Innovative GOCI algorithm to derive turbidity in highly turbid waters: a case study in the Zhejiang coastal area

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Abstract: An innovative algorithm is developed and validated to estimate the turbidity in Zhejiang coastal area (highly turbid waters) using data from the Geostationary Ocean Color Imager (GOCI). First, satellite-ground synchronous data (n = 850) was collected from 2014 to 2015 using 11 buoys equipped with a Yellow Spring Instrument (YSI) multi-parameter sonde capable of taking hourly turbidity measurements. The GOCI data-derived Rayleigh-corrected reflectance ($R_{rc}$) was used in place of the widely used remote sensing reflectance ($R_{rs}$) to model turbidity. Various band characteristics, including single band, band ratio, band subtraction, and selected band combinations, were analyzed to identify correlations with turbidity. The results indicated that band 6 had the closest relationship to turbidity; however, the combined bands 3 and 6 model simulated turbidity most accurately ($R^2 = 0.821, p<0.0001$), while the model based on band 6 alone performed almost as well ($R^2 = 0.749, p<0.0001$). An independent validation data set was used to evaluate the performances of both models, and the mean relative error values of 42.5% and 51.2% were obtained for the combined model and the band 6 model, respectively. The accurate performances of the proposed models indicated that the use of $R_{rc}$ to model turbidity in highly turbid coastal waters is feasible. As an example, the developed model was applied to 8 hourly GOCI images on 30 December 2014. Three cross sections were selected to identify the spatiotemporal variation of turbidity in the study area. Turbidity generally decreased from near-shore to offshore and from morning to afternoon. Overall, the findings of this study provide a simple and practical method, based on GOCI data, to estimate turbidity in highly turbid coastal waters at high temporal resolutions.

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OCIS codes: (010.0280) Remote sensing and sensors; (010.7340) Water.

References and links


1. Introduction

Water turbidity is directly related to variations in marine ecology and multiple biogeochemical processes, including phytoplankton photosynthesis and growth [1, 2], heat transfer in the upper water layer [3–5], and sediment transport and resuspension [6, 7]. As a
simple proxy for total suspended matter (TSM) concentrations, turbidity is an indispensable water quality monitoring indicator that provides valuable information about the optical environment [8]; it has been listed as a mandatory observation measure in the Marine Strategy Framework Directive [9]. Satellite mapping of turbidity is thus a continuously significant subject in the field of ocean color remote sensing.

Many algorithms reportedly ascertain the turbidity of water bodies by processing various satellite data. Landsat Thematic Mapper (TM) and Systeme Probatoire d’Observation de la Terre (SPOT) red bands have been used to establish retrieval algorithms for mapping low-level turbidity in water bodies, including in the Tutel Creek Reservoir, USA (turbidity range of 3-15 NTU) [10] and the Guadalquivir River, Spain (1.5-8 NTU) [11]. Chen et al. [12] developed a Moderate Resolution Imaging Spectrometer (MODIS) based model that used the 645-nm band to map the turbidity in the Tampa Bay (USA), which ranged from 0.9 to 8 NTU. Petus et al. [13] established a MODIS-Aqua-based quadratic model using the 250-m red band to analyze turbidity in the Bay of Biscay (France). The model was successfully applied in water bodies with a turbidity range of 0.5-70 NTU. The Medium Resolution Imaging Spectrometer (MERIS) data have also been used to map the turbidity of water bodies. For instance, Potes et al. [14] developed a linear model using the band ratio for the green and blue MERIS bands and applied it to the Alqueva Reservoir, where they identified a maximum turbidity of 60 NTU. Ouillon et al. [15] reported that the MERIS 681-nm band relates closely to the 1 to 25 NTU turbidity range in coastal waters. Although many turbidity algorithms have been proposed, few have yet to focus on highly turbid waters (e.g., >100 NTU).

High turbidity levels frequently occur in certain coastal and near-shore marine waters. For instance, data indicate that the East China Sea (ECS) has a rather wide turbidity range (approximately 0-1000 NTU), with mean values of 165.7, 112.4, and 270.7 NTU for spring 2007, autumn 2007, and winter 2006, respectively [16]. Therefore, it is imperative that we explore remote sensing algorithms that are able to model data from highly turbid waters.

