Multi-source high-resolution satellite products in Yangtze Estuary: cross-comparisons and impacts of signal-to-noise ratio and spatial resolution

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Abstract: In this study, cross-comparisons of the reflectance at the top of atmosphere (ρTOA), atmospherically corrected water-leaving reflectance (Rrs), and suspended sediment matter (SPM) concentration derived from three high spatial resolution sensors (Landsat-8/OLI, Sentinel-2A/MSI and GF-1/WFV) were conducted. The purpose was to examine the consistency among multi-source satellite products and their potential to fill the temporal gap of high-resolution satellites time series. Geostationary ocean color imager (GOCI) data and in situ data were used to verify the accuracy and reliability of the high-resolution satellite derived products. The results showed that the ρTOA and Rrs data of high-resolution sensors were consistent with GOCI data, especially at the red spectral ranges. The satellite-derived SPM concentrations exhibited good agreement and acceptable errors when compared with both GOCI-derived and in situ SPM data. With regard to the influence of the signal-to-noise ratios, the results showed that the radiometric sensitivities of GF-1/WFV and Landsat-8/OLI were relatively high and presented minimally detectable variations greater than 0.06% in the ρTOA and 0.5 mg/L in the SPM concentration for solar zenith angles < 30°. However, the spatial resolution’s impact on the SPM data can be greater than that of the signal-to-noise ratio for turbid waters.

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1. Introduction

Estuaries are areas with strong land-sea interactions. Under the complex hydrodynamic environment caused by interactions among river runoff and tidal currents, a highly heterogeneous spatial and temporal distribution of sediments is observed in estuaries, which has a great impact on navigation paths and sediment dredging. Although acceptable sediment concentrations can be estimated using ocean color satellites with coarse spatial resolution (> 300 m), such as the Moderate Resolution Imaging Spectroradiometer (MODIS), the Medium Resolution Imaging Spectrometer (MERIS) and GOCI [1], the subtle variations in the distribution of suspended particulate matter (SPM) in medium- and small-scale estuaries are difficult to observed with such sensors. Davis et al. [2] demonstrated that the optimal ground resolution of turbid nearshore waters should be less than 100 m.

High-resolution satellites have great potential for use in estuary and coastal applications [3–6]. However, the high-resolution satellites initially designed for terrestrial applications had a low revisit frequency and lower signal-to-noise ratio and radiation sensitivity, which resulted in errors in the inversion of water color components and concentrations. With the development of remote sensing technology in recent years, high-resolution satellite sensors...
have gradually supported applications for inland and coastal waters. The technical feature of the sensors, such as the signal-to-noise ratio (SNR), have been notably improved. The settings of short-wave infrared bands, e.g., from Landsat-8/OLI and Sentinel-2/MSI, are very helpful for performing atmospheric corrections of estuarine and coastal waters. In addition, the red-edge bands and part hyperspectral bands from Sentinel-2/MSI have also enriched water color information. The modes of multi-camera synchronous observation (e.g., GF-1 missions) and multi-satellite combination (e.g., Sentinel-2 missions) greatly shorten the revisit period and increase the observation frequency for targets.

The objectives of this work are as follows: (1) to explore whether high spatial resolution sensors initially designed for terrestrial applications, i.e., Landsat-8/OLI, Sentinel-2/MSI and GF-1/WFV, are adequate for SPM observations in medium- and small-scale estuaries, e.g., in the Yangtze Estuary; (2) to examine the consistency of estuarine observations by multiple high-resolution sensors to enhance our confidence in the use of such data and products by performing a cross-comparison of the $\rho_{\text{TOA}}$, $R_s$ (also called remote sensing reflectance) and SPM concentration from multiple sensors; and (3) to assess the impacts of the SNR and spatial resolution of the different products. The data and products from three in-orbit high-resolution satellite sensors were selected for cross-comparison. Corresponding data from the GOCI and in situ turbidity data set were used to validate the high-resolution products.

2. Study area and data

2.1 Study area

The Yangtze (Changjiang) Estuary (Fig. 1) is one of the largest estuaries in the world in terms of river discharge and scale, and it has three-order bifurcations (see the South and North Branches, South and North Harbors and South and North Channels in Fig. 1) and four outlets into the East China Sea. The SPM concentration varies in each branch of the Yangtze Estuary and exhibits a heterogeneous spatial-temporal distribution, and this distribution is mainly influenced by the interactions of river outflows, tidal currents and wind-driven waves [7–9]. Thus, the Yangtze Estuary was selected as the study area to estimate the capability and accuracy of the inversions of products from high-resolution satellites sensors.

