Impact of Monsoon-Transported Anthropogenic Aerosols and Sun-Glint on the Satellite-Derived Spectral Remote Sensing Reflectance in the Indian Ocean

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Abstract: Spectral remote sensing reflectance (Rs(λ), sr⁻¹) is one of the most important products of ocean color satellite missions, where accuracy is essential for retrieval of in-water, bio-optical, and biogeochemical properties. For the Indian Ocean (IO), where Rs(λ) accuracy has not been well documented, the quality of Rs(λ) products from Moderate Resolution Imaging Spectroradiometer onboard both Terra (MODIS-Terra) and Aqua (MODIS-Aqua), and Visible Infrared Imaging Radiometer Suite onboard the Suomi National Polar-Orbiting Partnership spacecraft (VIIRS-NPP), is evaluated and inter-compared based on a quality assurance (QA) system, which can objectively grade each individual Rs(λ) spectrum, with 1 for a perfect spectrum and 0 for an unusable spectrum. Taking the whole year of 2016 as an example, spatiotemporal pattern of Rs(λ) quality in the Indian Ocean is characterized for the first time, and the underlying factors are elucidated. Specifically, QA analysis of the monthly Rs(λ) over the IO indicates good quality with the average scores of 0.93 ± 0.02, 0.92 ± 0.02 and 0.92 ± 0.02 for VIIRS-NPP, MODIS-Aqua, and MODIS-Terra, respectively. Low-quality (-0.7) data are mainly found in the Bengal Bay (BB) from January to March, which can be attributed to the imperfect atmospheric correction due to anthropogenic absorptive aerosols transported by the northeasterly winter monsoon. Moreover, low-quality (-0.74) data are also found in the clear oligotrophic gyre zone (OZ) of the south IO in the second half of the year, possibly due to residual sun-glint contributions. These findings highlight the effects of monsoon-transported anthropogenic aerosols, and imperfect sun-glint removal on the Rs(λ) quality. Further studies are advocated to improve the sun-glint correction in the oligotrophic gyre zone and aerosol correction in the complex ocean–atmosphere environment.

Keywords: remote sensing reflectance; data quality; the Indian Ocean; accuracy

1. Introduction

Satellite ocean color remote sensing plays an unique and important role in the aquatic science researches of ocean biogeochemical cycles [1–4], water quality variability [5–7], and climate change [8–10], through providing long term, high-quality, and consistent data records in a large scale (globally or regionally).

As the most important ocean optical parameter derived from satellite ocean color observations, spectral remote sensing reflectance (Rs(λ), sr⁻¹) is key for retrieval of the in-water bio-optical and biogeochemical properties [11,12]. Uncertainties of satellite derived Rs(λ) is thus of particular importance in terms of the spatial, temporal, and spectral distributions [13–16], which are usually derived through comparison with concurrent in situ
observations based on vessels, buoys, and fixed offshore platforms, etc. Insights into $R_{\text{s}}(\lambda)$ uncertainties, mainly attributed to imperfect atmospheric correction and sensor calibration, have been gained for major ocean color missions of Sea-viewing Wide Field-of-view Sensor (SeaWiFS), Moderate Resolution Imaging Spectroradiometer (MODIS), Medium Resolution Imaging Spectrometer (MERIS), and Visible infrared Imaging Radiometer (VIIRS) from numerous dedicated validations based on in situ measurements in various parts of the global ocean. The 5% uncertainty in the blue bands over oligotrophic waters is usually used as the goal of ocean color sensors [13,14]. Bailey and Werdell [13] found that SeaWiFS data approached the target uncertainties of $\pm 5\%$ for clear water as defined prior to launch. It was also found that the goal of 5% uncertainty was reached for MERIS and MODIS-Aqua derived $R_{\text{s}}(\lambda)$ in the blue bands in clear waters [14,17]. Based on in situ-satellite matchups, Moore et al. [15] also found that the desired goal of 5% accuracy for SeaWiFS and MODIS-Aqua derived water-leaving radiance in blue bands in the open ocean had yet to be achieved. Buoy-based validation in the Mediterranean Sea showed that blue band ($R_{\text{s}}(412)$) of MERIS, SeaWiFS, and MODIS-Aqua had poor performance, with average relative percent difference of 60.2%, 20.6%, and 21.4% respectively [18]. Vessel-based validation in turbid waters along China coast showed that $R_{\text{s}}(\lambda)$ at the blue-green and green bands derived from MERIS, MODIS-Aqua, and SeaWiFS had the lowest uncertainties with a median of the absolute percentage difference of 15–27%, whereas the $R_{\text{s}}(\lambda)$ uncertainty at 412 nm is highest (47–62%) [19,20]. Most of the validation activities are dedicated to the Pacific and Atlantic Oceans [13,14,17,19–22]. While, to our best knowledge, there has been few dedicated studies on the $R_{\text{s}}(\lambda)$ validation in the Indian Ocean (IO), except a few studies on ocean optical classification. For example, Lee and Hu [23] showed that most of the IO waters were optically Case-1 water. Optical diversity analysis of the IO coastal regions using global SeaWiFS $R_{\text{s}}(\lambda)$ data also showed that most of the IO coastal waters were also Case-1 [24]. Recent study based on the monthly climatological datasets of $R_{\text{s}}(\lambda)$ identified eight optical classes of the coastal waters in the northern IO, among which classes 1–6 belong to Case-1 waters and 7–8 correspond to Case-2 waters [25]. More importantly, as the in situ measurements are sparse in space [17,18,21] and time [19,20], these validation results can hardly characterize the spatial and temporal distribution of $R_{\text{s}}(\lambda)$ data quality [14,26].

