Comparisons of algorithms to estimate water turbidity in the coastal areas of China

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\textbf{ABSTRACT}

Turbidity is an important indicator of water environments and water-quality conditions. Ocean colour remote sensing has proved to be an efficient way of monitoring water turbidity because of its wide synoptic coverage and repeated regular sampling. However, operational tasks are still challenging in high-turbidity waters, especially in estuaries and the coastal regions of China. In these areas, the existing algorithms derived from remote-sensing reflectance ($R_{rs}$) are usually invalid because it is difficult to correctly estimate the reflectance $R_{rs}$ from satellite data such as Moderate Resolution Imaging Spectroradiometer (MODIS) data. A new algorithm that uses Rayleigh-corrected reflectance ($R_{rc}$) instead of $R_{rs}$ has been recently introduced and was used to estimate water turbidity in Zhejiang (ZJ) coastal areas from Geostationary Ocean Color Imager (GOCI) data. The $R_{rc}$ algorithm has previously shown a capability to estimate water turbidity. However, its performance still requires careful evaluation. In this article, we compared the new $R_{rc}$ algorithm with two other existing algorithms. Differences among the three algorithms were assessed by comparing the results from using $R_{rc}$ data and $R_{rs}$ reflectance data derived from both GOCI and MODIS imagery data. The capability of the new $R_{rc}$ algorithm to estimate water turbidity in larger areas and extended seasons in the coastal seas of China was also estimated. The results showed that the new $R_{rc}$ algorithm is suitable for the coastal waters of China, especially for highly turbid waters.

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\section{1. Introduction}

Water turbidity is the integrated appearance of the optical properties of water conditions and is an important water-quality indicator. In 2008, turbidity was proposed as one of the monitoring requirements by the European Union’s Marine Strategy Framework Directive for evaluating ecosystem function (Parliament 2008). Moreover, turbidity is often used as a simplified proxy for total suspended matter (TSM) or for optical
parameters such as the diffuse attenuation coefficient for downwelling irradiance, $K_d$ (Davies-Colley and Smith 2007; Shi and Wang 2010).

Traditional methods to monitor water turbidity at fixed geographical locations at fixed intervals are limited by their high costs and time consumption and low spatial resolution. Remote sensing offers a good approach to reduce these limitations. Turbidity estimation and monitoring were commonly achieved using ocean colour remote-sensing techniques, which are usually applied to marine primary productivity estimation, ocean ecological environment monitoring, marine dynamics, fishery development, and management services. Algorithms to estimate water turbidity from satellite data have developed over the last few decades, and they are usually classified as empirical algorithms and semi-empirical algorithms.

Empirical algorithms are the most widely implemented by establishing linear or nonlinear regression functions between remote-sensing reflectance ($R_{rs}$) data (single band or band combinations) and water-quality parameters. For instance, Nechad, Ruddick, and Neukermans (2009) developed a single-band algorithm to relate the turbidity and reflectance by using a bio-optical model (Nechad et al. 2003) with the best band at 681 nm. Dogliotti et al. (2011) established a two-band bio-optical model to estimate turbidity in the Samborombón Bay. The model was validated using the Rayleigh-corrected reflectance ($R_{rc}$) in the near-infrared (NIR) band (858 nm) and the shortwave near-infrared (SWIR) band (1240 nm) of the Moderate Resolution Imaging Spectroradiometer (MODIS). Mao et al. (2012) designed a model based on a complex proxy of $R_{rs}$ that converted the nonlinear relationship between reflectance and TSM to a quasi-linear function and then estimated the turbidity based on a linear correlation between TSM and turbidity on a logarithmic scale. Moreover, He et al. (2013) developed a regional empirical TSM algorithm by using GOCI (Geostationary Ocean Color Imager (Ryu et al. 2012)) data for the Hangzhou Bay (HZB) and then used band ratios of 745 and 490 nm to obtain a linear correlation between TSM and turbidity.

Semi-empirical algorithms can be established based on the relationships between the water constituents and their inherent optical properties (IOPs) within the water (Gordon et al. 1988; Morel and Prieur 1977). Gohin (2011) estimated turbidity by using concentrations of chlorophyll-a and non-algal particles that were derived from a semi-empirical algorithm by using reflectance at the 555 nm and 670 nm bands. Recently, Hu, Chen, and Zhang (2015) estimated the turbidity in the East China Sea (ECS) during the period 2009–2013 by using the backscattering coefficient at 532 nm ($b_{bp,532}$) calculated from the MODIS-Aqua Level 2 data, using the Quasi-Analytical Algorithm (QAA) of Lee et al. (2009).

Those algorithms were used to estimate turbidity mainly from the derived $R_{rs}$ data that were processed from satellite data using atmospheric corrections. However, because of the complex water properties and atmospheric conditions that are common in and over highly turbid waters, traditional atmospheric corrections have presented a large challenge. At present, the contributions of the radiation of air molecules can be estimated precisely by Rayleigh corrections and the most significant problem of atmospheric corrections is that it is difficult to estimate the aerosols correctly. Moreover, complex aerosol variations at the land–sea interface will lead to incorrect masking during data processing, which will cause serious missing data for $R_{rs}$. Therefore, the
remote-sensing algorithms based on $R_{rs}$ are significantly limited in highly turbid areas (Wang and Shi 2005; Mao et al. 2013).

To resolve the above-mentioned problems, advances in atmospheric corrections have been made in highly turbid waters, such as the coastal areas of China. Wang, Shi, and Jiang (2012) proposed a regional NIR-normalized water-leaving reflectance ($L_{wn,\lambda}$) model in the Bohai Sea (BS), the Yellow Sea (YS), and the ECS. The method was first developed as the SWIR atmospheric correction algorithm for MODIS-Aqua data and then was adjusted for GOCI data based on long-term measurements. He et al. (2012) established another atmospheric correction algorithm (hereafter called the UV-AC algorithm) by using GOCI data at ultraviolet wavelengths. Case studies showed that the UV-AC algorithm can be successfully applied in HZB in China (He et al. 2012, 2013). Although progress has been achieved, as was previously mentioned, atmospheric corrections remain a problem for the coastal China seas (Mao et al. 2013).