![Fig. 1. Map of the study area from the GF-1/WFV image on March 11, 2014. The colored dots indicate the locations of three autonomous turbidity observation stations.](image)

2.2 In situ data

An autonomous turbidity observation system installed at the Chongxi station was used to obtain in situ turbidity data set. Turbidity data from optical backscatter sensors (OBSs) at this hydrologic station have been collected since 2009, which greatly increased the number of
matchups between satellite derived and in situ SPM. The OBSs were calibrated before being installed or replaced to generate reliable parameters, such as pressure, salinity and turbidity data. Every two weeks, a regular cleaning of optical sensors is executed to eliminate data abnormalities caused by the attachment of biological organisms and water body occlusions. Liu et al. [10] indicated that a good correlation occurred between the turbidity measured by OBSs and SPM, and $R^2$ values over 0.9 were obtained for both spring-neap tides.

The formula for calculating SPM concentrations from in situ turbidity is based on two empirical algorithms [1,11]. Shen et al. [1] adopted in situ observations (e.g., from the Chongxi, Nanmen and Baozhen stations in Fig. 1) from OBSs with simultaneous water samplings for SPM concentration in the Yangtze Estuary from 2 to 3 July, 2011 and proposed a linear relationship:

$$ y = 0.001x - 0.07, \quad (1) $$

where $R^2 = 0.935$, $n = 17$ and $p < 0.001$. Another relationship proposed by Xue et al. [11] is based on water samples from the South Branch and synchronous OBS measurements, and it is expressed by:

$$ y = 0.0017x + 0.0202, \quad (2) $$

where $R^2 = 0.77$. In Eq. (1) and (2), $x$ and $y$ stand for turbidity and SPM concentration, respectively. The average of SPM concentration in Eq. (1) and (2) is considered the in situ SPM. However, the turbidity measured by an OBS instrument is influenced by the size, shape, particle composition, bubbles, and chemical and biological fouling [1]. Nevertheless, using the OBS data from the fixed station is the most effective method for validating the satellite-derived SPM.

2.3 Satellite data

Data from three high-resolution satellite sensors, i.e., Sentinel-2/MSI (S2/MSI), Landsat-8/OLI (L8/OLI) and GF-1/WFV, were used for cross-comparison with ocean color data. GOCI is a typical ocean color sensor with the SNR of more than 750, and its data and products were adopted as the references. The technical characteristics of the four sensors are listed in Table 1, and detailed spectral response curves are shown in Fig. 2.

| Satellite and sensor | Sentinel-2/MSI | Landsat-8/OLI | GF-1/WFV | GOCI |
|---------------------|----------------|--------------|----------|------|
| B1:433-453          |                |              |          |      |
| B2:455-523          |                |              |          |      |
| B3:453-578          |                |              |          |      |
| B4:650-680          |                |              |          |      |
| B5:698-713          |                |              |          |      |
| B6:733-748          |                |              |          |      |
| B7:773-793          |                |              |          |      |
| B8:815-875          |                |              |          |      |
| B9:935-955          |                |              |          |      |
| B10:1360-1390       |                |              |          |      |
| B11:1565-1655       |                |              |          |      |
| B12:2100-2280       |                |              |          |      |
| Spatial resolution (m) | 10, 20, 60   | 15, 30       | 16       | 500  |
| Swath (km)          | 290           | 185          | 800      | 2500 |
| revisit (days)      | 10            | 16           | 4        | 1/8  |
| SNR range          | 50-174        | 166-450      | 34-294   | 750-1170 |

Due to different observation purposes, the design of satellite sensors may present variations in the position and width of the wavebands and spectral response functions. Figure 2 shows the spectral response curves of the four sensors (i.e., L8/OLI, S2/MSI, GF-1/WVF and GOCI), including the spectral curves of remote sensing reflectance from in situ
measurements for typical turbid and clear waters. Spectral response curves are obtained from satellite official networks (such as GF-1/WVF), internal data (such as GOCI), and commercial software ENVI 5.3.1 (L8/OLI and S2/MSI). Compared with GF-1/WVF, GOCI and S2/MSI have relatively narrow spectral bands, which exhibit more sensitive spectral responses to the specific features (e.g., phytoplankton) of water color components.

Landsat-8 (L8) was launched in February 2013. The OLI is a payload on L8 with a 30 m spatial resolution and 16-day revisit period. The L8/OLI is based on the Landsat satellite series, and it includes two shortwave infrared (SWIR) bands that allows for SWIR-based atmospheric corrections for coastal waters [12]. The L8/OLI level 1TP data products are released by the Earth Explorer (https://earthexplorer.usgs.gov/) with well-characterized radiometry and intercalibrated across the different Landsat instruments.