Recently, a novel $R_{\text{s}}(\lambda)$ quality assurance (QA) method was developed by Wei et al. [27], which can be used to objectively evaluate the quality of the $R_{\text{s}}(\lambda)$ spectrum for each valid pixel in a satellite image, yielding a quality score from 0 to 1 (hereafter termed QA). Compared to the in situ based validation, advantages of this method are at least two folds. Firstly, dependence of satellite validation on in situ measurements is avoided. Secondly, spatial pattern and temporal variability of $R_{\text{s}}(\lambda)$ quality can be revealed. The QA method has been successfully used in the validation of $R_{\text{s}}(\lambda)$ products [5,21,28] and has been adopted within NOAA Multi-Sensor Level-1 to Level-2 (MSL12) ocean color data processing system [21]. The objective of this paper is to (1) characterize the data quality of $R_{\text{s}}(\lambda)$ products, especially the spatial pattern and temporal variability, of MODIS-Aqua, MODIS-Terra, and VIIRS-NPP in the IO based on the QA method, and (2) explore the factors influencing the spatiotemporal pattern of $R_{\text{s}}(\lambda)$ uncertainty in the IO, especially the monsoon-transported anthropogenic aerosol and sun-glint. This paper is arranged as follows. Section 2 describes the satellite and in situ data, as well as QA method. Validation results are presented in Section 3, followed by discussions in Section 4, and conclusions in Section 5.

2. Data and Methods

2.1. Study Area

The IO is bounded by Asia on the north, Africa on the west, Australia on the east, and the Southern Ocean on the south (Figure 1), with the average depth of 3741 m [29]. Due to the significant influence of wind, the IO can be subdivided into two general latitudinal climatic zones, which are the trade wind zone and monsoon zone [30].
zone lies between 10° S and 30° S (the southern IO), with steady southeasterly trade wind throughout the year [30]. The monsoon zone extends north from latitude 10° S (the northern IO) with two contrasting monsoons, winter monsoon, and summer monsoon [31]. The summer monsoon, also known as the southwest monsoon, usually starts from May to September. During this period, winds are mainly southwesterly or westerly. The winter monsoon (also called the northeast monsoon) starts from October and continues until April. During this period, northeast winds are prevailing [32]. Hence, the IO is a dynamically complex and highly variable system, which in turn, results in substantial variations in marine biogeochemical and ecosystem responses [33,34].

![Image of the study area and in situ Rrs(λ) measurement stations](image)

**Figure 1.** Study area and in situ \( R_{rs}(\lambda) \) measurement stations (green triangles) along four transects of 0°, 5° S, 10° S, and 88° E (red dashed lines). Annual average of the global chlorophyll a concentration from Moderate Resolution Imaging Spectroradiometer (MODIS)-Aqua in 2016 is overlaid on the map. The dotted rectangle outlines the oligotrophic gyre in the south Indian Ocean characterized by the extremely low chlorophyll a concentration (Chla) (typically \( \leq 0.1 \text{ mg/m}^3 \)).

The study area of this paper is shown in Figure 1.

2.2. In Situ Data

In situ \( R_{rs}(\lambda) \) at 21 stations were collected from a cruise in December 2016, including 4 transects of 0° S, 5° S, 10° S, and 88° E (Figure 1), using a well calibrated hyperspectral radiometric profiler (350–800 nm, Satlantic Inc., Richmond, BC, Canada). The \( R_{rs}(\lambda) \) was measured following the ocean optics protocols [35] under favorable weather conditions, with wave height of 0.7–2.4 m and wind speed of 1.8–10.5 m/s. The depths of the stations were 3600–4400 m, with transparency of 22–32 m.

The hyperspectral profiler data processing follows the National Aeronautics and Space Administration (NASA) ocean optics protocols [35]. Firstly, the spectral water-leaving radiance \( (L_w(\lambda)) \) was derived from measured profiles of upwelling radiance \( (L_u(\lambda,z)) \) propagated to just above the sea surface \( (0^+) \), using the determined diffuse attenuation coefficient for the upwelling radiance, as well as the radiance transmittance [36]. Then \( R_{rs}(\lambda) \) was derived as the ratio of \( L_w(\lambda) \) to the measured \( E_s(\lambda) \), and corrected for the bidirectional effects using the look-up table method [37]. The derived \( R_{rs}(\lambda) \) spectra are shown in Figure 2, with typical spectral characteristics of Case-1 clear oceanic waters [38].
The in situ $R_{rs}(\lambda)$ spectra were used for the verification and comparison with the satellite derived $R_{rs}(\lambda)$.

![Figure 2. Measured $R_{rs}(\lambda)$ spectra at 21 stations in the Indian Ocean (IO) from a cruise in December 2016.](image)

2.3. Satellite Data

The level 2 and level 3 $R_{rs}(\lambda)$ products with the spatial resolution of 1 km and 4 km respectively, in 2016 of MODIS-Aqua and MODIS-Terra, and VIIRS-NPP were collected from National Aeronautics and Space Administration (NASA) Goddard Space Flight Center (GSFC) archives (https://oceancolor.nasa.gsfc.gov). The level 2 products were used to evaluate the consistency between satellite derived and in situ measured $R_{rs}(\lambda)$. Due to effects of cloud, haze, sun glint, and other factors, valid MODIS observations over the oceans are only ~4.9% per day [39]. Therefore, level 3 monthly (rather than daily) products were used to characterize the spatiotemporal distribution of $R_{rs}(\lambda)$ uncertainties by the QA method, due to its higher spatial coverage.

The level 2 $R_{rs}(\lambda)$ products were processed with the atmospheric correction based on near infrared (NIR) iterative approach [40,41]. The level 3 $R_{rs}(\lambda)$ products were generated from level 2 $R_{rs}(\lambda)$ data using spatial and temporal binning algorithm [42]. The processing versions of the satellite data used in this paper were R2018 (Ocean Biology Processing Group, OBPG), 2018, the latest processing version. It is well known that MODIS-Terra suffers from uncertainties and instabilities, particularly the 412 nm band [43]. The improvement has been made by NASA through reprocessing based on improved calibration of the MODIS-Terra visible (VIS)–NIR bands [44,45]. For comparison, the MODIS Terra $R_{rs}(\lambda)$ products of previous processing version R2014 were also validated (OBPG, 2014). The spatiotemporal match-up dataset of satellite and in situ measured $R_{rs}(\lambda)$ was established according to the method of Cui et al. [19] with a spatial window of $3 \times 3$ pixels and a temporal window of 3 h. There were 4, 8, and 7 match-ups for MODIS-Aqua, MODIS-Terra and VIIRS-NPP, respectively.