Existing algorithms which need to derive remote sensing reflectance ($R_{rs}$) data are all based on accurate atmospheric corrections; however, highly turbid coastal waters are prone to inaccurate atmospheric corrections resulting from complex aerosol variations at the land-sea interface causing unnecessary errors and a large amount of incorrect data masking [17–20]. This likely limits the effectiveness of existing algorithms when they are applied to highly turbid coastal waters. Hence, two approaches are being taken to address the need of improving algorithm accuracy: (1) continuing to process atmospheric corrections for turbid coastal waters [19, 20]; and (2) modeling turbidity using remote sensing signals without atmospheric correction, and the models are being developed by Rayleigh-corrected reflectance ($R_{rc}$) in place of the widely used $R_{rs}$ [21–25].

To our knowledge, the satellite-ground synchronous data sets that could provide the foundation for high-turbidity calculation algorithms are currently limited and often incomplete. This is because ocean color remote sensing satellites are typically sun-synchronous satellites that capture instantaneous images of interesting water regions, such as MODIS, MERIS, and Sea-viewing Wide-field-of-view Sensor (SeaWiFS). As the first ocean color observation satellite, the Geostationary Ocean Color Imager (GOCI) collects images around the Korean Peninsula during every daylight hour, enabling hourly monitoring of variations in ocean properties [26]. GOCI thus provides new possibilities for the collection of satellite-ground synchronous data sets. On the other hand, traditional shipboard investigations often have few opportunities to collect in situ data concurrent with satellite data. Buoys are better able to collect satellite-synchronous data.

The focus areas for this study are the highly turbid coastal waters around Zhejiang Province in the ECS. A large satellite-ground synchronous data set was collected; in situ turbidity measurements were obtained from 11 buoys in and around the study area, and concurrent GOCI images were also acquired. A regional remote sensing algorithm was developed using these data to map the turbidity in a highly turbid, complex water region. The
model is novel in its use of the Rayleigh-corrected reflectance \((R_{rc})\) in the developed algorithm. The \(R_{rc}\) algorithm was evaluated using independent data to a certain degree of satisfaction, and a sample application was provided.

2. Data and methods

2.1 In situ data collection

*In situ* data used in this study were collected from the Zhejiang coastal area (ZCA) in the ECS. This area is known for its strong upwelling and high primary production, is the largest coastal fishing ground in China and is the site of frequent red tide events [27, 28] (Fig. 1). The ZCA is significantly influenced by sediment flows from the Changjiang River, especially in winter. The Changjiang River, the third longest river in the world, discharges approximately \(240 \times 10^6\) t of sediment into the ECS annually, and approximately 32% of that is thought to be deposited in the ZCA and Fujian coastal region [29]. In addition to Changjiang, several other rivers, including the Qiantang, directly drain large quantities of freshwater high in nutrients and sediments into the ZCA [30, 31]. Tidal action is typically strong in the ZCA, especially in the Hangzhou Bay, one of the world’s strongest tidal bays; and it causes significant resuspension of sediment. As a result, turbidity in the ZCA is usually high but follows clear temporal and diurnal variations [30, 32].

Eleven buoys were placed in the ZCA to continuously monitor the ocean environment from 2014 to 2015. In order to assure the data quality, the instruments deployed on the buoys would be maintained routinely by the Marine Monitoring and Forecasting Center of Zhejiang Province (Hangzhou, China), including periodical calibration, cleaning, testing of equipment. A YSI EXO2 multi-parameter sonde (Yellow Springs, OH, USA) was mounted on each buoy to measure turbidity, temperature, pH, dissolved oxygen, etc., once a quarter of an hour during 6:00-18:00 local time each day. In this study, we measured turbidity in Nephelometric Turbidity Units (NTU) and used these measurements to develop and validate our new algorithm.

![Fig. 1. Location of the Zhejiang coastal area in the East China Sea. The magenta triangle symbols indicate the locations of the 11 buoys labelled S01-11.](image-url)
2.2 Satellite data

As the world’s first geostationary ocean color satellite sensor GOCI was launched on June 26, 2010. GOCI takes images of the Northeast Asian region 8 times a day from 8:15 to 15:15 local time at a 500-m spatial resolution and 1-hour temporal resolution. After an in-orbit test of the satellite, the GOCI data have been managed by the Korea Ocean Satellite Center (KOSC) of the Korea Institute of Ocean Science and Technology (KIOST). KOSC has provided 8 sets of GOCI satellite images from 2014 to date and has designed the GOCI Data Processing System (GDPS) for the real-time generation of various products.

