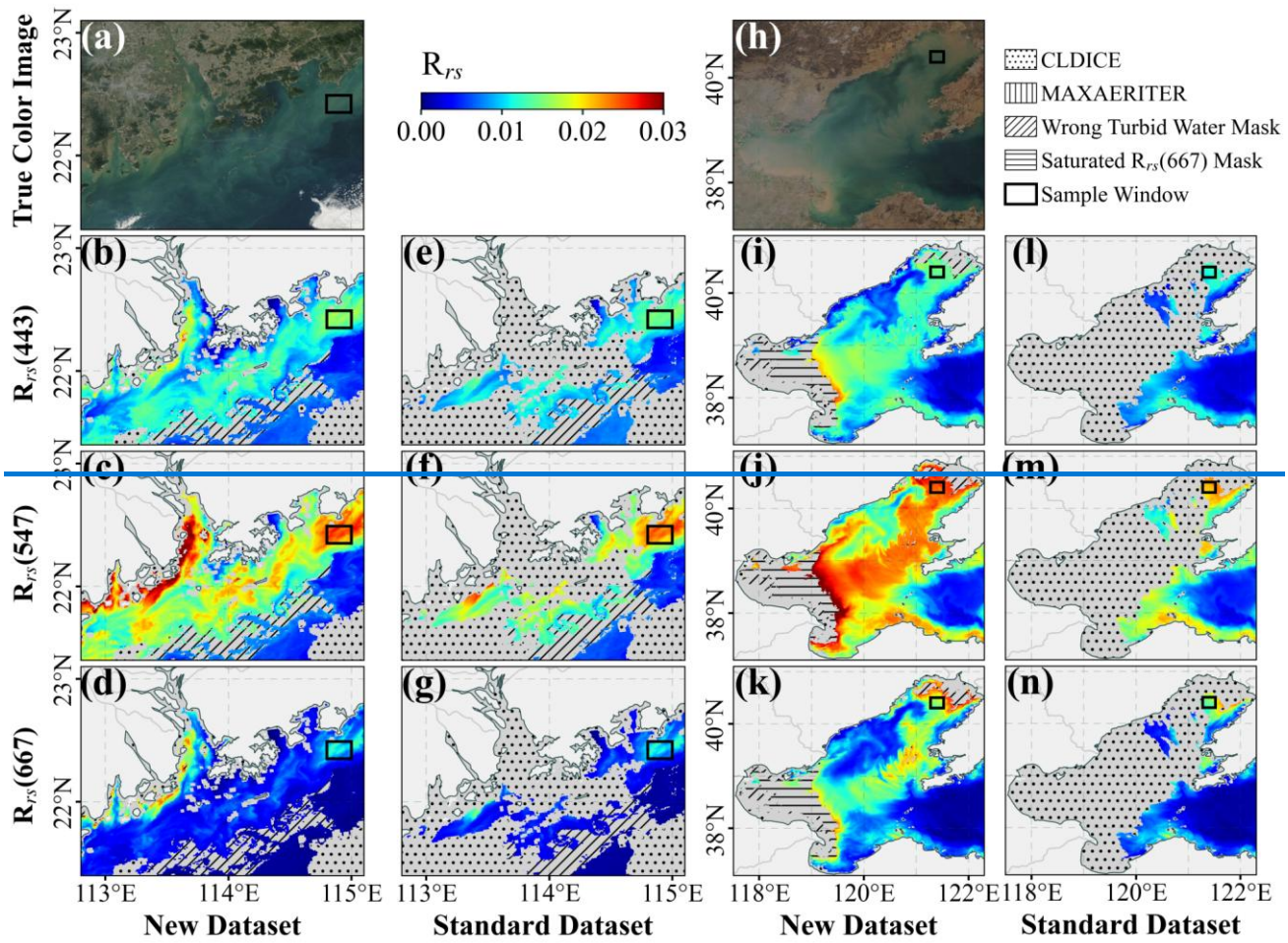
The QC mask analysis reveals that most of the QC masks provides further insight. The missing valuespixels in the standard productsproduct are primarily flagged as cloud- or ice-contaminated. In contrast, the successful retrievals in the new dataset suggest that these regions are actually cloud free but exhibit high reflectance due to intense turbidity, leading to, which is a misclassification by the standard cloud mask. By adopting a revised cloud mask threshold and aerosol models better suitedattributable to turbid conditions, the new dataset retains a greater number of valid pixels, thereby enabling a more complete and accurate depiction of regional R_{rs} patterns. For example, in the western nearshore region of the Pearl River Estuary, the new dataset reveals a distinct high reflectance band likely associated with suspended sediments along the coast—a feature entirely absent in the standard products due to cloud misclassification. This highlights the improved capability of the new dataset to preserve fine scale coastal structures that are frequently lost under conventional processing.

Notably, further inspection of the QC masks reveals that, in addition to improved retention of valid water pixels through thethe high reflectance of turbid water at 869 nm. Our updated cloud mask, some pixels—though not flagged as clouds—were still excluded by the—successfully recognizes these pixels as valid water observations. Furthermore, the new dataset's complementary QC filters (e.g., the “Wrong Turbid Water Mask” and “Saturated $R_{rs}(667)$ Mask” (i.e., the spectral shape and saturation-based QC filters introduced in Sect. Section 2.2.2). This suggests that the newly implemented QC) work in tandem with the relaxed cloud mask. These filters play a complementary role to cloud masking by identifying additional suspect pixels—such as those with atypical spectral shapes or signal saturation—that might otherwise be retained. This added filtering helps enhance the overall reliability of the retained R_{rs} databy screening out pixels with anomalous spectral features, ensuring that data quality is maintained even if the detection constraints are relaxed.

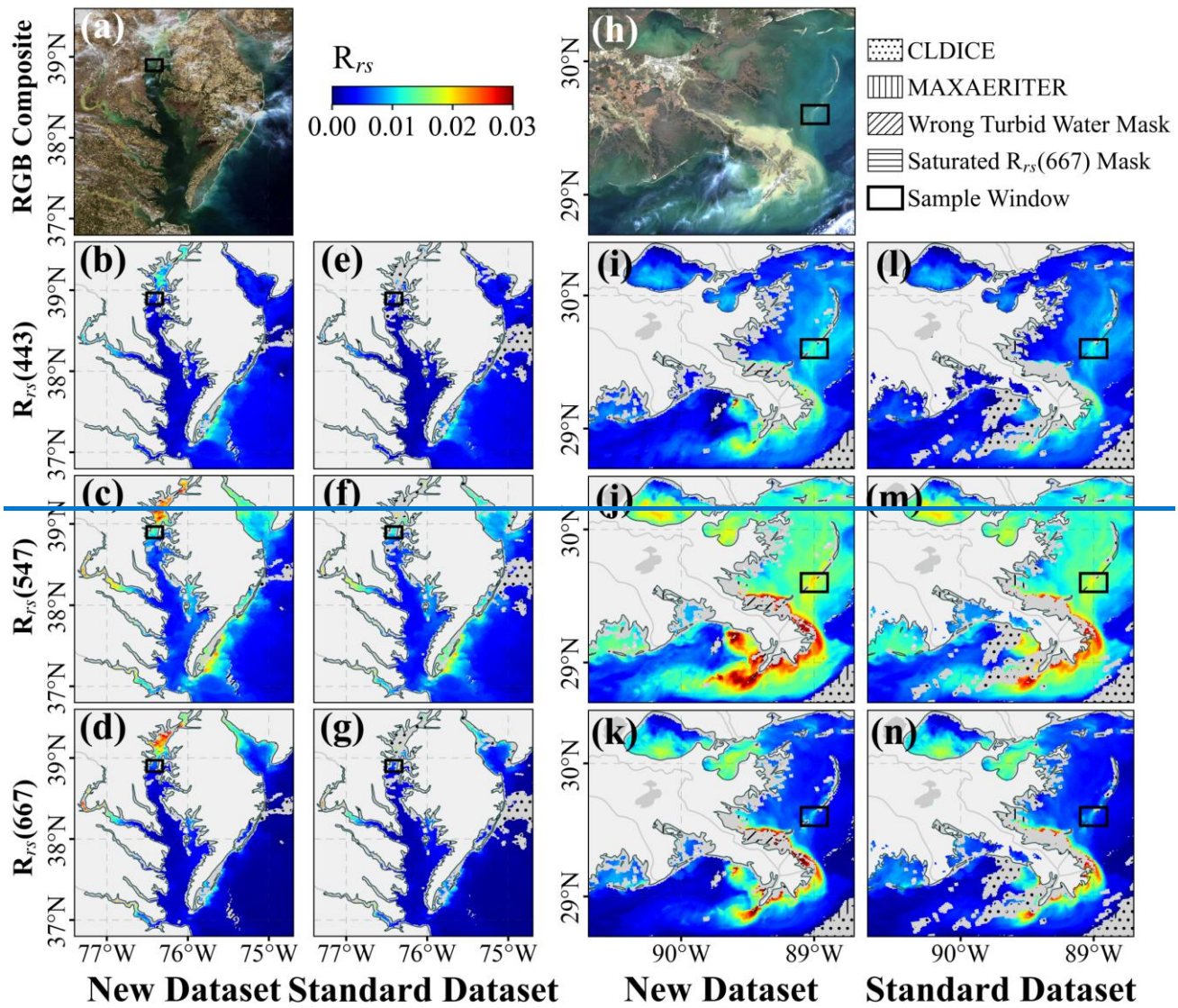
In addition to enhanced coverage, the new dataset also exhibits slightly higher R_{rs} values at identical locations. For instance, in the Pearl River Estuary, the average $R_{rs}(547)$ in the sample window (indicated by black rectangles in Figure 8; the same symbol is used for other sample windows below) increases from approximately 0.0227 to 0.0239 sr^{-1} ; in Bohai Bay, the value rises from 0.0213 to 0.0244 sr^{-1} . These differences underscore the improved retrieval capability of the improved processing framework, particularly in mitigating the underestimation tendency associated with AF10 models (as also evidenced in Figure 3).