The daily level 3 absorption aerosol optical depth (AAOD) products at 388 nm of Ozone Monitoring Instrument (OMI) onboard NASA’s Aura satellite in 2016 were also collected from NASA’s GSFC (http://disc.gsfc.nasa.gov/Aura/OMI/), for the mechanism analysis of $R_{rs}(\lambda)$ uncertainties.

2.4. QA Method

In the QA system, the global ocean was clustered into 23 optical water types [24,46]. Each water type has an unique reference of the normalized $R_{rs}(\lambda)$ spectrum ($nR_{rs-ref}(\lambda)$, dimensionless), with an upper and a lower bound obtained from a wide range of in situ measurements [24]. The target $R_{rs}(\lambda)$ spectrum is compared with the reference spectrum and a score is assigned, with 1 for perfect $R_{rs}(\lambda)$ spectrum and 0 for unusable $R_{rs}(\lambda)$ spectrum.
There are several steps to perform QA method. Step 1 is to calculate $nR_{rs}(\lambda)$ for each pixel by dividing the spectrum by its root sum of squares. Step 2 is to assign a water type to the target $R_{rs}(\lambda)$ by comparing it with the reference $nR_{rs-ref}(\lambda)$ spectra using a spectral angle mapper (SAM). Step 3 is to calculate the QA scores by comparing the target $nR_{rs}(\lambda)$ with the upper and lower boundaries of reference $nR_{rs-ref}(\lambda)$ spectra. At each wavelength $\lambda_i$, once the target $nR_{rs}(\lambda_i)$ is found beyond either the upper or lower boundary of the reference $nR_{rs-ref}(\lambda_i)$ spectra, the score at this wavelength $C(\lambda_i)$ will be assigned 0, otherwise 1. Moreover, the score of each spectrum ($C_{tot}$) is the arithmetic average of scores at each wavelength ($C(\lambda_i)$), varying from 0 to 1.

$$C_{tot} = \frac{C(\lambda_1) + C(\lambda_2) + \ldots + C(\lambda_N)}{N}\quad(1)$$

where $N$ is the total number of wavelengths. A higher score indicates higher data quality [24].

To evaluate the quality of each sensor band in the IO, the percentage of pixels ($P(\lambda_i)$) with $C(\lambda_i)$ of 1 over the study area for each band $\lambda_i$, is calculated as follows.

$$P(\lambda_i) = \frac{N_{q}(\lambda_i)}{N_{total}}\quad(2)$$

where $N_{q}(\lambda_i)$ is the number of pixels with score of 1 for the whole study area and $N_{total}$ is the number of total valid pixels of the study area. A subjective threshold of 0.75 is adopted, and if $P(\lambda_i) < 0.75$, the band $\lambda_i$ is regarded as “low-quality” band.

3. Results

3.1. Validation Results

Level 3 monthly $R_{rs}(\lambda)$ products of MODIS-Aqua, MODIS-Terra and VIIRS-NPP acquired in 2016 were evaluated using the QA method. Eight bands of MODIS $R_{rs}(\lambda)$ were involved in the evaluation, including 412 nm, 443 nm, 488 nm, 531 nm, 547 nm, 555 nm, 667 nm, and 678 nm. Five bands of VIIRS-NPP $R_{rs}(\lambda)$ were evaluated, including 410 nm, 443 nm, 486 nm, 551 nm, and 671 nm. Regional averaged scores of monthly $R_{rs}(\lambda)$ of the three sensors are shown in Table 1.

(1) MODIS-Aqua

From Table 1 and Figure 3, it is found that generally speaking, MODIS-Aqua level 3 $R_{rs}(\lambda)$ monthly products have good quality, as indicated by the average score of 0.92 ± 0.12. Annual maximum (0.95) and minimum (0.88) of monthly scores are found in April and May, and September and October, respectively (Figure 4a). Spatially, low scores (warm colors in Figure 3) are mainly distributed in the BB, with average scores of 0.83 ± 0.18 (Table 1). Surprisingly, it is found that scores in clear waters of OZ (light blue pixels in Figure 3) are low in the second half of the year (average score of 0.86 vs. 0.97 in the first half of the year), although it is commonly recognized that atmospheric correction algorithms perform well in the oceanic waters [13,14,17,47,48]. Further quality check at all bands indicates that low QA score of a spectrum is mainly attributed to its performance in the blue bands (412 nm and 443 nm), as shown in Figure 5.

Furthermore, we extracted $R_{rs}(\lambda)$ samples with low scores in the BB (<0.3) and oligotrophic gyre zone (<0.7), and found that there were defects in the $R_{rs}(\lambda)$ spectra with low scores. The $R_{qs}(\lambda)$ spectra from the BB at the blue bands are significantly underestimated, as indicated by negative values at 412 nm and 443 nm bands (Figure 6a). $R_{rs}(\lambda)$ spectra samples from the OZ also show anomaly at 443 nm band, compared to the in situ measured $R_{rs}(\lambda)$ (Figure 6b). The satellite derived $R_{rs}(\lambda)$ have a small peak at 443 nm, while the in situ measured $R_{rs}(\lambda)$ spectra do not show this feature.
Table 1. Scores and their standard deviations over the study area of MODIS-Aqua, MODIS-Terra (Versions R2018 and R2014) and VIIRS-NPP level 3 $R_m(A)$ monthly products based on quality assurance (QA) method (Formula (1)), with 1 for a perfect spectrum and 0 for an unusable spectrum. Numbers in bold are the annual maximum and minimum of monthly scores. IO, BB, AS, and OZ represent the Indian Ocean, Bengal Bay, Arabian Sea and oligotrophic gyre zone in the southern Indian Ocean, respectively.