Another way forward is to establish a connection between the water properties and the data before atmospheric corrections are made (Qi et al. 2014). Using this idea, Qiu et al. (2015) recently developed an algorithm to estimate water turbidity by using the GOCI data. A large satellite-ground synchronous data set was developed for algorithm calibration by matching GOCI $R_{rc}$ with in situ data from buoys. Turbidity ($T$) in the Zhejiang (ZJ) coastal waters ranged from 2.4 to 363.9 and was used to validate the algorithm; the correlation coefficient of determination ($R^2$), root mean square error (RMSE), mean absolute error (MAE), and mean relative error (MRE) were 0.821, 52.6, 35.6, and 48.6%, respectively. The best advantage of this $R_{rc}$-based algorithm is that it avoids the problems related to inaccurate atmospheric corrections.

Although the $R_{rc}$-based algorithm proposed by Qiu et al. (2015) was successfully used to estimate water turbidity in the ZJ coastal areas by using GOCI data, its applicability remains unknown in other areas or seasons or for other sensors. In addition, the differences between $R_{rc}$-based and $R_{rs}$-based algorithms and the effect of atmospheric corrections on accurately estimating water turbidity still require investigation.

Therefore, in this article we compare remote-sensing algorithms for estimating water turbidity in the coastal China seas. The objectives are: (1) to verify the capability of the $R_{rc}$-based algorithm in other areas and seasons; (2) to evaluate the effect of atmospheric corrections on water turbidity estimates in highly turbid waters by comparing $R_{rc}$-based and $R_{rs}$-based algorithms; (3) to determine whether the $R_{rc}$-based algorithm, developed based on GOCI data, can be extended to other sensors; and (4) to evaluate the performance of the $R_{rc}$-based algorithm by comparing it with other algorithms. The two algorithms proposed by He et al. (2013) and Hu, Chen, and Zhang (2015) were chosen for comparison as representative empirical and semi-empirical algorithms, respectively.

2. Data and methods

2.1. Research areas

The research areas included BS, YS, and the ECS (shown in Figure 1), some of the most turbid seas in the world (Qiu, Wu, and Su 2013; Qiu et al. 2014; Chen et al. 2014). Hundreds of millions of tons of sediment are downloaded annually from the Changjiang
River, the Yellow River, and other rivers, and thus large amounts of sediment as well as other particulate matters have accumulated on the seabed. The concentrations of TSM can be over 5000 g m$^{-3}$, and the turbidity in these areas usually reaches up to around 100 Nephelometric Turbidity Units (NTU) (Mao et al. 2012).

### 2.2. In situ measurements

#### 2.2.1. Buoy observations

In situ data sets collected by 12 buoys were used in this study. One buoy is located in the Sheyang station in the north of the Jiangsu (JS) coastal area (hereafter called the JS buoy), and the other 11 buoys are moored in the coastal areas of ZJ (hereafter called the ZJ buoys) (Figure 1(a)).

Observations from the 11 ZJ buoys were selected between 2014 and 2015 to match the GOCI data at an in situ observation frequency of 15 min. A total of 850 samples were selected with turbidity values from 2.4 to 363.9 NTU. For more details, readers can refer to the article by Qiu et al. (2015). Observations from the JS buoy were chosen from January to June in 2015 at an observation frequency of 1 h. The turbidity varied from 6.8 to 467 NTU.

The histograms of the in situ buoy observations are shown in Figure 2 with the x-axes displayed in logarithmic coordinates. As shown in Figure 2(a), an approximately log-normal distribution of turbidity was observed from the 11 ZJ buoys. The majority of the data (79.06%) fell within 16–256 NTU and the other 14.00% and 6.94% of the data were accounted for by samples <16 NTU and > 256 NTU, respectively. The same log-normal distribution was observed from the JS area (Figure 2(b)). The majority of the data...
(78.76%) were located within 16–256 NTU and the other 6.19% and 15.04% of the data were accounted for by samples <16 NTU and >256 NTU, respectively.

**2.2.2. Cruise observations**

Turbidity from water samples was also collected at 387 stations during four cruises in the BS and YS areas. These cruises were conducted in the different seasons of spring (April–May 2014), summer (June–July 2011), autumn (October–November 2013), and winter (November–December 2011). Hydrological parameters such as water temperature, optical parameters such as $R_{rs}$, backscattering coefficients, and environmental parameters such as turbidity were measured at each station. The Seapoint turbidity sensor was used to measure turbidity and was mounted to the Seabird SBE19plus CTD (Seabird Electronics, Bellevue, Washington). Data were collected round-the-clock at intervals of 1–2 h. It was noted that the turbidity is in Formazin Turbidity Units (FTU). According to Telesnicki and Goldberg (1995), FTU is equal to NTU. Therefore, we used NTU instead of FTU in this study.

Figure 1(b) shows the spatial distribution of the turbidities observed from the cruises. High turbidity was observed near the shore compared with low turbidity in the middle areas. The turbidity values were at very low levels in the northern and central parts of the YS area.

A histogram of the turbidity distribution is also shown in Figure 2(c). The distribution pattern is different from those of buoy observations, with no obvious lognormal distribution. Slight variations occurred and most of the values were smaller than 10 NTU. Approximately 50% of the samples were smaller than 2 NTU.

**2.3. Satellite data**

GOCI receives images eight times a day in hourly intervals from 00:15 to 07:45 GMT (8:15 to 15:15 local time) at a 500 m spatial resolution and 1 h temporal resolution.