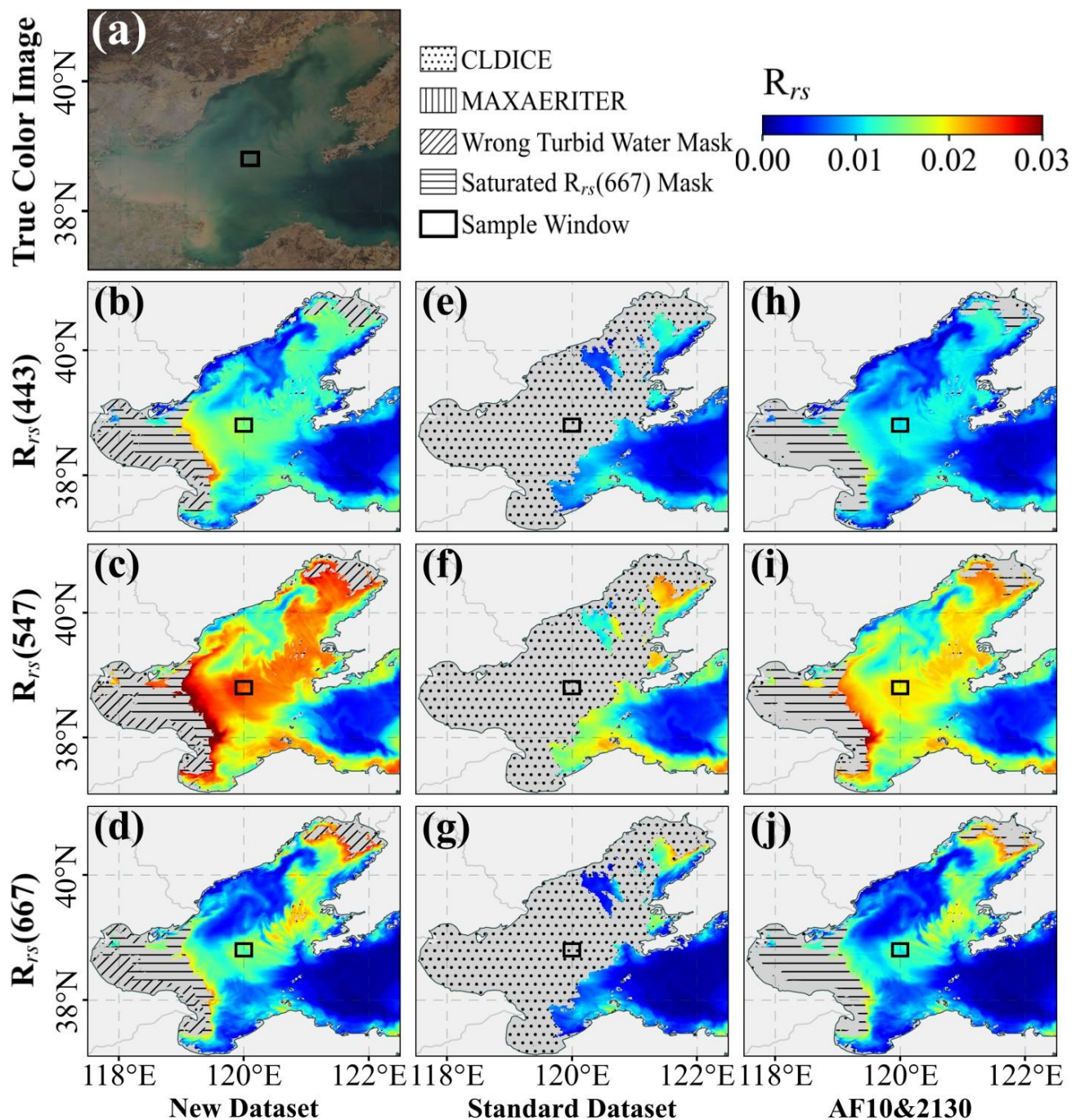
Nevertheless, the new dataset still fails to retrieve valid data in certain extremely turbid zoneswaters, such as partsportions of the western Bohai Sea, pointing toindicating remaining challenges in processing waters with extremely high reflectance. AC for waters with exceptionally high reflectance. In summary, the integrated framework underlying our new dataset delivers a substantial advancement: it significantly increases data availability in coastal zones through a tailored cloud mask, while

concurrently ensuring the radiometric accuracy of the recovered data through optimized aerosol correction and specialized QC filters. This dual improvement enhances the dataset's suitability for detailed ocean color analysis and reliable water quality monitoring in optically complex nearshore environments.



We further examined two representative regions in the US coastal waters: the Chesapeake Bay and the Mississippi Estuary. As shown in Figure 9, both datasets reveal generally consistent spatial distributions of R_{rs} , supporting the reliability of the new dataset. However, clear differences in data availability are observed. True color composite combined with mask analysis reveals that the new dataset exhibits greater resistance to thin cloud contamination, allowing successful retrievals over pixels that are missing in the standard products, such as those in the northern Chesapeake Bay and western Mississippi River Delta. The relaxed cloud mask helps preserve these pixels, while the adoption of more appropriate aerosol models enables more accurate retrievals rather than underestimation. Within the highlighted sample windows, the new dataset also yields slightly elevated R_{rs} values—for example, approximately 0.0113 sr^{-1} vs. 0.0097 sr^{-1} in the Chesapeake Bay, and 0.0169 sr^{-1} vs. 0.0156 sr^{-1} in the Mississippi Estuary—further indicating improved performance in mitigating overcorrection caused by the AF10 models. These results suggest that the observed improvements are not region specific but hold across geographically and optically diverse coastal waters.