| Area | Sensor   | January | February | March | April | May    | June   | July   | August | September | October | November | December | Average |
|------|----------|---------|----------|-------|-------|--------|--------|--------|--------|-----------|---------|----------|----------|---------|
| IO   | MODIS-Aqua | 0.92 ± 0.12 | 0.91 ± 0.13 | 0.94 ± 0.12 | 0.95 ± 0.10 | 0.95 ± 0.11 | 0.94 ± 0.11 | 0.93 ± 0.11 | 0.91 ± 0.13 | 0.88 ± 0.14 | 0.88 ± 0.14 | 0.90 ± 0.12 | 0.91 ± 0.11 | 0.92 ± 0.12 |
|      | MODIS-Terra R2014 | 0.80 ± 0.14 | 0.81 ± 0.15 | 0.86 ± 0.13 | 0.88 ± 0.12 | 0.84 ± 0.13 | 0.81 ± 0.13 | 0.78 ± 0.14 | 0.77 ± 0.14 | 0.75 ± 0.16 | 0.79 ± 0.14 | 0.80 ± 0.15 | 0.81 ± 0.14 | 0.81 ± 0.14 |
|      | MODIS-Terra R2018 | 0.93 ± 0.11 | 0.92 ± 0.13 | 0.93 ± 0.12 | 0.99 ± 0.09 | 0.95 ± 0.01 | 0.92 ± 0.11 | 0.92 ± 0.12 | 0.91 ± 0.13 | 0.88 ± 0.13 | 0.89 ± 0.12 | 0.90 ± 0.12 | 0.92 ± 0.11 | 0.92 ± 0.12 |
|      | VIIRS-NPP | 0.95 ± 0.11 | 0.96 ± 0.01 | 0.96 ± 0.09 | 0.96 ± 0.09 | 0.95 ± 0.01 | 0.92 ± 0.13 | 0.92 ± 0.13 | 0.91 ± 0.14 | 0.90 ± 0.15 | 0.90 ± 0.15 | 0.91 ± 0.14 | 0.92 ± 0.13 | 0.93 ± 0.12 |
| BB   | MODIS-Aqua | 0.78 ± 0.19 | 0.70 ± 0.21 | 0.80 ± 0.2 | 0.86 ± 0.17 | 0.87 ± 0.16 | 0.90 ± 0.14 | 0.80 ± 0.18 | 0.82 ± 0.17 | 0.90 ± 0.13 | 0.87 ± 0.15 | 0.88 ± 0.15 | 0.87 ± 0.15 | 0.83 ± 0.18 |
|      | MODIS-Terra R2014 | 0.60 ± 0.16 | 0.55 ± 0.18 | 0.67 ± 0.16 | 0.76 ± 0.15 | 0.76 ± 0.15 | 0.74 ± 0.14 | 0.64 ± 0.17 | 0.65 ± 0.17 | 0.72 ± 0.14 | 0.70 ± 0.14 | 0.69 ± 0.15 | 0.68 ± 0.16 |
|      | MODIS-Terra R2018 | 0.81 ± 0.16 | 0.73 ± 0.19 | 0.79 ± 0.19 | 0.89 ± 0.15 | 0.91 ± 0.13 | 0.86 ± 0.15 | 0.78 ± 0.17 | 0.87 ± 0.14 | 0.87 ± 0.13 | 0.89 ± 0.14 | 0.89 ± 0.13 | 0.84 ± 0.17 |
|      | VIIRS-NPP | 0.88 ± 0.15 | 0.89 ± 0.13 | 0.9 ± 0.12 | 0.93 ± 0.12 | 0.94 ± 0.11 | 0.95 ± 0.1 | 0.91 ± 0.13 | 0.92 ± 0.11 | 0.93 ± 0.12 | 0.95 ± 0.1 | 0.93 ± 0.12 | 0.93 ± 0.11 | 0.92 ± 0.12 |
| AS   | MODIS-Aqua | 0.93 ± 0.11 | 0.91 ± 0.13 | 0.86 ± 0.16 | 0.89 ± 0.14 | 0.87 ± 0.17 | 0.78 ± 0.19 | 0.83 ± 0.17 | 0.84 ± 0.18 | 0.83 ± 0.17 | 0.89 ± 0.14 | 0.87 ± 0.15 | 0.91 ± 0.13 | 0.88 ± 0.15 |
|      | MODIS-Terra R2014 | 0.71 ± 0.12 | 0.72 ± 0.14 | 0.72 ± 0.14 | 0.77 ± 0.14 | 0.76 ± 0.18 | 0.68 ± 0.16 | 0.65 ± 0.16 | 0.67 ± 0.16 | 0.66 ± 0.16 | 0.75 ± 0.17 | 0.66 ± 0.17 | 0.70 ± 0.14 | 0.71 ± 0.15 |
|      | MODIS-Terra R2018 | 0.92 ± 0.1 | 0.90 ± 0.13 | 0.85 ± 0.16 | 0.89 ± 0.12 | 0.88 ± 0.16 | 0.78 ± 0.16 | 0.79 ± 0.17 | 0.82 ± 0.16 | 0.83 ± 0.16 | 0.89 ± 0.12 | 0.88 ± 0.13 | 0.92 ± 0.12 | 0.88 ± 0.14 |
|      | VIIRS-NPP | 0.96 ± 0.09 | 0.95 ± 0.1 | 0.94 ± 0.1 | 0.96 ± 0.08 | 0.96 ± 0.09 | 0.92 ± 0.13 | 0.94 ± 0.12 | 0.93 ± 0.12 | 0.93 ± 0.11 | 0.95 ± 0.1 | 0.93 ± 0.12 | 0.94 ± 0.11 | 0.95 ± 0.10 |
| OZ   | MODIS-Aqua | 0.95 ± 0.09 | 0.96 ± 0.07 | 0.99 ± 0.04 | 1.00 ± 0.03 | 0.99 ± 0.04 | 0.96 ± 0.08 | 0.94 ± 0.1 | 0.87 ± 0.13 | 0.79 ± 0.13 | 0.78 ± 0.11 | 0.88 ± 0.09 | 0.90 ± 0.08 | 0.92 ± 0.11 |
|      | MODIS-Terra R2014 | 0.86 ± 0.09 | 0.88 ± 0.10 | 0.95 ± 0.07 | 0.95 ± 0.08 | 0.85 ± 0.11 | 0.76 ± 0.11 | 0.73 ± 0.11 | 0.75 ± 0.10 | 0.74 ± 0.11 | 0.77 ± 0.10 | 0.83 ± 0.10 | 0.85 ± 0.10 | 0.83 ± 0.10 |
|      | MODIS-Terra R2018 | 0.96 ± 0.07 | 0.98 ± 0.07 | 0.99 ± 0.05 | 0.99 ± 0.04 | 0.99 ± 0.05 | 0.95 ± 0.09 | 0.92 ± 0.11 | 0.89 ± 0.13 | 0.83 ± 0.13 | 0.81 ± 0.11 | 0.88 ± 0.1 | 0.91 ± 0.08 | 0.92 ± 0.11 |
|      | VIIRS-NPP | 0.95 ± 0.1 | 0.98 ± 0.06 | 0.99 ± 0.04 | 0.98 ± 0.07 | 0.95 ± 0.11 | 0.83 ± 0.16 | 0.83 ± 0.16 | 0.81 ± 0.17 | 0.78 ± 0.18 | 0.74 ± 0.17 | 0.81 ± 0.16 | 0.86 ± 0.13 | 0.88 ± 0.16 |
From Table 1 and Figure 3, it is found that generally speaking, MODIS-Aqua level 3 \( R_{rs}(\lambda) \) monthly products have good quality, as indicated by the average score of \( 0.92 \pm 0.12 \). Annual maximum (0.95) and minimum (0.88) of monthly scores are found in April and May, and September and October, respectively (Figure 4a). Spatially, low scores (warm colors in Figure 3) are mainly distributed in the BB, with average scores of \( 0.83 \pm 0.18 \) (Table 1). Surprisingly, it is found that scores in clear waters of OZ (light blue pixels in Figure 3) are low in the second half of the year (average score of 0.86 vs. 0.97 in the first half of the year), although it is commonly recognized that atmospheric correction algorithms perform well in the oceanic waters [13,14,17,47,48]. Further quality check at all bands indicates that low QA score of a spectrum is mainly attributed to its performance in the blue bands (412 nm and 443 nm), as shown in Figure 5.