Sentinel-2A (S2) with the MSI payload was launched by the ESA in June 2015. The S2/MSI sensor has 13 bands and a 10 m resolution in the visible ranges and a 20 m resolution in the red to near-infrared (NIR) bands. The S2/MSI level 1C (L1C) products can be downloaded from Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home), and the images are split into orthorectified 100 km × 100 km tiles. The L1C products are spectral reflectance data at the top of atmosphere in UTM WGS84 projection, and these products have been processed via orthorectification and spatial registration on a global reference system with subpixel accuracy.

GF-1 is the first satellite of the Chinese High-resolution Earth Observation System series, and it is equipped with 4 sets of multi-spectral WFV cameras with 4 bands and 16-m resolution. Through mosaic processing, the GF-1/WVF scanning range can have a swatch width of 800 km × 800 km. The revisit period of 4 days greatly increases the number of cloud-free images, especially over the Yangtze Estuary. The level 1A products from the GF-1/WVF can be downloaded from the China Center for Resources Satellite Data and Application (CRESDA, http://www.cresda.com/EN/) according to the data agreement, and these products represent spectral radiance at the top of atmosphere. The radiometric calibration coefficients of GF-1/WVF have been updated every year since it was launched through vicarious sensor calibrations, e.g., using reference targets such as alkaline lands, Gobi deserts and clear lakes from high to low reflectance, so that its precision can satisfy the need of various target measurements. More details can be found on the CRESDA website.
The Geostationary Ocean Color Imager (GOCI) was launched in June 2010 by the Korean Ocean Research and Development Institute and is the first geostationary-orbiting communication ocean and meteorological satellite in the world [13]. As a typical ocean color sensor, GOCI has a high SNR of more than 750 for each band. GOCI level 1 and 2 data can be downloaded from the Korea Ocean Satellite Center (KOSC, http://kosc.kiost.ac.kr/eng/p10/kosc_p11.html) according to the data policy. The level 1B product is radiance data at the top of atmosphere after radiometric and geometric corrections. The level 2 data products can be obtained after processing the level 1 data through the ground data processing system (GDPS, http://kosc.kiost.ac.kr/eng/p30/kosc_p34.html) released by KOSC.

3. Methods

3.1 Top of atmosphere (TOA) reflectance

The raw data received by the sensors in digital number (DN) format can be transformed into radiance \( L_{\text{TOA}} \) in W m\(^{-2}\) sr\(^{-1}\) µm\(^{-1}\) by the following formula:

\[
L_{\text{TOA}} = \text{gain} \times \text{DN} + \text{offset}.
\]  

(3)

L8/OLI, S2/MSI and GF-1/WFV level 1 products provide the DN and the corresponding gain and offset in their header files, whereas GOCI level 1 products provide fixed gain and offset values equal to \(10^{-6}\) and 0, respectively, in their user manuals.

To remove the influence of sun geometry differences, \( L_{\text{TOA}} \) should be translated to the TOA reflectance before intercomparisons. Assuming that the TOA surface is a Lambertian reflectance plaque that is illuminated by irradiance \( M \) and the sunlight is incident to the surface at a zenith angle \( \theta \), the atmospheric surface irradiance \( E \) and the \( L_{\text{TOA}} \) are expressed as follows:

\[
E = E_0 \times \frac{\cos \theta}{d^2},
\]  

(4)

\[
L_{\text{TOA}} = \frac{M}{\pi},
\]  

(5)

where \( d \) is the Earth-Sun distance in astronomical units (AU) and \( E_0 \) is the average solar spectral irradiance in W m\(^{-2}\) µm\(^{-1}\). The TOA reflectance \( \rho_{\text{TOA}} \) is defined as follows:

\[
\rho_{\text{TOA}} = \frac{M}{E} = \frac{\pi \times L_{\text{TOA}}}{E_0 \times \cos \theta / d^2}.
\]  

(6)

3.2 Atmospheric correction

Different atmospheric correction methods have been used for satellite data due to differences in the widths and positions of the four sensors.

The ACOLITE code (version 20170718) for atmospheric corrections of both L8/OLI and S2/MSI data with the SWIR bands was proposed by Vanhelmont and Ruddick [3,12]. It performs Rayleigh correction [14], land and cloud masking [15] and SWIR atmospheric correction [16] in each pixel. Afterwards, the water-leaving radiance reflectance is obtained from the L8/OLI and S2/MSI level 1 data.

In the absence of SWIR bands, the SWIR dark pixel method is not applicable to the atmospheric corrections for GOCI and GF-1 data. We employed a full-band iterative optimization method for atmospheric correction of GOCI level 1B images over turbid waters in the Yangtze Estuary area, which was proposed by Pan et al. [17,18]. This method is called the Enhanced Spectral Optimization Algorithm (ESOA). In the proposed method, an aerosol model built based on the Aerosol Robotic Network (AERONET) observation data [19] and a water model named the semiempirical radiative transfer (SERT) model from Shen et al.
were coupled. Four variables, i.e. the relative humidity (RH), fine-mode fraction (FMF), aerosol optical thickness (AOT) and the SPM, were included in the coupled water-atmosphere model and related to the different sensor bands using a genetic algorithm to optimize the variables from the initial inputs.