470 Figure 9: Comparison of R_{rs} (units: sr^{-1}) derived from single-scene MODIS Aqua observations over the Bohai Sea (2020-03-11). The top image shows a true color composite (panel a), followed by R_{rs} at 443, 547, and 667 nm from the new dataset (panels b–d), from the standard dataset (panels e–g) and from the AF10&2130 configuration (panels h–j). Invalid pixels are marked with hatched

patterns based on quality control masks. Black rectangles mark the sample windows where average R_{rs} values are calculated and compared quantitatively in the text.

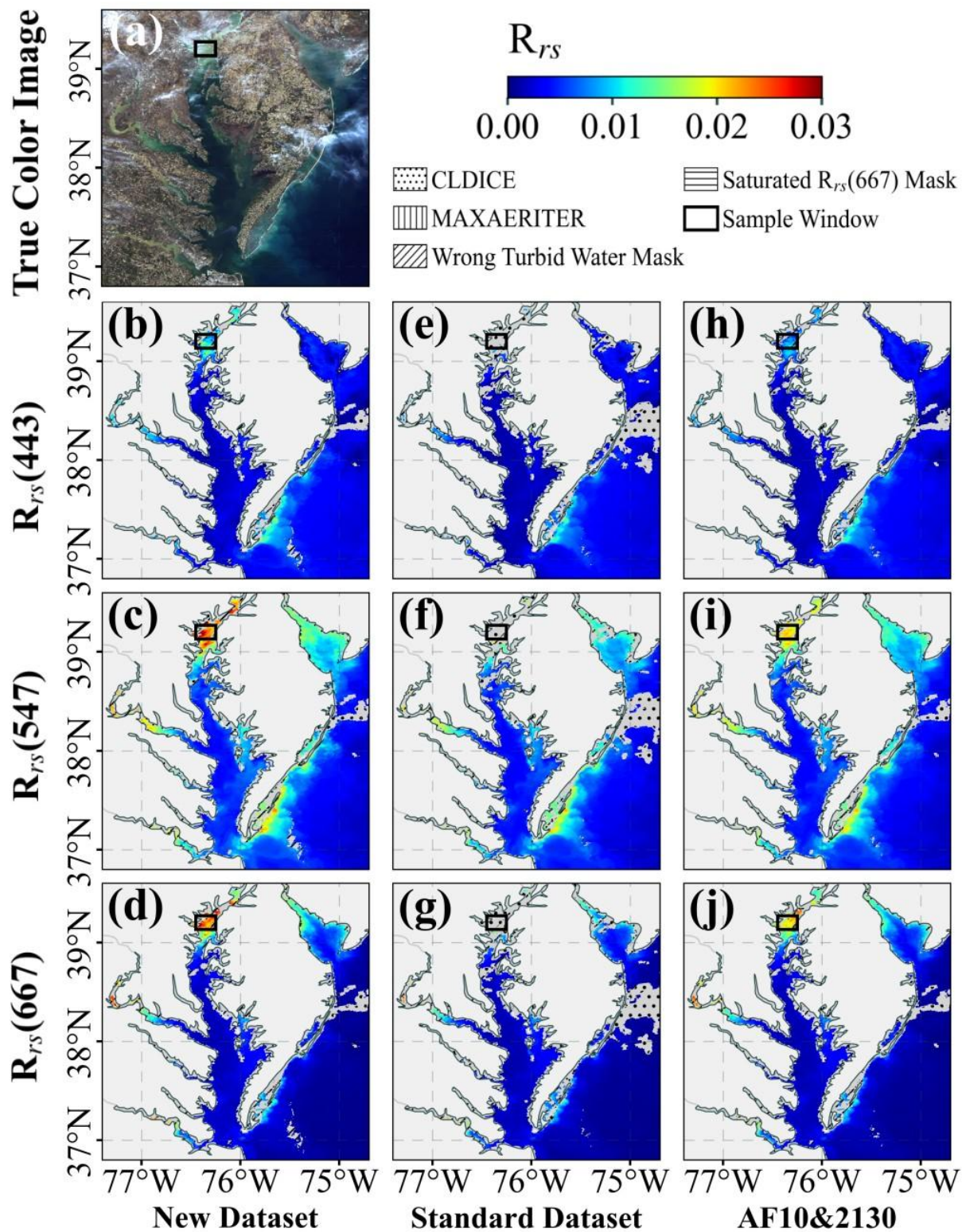


Figure 10: Comparison of R_s (units: sr^{-1}) derived from single-scene MODIS Aqua observations over the Chesapeake Bay (2019-02-05) and the Mississippi Estuary (2021-01-13). For each region, the top image shows a true color composite (panel a and h), followed by R_s at 443, 547, and 667 nm from the new dataset (panels b-d and i-k) and from the standard dataset (panels e-g and l-n), respectively, and from the AF10&2130 configuration (panels h-j). Invalid pixels are marked with hatched patterns based on quality control masks. Black rectangles indicate the sample windows used for regional comparison where average R_s values are calculated and compared quantitatively in the text.

In summary, the new dataset demonstrates superior performance in preserving valid retrievals and accurately capturing subtle gradients across optically complex coastal waters. These improvements enhance its suitability for detailed ocean color analysis and reliable assessment of water quality in challenging nearshore environments.