Figure 3. Monthly QA scores of MODIS–Aqua level 3 \( R_{rs}(\lambda) \) products from January (a) to December (l) in 2016 in the IO. The white color represents invalid pixels.
Figure 4. Monthly averaged scores (left $y$-axis, red squares) of MODIS–Aqua (a), VIIRS–NPP (b) and MODIS–Terra (c,d) level 3 $R_{rs}(\lambda)$ products over the IO in 2016. The valid data coverage (open symbols, right $y$-axis) is overlaid. The low-quality bands ($P(\lambda_i) < 75\%$) for each satellite dataset (if any) are also shown.

Figure 5. $R_{rs}(\lambda)$ QA scores at blue bands (412 nm and 443 nm) of MODIS–Aqua (a,d), MODIS–Terra (b,e), and VIIRS–NPP (c,f) in October, 2016. The red color represents score of 0 (low-quality data) and blue color represents score of 1 (high quality data). The white color represents invalid pixels. The yellow rectangles roughly outline the location of the oligotrophic gyre zone in the southern Indian Ocean.

Furthermore, we extracted $R_{rs}(\lambda)$ samples with low scores in the BB (<0.3) and oligotrophic gyre zone (<0.7), and found that there were defects in the $R_{rs}(\lambda)$ spectra with low scores. The $R_{rs}(\lambda)$ spectra from the BB at the blue bands are significantly underestimated, as indicated by negative values at 412 nm and 443 nm bands (Figure 6a). $R_{rs}(\lambda)$ spectra...
samples from the OZ also show anomaly at 443 nm band, compared to the in situ measured \( R_{rs}(\lambda) \) (Figure 6b). The satellite derived \( R_{rs}(\lambda) \) have a small peak at 443 nm, while the in situ measured \( R_{rs}(\lambda) \) spectra do not show this feature.

Figure 6. Samples of low quality \( R_{rs}(\lambda) \) spectra derived from MODIS-Aqua, in the BB (scores < 0.3) characterized by negative values at 412 nm and 443 nm bands (a), and in the OZ (scores < 0.7) compared with in situ measured \( R_{rs}(\lambda) \) spectra (b).

(2) MODIS-Terra

MODIS-Terra \( R_{rs}(\lambda) \) (R2018) shows comparable quality (average score of 0.92) with MODIS-AQUA. Similar seasonal variability and spatial pattern are also found (Figure 7), with the highest (0.95) and lowest (0.88) monthly scores in April and September, respectively (Figure 4d). Waters in the BB exhibit low scores of 0.84 ± 0.17 (Table 1, Figure 7). Scores in the OZ of the southern IO decrease from 0.98 in the first half of the year to 0.88 in the second half of the year, which is also due to the poor performance of blue bands (412 nm and 443 nm), as shown in Figure 5.