In this study, we performed a preliminarily check of the ZCA GOCI images and found that most of the regions were covered by clouds during all seasons except winter. Therefore, the winter GOCI data were concentrated, and the scenes with minimal cloud cover were selected. Data for 16 days were obtained, including for January 1, 16, 23, 24, 25 and 27, November 4 and December 30, 2014; and January 1, 2, 4, 8 and 9, 2015. Level-1B data were obtained for each date and processed to Level 2 data using GDPS set to default parameters and standard atmospheric correction. The GOCI standard atmospheric correction was based on the standard SeaWiFS method found in Wang & Gordon [33]. In brief, the total reflectance at the top of atmosphere (ρt(λ)) can be expressed as:

\[
ρ_t(λ) = ρ_r(λ) + ρ_a(λ) + t ρ_w(λ),
\]

where ρr(λ) is the reflectance due to Rayleigh scattering by air molecules, ρa(λ) is the reflectance from multiple scattering by aerosols, ρw(λ) is the water-leaving reflectance, and t is the diffuse transmittance. The Rayleigh-corrected reflectance Rrc(λ) is defined as [20]

\[
R_{rc}(λ) = ρ_r(λ) - ρ(λ).
\]

The Rayleigh scattering correction (removing the Rayleigh item ρr(λ) from ρt(λ)) can be accurately performed [20, 34]. To do so, the GDPS adopted the typical radiative transfer theory with inputting the solar-sensor geometry (solar zenith angle, sensor zenith angle, solar azimuth angle and satellite azimuth angle) from a four-dimensional lookup table, atmospheric pressure, and wind speed [34–38]. Rrc(λ) can be obtained from Level-2C data generated during the production of Level-2 data.

This study attempted to develop a method that could directly draw on Rrc(λ) to estimate turbidity. We matched the GOCI Rrc(λ) with in situ measured turbidity. In total, 850 data points were generated by strictly synchronizing the GOCI and in situ buoy data. The real time synchronization between GOCI data and the in situ buoy data was approximately ± 15 min due to slight differences in measurement times. In space, the synchronization between GOCI data and the in situ buoy data was defined at a tolerance spatial range of ± 500m, considering that the COCI data has this spatial resolution.

2.3 Model accuracy assessment

To assess the model’s performance, we compared in situ and derived turbidity by applying a type II reduced major axis linear regression commonly used in the validation of ocean color algorithms [39]. The model performance was also evaluated using root mean square error (RMSE), mean absolute error (MAE) and mean relative error (MRE) [40–42]. These three statistical indicators can be expressed as

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [y_i - y_i']^2}
\]

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - y_i'|
\]
MRE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - y_i'}{y_i} \right| \times 100\% \quad (5)

where $y_i$ and $y_i'$ indicate the in situ and derived turbidity for the $i$th sample, respectively; $N$ represents the total number of samples.

3. Results

3.1 Data distribution

The turbidity of all samples collected from buoy measurements varied widely within the ZCA, ranging from 2.4 to 363.9 NTU. The mean value, standard derivation and coefficient of variation were 96.3 NTU, 87.4 NTU and 90.8%, respectively (Table 1). In general, turbidity had an approximately log-normal distribution, as shown in Fig. 2. The majority of data points (69.5%) fell within 20 – 250 NTU, and samples < 20 NTU and > 250 NTU account for 22.6% and 7.9% of the total data, respectively.