As for the atmospheric correction of the GF-1 data, the level 2 product generator in SeaDAS (SeaDAS/l2gen) was employed. In SeaDAS/l2gen, the calculations of both Rayleigh and aerosol radiance were based on a look-up table (LUT) method. However, the current SeaDAS/l2gen version cannot process GF-1 data and does not contain the LUTs for the GF-1 sensor. To solve this issue, a solution with two steps was adopted. In the first step, the Rayleigh and aerosol radiance for the Hyperspectral Imager for the Coastal Ocean (HICO), was calculated. Considering the high spectral resolution (approximately 5 nm) of HICO, the Rayleigh and aerosol radiance values were interpolated to 1 nm. In the second step, by introducing the spectral response curves for the GF-1 sensor, the band-averaged radiance was derived by integrating the radiance for the band range of the spectral response curve. See the Ocean Color website (https://oceancolor.gsfc.nasa.gov/docs/rsr) for the details of the integration method. In addition, to calculate the aerosol radiance for GF-1, the AOT and aerosol type (such as RH and FMF) should be known. In this study, the RH, FMF and AOT values for the atmospheric correction of GF-1 can be estimated from the GOCI data by using the ESOA algorithm [17], assuming that the GF-1 passes over the study area at nearly the same time as GOCI, and the quasi-simultaneous images from GF-1 and GOCI may have the same aerosol type and the AOT. A similar method is presented in Pan et al. [18].

### 3.3 SPM inversion

The SPM inversion algorithm proposed by Shen et al. [1,20,21] for highly turbid waters of the Yangtze Estuary area is arithmetically expressed as follows:

$$C_{SPM} = \frac{2 \times \alpha \times R_{rs}}{\beta \times (\alpha - R_{rs})},$$

where $C_{SPM}$ is the SPM concentration in g/L, $R_{rs}$ is the remote sensing reflectance in sr$^{-1}$ obtained from atmospheric correction, and $\alpha$ and $\beta$ are empirical and wavelength-dependent coefficients. According to the spectral response curves of the four sensors (see Fig. 2), the $\alpha$ and $\beta$ coefficients at corresponding sensor-based wavebands can be determined by in situ data sets, which are shown in Table 2. For the SPM in a wide range of concentrations over the Yangtze Estuary and adjacent coasts, the algorithm scheme for multiple spectral band shifting is applied to avoid reflectance saturation. However, the radiation calibration of GF-1 is not stable; thus, to illustrate the accuracy of the satellite inversion of SPM, only red bands were selected for inversion. In this case, the SPM concentration may be underestimated in the non-sensitive areas of the red band (SPM < 0.1 g/L or SPM > 0.8 g/L), such as in Hangzhou Bay. In this study, the L8/OLI band centered at 655 nm, S2/MSI band centered at 665 nm, GF-1/WFV band centered at 665 nm and GOCI band centered at 660 nm were proposed for the SPM retrieval using Eq. (7).

| Sensor     | Band number | Center band (nm) | $\alpha$  | $\beta$  |
|------------|-------------|------------------|-----------|----------|
| L8/OLI     | 4           | 655              | 0.0763    | 11.5306  |
| GOCI       | 5           | 660              | 0.0771    | 11.0158  |
| S2/MSI     | 4           | 665              | 0.0779    | 10.7085  |
| GF-1/WFV   | 3           | 665              | 0.0779    | 10.7085  |

Table 2. $\alpha$ and $\beta$ coefficients in Eq. (7) for GF-1/WFV, GOCI, S2/MSI and L8/OLI data at red bands (~660 nm) appropriate for the highly turbid waters of the Yangtze Estuary.
3.4 Noise-equivalent reflectance and SPM

The SNR of a sensor is one of the most important parameters in quantitative remote sensing, which largely affects the accuracy and sensitivity of remote sensing products. High-resolution Landsat-8/OLI, Sentinel-2/MSI and GF-1/WFV sensors were initially designed for land applications and thus have lower SNR values than ocean color sensors (see Tables 1). To quantify the sensitivities of these sensors, the noise-equivalent reflectance ($NE_{\rho}$) is proposed to define the minimum detectable variation in reflectance [18] or the expected uncertainty caused by the sensor noise [14]. The sensor’s $NE_{\rho}$ is determined as follows:

$$NE_{\rho} = \frac{NE_{L} \times \pi \times d^2}{E_0 \times \cos \theta},$$

and $NE_{L}$ is expressed as follows:

$$NE_{L} = \frac{L_{\text{ref}}}{\text{SNR}},$$

where $E_0$ is the average solar spectral irradiance and $\theta$ is the solar zenith angle. $NE_{L}$ is the noise-equivalent radiance, and $d$ represents the Earth-Sun distance in AU. $L_{\text{ref}}$ is the reference radiance, and SNR is the signal-to-noise ratio corresponding to $L_{\text{ref}}$. In Eq. (9), $d$ can be regarded as 1, as it is changes by only 4% throughout the year. The SNR and $L_{\text{ref}}$ values for different sensors are given in Table 3.