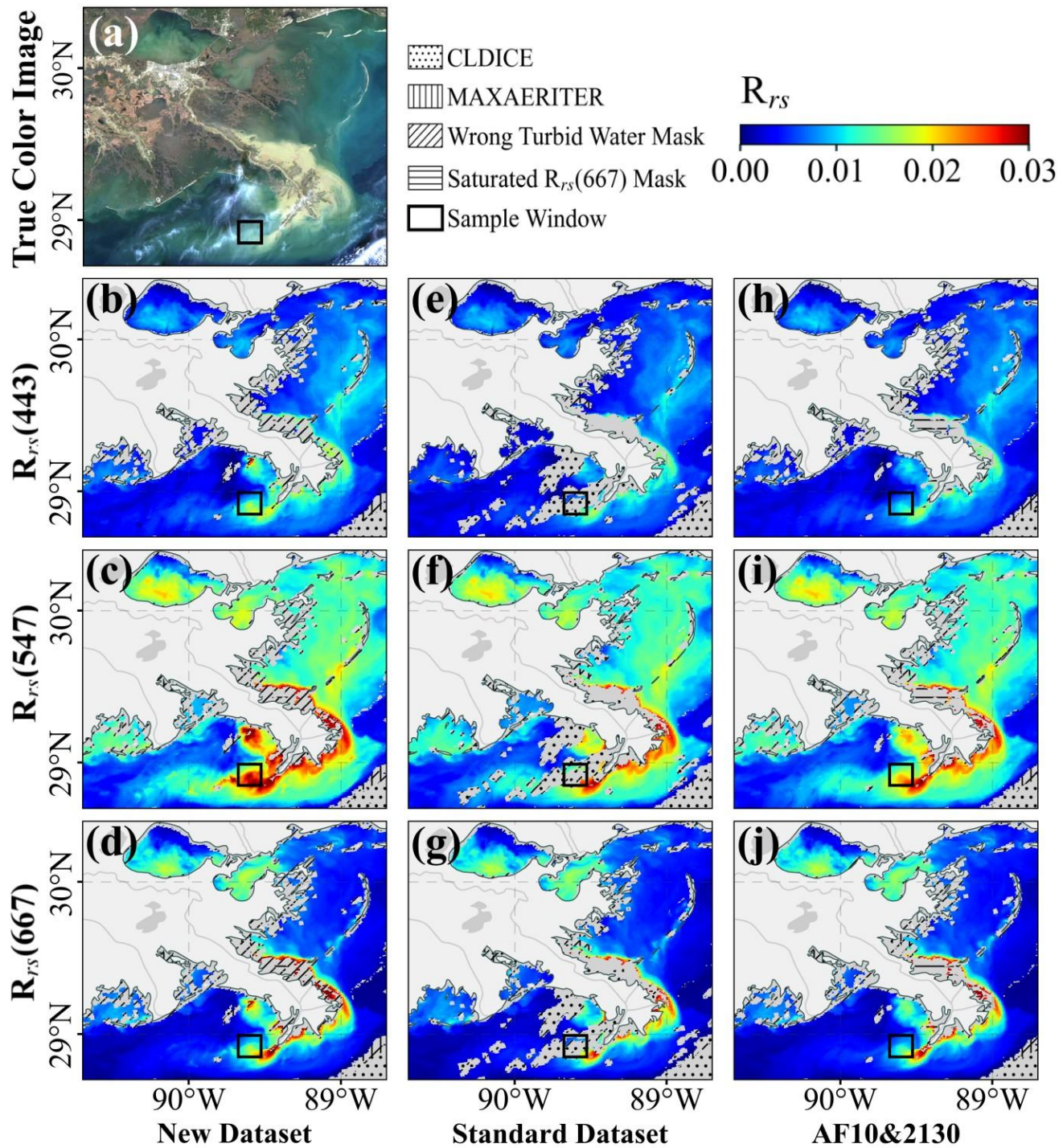


Figure 11: Comparison of R_{rs} (units: sr^{-1}) derived from single-scene MODIS Aqua observations over the Mississippi River Estuary (2021-01-13). The top image shows a true color composite (panel a), followed by R_{rs} at 443, 547, and 667 nm from the new dataset

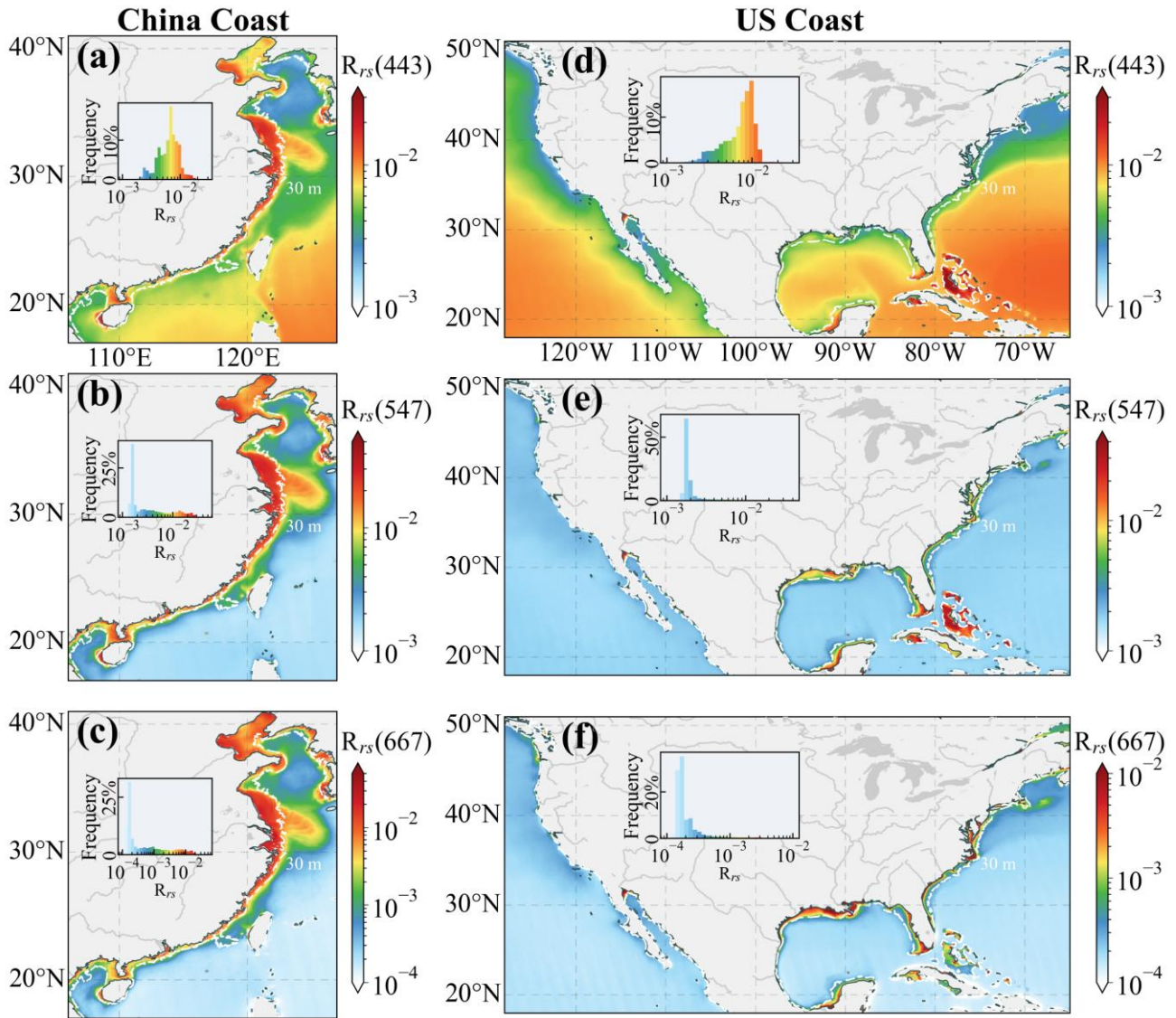
(panels b–d), from the standard dataset (panels e–g) and from the AF10&2130 configuration (panels h–j). Invalid pixels are marked with hatched patterns based on quality control masks. Black rectangles mark the sample windows where average R_{rs} values are calculated and compared quantitatively in the text.

3.4 Spatiotemporal Patterns and Trends

Figure 1012 illustrates the spatial distribution of long-term mean R_{rs} values at 443, 547, and 667 nm for the coastal waters of China and the US over the 2003–2022 period. These patterns reveal clear wavelength dependence and regional variability.

In Chinese coastal waters (Figures 10a12a–c), the regional average $R_{rs}(443)$ is 0.00679 sr^{-1} , rising to 0.00866 sr^{-1} within the 30 m isobath (marked by the white dashed line), where optically complex conditions dominate. Notably high $R_{rs}(443)$ values are observed in nearshore areas such as the western Bohai Sea (0.00738 sr^{-1}), the Yangtze River Estuary and Hangzhou Bay (0.01213 sr^{-1}), the Pearl River Estuary, and the eastern Beibu Gulf. These high $R_{rs}(443)$ values persist despite strong absorption by high concentrations of CDOM and Chl, suggesting that backscattering by suspended sediments dominates the blue reflectance signal in these turbid waters (Kirk, 2010; Feng et al., 2014; Ye et al., 2016). In contrast, significantly low $R_{rs}(443)$ values ($<0.003 \text{ sr}^{-1}$) occur in the central and northern Yellow Sea, where sediment loads are reduced and absorption remains high, resulting in suppressed reflectance in the blue band (Kirk, 2010; Ye et al., 2016; Ling et al., 2020). At longer wavelengths (547 and 667 nm), high R_{rs} values are more restricted to highly turbid nearshore and estuarine waters. Within the 30 m isobath, the mean $R_{rs}(547)$ and $R_{rs}(667)$ values reach 0.01551 sr^{-1} and 0.00819 sr^{-1} , respectively, decreasing to 0.00506 sr^{-1} and 0.00184 sr^{-1} farther offshore. These spatial patterns reflect the varying contributions of optically active constituents to spectral reflectance.

In US coastal waters (Figures 10d12d–f) the long-term mean R_{rs} values exhibit distinct spatial features. At 443 nm, high R_{rs} values ($>0.03 \text{ sr}^{-1}$) are found around the shallow Bahamas Banks, while low values ($<0.003 \text{ sr}^{-1}$) dominate the East and West Coasts of the US, indicative of strong absorption by CDOM and Chl (Mannino et al., 2008; Kirk, 2010). At 547 nm and 667 nm, high R_{rs} values are observed in regions such as the northwestern Gulf of California, the Gulf of Mexico coast, and around Chesapeake Bay. As in the Chinese coastal waters, R_{rs} decreases sharply with increasing distance from shore.