![Histogram showing the frequency distribution of in situ turbidity. The numbers above each bar indicate the number of samples within each bin. The gray line is a log-normally distributed fitting curve.](image)

Similarly, the Rayleigh-corrected reflectance $R_{oc}(\lambda)$ of all samples varied significantly in both magnitude and spectral shape (Fig. 3). The general spectral characteristics of $R_{oc}(\lambda)$ were consistent with the $R_{oc}(\lambda)$ reported in turbid coastal waters by previous studies [30, 42, 43]. The $R_{oc}(\lambda)$ spectral peaks of most samples fell around the green bands (band 4, 5 or 6), while the spectral peaks of some samples had longer wavelengths (band 7 or 8). The largest differences in $R_{oc}(\lambda)$ magnitude were observed at bands 1, 7 and 8, which had coefficients of variation of 37.3%, 40.9% and 48.8%, respectively. Band 4 had the lowest variability with a coefficient of variation of 15.1% (Table 1). On average, high $R_{oc}(\lambda)$ values were located in bands 5 and 6, and the highest averages lay in band 6.

![Rayleigh-corrected reflectance spectra $R_{oc}(\lambda)$ of all GOCI data samples at 8 bands. The blue line represents the mean spectra, and the vertical bars indicate standard deviation.](image)
In this study, the complete \textit{in situ} turbidity and $R_{c}(\lambda)$ data sets were randomly divided into two subsets. The first subset contained approximately four-fifths of the samples ($N = 680$) and was used for model calibration, and the second subset contained the remaining one-fifth of the samples ($N = 170$) and was used for model validation. The statistical parameters for the calibration and validation of \textit{in situ} turbidity and $R_{c}(\lambda)$ are also summarized in Table 1.

**Table 1. Statistical parameters for turbidity T (NTU) and Rayleigh-corrected reflectance $R_{c}(\lambda)$ (dimensionless) of full data set, calibration subset and validation subset.**

<table>
<thead>
<tr>
<th></th>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>CV</th>
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<td>T</td>
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<td>96.3</td>
<td>87.4</td>
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<td>0.181</td>
<td>0.111</td>
<td>0.027</td>
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<tr>
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<td>Band6</td>
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<td>0.188</td>
<td>0.112</td>
<td>0.029</td>
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<td>0.231</td>
<td>0.086</td>
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<td>97.7</td>
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<tr>
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<td>0.024</td>
<td>0.216</td>
<td>0.085</td>
<td>0.043</td>
<td>50.6</td>
</tr>
</tbody>
</table>

3.2 Model development and validation

The turbidity is often highly correlated with TSM as observed by previous studies [30]. Many studies have demonstrated that spectra showed good correlation with log-transformed TSM [44, 45], which implies that relationship between $R_{c}(\lambda)$ and T may also follow the similar function with that between spectra and TSM. This was confirmed by a correlation analysis experiment designed in this study.

As previous studies showed, spectra band at approximately 680nm is sensitive to high TSM values [10, 11, 15]. In order to verify that the turbidity is a similar relationship, a correlation analysis experiment was designed to investigate the relationship between turbidity $R_{c}(\lambda)$ and T. During this experiment, we analyzed the correlation between $R_{c}(\lambda)$ and T, the correlation between log$_{10}(R_{c}(\lambda))$ and T, and the correlation between $R_{c}(\lambda)$ and log$_{10}(T)$ at each $R_{c}(\lambda)$ band. The analysis results are shown in Fig. 4. These results clearly show that the
correlation coefficient \( R \) of \( R_{\text{rc}}(\lambda) \) and \( \log_{10}(T) \) was highest for all bands except band 8 (865 nm), and the maximum \( R \) value (0.84) lay on band 6 (680 nm). These results indicate that the relationship between \( R_{\text{rc}}(\lambda) \) and \( T \) follows an exponential function, and \( R_{\text{rc}}(\lambda) \) at band 6 was most sensitive to \( T \).

Semi-empirical/empirical methods, using single band, band ratios, and band combinations, are particularly widespread since they are simple and easy to be developed for water quality parameters (such as TSM) estimation [30]. Because of close correlation between turbidity and TSM, many band designs for TSM algorithms were equally applied to turbidity algorithms. In addition, turbidity as an optical property is not affected by the mass density of particulate material [8, 13, 15]. Base on the above facts, the algorithm for estimating turbidity \( T \) from \( R_{\text{rc}}(\lambda) \) was set as

\[
T = 10^{(c_0 + c_1 X + c_2 X^2)}
\]