To assess how much the SNR impacts the satellite-derived SPM, we assume that the sensitivity of $\rho_{\text{TOA}}$ is equal to that of $R_{\text{s}}$ at the same sensor bands. $NE_{\text{SPM}}$ can be calculated by substituting $NE_{\rho}$ into the SERT model by the following equation:

$$NE_{\text{SPM}}(\lambda) = \text{SERT}(\frac{NE_{\rho}(\lambda)}{\pi}),$$

3.5 Coefficient of variation

To analyze the influence of different spatial resolutions on images, the coefficient of variation (CV) is proposed, which indicates the dispersion of $L_{\text{TOA}}$, and it can be expressed as follows:

$$\text{CV} = \frac{\text{SD}}{\text{MN}} \times 100\%,$$

where SD is the standard deviation of a data set ($L_{\text{TOA}}$ in a box), and MN is the mean value of a data set.

4. Results

To evaluate the quality of the data products from the different satellite sensors and derived products, two methods, i.e., cross-comparison of multi-sensor data or products and comparison with in situ ground truth data, are usually adopted.

4.1 Cross-comparison of TOA reflectance

Cloudless GF-1/WFV, L8/OLI, and S2/MSI $\rho_{\text{TOA}}$ images were collected on March 15, 2014, March 12, 2015, and July 20, 2016, and the GOCI $\rho_{\text{TOA}}$ was determined at the time closest to the visit times of the three high-resolution satellites. To generate a uniform resolution dimension, these images were resized to 30 m × 30 m ground pixel sizes before conducting the cross-comparison.
Figure 3 shows that L8/OLI and GF-1/WFV exhibits the strong correlation with the $\rho_{\text{TOA}}$ of GOCI in red bands. The $\rho_{\text{TOA}}$ values of GF-1/WFV and L8/OLI are slightly lower than that of GOCI because the polar orbiting satellites usually have lower zenith angles than geostationary satellites and less light is backscattered by atmospheric molecules and aerosols along the path from water to sensor illuminated by the sunlight. S2/MSI has higher $\rho_{\text{TOA}}$ values than GOCI, which may be related to the influence of sun glint. Nevertheless, all three scatterplots shown in Fig. 3 display good linear relations from low to high reflectance values, which can satisfy the need for satellite observations in waters with different turbidity. In addition to the $\rho_{\text{TOA}}$ at the red bands, the $\rho_{\text{TOA}}$ values were also compared to that of GOCI at other corresponding bands. Table 3 shows the correlation results of $\rho_{\text{TOA}}$ at conventional sensor bands, e.g., blue (~490 nm), green (~560 nm), red (~660 nm) and NIR (~865 nm). The result show that the $\rho_{\text{TOA}}$ from the three sensors in the red bands exhibits the closest similarity with that of GOCI in a 1:1 line, followed by the green bands. The $\rho_{\text{TOA}}$ at the NIR band from S2/MSI versus that from GOCI presents a lower correlation with $R^2 = 0.6721$ and MAPE = 44.15%, which might be related to the lower SNR of the S2/MSI NIR band.

### 4.2 Cross-comparison of remote sensing reflectance

Through cross-comparison, it is found in Fig. 4 shows that the $R_e$ values derived from the $\rho_{\text{TOA}}$ data of each sensor exhibited a good linear correlation with values derived from the GOCI data. The $R_e$ values in the red band derived from the L8/OLI, S2/MSI and GOCI data...
are basically equivalent for any type of water body. Figure 4(c) shows that the S2/MSI $R_{\text{rs}}$ against the GOCI $R_{\text{rs}}$ displays a “noisy” result (with RMSE = 0.0045 sr$^{-1}$ and MAPE = 33.22%), which may be related to its high dispersion in $\rho_{\text{TOA}}$ as shown in Fig. 3(c).

Fig. 4. Scatterplots of GOCI versus GF-1/WVF, L8/OLI and S2/MSI of $R_{\text{rs}}$ at red bands on March 15, 2014 (a), March 12, 2015 (b), and July 20, 2016 (c), in the Yangtze Estuary and adjacent coasts, respectively. The solid red line corresponds to the 1:1 line, and the blue dotted line corresponds to the linear regression for each sensor.