515 **Figure 12: Spatial distribution of long-term mean R_{rs} (units: sr^{-1}) at 443, 547, and 667 nm for China (a - c) and US (d - f) coastal waters, derived from the new dataset (2003-2022). White dashed lines indicate the approximate 30 m isobath.**

Figure 4-13 illustrates the spatial distribution of long-term R_{rs} trends ($\% \text{ yr}^{-1}$) for the same wavelengths, as estimated using the seasonal Mann-Kendall test over the 240-month period.

520 In Chinese coastal waters (Figures 4-13a-c), $R_{rs}(443)$ generally shows increasing trends, with a mean rate of $0.64\% \text{ yr}^{-1}$ and localized peaks reaching $6.85\% \text{ yr}^{-1}$ in the central Yellow Sea. $R_{rs}(547)$ and $R_{rs}(667)$ also exhibit upward trends in this region, potentially reflecting rising suspended sediment concentrations and declining Chl and CDOM levels in recent years, as

previously observed by Wang et al. (2023). In contrast, most of Laizhou Bay, Bohai Bay, and the eastern Liaodong Bay show consistent negative trends across all three wavelengths, possibly indicating a reduction in suspended sediment loads. This trend aligns with earlier findings that attribute such declines to weakening wind-driven sediment resuspension (Li et al., 2022; Zhao et al., 2022). The mean trends for $R_{rs}(547)$ and $R_{rs}(667)$ are $0.18\% \text{ yr}^{-1}$ and $0.24\% \text{ yr}^{-1}$, respectively, although widespread declines are also evident in other areas, such as the northern South China Sea, with maximum decreases reaching $-6.70\% \text{ yr}^{-1}$ and $-9.08\% \text{ yr}^{-1}$.

In the US coastal waters (Figures 4d–f), $R_{rs}(443)$ exhibits a mean increase of $0.28\% \text{ yr}^{-1}$, with peak increases reaching $7.22\% \text{ yr}^{-1}$. Strong positive trends are observed along the US West Coast, near the Bahamas, and within the Gulf Stream region. In contrast, notable declines occur in areas such as southern Florida Peninsula and the western Gulf of Mexico, with rates reaching $-6.06\% \text{ yr}^{-1}$. For $R_{rs}(547)$ and $R_{rs}(667)$, the overall trends are slightly negative ($-0.004\% \text{ yr}^{-1}$ and $0.042\% \text{ yr}^{-1}$, respectively), with most coastal regions—except the western Gulf of Mexico—showing decreasing trends, with minimum values of $-5.68\% \text{ yr}^{-1}$ and $-7.51\% \text{ yr}^{-1}$, respectively. A particularly complex pattern emerges along the Gulf Stream: while $R_{rs}(443)$ increases significantly, $R_{rs}(547)$ and $R_{rs}(667)$ exhibit moderate decreases. This may reflect the growing influence of oligotrophic Gulf Stream waters (Leonelli et al., 2022) and enhanced upper-ocean stratification associated with regional ocean warming (Todd and Ren, 2023). These processes are known to suppress vertical mixing and nutrient supply (Li et al., 2020), leading to reduced phytoplankton biomass (Yu et al., 2023) and lower concentrations of suspended matter (Wei et al., 2021) in the surface layer. Such reductions in optically active constituents diminish absorption in the blue bands and scattering in the green and red bands, consistent with the observed R_{rs} trends in this region. Additionally, the magnitude of R_{rs} trends is greater in the Chinese coastal waters than in the US coastal waters, likely reflecting stronger anthropogenic influences, hydrological variability, and regional-specific geomorphological settings.

The observed spatiotemporal patterns and trends in R_{rs} underscore the robustness of the new dataset in capturing diverse coastal optical dynamics. Their consistency with previously reported trends lends further confidence in the dataset's reliability and demonstrates its value as a foundation for future research into long-term environmental change, human impacts, and climate-related ecosystem responses in coastal waters.

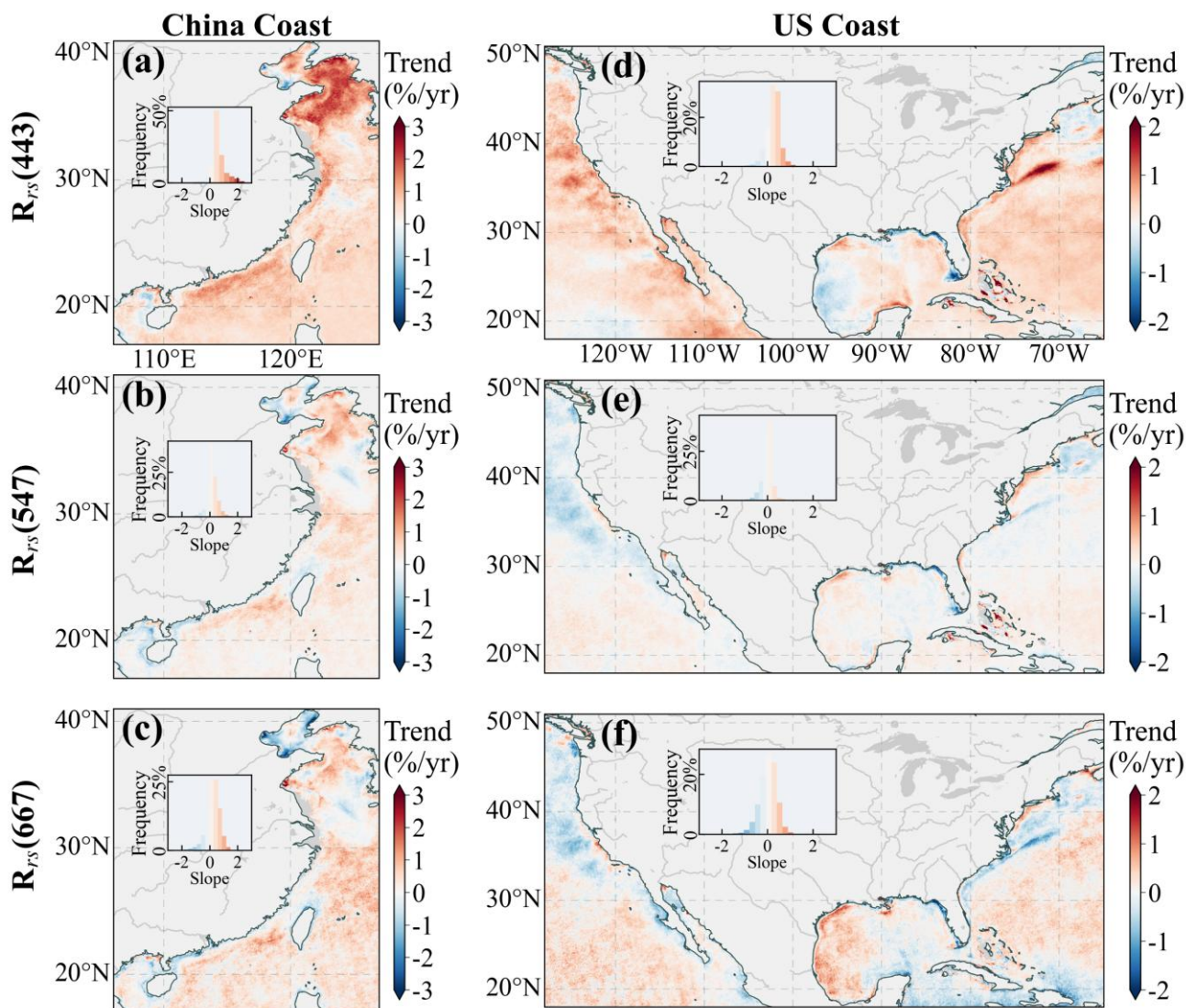


Figure 13: Long-term R_{rs} trends (units: $\% \text{ yr}^{-1}$) from 2003 to 2022, derived using the seasonal Mann-Kendall test at 443, 547, and 667 nm for China (a - c) and US (d - f) coastal waters. Rates are computed as the Mann-Kendall slope divided by the corresponding 20-year average R_{rs} .