where \( X \) is a function of \( R_{\text{rc}}(\lambda) \); and \( c_0, c_1 \) and \( c_2 \) are constant coefficients that can be obtained through a regression analysis of \( X \) and \( T \). Different values of \( X \) constructed from \( R_{\text{rc}}(\lambda) \) would generate different types of models. In this study, we tested 8 values of \( X \), representing single bands, band ratios, as well as other combinations of different bands’ \( R_{\text{rc}}(\lambda) \) (Table 2). For each form of \( X \), all possible combinations of \( R_{\text{rc}}(\lambda) \) from 8 bands were examined, and the best band combinations with the highest correlation coefficient \( R \) with \( \log_{10}(T) \) were determined, as shown in Table 2. \( X_5 = (B6 - B3)/(B6 / B3) \), \( X_7 = (B6 + B4 + B5)/(B3 / B6) \), and \( X_8 = (B6 - B4 + B5)/(B3 / B6) \) correlated best with \( \log_{10}(T) \), with \( R \) values of 0.904, 0.905 and 0.899, respectively. It should be noted that \( X_7 \) and \( X_8 \) were constructed from 4 bands, while \( X_5 \) only uses information from two bands. The greater the number of bands incorporated into the calculation, the greater the likelihood that uncertainties will be introduced into the estimation model. Therefore, we used \( X_5 \) in our model and recommend it as the best choice to derive turbidity estimations. Although the single band form \( (X_1 = B6) \) had the lowest correlation with \( \log_{10}(T) \), \( R \) still reached 0.856. Therefore, we also considered the simplest form of \( X_1 \) and its ability to estimate turbidity in this study.

The \( X_1 = B6 \) and \( X_5 = (B3 + B6)/(B3 / B6) \) models were calibrated using the calibration sample subset \( (N = 680) \). As expected, the \( X_5 \)-based model had a better fit than the \( X_1 \)-based model, with more data clustered approximately 1:1 around the line (Fig. 5). The \( R^2 \) values were 0.749 and 0.821 for the \( X_1 \) and \( X_5 \) models, respectively. Meanwhile, estimated turbidities were also compared with in situ values. The RMSE, MAE, and MRE values of the \( X_1 \) model were 62.6, 43.1 and 61.9%, respectively; and those for the \( X_5 \) model were 52.6, 35.6, and 48.6%, respectively. The model parameters and the statistical indicators are summarized in Table 3.
Table 2. Correlations between log_{10}(T) and X derived from GOCI $R_c(\lambda)$. X1 to X8 indicate the 8 forms of X, respectively; B1 to B8 indicate $R_c(\lambda)$ at bands 1 to 8, respectively; and $R$ is the correlation coefficient.

<table>
<thead>
<tr>
<th>X</th>
<th>General form</th>
<th>Best band combination</th>
<th>$R$</th>
</tr>
</thead>
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<td>X1</td>
<td>$R_c(\lambda)$</td>
<td>$R_c(\lambda) = B6$</td>
<td>0.856</td>
</tr>
<tr>
<td>X2</td>
<td>$R_c(\lambda) - R_c(\lambda)$</td>
<td>$R_c(\lambda) = B6, R_c(\lambda) = B4$</td>
<td>0.883</td>
</tr>
<tr>
<td>X3</td>
<td>$R_c(\lambda)/ R_c(\lambda)$</td>
<td>$R_c(\lambda) = B6, R_c(\lambda) = B4$</td>
<td>0.883</td>
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<tr>
<td>X4</td>
<td>$R_c(\lambda) + R_c(\lambda) + R_c(\lambda)$</td>
<td>$R_c(\lambda) = B6, R_c(\lambda) = B4$</td>
<td>0.879</td>
</tr>
<tr>
<td>X5</td>
<td>$R_c(\lambda)/ R_c(\lambda)$</td>
<td>$R_c(\lambda) = B3, R_c(\lambda) = B6$</td>
<td>0.904</td>
</tr>
<tr>
<td>X6</td>
<td>$R_c(\lambda) + R_c(\lambda)$</td>
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<td>0.858</td>
</tr>
<tr>
<td>X7</td>
<td>$R_c(\lambda) + R_c(\lambda) + R_c(\lambda)$</td>
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</tr>
<tr>
<td>X8</td>
<td>$R_c(\lambda) + R_c(\lambda) + R_c(\lambda)$</td>
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<td>0.899</td>
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</tbody>
</table>

Fig. 5. Scatter plots of (a) $X_1 = B6$ and (b) $X_5 = (B3 + B6) / (B3 / B6)$ versus turbidity (T). The solid red lines are fitted curves and dotted red lines are 95% confidence bounds.