The correlation results of $R_{\text{rs}}$ at the blue (~490 nm), green (~560 nm), red (~660 nm) and NIR (~865 nm) bands are shown in Table 4. The results indicate that the $R_{\text{rs}}$ at the red band of the high-resolution sensors exhibits better correspondence and a lower MAPE compared with that of GOCI among the four visible and NIR bands, which is why this band is used to derive the SPM concentration. The $R_{\text{rs}}$ of GF-1/WVF and L8/OLI is consistent with that of GOCI, especially at the red and blue bands, while the $R_{\text{rs}}$ of S2/MSI exhibits a low $R^2$ value when compared with that of GOCI, which can be attributed to the low SNR of the sensor. S2/MSI presents lower $R_{\text{rs}}$ values than GOCI, which may be influenced by sun glint, which can cause an overestimation of the AOT during atmospheric correction. Some large values of MAPE are observed in NIR bands, where the $R_{\text{rs}}$ of GOCI in some regions are close to zero. For the blue band, the three sensors have low $R^2$ values when compared with GOCI because this band is insensitive to SPM changes; thus, the resolution differences have a significant effect on the $R^2$ value.

Table 4. Cross-comparison results of $R_{\text{rs}}$ at four bands (GF-1/WVF, L8/OLI, and S2/MSI images on March 15, 2014, March 12, 2015, and July 20, 2016, respectively). The gain and offset values are the fitting coefficients (GOCI vs other sensors) shown in Fig. 4.

| Bands | Gain $R_{\text{rs}}$ GF-1/WVF | Gain $R_{\text{rs}}$ L8/OLI | Offset $R_{\text{rs}}$ L8/OLI | $R^2$ | MAPE | RMSE (sr$^{-1}$) |
|-------|-------------------------------|-----------------------------|-------------------------------|------|------|-----------------|
| Blue  | 1.0709                        | 0.7775                      | −0.0026                       | 0.7565 | 6.10% | 0.0016          |
|       | L8/OLI                        |                             |                               |      |      |                 |
|       | S2/MSI                        |                             |                               |      |      |                 |
|       | GF-1/WVF                      |                             |                               |      |      |                 |
|       | Green                         |                             |                               |      |      |                 |
| Green | LG/OLI                        | 0.7775                      | 0.0059                        | 0.7302 | 4.33% | 0.0013          |
|       | S2/MSI                        | 0.9410                      | −0.0043                       | 0.5625 | 65.94%| 0.0061          |
|       | GF-1/WVF                      | 1.1275                      | 0.0025                        | 0.8935 | 17.17%| 0.0063          |
| Red   | LG/OLI                        | 1.1838                      | −0.0068                       | 0.9006 | 6.76% | 0.0020          |
|       | S2/MSI                        | 0.9936                      | −0.005                        | 0.6271 | 34.80%| 0.0058          |
|       | GF-1/WVF                      | 0.9815                      | 0.0001                        | 0.9838 | 3.75% | 0.0013          |
| NIR   | LG/OLI                        | 1.0163                      | −0.0005                       | 0.9430 | 5.87% | 0.0019          |
|       | S2/MSI                        | 1.0571                      | −0.005                        | 0.9016 | 33.22%| 0.0045          |
|       | GF-1/WVF                      | 1.0200                      | −0.0001                       | 0.9661 | 12.02%| 0.0022          |
|       | L8/OLI                        | 0.9343                      | −0.0041                       | 0.9709 | 90.57%| 0.0055          |
|       | S2/MSI                        | 0.9115                      | −0.0032                       | 0.8300 | 159.47%| 0.0060          |
4.3 Cross-comparison of derived SPM and in situ data

Because of the wide range of SPM concentrations (from $10^0$ to $10^3$ mg/L) in the Yangtze Estuary, Shen et al. [1,20,21] proposed a scheme of multiple band shifting for SPM retrievals. To examine the compatibility of the SPM retrieval algorithm applied to multi-source satellite data, the $R_{\text{rs}}$ value at the red bands from the GF-1/WFV, L8/OLI and S2/MSI products with the best consistency was adopted for the SPM inversion, although using a single red band for the retrieval might lead to underestimated SPM values for extremely high SPM waters. A comparison of three pairs of images, GF-1/WFV vs. GOCI images on March 15, 2014, L8/OLI vs. GOCI images on March 12, 2015, and S2/MSI vs. GOCI images on July 20, 2016, is shown in Fig. 5, and the results indicate that the SPM distributions from each pair of images exhibit a good consistency.