![Image](image_url)

**Figure 1**. Histogram of *in situ* observations from (a) the ZJ buoy, (b) the JS buoy, and (c) the cruise stations matched with the GOCI cloud-free images.
GOCI Level-1B data were obtained from the Korea Ocean Satellite Center (KOSC) during cloud-free or low cloud coverage conditions from 1 January 2014 to 31 January 2015. The Level-1B data contain the total radiances at the top of the atmosphere at eight spectral bands (412, 443, 490, 555, 660, 680, 745, and 865 nm bands), and it is saved as a digital number (DN) value of a 32-bit integer. Radiometric and geometric corrections of the GOCI Level-1B data had previously been performed using an automated preprocessing system called the GOCI Data Processing System (GDPS) (Ahn et al. 2012; Ryu et al. 2012). Thereafter, the atmospheric corrections were generated using the GDPS, which is based on the algorithm established for Sea-viewing Wide Field-of-view Sensor (SeaWiFS) data by Wang and Gordon (Wang and Gordon 1994).

During the atmospheric correction process, \( R_{rc} \) can be accurately computed, defined as follows (Gordon and Wang 1992, 1994; Wang 2002; Wang and Shi 2005):

\[
R_{rc} = \rho_t - \rho_r = \rho_a + t_v \rho_w, \tag{1}
\]

where \( \rho_t \) is reflectance at top-of-atmosphere (TOA), \( \rho_r \) is the reflectance due to Rayleigh scattering by air molecules in the absence of aerosols, \( \rho_a \) is the reflectance from multiple scattering by aerosols, \( \rho_w \) is the water-leaving reflectance, and \( t_v \) is diffuse transmittance from the pixel to the sensor. The reflectance \( \rho \) is related to the radiance \( L \) (Gordon and Wang 1994) by

\[
\rho = \frac{\pi L}{F_0 \cos \theta_s}, \tag{2}
\]

where \( F_0 \) is the spectral mean extraterrestrial solar irradiance (solar constant) and \( \cos \theta_s \) is the cosine of the solar zenith angle (\( \theta_s \)).

Because \( \rho_t \) and \( \rho_r \) were accurately obtained, we calculated the values of \( R_{rc} \) from the GOCI data using GDPS. At the same time, the UV-AC algorithm for GOCI data derived by He et al. (2013) was applied to the \( R_{rc} \) data to obtain \( R_{rs} \).

Moreover, MODIS-Aqua Level-1B data for 2014–2015 were collected from the website (https://earthdata.nasa.gov/about/daacs/daac-laads) of NASA Level 1 and the Atmosphere Archive and Distribution System (LAADS). MODIS data were processed by the program l2gen of SeaDAS version 6.4. The program outputs included calibrated TOA radiance \( (L_t) \), Rayleigh radiance \( (L_r) \), and \( \theta_s \).

The Rayleigh-corrected radiance \( L_{rc} \) has had the contribution of Rayleigh scattering \( L_r \) from the sensor radiance \( L_t \) removed (Gordon and Wang 1992) as follows:

\[
L_{rc} = L_t - L_r. \tag{3}
\]

Based on Equations (1)–(3), the \( R_{rc} \) data could be calculated from the MODIS data.

### 2.4. Field-satellite data sets

Because cloud cover may drastically limit the number of matches between satellite estimates and in situ observations, a total of 54 days of GOCI data were chosen. The matchup data sets were established according to the procedure described in the following paragraphs.

Spatial matchup windows of 3 × 3 pixels were selected after much testing. The average values of all nine pixels were used as the final field matching values (Bailey...
Temporal matchup windows were selected separately for buoy observations and cruise observations. Because of the relatively high observation frequency of buoys, the temporal windows were chosen as within ±15 min. However, the temporal windows were set as approximately ±6 h for matching satellite data and data from cruise observations.

The statistics of the field-satellite matchup data sets are illustrated in Table 1. The numbers of 850, 113, and 93 matchup observations for the GOCI sensor were found in the ZJ and JS areas and the observation region of the cruise (BS, YS, and BY), respectively. At the same time, the matchup data set was established between the MODIS data and the ZJ buoy observations. Following the above processing scheme, we finally obtained 170 matchup observations, as shown in Table 1. In the data sets, 80% of the data were randomly selected for calibration and the remaining data were used for validation (see Table 1).

### 2.5. Algorithm comparisons

Three algorithms were chosen for comparison and were calibrated using the $R_{rc}$ and $R_{rs}$ data.

The first algorithm (model A) was proposed by Qiu et al. (2015) and estimates the turbidity $T$ from $R_{rc, \lambda}$ as follows:

$$\begin{align*}
T &= 10^{(c_0 + c_1 X + c_2 X^2)}, \\
X &= (R_{rc,490} + R_{rc,680}) / (R_{rc,490}/R_{rc,490}),
\end{align*}$$

where $X$ is a function of $R_{rc, \lambda}$ at various bands. $R_{rc, \lambda}$ is the Rayleigh-corrected reflectance at a given wavelength $\lambda$ and $c_0$, $c_1$, and $c_2$ are constant coefficients that can be obtained by a regression analysis of $X$ and $T$.

The second algorithm (model B) was derived by He et al. (2013). TSM is first retrieved using $R_{rs}$ data at 745 nm and 490 nm and then turbidity $T$ is estimated from the derived TSM as follows:

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**Table 1.** Statistics of turbidity $T$ (NTU) of the total data set, the calibration subset, and the validation subset.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Data sets</th>
<th>Location</th>
<th>$N$</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>CV</th>
</tr>
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<tbody>
<tr>
<td>GOCI</td>
<td>T</td>
<td>ZJ</td>
<td>850</td>
<td>2.4</td>
<td>363.9</td>
<td>96.3</td>
<td>87.4</td>
<td>90.8</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>ZJ</td>
<td>680</td>
<td>2.4</td>
<td>363.9</td>
<td>97.7</td>
<td>87.4</td>
<td>89.5</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>ZJ</td>
<td>170</td>
<td>2.8</td>
<td>327.9</td>
<td>134.1</td>
<td>107.3</td>
<td>80.1</td>
</tr>
<tr>
<td></td>
<td>ZJ</td>
<td>74</td>
<td>0.1</td>
<td>23.8</td>
<td>134.1</td>
<td>107.3</td>
<td>80.1</td>
<td>80.1</td>
</tr>
<tr>
<td></td>
<td>JS</td>
<td>90</td>
<td>6.8</td>
<td>461.1</td>
<td>134.6</td>
<td>108.3</td>
<td>80.4</td>
<td>80.4</td>
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<tr>
<td></td>
<td>BY</td>
<td>74</td>
<td>0.1</td>
<td>23.8</td>
<td>134.1</td>
<td>108.3</td>
<td>80.4</td>
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<td></td>
<td>93</td>
<td>6.8</td>
<td>467.0</td>
<td>134.6</td>
<td>108.3</td>
<td>80.4</td>
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<td>6.8</td>
<td>467.0</td>
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<td>80.4</td>
<td>80.4</td>
<td></td>
</tr>
<tr>
<td>MODIS</td>
<td>T</td>
<td>ZJ</td>
<td>170</td>
<td>2.5</td>
<td>327.8</td>
<td>101.6</td>
<td>89.3</td>
<td>87.9</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>ZJ</td>
<td>136</td>
<td>2.5</td>
<td>327.8</td>
<td>101.6</td>
<td>89.3</td>
<td>87.9</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>ZJ</td>
<td>34</td>
<td>5.2</td>
<td>273.9</td>
<td>87.5</td>
<td>79.0</td>
<td>90.3</td>
</tr>
</tbody>
</table>

$T$: total data set; $C$: calibration data set; $V$: validation data set; ZJ: Zhejiang coastal areas; JS: Jiangsu coastal areas; BY: The Bohai Sea and the Yellow Sea; $N$: number of samples; Max: maximum; Min: minimum; SD: standard deviations; CV: coefficients of variations.
where $a_0$ and $a_1$ are constant coefficients.

The third algorithm (model C) was deduced by Hu, Chen, and Zhang (2015); the particulate backscattering coefficients $b_{bp,532}$ are first estimated using the QAA model developed by Lee et al. (2009) and then turbidity $T$ is estimated from the derived $b_{bp,532}$. Because the band at 532 nm is not available for GOCI, the band at 555 nm was chosen instead.

$$T = d_1 X d_2, \quad (9)$$

$$X = b_{bp,555}, \quad (10)$$

where $b_{bp,555}$ is calculated using QAA with $R_{rs,\lambda}$ data derived by the UV-AC algorithm and $d_1$ and $d_2$ are constant coefficients obtained by a regression analysis of $b_{bp,555}$ and $T$. It should be noted that the parameters $g_0$ and $g_1$ in QAA were adjusted to 0.084 and 0.17, respectively, to fit the research areas (Lee et al. 1999).

### 2.6. Calculation assessments

Four statistical indicators, including $R^2$, RMSE, MAE, and MRE, were used to measure the performance of the regression models (Le et al. 2013; Sun et al. 2014). Referring to the Ocean Colour Climate Change Initiative (OC-CCI) methodology for the comparison of the performance of algorithms (Müller et al. 2015; Brewin et al. 2015), a points scoring classification was simplified and used in this study to objectively rank the performance of the algorithms, using the $R^2$, RMSE, MAE, and MRE values of the algorithms as evaluation indicators during the score calculation. The evaluation score was assigned in the following manner.

1. The best algorithm is the one with the best evaluation indicator and is assigned 2 points, whereas the worst receives 0 points. For example, if an algorithm has the highest $R^2$ value and the lowest RMSE, MAE, and MRE values, it will receive a total of 8 points.

2. If the evaluation indicator falls between the best and the mean of all algorithms (or equals to the mean), the algorithm receives 1.5 points.

3. If the evaluation indicator of one algorithm is not better than the mean, but is better than the worst, then the algorithm receives 0.5 points.

4. The score of one algorithm is equal to the average value of the total points that are calculated based on the four evaluation indicators.
3. Results

3.1. Model calibrations

The three algorithms introduced in Section 2.5 were calibrated using the MathWorks MATLAB software. For convenience, Equations (9) and (10) were replaced by Equation (4) and the tests proved that no significant variations were observed for this change, at least in the calibration data sets. Two calibration schemes were performed by introducing the \( R_{rc} \) and \( R_{rs} \) data sets (Table 2). The negative results of \( R_{rs} \) were removed, which decreased the number of observations in the calibration data sets in the ZJ, JS, and BY areas to 537, 89, and 71, respectively, for 695 observations. Calibrations of (a), (b), and (c) are denoted as models A, B, and C, as calibrated with the \( R_{rc} \) data (\( N = 844 \)), and are hereafter referred to simply as models \( A_c \), \( B_c \), and \( C_c \), respectively. Correspondingly, calibrations of (d), (e), and (f) are denoted as models \( A_s \), \( B_s \), and \( C_s \). This latter notation indicates models A, B, and C calibrated with the \( R_{rs} \) data (\( N = 695 \)), respectively. The calibrated coefficients are also shown in Table 2.

From the performance of model calibrations summarized in Table 2, we determined that all six calibrations performed well, which indicates that the model choices were reasonable. Similar performances were observed between the models calibrated using the \( R_{rc} \) data and those calibrated using the \( R_{rs} \) data. The best fit was obtained by model \( A_c \), for which the values of \( R^2 \), RMSE, MAE, and MRE for model \( A_c \) were 0.811, 56.02, 37.37, and 85.37, respectively, and for model \( A_s \), for which the values were 0.837, 56.72, 34.03, and 68.42, respectively. Model B resulted in the worst fit; the values of \( R^2 \), RMSE, MAE, and MRE for model \( B_c \) were 0.528, 66.33, 45.53, and 225.96, respectively, and for model \( B_s \) the values were 0.603, 65.09, 44.17, and 174.05, respectively. The performances of model B calibrated using the \( R_{rs} \) data were better than those using the \( R_{rc} \) data. However, there is no clear evidence to support the suggestion that the performances of model A or model B calibrated using the \( R_{rs} \) data should be better than those using the \( R_{rc} \) data.