4 Discussion

4.1 Comparison Against Other AC Algorithms for Coastal Waters

To further contextualize the performance of our framework, we conducted a scene-based intercomparison with three advanced AC algorithms for complex waters: OC-SMART(Fan et al., 2021), POLYMER(Steinmetz et al., 2011), and NIR-SWIR, using

the same four representative regions from Section 3.3. This analysis also included results from the standard NIR iterative algorithm with AF10 aerosol models and relaxed cloud mask (AF10&2130, as mentioned before). This configuration provides a reference baseline that embodies the persistent low bias, so the corrective effect of other algorithms can be assessed against it. For a fair and controlled comparison, the NIR-SWIR and AF10&2130 configurations used the same cloud mask and quality control steps as our new dataset, while OC-SMART and POLYMER were run with their default settings.

The comparative imagery (Figures 14-17) demonstrates the superior performance of our framework. While all five methods successfully capture major spatial patterns associated with turbid water features (e.g., sediment plumes) in the 547 nm and 667 nm bands, our new dataset consistently retrieves the highest R_{rs} values in the most turbid regions across all scenes and bands (443, 547, 667 nm). In contrast, the R_{rs} values retrieved by OC-SMART, POLYMER, and NIR-SWIR in these challenging areas are frequently comparable to, or only marginally higher than, those of the AF10&2130 configuration. Given that the AF10&2130 configuration is quantitatively demonstrated to suffer from systematic underestimation (Section 3.1, Figure 3), this indicates that the corrective effect of these other algorithms on the low bias is limited in optically extreme waters, whereas our improved framework provides the most robust correction.

Regarding data quality, NIR-SWIR results exhibit increased image noise due to the low signal-to-noise ratio of MODIS Aqua's SWIR bands. While POLYMER and OC-SMART generally perform well, isolated issues such as unmasked anomalous pixels (Bohai Sea for POLYMER) and striping artifacts (Mississippi River Estuary at 443 nm for OC-SMART) were observed. In terms of data coverage, the default masks for OC-SMART and POLYMER retained slightly more data in the Pearl River Estuary than our more conservative QC chain.

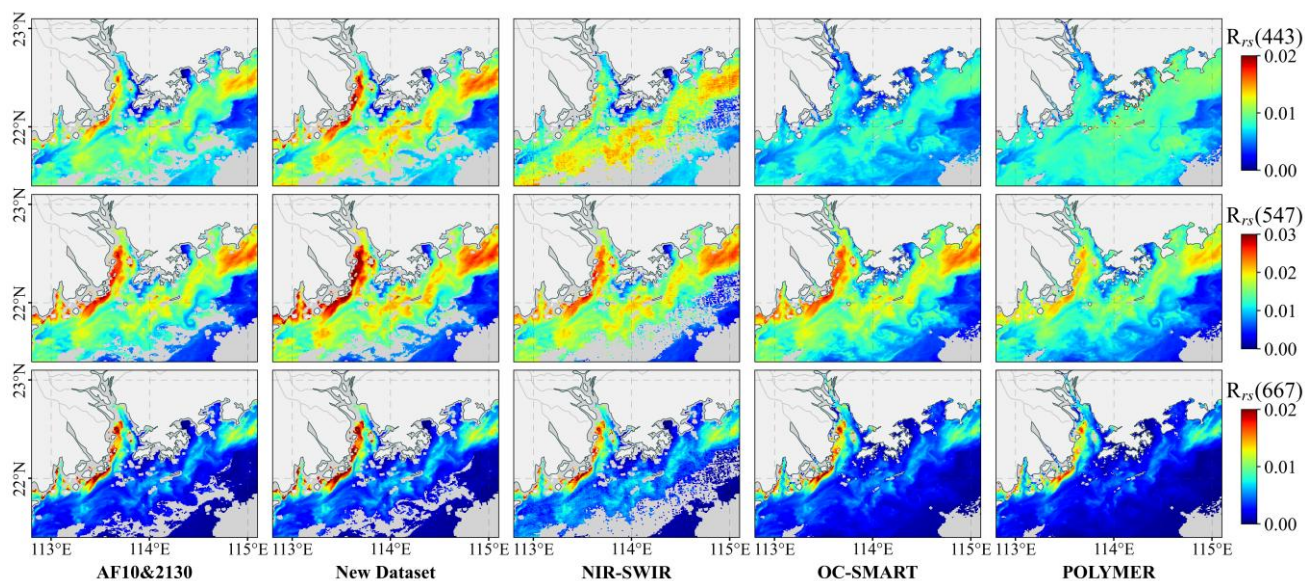


Figure 14: Comparison of R_{rs} (units: sr-1) derived from single-scene MODIS Aqua observations over the Pearl River Estuary (2014 12-14). The figure shows R_{rs} at 443 nm (top row), 547 nm (middle row), and 667 nm (bottom row) as processed by the AF10&2130 configuration (first column), our new dataset (second column), the NIR-SWIR algorithm with AF10 aerosol models and $R_{rc,2130}=0.037$ as cloud mask threshold (third column), OC-SMART (fourth column), and POLYMER (fifth column).

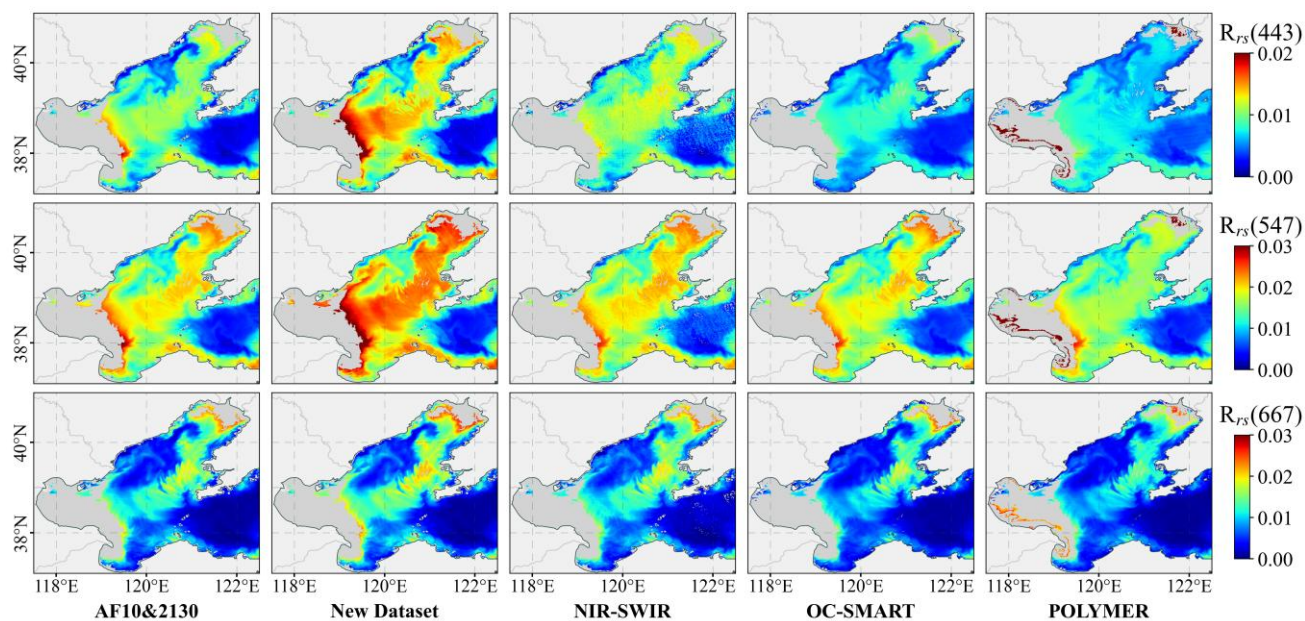


Figure 15: Comparison of R_{rs} (units: sr-1) derived from single-scene MODIS Aqua observations over the Bohai Sea (2020-03-11). The figure shows R_{rs} at 443 nm (top row), 547 nm (middle row), and 667 nm (bottom row) as processed by the AF10&2130 configuration (first column), our new dataset (second column), the NIR-SWIR algorithm with AF10 aerosol models and $R_{rc,2130}=0.037$ as cloud mask threshold (third column), OC-SMART (fourth column), and POLYMER (fifth column).