![SPM images](image)

Fig. 5. SPM concentrations derived from data from four satellites in the Yangtze Estuary and Hangzhou Bay area.
Furthermore, the scatterplots of the derived SPM shown in Fig. 6 indicate better agreements by the pairwise contrasts, although the L8/OLI-derived SPM exhibits slight underestimation for extremely turbid waters (e.g., SPM > 0.4 g/L) compared with the GOCI-derived SPM. This underestimation is caused by the underestimation of L8/OLI \( R_a \) (see Fig. 4(b)) originating from the SWIR-based method for the atmospheric correction algorithm, which may produce an error over extremely turbid waters according to Pan et al. [12]. GF-1-derived SPM shows the best result with \( R^2 = 0.9898 \) and RMSE = 0.0151 g/L.

A total of 55 SPM data points derived from GOCI imagery without cloud coverage over the Chongxi station were observed in 2014 to 2016, and 27 match-ups with GF-1/WFV data, 13 match-ups with L8/OLI data, 3 match-ups with S2/MSI data and 38 match-ups with in situ data were used for the cross-comparison. To ensure the quality of the GOCI images, only GOCI images collected at 10:30 were selected, and they are shown in Fig. 7. The empty points indicate that the high-resolution sensor-derived SPM concentrations have bigger differences from the GOCI-derived concentrations.

Figure 7 indicates that the GOCI-derived SPM and in situ SPM values are approximately the same and consistent with the overall change trend. The SPM values derived from GF-1/WFV are similar to those derived from GOCI. However, some empty squares shown in 2014 were mostly caused by the instability of the radiation calibration. The SPM values derived from L8/OLI on February 27, 2016, and July 20, 2016 (empty pink circles), are slightly lower due to the contribution from high reflectance in the SWIR band caused by high turbidity water and the differences between actual and standard atmosphere [3] in Rayleigh and ozone optical thickness. Therefore, these empty points are not included in the statistics. Obviously, multiple in-orbit high-resolution satellite missions can greatly increase the number of high-resolution images and shorten the revisit period, especially with the multi-camera
technology equipped on GF-1 and dual stars of S2 achieved in March 2017, which are beneficial to studies of aquatic environments in estuaries and coasts.

5. Discussion

5.1 Cross-comparison of multiple sensors

In the cross-comparison between multi-source satellite data, the first important step is the radiometric calibration for converting sensor-received signals to physical variables such as $\rho_{\text{TOA}}$. For in-orbit satellite missions, the coefficients for radiometric calibration can be recalibrated and readjusted by incorporating onboard solar/lunar calibration and in-orbit vicarious calibration. For instance, the absolute radiance-calibrated operational products from L8/OLI were determined to have an uncertainty of approximately 2-3% compared to ground measurements and other in-orbit measurements after the launch of the satellite [22]. Our results in Figs. 3 and 4 show that the L8/OLI data exhibit good consistency with the GOCI data in red band of the $\rho_{\text{TOA}}$. The results from Li et al. [23] indicated that the $\rho_{\text{TOA}}$ of S2/MSI was approximately consistent with the $\rho_{\text{TOA}}$ of L8/OLI at each waveband over coastal waters. However, the reflectance was slightly higher in the red band, which was also observed in our results as shown in Fig. 3. A study on the vicarious calibration of GF-1 data carried out in June 2013 showed that the uncertainty of the calibration based on multiple ground measurements was 5.35% [24], which was slightly higher than that of the L8/OLI data.

Figure 4(b) shows that the L8/OLI $R_s$ derived from ACOLITE code compared to the GOCI $R_s$ derived from the method proposed by Pan et al. [18] remained at approximately the 1:1 line. However, the L8/OLI $R_s$ at the red band (e.g., 660 nm) was slightly lower than the GOCI $R_s$ and seemed to be underestimated in extremely turbid waters, such as in Hangzhou Bay. The results suggested that the atmospheric correction of L8/OLI data based on the SWIR dark pixel method might not be ideal for extremely turbid waters. The S2/MSI sensor was also processed using the ACOLITE code, and it exhibited acceptable correspondence with GOCI $R_s$ values along the 1:1 line. In addition, GF-1/WFV showed the closest relationship with the $R_s$ values of GOCI, with $R^2 = 0.9838$ and RMSE = 0.0013 sr$^{-1}$.

5.2 Impact of SNR

The $NE_{\rho}$ and $NE_{\text{SPM}}$ were calculated according to section 3.4 and Table 5. Because $NE_{\rho}$ and $NE_{\text{SPM}}$ are largely influenced by the solar zenith angle, Fig. 8 shows the changes in the $NE_{\rho}$ values (left panel) and $NE_{\text{SPM}}$ values (right panel) with increases in the solar zenith angle from 0° to 80° in the visible and NIR bands.