Table 3. Parameters and accuracy assessment indicators for turbidity estimation models ($N = 680$)

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Coefficient of models</th>
<th>$N$</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>MAE</th>
<th>MRE%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>$c_0 = -0.775, c_1 = 30.959, c_2 = -71.535$</td>
<td>680</td>
<td>0.749</td>
<td>62.6</td>
<td>43.1</td>
<td>61.9</td>
</tr>
<tr>
<td>$X_5$</td>
<td>$c_0 = -0.016, c_1 = 7.818, c_2 = -4.494$</td>
<td>680</td>
<td>0.821</td>
<td>52.6</td>
<td>35.6</td>
<td>48.6</td>
</tr>
</tbody>
</table>

Following calibration, the established models were validated using the validation subset ($N = 170$) to assess each model’s ability. The scatter plots comparing observed and derived turbidity values for the $X_1$ and $X_5$ models are shown in Fig. 6. Remarkably, both models showed encouraging results, with $R^2$ values of 0.789 and 0.848, RMSE values of 51.7 and 43.0, MAE values of 32.8 and 28.4, and MRE values of 51.2% and 42.5%, for the $X_1$ and $X_5$ models, respectively. A comparison of these statistical indicators reveals that the $X_5$ model performed much better than the $X_1$ model. These results indicate that the turbidity estimation
models described here have great potential to be applied to GOCI $R_{\text{sc}}(\lambda)$, and the $X5$ model performs best.

![Graphs showing comparison between observed and estimated turbidity levels using (a) $X1$ model and (b) $X5$ model for validation (dotted line: 1:1)]

### 3.3 Model application to GOCI data

Eight hourly GOCI images obtained on December 30, 2014 were taken as a case study to derive turbidity in the ZCA using our $X5$ band combination model (Fig. 7). A color range from blue to red represents low to high turbidity across the study area. Figure 7 reveals obvious spatial variations in turbidity, which generally decrease from the coast to offshore regions; significant temporal variations are also evident.

![Hourly turbidity maps of the Zhejiang coastal area as derived from GOCI data using an $R_{\text{sc}}$-algorithm; December 30, 2014.](image)
In order to see these variations more clearly, we selected three cross sections, as marked on the 15:15 (h) map in Fig. 7(h). The turbidity profiles along the three transects are shown in Fig. 8. The Hangzhou Bay transect (line 1) reveals relatively high turbidity values and large fluctuations in those values. The turbidity profiles along the other two lines (line 2 and line 3) show simple and similar variation patterns. The turbidity along both of these lines significantly decreased from the coast to offshore areas, and then remained at a low, stable level. Hourly variability in turbidity along all three lines was also clearly observed. In general, turbidity near the coast (west part of these lines) was greatest in the morning and decreased until around noon, though this trend is much more evident in lines 2 and 3 than in line 1 (Figs. 8(b) and 8(c)). Understanding the reasons for these spatial and temporal variations is beyond the scope of this study; however, tides, winds, and discharges from the Changjiang and Qiantang rivers may be possible causes, as suggested by previous studies [30, 46].