The fitting curves of the regression analyses of the six different algorithms are summarized in Figure 3. The performance of all six calibrations can meet the requirements for water turbidity estimations for the total calibration data sets. The three models performed differently. For comparison, the points calibrated by models A and C were close to the fitting curves, but differed when calibrated by model B. Differences are also shown from the different data sets. Models \( A_c \) and \( A_s \) can estimate the buoy data better, with fewer buoy data points outside the 95% confidence bounds (light blue- and blue-coloured points). Models \( C_c \) and \( C_s \) also

<table>
<thead>
<tr>
<th>Equation (4) with X</th>
<th>Calibrated coefficients</th>
<th>( R^2 )</th>
<th>RMSE</th>
<th>MAE</th>
<th>MRE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) ( (R_{rc,490} + R_{rc,680}) / (R_{rc,490} / R_{rc,680}) )</td>
<td>(-11.79) (11.69) (-0.52) 0.811</td>
<td>56.02</td>
<td>37.37</td>
<td>85.37</td>
<td></td>
</tr>
<tr>
<td>(b) ( R_{rc,490} / R_{rc,745} )</td>
<td>(-0.80) 3.06 (-0.58) 0.528</td>
<td>66.33</td>
<td>45.53</td>
<td>225.96</td>
<td></td>
</tr>
<tr>
<td>(c) ( b_{bp,555} )</td>
<td>(-10.03) (11.77) (-0.86) 0.749</td>
<td>67.69</td>
<td>44.71</td>
<td>84.27</td>
<td></td>
</tr>
<tr>
<td>(d) ( (R_{rs,490} + R_{rs,680}) / (R_{rs,490} / R_{rs,680}) )</td>
<td>(-125.96) 34.27 (-0.02) 0.837</td>
<td>56.72</td>
<td>34.03</td>
<td>68.42</td>
<td></td>
</tr>
<tr>
<td>(e) ( R_{rs,490} / R_{rs,745} )</td>
<td>(-0.35) 1.71 0.32 0.603</td>
<td>65.09</td>
<td>44.17</td>
<td>174.05</td>
<td></td>
</tr>
<tr>
<td>(f) ( b_{bp,555} )</td>
<td>(-10.87) (10.95) (-0.32) 0.763</td>
<td>71.37</td>
<td>47.08</td>
<td>80.96</td>
<td></td>
</tr>
</tbody>
</table>
performed well. The fitting accuracy of the band ratio used in model B for the JS buoy measurements was better than the ZJ buoy measurements. Obviously, it is more difficult to calibrate the low-turbidity data, which were mostly from the BY cruises (magenta-coloured points). There were relatively more points of cruise data beyond the 95% confidence bounds using algorithms B<sub>c</sub> and B<sub>s</sub> (Figures 3(b and e)). Models A<sub>c</sub>, C<sub>c</sub>, A<sub>s</sub>, and C<sub>s</sub> can better estimate the cruise data, and among the four models, models A<sub>s</sub> and C<sub>s</sub> were the best.

### 3.2. Model validations

After calibration, the models were tested using the validation data sets (Table 1). A total of 212 matchups of $R_{rc}$ data were used: 170 were in ZJ, 23 in JS, and 19 in BY. Because some of the negative $R_{rs}$ data were missing, the number of matchups of $R_{rs}$ data available for validation was decreased to 171, with 129 in ZJ, 23 in JS, and 19 in BY. Comparisons using $R_{rc}$ data are shown in Figure 4, and those using $R_{rs}$ data are shown in Figure 5.

The scatter distributions of turbidity derived from model A<sub>c</sub> were located close to the dotted 1:1 line (Figure 4). The same pattern was observed for model C<sub>c</sub>. The distributions of model B<sub>c</sub> were more dispersed than those of the other two models. Model A<sub>c</sub>
performed well, with $R^2$, RMSE, and MAE values of 0.838, 49.45, and 31.25, respectively; however, the MRE value was not the best (68.55). Model C performed similarly. However, an $R^2$ value of only 0.436 was achieved from model B.

Many differences in model performances were also found between the different data sets. The turbidity derived from model A was much closer to the buoy measurements than to the cruise observations. Estimates of higher turbidity were more accurate than those of lower turbidity. Cruise turbidities lower than 1 NTU were overestimated, which was also noticed for models B and C. Slight differences existed in two buoy measurements. The turbidities derived from models A and C were close to the ZJ buoy measurements; however, they were different from model B turbidities. Moreover, JS buoy observations were also overestimated by models A and C, whereas they were underestimated by model B.

The scatter distributions of turbidity derived from models A, B, and C are shown in Figure 5; the pattern is similar to that of Figure 4. According to the statistical indicators, model A had the best performance with the best $R^2$, RMSE, MAE, and MRE values (0.837, 56.72, 34.03, and 68.42, respectively). Model C also performed well, with an $R^2$ value of 0.803, an RMSE value of 71.20, an MAE value of 44.51, and an MRE value of 80.22. Model B had the worst performance; $R^2$ was lower than 0.6 and the errors were relatively
higher. Although there was little difference in the statistical indicators, as a whole, using $R_{rs}$ data revealed results similar to the results from using $R_{rc}$ data.

Differences in model performances from the different data sets are also shown in Figure 5. The turbidity derived from model $A_s$ was much closer to the buoy measurements than to the cruise observations. Estimates of higher turbidity were better than those of lower turbidity. The cruise turbidity data lower than 1 NTU were overestimated by the three models, and the most serious overestimation was observed from model $B_s$. The turbidities higher than 1 NTU from cruise measurements were underestimated by models $A_s$ and $C_s$. Slight differences existed between the two buoy measurements. The turbidities derived from models $A_s$ and $C_s$ were close to the ZJ buoy measurements, but were different from those from model $B_s$. Additionally, slight overestimates of the JS buoy observations were also observed from models $A_s$ and $C_s$, with underestimates from model $B_s$.