From comparison between Figures 7 and 8, it can be found that the quality of MODIS-Terra \( R_{rs}(\lambda) \) has been improved by recent reprocessing through updating sensor calibration and vicarious calibration (OBPG, 2018), as indicated by the increase of scores from 0.81 (R2014) to 0.92 (R2018) (Figure 4c,d, Table 1). Moreover, the annually averaged high-score percentage \( P(\lambda_i) \) at bands of 412 nm, 443 nm, 488 nm, 531 nm, 547 nm, 555 nm, 667 nm, and 678 nm of MODIS-Terra (R2014) are 74.82%, 56.54%, 85.01%, 87.21%, 91.93%, 54.23%, 96.53%, and 95.92%, respectively, indicating that the lower scores of R2014 MODIS-Terra data are mainly caused by the imperfect \( R_{rs}(\lambda) \) data quality at bands of 412 nm, 443 nm, and 555 nm.

(3) VIIRS-NPP

VIIRS-NPP \( R_{rs}(\lambda) \) products show the best data quality among the three satellite datasets, in terms of its highest average score (0.93), which is mainly attributed to the better performance in the BB with the average scores of 0.92 ± 0.12 (Table 1). Annual maxima (0.96) are found in February, March, and April, and minima (0.90) are in September and October (Figure 4b). Low quality pixels (with average scores of 0.88 ± 0.16, light blue colors in Figure 9) are mainly located in the OZ of the IO, especially from June to December, which is also attributed to the poor performance at blue bands (412 nm and 443 nm), as shown in Figure 5.
3.2. Mechanisms of \( R_s(\lambda) \) Quality Spatiotemporal Distribution

Low quality \( R_s(\lambda) \) products derived from MODIS-Aqua, MODIS-Terra, and VIIRS-NPP are all found in the BB of the northern IO and the OZ of the southern IO. Different driving mechanisms in these two regions are analyzed as follows.

3.2.1. Monsoon in the Northern IO

Results showed that the data quality of \( R_s(\lambda) \) products in the northern IO (AS and BB) was significantly affected by the two contrasting monsoons, winter monsoon and summer monsoon.
Figure 8. Monthly QA scores of MODIS–Terra level 3 \( R_{rs}(\lambda) \) products (R2014) from January (a) to December (l) in 2016 in the IO. The white color represents invalid pixels.

In the winter monsoon, the lower scores are mainly found in the BB. Samples from the BB show that \( R_{rs}(\lambda) \) at the blue bands are significantly underestimated, as indicated by negative values at 412 nm and 443 nm bands (Figure 6a), which may be attributed to the increase of AAOD. During the winter monsoon, the northeast winds transport large amounts of anthropogenic aerosols, including high absorptive black carbon (BC) [49,50], brown carbon (BrC) [51,52] and dust [53], which are originated from the biomass or fossil fuel combustion, to the BB and offshore area of the AS [54,55]. Statistics from OMI AAOD show that the average AAOD at 388 nm of BB (0.053) in the winter monsoon increased by 26.43%, compared to that in the summer monsoon (0.042). Correlation analysis between the monthly AAOD and QA scores of MODIS-Aqua, MODIS-Terra and VIIRS-NPP in the BB during the winter monsoon show significant negative correlation (\( R = -0.82, p = 0.001 \); \( R = -0.80, p = 0.002 \); \( R = -0.72, p = 0.009 \)) in the BB (Figure 10a). Taking February as an example, we analyzed the relationship between the daily AAOD and scores of MODIS-Aqua, MODIS-Terra, and VIIRS-NPP. For most pixels with scores <0.5, the AAODs are more than the annual averaged AAOD of 0.02 in the IO (Figure 10b–d). The satellite-observed
radiance is a combination of aerosol radiance contribution and ocean radiance contribution. The presence of absorptive aerosols results in overestimation of aerosol contributions, which in turn leads to the underestimation of ocean contribution at shorter wavebands \cite{56,57}. Therefore, the over-corrected aerosol contribution leads to the underestimation of $R_{rs}(\lambda)$. 

![Figure 9. QA Scores of VIIRS–NPP level 3 $R_{rs}(\lambda)$ monthly products from January (a) to December (l) in 2016 in the IO. The white color represents invalid pixels.](image)

It is noted that although AS is also affected by the winter monsoon, the $R_{rs}(\lambda)$ perform better than that in the BB during winter monsoon (Table 1). This may be attributed to the clearer atmosphere in the AS. Different from the BB, the average AAOD (0.02) in the AS decreased during the winter monsoon, compared to that of summer monsoon (0.04). Correspondingly, the average scores of MODIS-Terra, MODIS-Aqua, and VIIRS-NPP are 0.89, 0.89, and 0.92 respectively in the winter monsoon, and 0.82, 0.83, and 0.93 in the summer monsoon. Existing literatures also showed that the atmosphere over BB was more turbid than that of AS in the winter monsoon \cite{58} and contained less absorptive aerosols than the BB \cite{59}. Hence, the data quality of $R_{rs}(\lambda)$ in the AS is better than that in the BB during the winter monsoon.
Figure 10. Monthly absorption aerosol optical depth (AAOD) and QA score in the BB, which shows significant negative correlation between AAOD and score (a). Histogram of AAODs corresponding to the low quality (score < 0.5) pixels of MODIS–Aqua (b), VIIRS–NPP (c), and MODIS–Terra (d) daily R_{rs}(λ) products of BB in February.

During the summer monsoon, the southwest wind prevails, which brings sea salt and mineral dust aerosols to the northern IO [29]. The sea salt contributes ~60% of the composite aerosol optical depth [60], which will be in favor of the accurate atmospheric correction [61] and thus higher R_{rs}(λ) data quality. However, the summer monsoon period is the main rainy season in the northern IO, leading to the low valid data coverage (Figure 4). The average valid data coverage of the three sensors in the BB and AS are only 52% and 48%, respectively, compared to 88% and 95% in the winter monsoon season. The lowest valid data coverage is only 12% in the AS (Figure 4). The low valid data coverage in summer results in loss of large amounts of high-score pixels in the south of AS and BB, leading to the decrease of the average scores, which amplifies the seasonal difference in R_{rs}(λ) data quality.