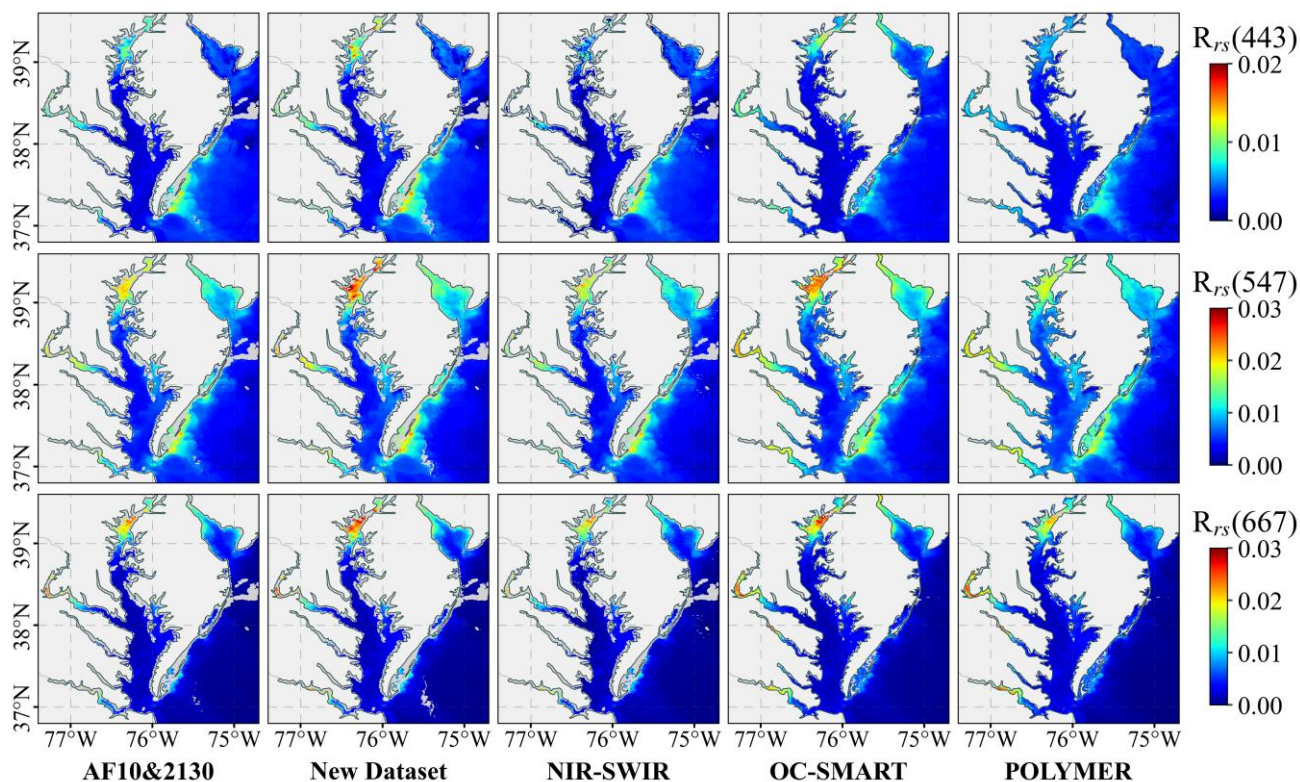


Figure 16: Comparison of R_{rs} (units: sr^{-1}) derived from single-scene MODIS Aqua observations over the Chesapeake Bay (2019-02-05). The figure shows R_{rs} at 443 nm (top row), 547 nm (middle row), and 667 nm (bottom row) as processed by the AF10&2130 configuration (first column), our new dataset (second column), the NIR-SWIR algorithm with AF10 aerosol models and $R_{rc,2130}=0.037$ as cloud mask threshold (third column), OC-SMART (fourth column), and POLYMER (fifth column).

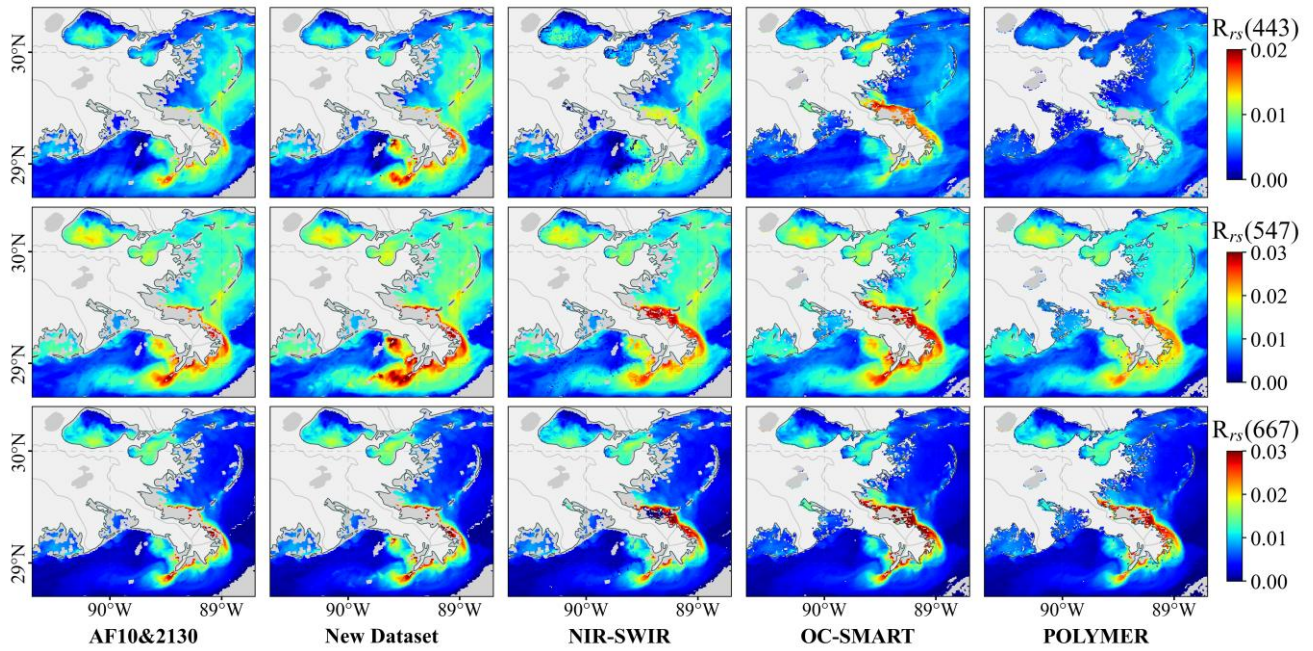


Figure 17: Comparison of R_{rs} (units: sr-1) derived from single-scene MODIS Aqua observations over the Mississippi River Estuary (2021-01-13). The figure shows R_{rs} at 443 nm (top row), 547 nm (middle row), and 667 nm (bottom row) as processed by the AF10&2130 configuration (first column), our new dataset (second column), the NIR-SWIR algorithm with AF10 aerosol models and $R_{rc,2130}=0.037$ as cloud mask threshold (third column), OC-SMART (fourth column), and POLYMER (fifth column).

Beyond these empirical results, our methodological approach itself warrants discussion. It enhances a physically based, modular component (aerosol modeling) within the radiative transfer framework. This differs from strategies that depend on comprehensively pre-trained spectral or bio-optical models (e.g., POLYMER, OC-SMART), whose performance is inherently tied to the optical domains covered during their training or optimization. Adapting our framework to a new coastal region would primarily involve updating the modular aerosol prior with local or regional climatological data. In contrast, methods like POLYMER or OC-SMART may require significant recalibration or retraining to maintain performance outside their original optimization domain. Thus, our design offers a more straightforward and transparent path for regional scalability.