**Fig. 8.** Turbidity profiles along transect line 1 (a), line 2 (b) and line 3 (c), as marked in Fig. 7(h) (15:15 (h)).

### 4. Discussion

#### 4.1 Data distribution

In the present study, a regional turbidity algorithm derived from a combination of 490-nm and 680-nm bands was evaluated to assess its accuracy in waters with moderate to high turbidity and showed a good availability for a wide turbidity ranging from 2 to 350 NTU approximately, was also assessed. Both the single and combined band forms chosen in this study are similar to those bands used in existing works, for example, Landsat band 3 (630–690 nm) [11], LISS-I red band (620–680 nm) [47], SPOTHRV2 red band (610–680 nm) [10], MODIS 250-m resolution band at 645 nm [13, 48, 49] and MERIS 681-nm band [15]. A good correlation has been found between turbidity and reflectance along satellite bands located in the red part of the spectrum.
However, most existing works offer site-specific empirical relationships between turbidity and remote sensing reflectance at specific satellite wavebands. In those studies, reflectance was often field-measured or satellite-derived based on precise atmospheric corrections. Unlike these previous works, we used Rayleigh corrected reflectance in place of remote sensing reflectance. It is important to note the difference between $R_{rc}$ in this study and $R_{rs}$ in existing works. Though the band choice in this study is similar to those bands chosen in previous works, the use of the Rayleigh corrected reflectance requires us to examine the $R_{rc}$ algorithm sensitivity carefully.

We added random errors to the validation data set inputs for Eq. (6), with a standard deviation of 5% and average value of 0. The process was repeated 50 times so that an approximately normal distribution was generated in the added random errors. By averaging the errors across the 50 repetitions, we found that the mean related errors in turbidity the calculations were 1.0% and 5.4% for bands 3 and 6, respectively (Fig. 9).

Band 6 clearly displayed greater sensitivity than band 3. The results revealed that band 6 is more sensitive and therefore is a better choice for deriving turbidity, which corresponds to the $R_{rs}$ algorithms in existing works, including band choices of (630–690 nm) [11], (620–680 nm) [47], and (610–680 nm) [10].

Even though band 6 was more sensitive than band 3, calculation errors were nearly ± 5% when ± 5% errors were added in band 6. The results show that the input errors do not grow in the algorithm. That is to say, the (B3 + B6) / (B3 / B6) band combination is robust for turbidity calculations.

**Fig. 9.** The comparison between observed and estimated T when adding ± 5% random errors to $R_{rc}$ at B3 (a) and B6 (b). The error bar is used to specify a range between a minimum and a maximum of one resultant point. (Dotted line log$_{10}$2: log$_{10}$1 dashed line: 1:1)

### 4.2 $R_{rs}$ algorithms versus $R_{rs}$ algorithms

Many calculation algorithms have been successfully proposed based on site-specific empirical relationships between turbidity and remote sensing reflectance derived from field-measured data. The success of the application of these types of models to satellite data depends heavily on the accuracy of the atmospheric correction procedure and the accurate calculation of reflectance.

Atmospheric correction is often unreliable even under optimal observing conditions (cloud free, thin aerosols, negligible sun glint) due to the optical complexity of in-water elements, especially in highly turbid waters such as those of the Zhejiang coastal area. High backscattering in highly turbid waters prohibits us from taking the $R_{rs}$ in the NIR region as zero. Therefore, there is no valid atmospheric correction approach that has proved universally robust in the NIR region across waters with varying geophysical characteristics [50].
example, the use of SeaDAS-embedded standard atmospheric correction [51–53] and its associated quality control protocols [54] often leads to false masking, resulting in significant data loss in derived $R_{rs}$. In theory, the model proposed by Wang et al. [55], which uses shortwave infrared (SWIR) bands for aerosol model selection, may be a feasible option; however, some practical experiments with MODIS data have shown that the extent of its improvement is limited by the considerably lower sensor SNR values of the MODIS SWIR bands [56].

Therefore, major challenges caused by atmospheric correction have made utilizing satellite ocean color data and $R_{rs}$ algorithms to estimate long-term variability in the water quality of nearshore water bodies difficult. However, in the absence of complete atmospheric correction, an $R_{rc}$ algorithm with a partial correction to remove gaseous absorption and the Rayleigh-scattering effect was shown to be sufficient to derive turbidity with acceptable uncertainties.

The outstanding advantage of the $R_{rc}$ algorithm, which does not require knowledge of aerosol amounts or types, is its simplicity and the rapidity of its execution. Compared with $R_{rs}$ algorithms, the $R_{rc}$ algorithm provides a new way of thinking about calculating turbidity in highly turbid waters and makes it possible to estimate turbidity or TSM without a complex atmospheric correction. However, the most significant advance brought about in this design is the tremendous increase in data coverage that it provides, which is not possible using the $R_{rs}$ algorithm.