### 3.3. Assessment scores

Figure 6 provides the assessment scores of models using the methods introduced in Section 2.6. The scores of the entire data set and its three parts (ZJ, JS, and BY areas) were estimated for all of the models separately. Note that the algorithm with the higher score performs better.

The average situation can be observed from the dashed line. The best score was achieved by model $A_c$ (value of 1.625); the second best score was 1.436, achieved by model $A_s$; the third best score was 1.375, achieved by model $C_c$. Other models had mean scores less than 1.5. Similarly, the best score for the entire data set was also from model $A_c$ (1.875), followed by $C_c$ (1.625) and $A_s$ (1.5).

Not all the scores of model $A_c$ were the highest for all parts of the entire data set. Figure 6 shows separate scores for the ZJ, JS, and BY areas. For the ZJ data set, the highest score was from model $A_c$ (2), followed by models $C_c$ (1.5) and $A_s$ (1.5). Others were less than 1. For the JS data set, the highest score was also from model $A_c$ (1.875),

![Figure 6. Score results using a simplified points scoring classification. The abscissa represents the label of the six algorithms being compared (as listed in Table 2).](image-url)
followed by $A_s$ (1.25), $C_c$ (1.125), and $B_s$ (1.125). For the BY data set, the highest score was also from model $C_c$ (2), followed by $A_s$ (1.5) and $C_c$ (1.25). The good scores for the JS and BY data show the potential for reliable turbidity estimations in other seasons by using these three models.

4. Discussion

4.1. Model performance

Results from Section 3 show that model A performed the best compared to models B and $C_c$ at least in the data sets. Considering that the three models were calibrated by using the same formula (Equation (4)), the main differences in model performance came from the combinations and the band choices.

Model A was derived from a combination of the 490 nm and 680 nm bands and showed good availability for a wide turbidity range of approximately 1–460 NTU. Many researchers have proved that the wavelength of approximately 680 nm is sensitive to the water turbidity or TSM (Tassan 1994; Goodin et al. 1996; Nechad et al. 2003; Petus et al. 2010; Avinash et al. 2012). Correlation between TSM and reflectance along satellite bands has been found more closely in the red part of the spectrum with the increase of the concentration of TSM on a logarithmic scale. Moreover, the wavelength of 490 nm was found to be in the slope zone of the absorption spectra of chlorophyll, depending on chlorophyll concentration (Tassan 1994). The first factor of model A, $R_{rc,490} + R_{rc,680}$ (or $R_{rs,490} + R_{rs,680}$), included information about the water turbidity and chlorophyll. Although adding other bands into the factor, such as the 555 nm and 660 nm bands, could slightly increase the estimation accuracy (Qiu et al. 2015), the choice of the 490 nm and 680 nm bands met the accuracy requirement. The second factor, $R_{rc,490} / R_{rc,680}$ (or $R_{rs,490} / R_{rs,680}$), could be a compensating term. Similar formulations for the dependencies on bands have already been shown to be reasonable in some existing works such as the models proposed by Tassan (1994) and Avinash et al. (2012).

Model B estimated the water turbidity by using the 490 nm and 745 nm bands. The model proposed by He et al. (2013) performed well for the Changjiang River Estuary and HZB, which has the highest water turbidity with a maximal TSM concentration of up to 5000 mg l$^{-1}$. Moreover, the use of NIR wavelengths (extending from 700 nm to 1 mm) also has advantages for the estimation of TSM in the HZB area in the results of other researchers (Bai et al. 2010), which indicates the potential of the NIR band (779 nm) in estimating optical parameters in highly turbid waters. Although the recent research suggests that the band ratios $R_{rs,670} / R_{rs,490}$ and $R_{rs,765} / R_{rs,490}$ of Medium Resolution Imaging Spectrometer (MERIS) data both have good correlations with the TSM data in the ECS (Mao et al. 2012), the result of replacing the 745 nm band with the 680 nm band in the band ratio (Figure 7) shows that the 680 nm band is better than the 745 nm band for the ZJ, JS, and BY areas, at least for the data sets summarized in Table 1. Therefore, it can be inferred that model B is more likely to be a regional model, especially for the highly turbid waters in the Changjiang River Estuary and the HZB area. The use of the NIR wavelength could be the reason why the model was less useful in the clear waters.

The good performance of model C in this study proves the applicability and stability of the QAA algorithm. Model C had an especially obvious advantage in estimating
turbidity in clear waters (Figure 6). However, the estimation accuracy was not much better than that of model A. The relatively complex intermediate steps in the QAA algorithm constitute the probable error sources. The parameter setting is also a possible source. In this study, the values of $g_0$ and $g_1$ are found to be important factors that could affect the estimation accuracy. Errors decreased somewhat when the $g_1$ parameter was increased appropriately, which suggests that further study of the parameter settings could be conducted for a more accurate semi-analytical model for the highly turbid waters in the coastal areas of China.

4.2. $R_{rc}$ versus $R_{rs}$

To compare the model performance by inputting $R_{rc}$ data with $R_{rs}$ data, the UV-AC algorithm was chosen to perform the atmospheric corrections. The objective of this article is not to pursue a precise set of atmospheric corrections; therefore, the accuracy of the UV-AC algorithm has not been validated here. Readers who are interested in the performance of the UV-AC algorithm are advised to consult He et al. (2012, 2013) for more details.

Comparisons indicated that almost every model performed better when using $R_{rc}$ data than $R_{rs}$ data. It will now be discussed whether or not the atmospheric corrections are necessary when estimating turbidity from satellite remote sensing in the coastal seas of China.