4.2 Considerations on the Aerosol Model Selection Strategy

A pivotal component of our improved AC framework is the dynamic selection of aerosol models, guided by the normalized water-leaving radiance in the NIR band ($[L_w(NIR)]_N$). This design is predicated on the strong empirical spatial co-occurrence observed in coastal zones: waters exhibiting high turbidity (and thus elevated $[L_w(NIR)]_N$) are typically nearshore, and this high turbidity spatially co-occurs with prevalent continentally influenced, often absorbing aerosols. Conversely, in offshore regions, waters are generally clear (with low $[L_w(NIR)]_N$) and maritime aerosols prevail. We leveraged this consistent

610 geographic pattern as a practical and effective proxy to implement a necessary transition between aerosol models across the land-ocean gradient. This spatially adaptive selection prevents the systematic underestimation that would occur if AF10 models were applied to turbid nearshore waters, while simultaneously avoiding the overestimation that would arise if gridded models representing absorbing aerosols were used in clear offshore waters. The success of this approach is evidenced by the reduction of systematic bias (Figure 3) and the spatially coherent R_{rs} fields without discontinuities (e.g., Figures 8, 9).

615 It is important to clarify that this strategy does not assert a direct physical causation between water optical properties and aerosol characteristics. Rather, it is a pragmatic solution that capitalizes on their correlated spatial distributions driven by common terrestrial influences. Consequently, the performance of this approach is inherently tied to the robustness of this co-occurrence relationship. In regions or under conditions where this relationship weakens or decouples (e.g., during long-range transport of dust or smoke over clear ocean), the proxy may be less effective. To overcome this limitation and extend the

620 framework's applicability, research could focus on integrating direct, physically based aerosol indicators (e.g., from multi-angle or polarimetric sensors). Alternatively, developing regionally adapted or higher-resolution co-occurrence models could refine the proxy and enhance the robustness of the aerosol selection process.

4.3 Considerations on Quality Control Strategies

The QC strategy is integral to the reliability of any ocean color dataset. Our framework combines a relaxed cloud mask ($R_{rc,2130}=0.037$) with additional filters (e.g., the “Wrong Turbid Water Mask”), to prioritize the retention of valid turbid water pixels that are routinely discarded by standard processors, while implementing safeguards against anomalous retrievals.

However, when comparing with OC-SMART and POLYMER (Section 4.1, Figure 14), we observed that their default masks retained slightly more valid pixels than our more conservative QC chain. This difference is primarily attributable to our “Wrong Turbid Water Mask,” (See Figure 8), which excluded some pixels based on spectral criteria. This illustrates an inherent tension

630 in QC design for coastal waters: an overly conservative spectral filter may reject some valid but optically extreme water pixels, whereas a more permissive mask risks retaining subtle cloud contamination or other artifacts. Our current strategy prioritizes per-pixel confidence over initial data yield, accepting a minor reduction in the latter for enhanced overall reliability.

Looking forward, cloud and cloud-shadow detection remains one of the most persistent challenges in global aquatic remote sensing. Although the QC framework used in this study performs robustly in the target regions, its universal optimization is

635 non-trivial due to the vast diversity of atmospheric and aquatic conditions. The development and integration of more advanced, physically based or machine-learning-driven cloud masking algorithms, capable of regional adaptation and distinguishing between high turbidity and true cloud cover, represents a critical future direction. Such advancements could potentially obviate the need for heuristic spectral filters like the “Wrong Turbid Water Mask”, further automating the pipeline and enhancing the consistency and yield of quality-controlled data products across all coastal zones.

4.4 Considerations on Model Representativity

The performance of our AC framework is inherently linked to the quality of the aerosol prior. The representational characteristics of the gridded aerosol models—namely, their spatial (5°) and temporal (monthly) resolution—thus constitute a fundamental aspect of the framework’s design. While these models have proven effective, their fixed resolution may not fully capture the high heterogeneity of aerosols in coastal areas at instantaneous and pixel scales. However, as integrated into our processing chain (Section 2.2.1), the model serves as an optimized starting point for iterative refinement, a design that mitigates the impact of imperfect prior matching. The validation results (Figure 3) and scene-based comparison (e.g., Figure 8) confirm that this approach yields a significant and effective correction of the systematic bias at the current model resolution. Future work to further enhance fine-scale coastal retrievals could therefore focus on developing regional aerosol climatology or integrating real-time assimilation products with higher spatiotemporal resolution, thereby providing an even more accurate AC starting point.

5 Data availability

The high-quality coastal R_{rs} dataset generated in this study is publicly available at <https://doi.org/10.5281/zenodo.16413443> (Zhao et al., 2025). The dataset is provided in monthly composites and stored in GeoTIFF format at 0.01° spatial resolution under the EPSG: 4326 (WGS84) spatial reference system.

5.6 Conclusion

This study has developed and validated an improved processing framework suitable for coastal waters by ocean color retrieval, integrating previous and operationalizing key advancements in aerosol models modeling and cloud masking strategies. A key central innovation lies in the implementation of a spatially adaptive aerosol model selection mechanism, which dynamically assigns models based on pixel level probabilities of aerosol models, guided by water turbidity as a proxy for continental aerosol influence. In addition, which effectively addresses the framework incorporates targeted masking strategies tailored to both possible residual cloud contamination due to systematic bias across the modified cloud masking threshold and the occurrence of extreme turbid waters. Using land-ocean gradient. Coupled with tailored quality control strategies, this framework, we generated was used to generate a high-quality, consistent MODIS Aqua R_{rs} dataset from MODIS Aqua observations (2003-2022) for the coastal waters of China and the United States from 2003 to 2022. The resulting dataset was rigorously evaluated against the NASA standard R_{rs} products through a series of comparative analyses under consistent and stringent quality control strategies.

Compared to the standard products, products generated with the improved processing framework exhibit new dataset demonstrates a decisive improvement: a substantial enhancements reduction in both retrieval accuracy and systematic low bias alongside a marked increase in valid retrieval coverage, particularly. This dual enhancement is most pronounced in turbid

670 ~~coastal regions where conventional AC approaches often suffer from overcorrection and cloud misclassification. These~~
~~enhancements are is~~ evident across ~~both pixel level validations and large scale analyses, demonstrating the new dataset's~~
~~improved ability to preserve valid water leaving signals and resolve all scales of analysis—from pixel-level validation to the~~
~~resolution of~~ fine-scale coastal features. ~~The revealed and long-term~~ spatiotemporal patterns ~~and long-term trends of R_{rs} further~~
~~underscore the new-. The dataset's capability to characterize thus provides a more reliable and complete observational~~
675 ~~foundation for characterizing~~ coastal optical variability, ~~supporting its application in long term monitoring, water quality~~
~~assessment, and environmental change studies.~~

~~The dataset is explicitly positioned as a complementary resource optimized for turbid coastal regions, estuaries, and bays,~~
~~filling a gap where standard products are less reliable.~~ Although this study focused on MODIS Aqua and two regional ~~ease~~
~~studiescases~~, the methodology is scalable and transferable to other sensors and global coastal zones. Future work may involve
680 broader *in situ* validation and the application of this dataset to retrieve biogeochemical parameters such as Chl, suspended
sediments, and CDOM, thereby extending its utility for coastal management and climate-related research.

67 Author contributions

JL, YW and SZ developed and implemented the improved atmospheric correction algorithm. YW and SZ designed quality
control strategies. JL and SZ collected and processed the data. SZ analyzed the data and wrote the paper. -DZ provided refined
685 aerosol models. YZ helped refine the scientific question. LF conceptualized the study and designed the research framework.
All of the co-authors revised the paper.

78 Competing interests

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

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