Furthermore, development of the $R_{rc}$ algorithm has been restricted by a lack of satellite-ground synchronous data sets. Theoretically, the synchronous data require the satellite data and in situ observations to be gathered at the exactly same time. However, due to limitations of operations, it is difficult to attain perfect synchronization. In practice, “synchronous” data are usually two types of observations made within one to three hours of one another. To our knowledge, the extent of “synchronous” data is still very limited, even ignoring the variability in optical properties that occurs over one to three hours [16].

Buoys located at specific sites could provide in situ observations at very high frequencies. At the same time, geostationary satellites can greatly enhance the frequency of remotely sensed observations beyond that provided by polar-orbit satellites. Compared with the once a day measurements of MODIS, SeaWiFS and MERIS, GOCI provides 8 observations per day. Combining the advantages of buoys and geostationary satellites will enhance the quality and quantity of satellite-ground synchronous data sets. The $R_{rc}$ algorithm in the present study did not require any in situ optical measurements. Instead, only turbidity observations from buoys were needed, making the acquisition of data simple and the modelling of turbidity easy to perform.

The $R_{rc}$ turbidity calculation algorithm had more advantages than an $R_{rs}$ algorithm in the present study. However, this does not mean that $R_{rc}$ data should always be used for algorithm development instead of $R_{rs}$ data [24]. This study is a special case in turbidity algorithm design. For example, if the same schemes were used to estimate Chla, the algorithm would perhaps perform poorly because of the impact of aerosol absorption in the blue bands. Furthermore, the effects of aerosols on $R_{rc}$ are not accounted for in the $R_{rc}$ algorithm, and the impacts of aerosol variability, such as seasonal variability, on $R_{rc}$ still remain unknown. That means the $R_{rc}$ algorithm cannot answer how aerosols’ changes affect the turbidity deriving or $R_{rc}$ variety. Therefore the studies on method for improving accuracy of atmospheric correction especially aerosol correction is still quite important. That is to say that the improved atmospheric correction is still required to obtain reliable $R_{rs}$ data in the long run, as most algorithms still rely on $R_{rs}$ data.

While efforts are still ongoing to improve the atmospheric correction of satellite data, alternative approaches for calculating turbidity that take into account these many difficulties must be developed. In particular, such approaches must be tolerant to perturbations that can result from variable aerosol conditions. The calibration and validation data sets used in this
study, which were primarily obtained in winter, only contained a narrow range of optical properties for aerosols and natural coastal waters. It is impossible to completely validate the accuracy of the model by this study alone because other seasons or water environments with different bio-optical properties were not taken into account. Thus, additional seasonal satellite-ground synchronous data sets are needed to validate the algorithm.

5. Conclusion

Knowledge of water turbidity informs our understanding of marine biogeochemical processes; however, mapping turbidity from remote sensing reflectance satellite data is often challenging in highly turbid waters due to poor atmospheric correction. In this study, we proposed an innovative method to estimate turbidity in highly turbid waters using Rayleigh-corrected reflectance, which can be easily and accurately derived. Based on a large synchronous data set of in situ turbidity measurements collected from buoys in the Zhejiang coastal area (ZCA) and \( R_{sc}(\lambda) \) measurements derived from GOCI satellite data, the relationship between turbidity and \( R_{sc}(\lambda) \) was investigated. Several \( R_{sc}(\lambda) \) band combinations were tested to estimate turbidity. The combined band 3 (490 nm) and band 6 (680 nm) GOCI \( R_{sc}(\lambda) \) algorithm was ultimately selected for further testing and recommended for use because of its outstanding performance.

The evaluation of the algorithm using an independent data set showed good model performance for a wide turbidity range (2.4 – 363.9 NTU), with \( R^2 \), RMSE, MAE and MRE values of 0.848, 43.0, 28.4 and 42.5\%, respectively. The new algorithm was robust and did not show error enlargement when errors were introduced on bands 3 (490 nm) and 6 (680 nm). These results indicate that the new algorithm has great potential for mapping turbidity in the ZCA, which was confirmed when we applied it to 8 hourly GOCI images in the ZCA and identified clear spatial and temporal variations in turbidity. Our new algorithm uses \( R_{sc}(\lambda) \) without a complex atmospheric correction so that it can be easily implemented in practice, and its applicability to other seasons in the ZCA, as well as in other regions, will be investigated in future.

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