Turbidity has been widely and successfully estimated based on empirical relationships between turbidity and in situ-measured $R_{rs}$ (Goodin et al. 1996; Bustamante et al. 2009; Petus et al. 2010; Dogliotti et al. 2011; Mao et al. 2012). Whether or not the relationships are suitable for satellite data largely depends on the accuracy of the atmospheric corrections. Furthermore, if there is a lack of a sufficiently large number of matched-up in situ $R_{rs}$ for validation, the accuracy of the atmospheric corrections cannot be ensured. Despite intense efforts to augment these data sets, the difficulty in deploying and maintaining instrumentation and the huge costs of the field surveys are the main limitations. Moreover, because the black pixel assumption (Siegel et al. 2000) is not

Figure 7. (a) Calibration and (b) validation of model B in which the 745 nm band was replaced with the 680 nm band.
appropriate in turbid waters, atmospheric corrections are challenging because of unreliable aerosol estimates. Although the SWIR atmospheric correction algorithm using two shortwave infrared bands (1.24 and 1.64 μm) was feasible for MODIS data in turbid waters (Wang and Shi 2005), it was limited by the considerably lower sensor signal-to-noise (SNR) values (Werdell, Franz, and Bailey 2010). Moreover, it is another limitation that no SWIR bands have been designed in GOCI. Furthermore, some unnecessary errors and serious missing Rs (or water-leaving radiance data) resulted from complex aerosol variations at the land–sea interface, which were also the problems for the atmospheric corrections (Hu, Carder, and Muller-Karger 2000; Wang and Shi 2005; Mao, 2013). Under these circumstances, the Rrc-based algorithms, which estimate turbidity from Rrc data directly instead of from Rs data, are reasonable alternatives.

Compared with Rs-based algorithms that are restricted by incorrect atmospheric corrections, the Rrc-based algorithms have obvious advantages. First, model development, calibration, and validation of an Rrc-based algorithm do not require water-leaving reflectance Rs, therefore, strict and arduous validation of Rs is avoided. Second, because in situ Rs values are not necessary for an Rrc-based algorithm, field-satellite matchup data sets are easily collected without considering instantaneous light or view angles, which are important for in situ Rs observations. In this article, for instance, when buoy observations with high sampling frequencies are chosen to match up with geostationary satellite measurements, the quality and quantity of field-satellite synchronous data sets are greatly enhanced. Third, sometimes atmospheric correction quality control protocols will lead to false masking and significant data loss, especially in coastal areas or turbid waters. The situation is largely avoidable when applying an Rrc-based algorithm. However, disadvantages also exist in Rrc-based algorithms. The major problem is that aerosols vary constantly and their contributions to the Rrc signals remain unknown and unpredictable. Therefore, Rrc data cannot always replace Rs data (Qi et al. 2014). Moreover, the flexible Rrc-based algorithm should be restrained in its application under certain conditions. Over the longer term, the Rrc algorithm has been shown to be feasible only in special cases and most algorithms still rely on Rs data, which still require improvements in the atmospheric corrections (Qiu et al. 2015).

4.3. GOCI versus MODIS

As the world’s first geostationary ocean colour satellite sensor, GOCI has showed great advantages with a high SNR at 750–1170 and world-class standards in temporal and spatial resolutions, which allows observations of short-term changes in coastal zones and oceans and can document regional characteristics in the Northeast Asian region (2500 km × 2500 km, Centre: 130°E, 36°N) (Ryu et al. 2012). Although they can make a global observation on oceans, Sun-synchronous polar-orbiting satellites, such as MODIS, face constraints in the observation of high-frequency changes. In contrast, GOCI has the ability to detect continuous changes of ocean based on hourly observations. Thus, GOCI has higher availability for the collection of satellite-ground synchronous data sets than MODIS. However, this unique feature of geostationary satellites also shows a limitation in spatial coverage rather than MODIS. Additionally, MODIS has more optional bands than GOCI, especially the SWIR bands, which are not there in GOCI. Therefore, it is
interesting to know the applications of the \( R_{rc} \)-based algorithm for MODIS, based on its greater number of bands and wider coverage.

We conducted an additional comparison between GOCI and MODIS to determine additional applications. A total of 170 pairs of data were selected from the 850 sample data set in the ZJ coastal areas. The same criteria were applied for both MODIS-Aqua data and GOCI data to match up with the \textit{in situ} turbidity measurements. Of the 170 pairs, 136 pairs were randomly selected for calibration and the other 34 pairs were used for validation (as shown in Table 1). \( R_{rc} \) of GOCI and MODIS were processed by the approach introduced in Section 2.3.

The spectra of \( R_{rc} \) of GOCI and MODIS are shown in Figures 8(a and b), respectively. The shapes of the spectra are distinct. In Figure 8(a), most of the GOCI \( R_{rc} \) spectral peaks fall within the range between 555 nm and 680 nm, although peaks at longer wavelengths (745 nm or 865 nm bands) were also observed. The largest differences in \( R_{rc} \) magnitude are observed at the 865 nm band. The 555 nm band had the lowest variability with a coefficient of 15.1%. The highest averages of \( R_{rc} \) values were at the 680 nm band. In Figure 8(b), the MODIS \( R_{rc} \) spectra do not peak at visible wavelengths, but reached a maximum average value at the 859 nm band. The largest differences in \( R_{rc} \) magnitude are at the 859 nm band as well. At NIR wavelengths, the average \( R_{rc} \) values decrease as the wavelength increases, which could not be determined from the GOCI data. It should be noted that the bands mentioned in Figure 8(b) do not contain all of the MODIS bands. Bands had previously been screened because the reflectance of MODIS saturates at some bands, which would lead to excessively high and unreasonable \( R_{rc} \) values. Saturation would not apply to GOCI because of its specific design. Therefore, although MODIS has more bands than GOCI, not all of the MODIS bands are available for use in turbid waters.

In the previous study (Qiu et al. 2015), the GOCI bands at 490 nm and 680 nm were successfully used to estimate turbidity in the ZJ coastal areas. The MODIS band with a central wavelength at 488 nm was selected for comparison with the GOCI 490 nm band. The MODIS band at 645 nm was also chosen because the visible wavelength range between 620 and 670 nm (Band 1) has been widely used to estimate turbidity and other parameters of water quality in coastal areas (Wong et al. 2008; Moreno-Madrinan et al. 2008).