3.2.2. Sun Glint in the OZ

Low-quality R_{rs}(λ) in the clear OZ of the southern IO in the second half of the year may be attributed to the contamination by the residual sun-glint signals. For sensors without a tilting capacity (such as MODIS and VIIRS), the ocean color observations in the tropical and sub-tropical oceans are more likely affected by the sun-glint (e.g., the north and south Atlantic gyres, and the South Indian gyro) [62–64], which is the bright pattern of the specular reflection of the sun by the wavy sea surface [64,65]. Morel and Gentili [63] indicated that the residual sun-glint resulted in the anomaly of level 3 R_{rs}(λ) products in the sub-tropical oligotrophic gyres and sun-glint effect migrated with the sun declination course.

During MODIS and VIIRS images processing from level 1 to level 2 implemented by the NASA Ocean Biology Processing Group (OBPG), the pixels are flagged as “HIGLINT” and “MODGLINT” if the normalized sun-glint surface-reflected radiance (L_{GN}) exceeds 0.005 sr\(^{-1}\) and 0.0001 sr\(^{-1}\), and then a glint correction [66] is applied according to the wind
identical with those of 8-band (Figure 12a, b), whereas large discrepancy is found for bands (Figure 12c). This phenomenon can be explained by results of score statistics at each band of MODIS-Terra (R2014), whose 5-band based scores are significantly lower than those of 8-bands. This is because the bands involved in QA analysis are different, with five bands for MODIS involving bands of 531 nm, 547 nm, and 678 nm that VIIRS does not have are excluded from MODIS QA analysis. QA results for MODIS-Aqua and MODIS-Terra (R2018) are almost identical with those of 8-band (Figure 12a,b), whereas large discrepancy is found for MODIS-Terra (R2014), whose 5-band based scores are significantly lower than those of 8-bands (Figure 12c). This phenomenon can be explained by results of score statistics at each band of MODIS-Terra (R2014). In the 5-band evaluation, three low quality bands of 412 nm, 443 nm, and 678 nm, which have good data quality and contribute to the higher average scores of the involved bands and leading to a lower average score. Whereas bands of 531 nm, 547 nm, and 678 nm, which have good data quality and contribute to the higher average scores of the involved bands and leading to a lower average score. Whereas bands of 531 nm, 547 nm, and 678 nm, which have good data quality and contribute to the higher average scores of the involved bands and leading to a lower average score. Whereas bands of 531 nm, 547 nm, and 678 nm, which have good data quality and contribute to the higher average scores of the involved bands and leading to a lower average score.

Figure 11. Pixel numbers of level 2 $R_{rs}(\lambda)$ with “MODGLINT” and “HIGLINT” flags corresponding to each level 3 pixel.

4. Discussion

4.1. QA Analysis

Except the dominant effects from monsoon and sun-glint, other potential factors affecting QA score are discussed in this section, including differences in band configurations between VIIRS and MODIS (5 bands vs. 8 bands) and level 3 product types (Daily vs. Monthly).

4.1.1. Bands Involved in QA Analysis

It is noted that the bands involved in QA analysis are different, with five bands for VIIRS and eight bands for MODIS. For the analysis of the effect of bands involved in QA analysis and fair quality comparison across sensors, bands of 531 nm, 547 nm, and 678 nm that VIIRS does not have are excluded from MODIS QA analysis. QA results for MODIS-Aqua, MODIS-Terra (R2018), and MODIS-Terra (R2014) are shown in Figure 12, based on $R_{rs}(\lambda)$ spectra at the remaining 5 bands of 412 nm, 443 nm, 488 nm, 555 nm, and 667 nm, which are also close to the nominal wavelengths of VIIRS-NPP.

The 5-band based QA scores for MODIS-Aqua and MODIS-Terra (R2018) are almost identical with those of 8-band (Figure 12a,b), whereas large discrepancy is found for MODIS-Terra (R2014), whose 5-band based scores are significantly lower than those of 8-bands (Figure 12c). This phenomenon can be explained by results of score statistics at each band of MODIS-Terra (R2014). In the 5-band evaluation, three low quality bands of 412 nm, 443 nm, and 555 nm are involved (Figure 12c), accounting for 60% of numbers of all the involved bands and leading to a lower average score. Whereas bands of 531 nm, 547 nm, and 678 nm, which have good data quality and contribute to the higher average scores of the 8-band evaluation, are excluded from 5-band statistics. Different from MODIS-Terra (R2014), high QA scores for MODIS-Aqua and MODIS-Terra (R2018) are achieved at all the
8 band and, thus, excluding bands of 531 nm, 547 nm, and 678 nm would have little effect on the score statistics.

Figure 12. Comparison between Rrs(λ) QA scores based on 5-band (red) and 8-band (purple) for MODIS-Aqua (a), MODIS-Terra (2018) (b), and MODIS-Terra (2014) (c).

The above results have implications in the QA method application. First, for the comparison between QA results of the same sensor by the different researcher, it is suggested to pay attention to the consistency of bands involved in the QA analysis. The QA results may be quite different when different bands are selected. Second, from the in-water parameter retrieval point of view, it would be more practical and indicative to evaluate the QA score for a spectrum only based on bands, which are involved in a specific retrieval algorithm rather than full bands.

4.1.2. Daily vs. Monthly Products

Statistics show that the percentage of valid observations of level 3 daily products in the study area is less than 10% for all these sensors, which implies that the level 3 daily data is not qualified for characterizing the spatial distribution of Rrs(λ) quality. Therefore, the level 3 monthly products were adopted for QA analysis due to its higher spatial coverage (~91.7%). To explore the differences in scores between daily and monthly products, the level 3 daily products are also validated by QA method. The noticeable agreement between these scores can be found in terms of their close values and consistent trend, especially for VIIRS (Figure 13). It is also noted that scores of monthly products are higher than that of daily ones to some extent (~2%), which may be attributed to the data quality improvement through spatiotemporal binning, as well as the abnormal values removal [42].