![Figure 8. Rayleigh-corrected reflectance spectra \( R_{rc} \) of (a) GOCI data samples at all the eight bands and (b) MODIS data samples at 11 available bands. The blue line represents the mean spectra, and the vertical bars indicate the standard deviation.](image-url)
Therefore, the \( R_{rc} \)-based algorithm for MODIS was:

\[
X = \left( \frac{R_{rc,488} + R_{rc,685}}{R_{rc,488}/R_{rc,685}} \right) / \left( \frac{R_{rc,488} + R_{rc,685}}{R_{rc,488}/R_{rc,685}} \right)
\]

The GOCI \( R_{rc} \)-based algorithm and the MODIS \( R_{rc} \)-based algorithm were calibrated using the calibration data subset (\( N = 136 \)) and then were validated using the validation data subset (\( N = 34 \)). The results are shown in Figures 9 and 10 for GOCI and MODIS data, respectively.

Apparent differences were observed in the validations between GOCI and MODIS data, with \( R^2 \) values of 0.818 and 0.573, RMSE values of 36.48 and 55.99, MAE values of 23.85 and 38.00, and MRE values of 47.72% and 98.59%, respectively. The GOCI \( R_{rc} \)-based algorithm performed better than the MODIS \( R_{rc} \)-based algorithm for the data set. Careful tuning is still necessary for MODIS \( R_{rc} \)-based algorithms. Although detailed discussions

\textbf{Figure 9.} (a) Correlation between \( X \left( R_{rc,488} + R_{rc,685}\right) / \left( R_{rc,488}/R_{rc,685}\right) \) using GOCI data and turbidity (\( T \)). The solid red line is the fitted curve and the dotted red lines are 95% confidence bounds. (b) Comparison between the observed and estimated turbidity levels for validation (dotted line: 1:1).

\textbf{Figure 10.} (a) Correlation between \( X = \left( R_{rc,488} + R_{rc,685}\right) / \left( R_{rc,488}/R_{rc,685}\right) \) using MODIS data and turbidity (\( T \)). The solid red line is the fitted curve and the dotted red lines are 95% confidence bounds. (b) Comparison between the observed and estimated turbidity levels for validation (dotted line: 1:1).
on building an appropriate MODIS $R_{rc}$-based algorithm are beyond the scope of this article, the results illustrate the applicability of $R_{rc}$-based algorithms to estimate turbidity using the MODIS data and the potential by using other satellite sensors.

### 4.4. Algorithm applicability and improvement

The comparisons shown in this article suggest that the GOCI $R_{rc}$-based algorithm can produce reliable turbidity estimates, especially in highly turbid waters. However, its performance decreases in low-turbidity waters, as shown in the BY cruise data sets. Water properties vary in different waterbodies and different areas, which may cause different performances, even with the same model. Considering the large variations of turbidity in the coastal areas of China, one formulation may not be sufficient to cover the entire turbidity range. For example, the GOCI $R_{rc}$-based algorithm performed well in turbid waters but still required adjustment for low-turbidity or clear waters. Therefore, it is better to model using subsection functions that deal separately with different ranges. This information may be of use to algorithm developers and to users who study environmental monitoring and pollution in the coastal waters of China.

The GOCI $R_{rc}$-based algorithm in this study had been developed in the coastal waters of China, which showed variable optical properties. For instance, the turbidity varied from 0.1 to 467.0 NTU, with a mean of 92.2 NTU by the data set used in this study; particulate backscattering coefficient ($b_{bp}$) in the 532 nm band in BY showed a variation from 0.001 to 1.315 $m^{-1}$ with a mean of 0.071 $m^{-1}$, based on another in situ data set collected from 228 stations in BY during April–May 2014 and October–November 2013; TSM concentrations showed a variation from 0.340 to 418.225 mg/l with a mean of 14.524 mg/l, based on the same in situ data set. In theory, the algorithms proposed in this study may be applicable, if other water areas would show water optical properties similar to our investigated waters. Thus, to some extent, our algorithms provide good support for the retrieval of turbidity in relatively turbid coastal waters, whereas quantitatively accurate assessment to the algorithms needs more in situ observed data sets collected from other water areas. Moreover, the general concept of the $R_{rc}$-based algorithm may show important reference meaning for other investigated water areas in the world, only if some tests would be carried out based on data available, as we did in this study. Therefore, this algorithm provides a new insight to solve similar problems in other water areas of interest. Here we expect more observations and quantitatively accurate assessments to be proceed in the future.

### 5. Conclusion

A new algorithm that uses $R_{rc}$ instead of $R_{rs}$ data and that uses GOCI satellite imagery data to estimate water turbidity in the ZJ coastal areas has recently been introduced (Qiu et al. 2015). This study conducted a series of comparisons to (1) verify the capability of the $R_{rc}$-based algorithm in other areas and seasons, (2) evaluate the performance of the $R_{rc}$-based algorithm by comparing it with other algorithms, (3) evaluate the effect of atmospheric corrections on water turbidity estimation in highly turbid waters, and (4) determine whether the $R_{rc}$-based algorithm developed based on GOCI data can be extended to other sensors.
The study compares the new $R_{tc}$-based algorithm proposed by Qiu et al. (2015) with an existing empirical algorithm proposed by He et al. (2013) and an existing semi-empirical algorithm proposed by Hu, Chen, and Zhang (2015). The UV-AC algorithm designed by He et al. (2013) was chosen to perform atmospheric corrections. The results showed that the new $R_{tc}$-based algorithm is capable of estimating water turbidity in large areas and in all seasons in the seas of China. The $R_{tc}$-based algorithm has attained the best performance compared with the other algorithms considered. Good accuracy appears in estimating the turbidity of highly turbid waters in the coastal areas of China. However, the performance needs to be improved for clear waters. Comparisons also showed that the $R_{tc}$ algorithm is more suitable than the $R_{rs}$ algorithm, at least in estimating the turbidity of highly turbid waters in the coastal areas of China. Finally, the results demonstrated that the $R_{tc}$-based algorithm developed based on GOCI data could be extended to other sensors, for instance MODIS, by careful tuning of the relevant parameters.

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Disclosure statement

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