4.2. Comparison between Results from In Situ-Based and QA Methods

To verify the QA method, we use both the in situ measured Rrs(λ) and QA method to evaluate the level 2 Rrs(λ) products simultaneously and compare the results. Compared with the in situ measured Rrs(λ), the median absolute percent difference (MPD) of MODIS-Aqua, MODIS-Terra and VIIRS-NPP derived Rrs(λ) are 8.4–15.2%, 8.9–15.7%, and 17.5–22.9% at bands of 412–555 (551) nm, respectively (Figure 14a–c). Correspondingly, the average validation scores by QA method are 0.92, 0.92, and 0.86, for MODIS-Aqua, MODIS-Terra and VIIRS-NPP, respectively. Validation results by in situ data and QA
method show good consistency and a significant negative correlation ($p = -1$) (Figure 14d). The high score data has small MPD.

![Figure 13](image1)

**Figure 13.** Comparison between QA scores based on level 3 daily and monthly $R_{rs}(\lambda)$ products from MODIS-Aqua (a), MODIS-Terra (b), and VIIRS-NPP (c).

![Figure 14](image2)

**Figure 14.** Scatter plots of the satellite–derived $R_{rs}(\lambda)$ versus in situ measurements (a–c). Solid line is 1:1 line. Dashed lines are 1:2 and 2:1 lines. The average scores and median absolute percent difference (MPD) of MODIS–Aqua, MODIS–Terra (R2018), and VIIRS–NPP level 2 $R_{rs}(\lambda)$ products concurrent with in situ measurements (d).
4.3. Implications

The in situ-based evaluation results may provide the valuable information about uncertainties at each band, with little clues of the rationality of the spectral shape, as shown in Figure 15. It is found that, Terra (R2014) $R_{rs}(\lambda)$ at all bands except for 412 nm band agree well with the in situ data. Nevertheless, it is noted that due to the underestimation at 412 nm, Terra (R2014) fails to retrieve the actual spectral shape of in situ $R_{rs}(\lambda)$. Different from the in situ-based validation method, the QA method can give the validation results based on the $R_{rs}(\lambda)$ spectrum shape. Moreover, the QA scores for Terra (R2014) and Terra (R2018) are 0.67 and 1, respectively, which reveals the defects of Terra (R2014) $R_{rs}(\lambda)$ spectrum. Therefore, it is necessary to involve the $R_{rs}(\lambda)$ spectrum shape when the validation of $R_{rs}(\lambda)$ is conducted, especially for the satellite ocean color algorithms based on the spectral shape, such as fluorescence line height (FLH) [69], maximum chlorophyll index (MCI) [70], and floating algae index (FAI) [71].

The potential negative effects of the low-quality $R_{rs}(\lambda)$ at 412 nm and 443 nm in the OZ on the accuracy of ocean color products should be envisaged, especially for Chla [12,72] and colored dissolved organic matter (CDOM) [73], which are usually retrieved by algorithms using the above bands. Taking OC3 and OC4 algorithms as examples, $R_{rs}(\lambda)$ quality degradation at 443 nm in the OZ may result in overestimation of $R_{rs}(443)/R_{rs}(555)$ by 6.45%, 8.23%, and 16.93% for VIIRS-NPP, MODIS-Aqua, and MODIS-Terra, respectively. Accordingly, Chla would be underestimated by 16.12%, 16.39%, and 30.83% for VIIRS-NPP, MODIS-Aqua, and MODIS-Terra, respectively. As the $R_{rs}(\lambda)$ quality degradation is significant in certain months, biased seasonality in the derived Chla would also probably occur in the OZ.

The same issue exists for the BB. In addition to the low $R_{rs}(\lambda)$ quality in the winter monsoon, the low valid data coverage is another obstacle to characterize the seasonal pattern of ocean color parameters in this region. The lower $R_{rs}(\lambda)$ data quality in the BB reveals that much more efforts are still required to improve the performance of atmospheric correction algorithms to address the influence of anthropogenic absorptive aerosols.

5. Conclusions

Satellite ocean color remote sensing plays an important role in the study of the Indian Ocean, which is a dynamically complex and highly variable system with complicated marine biogeochemical and ecological process. To facilitate quantitative satellite ocean color application in this area, taking the year of 2016 as an example, the spatial and temporal distribution of satellite-derived $R_{rs}(\lambda)$ quality from MODIS-Aqua, MODIS-Terra,
and VIIRS-NPP in the IO is characterized for the first time, using a recently developed quality assurance (QA) system.

QA analysis indicates that the satellite-derived \( R_{\text{rs}}(\lambda) \) products generally exhibit good quality, with the average scores of 0.93 ± 0.02, 0.92 ± 0.02, and 0.92 ± 0.02 for VIIRS-NPP, MODIS-Aqua, and MODIS-Terra, respectively. Low-score regions are mainly located in the BB and the OZ of the southern IO, due to the monsoon-transported anthropogenic absorptive aerosols and sun-glint contamination, respectively. As a result of the above effects, \( R_{\text{rs}}(\lambda) \) data quality shows clear seasonal pattern, with the highest quality (~0.95) in April and the lowest one in September (~0.90). Besides, quality of MODIS-Terra \( R_{\text{rs}}(\lambda) \) is found to be significantly improved after the latest reprocessing (R2018) through the calibration update, as indicated by an average QA score of 0.92 compared to 0.81 for previous (R2014) version.

These findings highlight the effects of monsoon-transported anthropogenic aerosols, imperfect sun-glint removal, and radiometric calibration on the \( R_{\text{rs}}(\lambda) \) quality. Further studies are advocated to improve the correction of sun-glint in the oligotrophic gyre and absorptive aerosol in the complex ocean–atmosphere environment.

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