![Fig. 8. $NE_{\rho}$ values (left panel) and $NE_{\text{SPM}}$ values (right panel) in the green, red and NIR bands of GF-1/WFV, S2/MSI, L8/OLI and GOCI with an increase in the solar zenith angle ($\theta$).]
Table 5. Information on $E_0$, SNR and $L_{ref}$ at the bands centered over the green, red and NIR spectral range for L8/OLI, GOCI, GF-1/WFV and S2/MSI sensors. SNR and $L_{ref}$ for L8/OLI, GOCI and S2/MSI can also be found in Observing Systems Capability Analysis and Review Tool (OSCAR, http://www.wmo-sat.info/oscar/spacecapabilities).

| Sensor       | Center band (nm) | $E_0$ (W m$^{-2}$ μm$^{-1}$) | SNR | $L_{ref}$ (W m$^{-2}$ sr$^{-1}$ μm$^{-1}$) |
|--------------|------------------|-----------------------------|-----|------------------------------------------|
| L8/OLI (Green) | 565              | 1893                        | 100 (low signal) | 30 (low signal) |
| L8/OLI (Red)   | 655              | 1603                        | 90 (low signal)  | 22 (low signal) |
| L8/OLI (NIR)   | 865              | 972.6                       | 90 (low signal)  | 14 (low signal) |
| GOCI (Green)   | 555              | 1529                        | 1070           | 56             |
| GOCI (Red)     | 660              | 1529                        | 1010           | 32             |
| GOCI (NIR)     | 865              | 1529                        | 750            | 16             |
| GF-1/WFV (Green) | 555            | 1849                        | 125*           | 28.2*          |
| GF-1/WFV (Red) | 665              | 1529                        | 77*            | 11.1*          |
| GF-1/WFV (NIR) | 823              | 1065                        | 34*            | 2.9*           |
| S2/MSI (Green) | 560              | 1536                        | 168            | 128            |
| S2/MSI (Red)   | 665              | 1536                        | 142            | 108            |
| S2/MSI (NIR)   | 865              | 1536                        | 72             | 52.4           |

*SNR and $L_{ref}$ of GF-1/WFV are referred to Li et al. [25].

Figure 8 shows that S2/MSI has a high $NE_ρ$ and is influenced largely by noise. L8/OLI and GF-1/WFV have the same approximate $NE_ρ$ values. In contrast, GOCI has the lowest $NE_ρ$ value among the four sensors because it is an ocean color sensor. The three high-resolution satellite missions acquire earth imagery at approximately 10:00 am Beijing time, when the solar zenith angle is less than 60° and the $NE_ρ$ values are less than 0.45% throughout the year in the Yangtze Estuary. Additionally, the sensitivities of one sensor in various bands are basically the same and present a deviation of less than 0.09%.

$NE_{SPM}$ is determined by both $NE_ρ$ and solar zenith angle. NIR bands have higher $NE_{SPM}$ values than red and green bands for the same sensor. Among the three high-resolution satellite sensors, GF-1/WFV and L8/OLI had sensitivities greater than 0.5 mg/L in SPM ($θ < 30°$), while S2/MSI had lower sensitivity, especially in the NIR band, which can only detect variations greater than 10 mg/L in turbid waters ($θ < 30°$). As indicated by Shen et al. [20], the decreased sensitivity would impact ocean color inversions, for instance, the SPM inversion using the NIR band when the SPM > 0.25 g/L in extremely turbid waters. However, such sensitivity is appropriate for lake or ocean observations.

5.3 Impact of spatial resolution

The spatial resolution should have a remarkable impact on the imaging accuracy of objects with high spatial variability. To quantify the impact of the spatial resolution, the S2/MSI image on July 20, 2016, was selected; the targets of a bounding and nail dam in a zoomed-in subimage were located in the Hengsha Dongtan, as shown in Fig. 9(a). The spatial resolution of the image was resized to 10 m (origin), 30 m and 500 m (Figs. 9(a-c)). The areas circled by blue (I, I’, I”) and orange (II, II’, II”) boxes are the $L_{TOA}$ samples in varied and unvaried regions. A cross-comparison of the $L_{TOA}$ in these regions is shown in Figs. 9(d-g).
The bounding and nail dam targets can be identified on the images with 10 m and 30 m spatial resolutions but are not recognized on the image with a 500 m resolution. For estuarine-scale observations, the optimum spatial resolution should be less than 100 m (or 50 m for some cases) [25]. The cross-comparison of S2/MSI images with fine and coarse resolutions revealed that the degraded resolution of the \( L_{TOA} \) values (e.g., from 10 to 30 m and 10 to 500 m) results in significant errors, especially in the high CV regions, i.e., \( \text{RMSE} = 7.1 \, \text{W m}^{-2} \, \text{sr}^{-1} \, \mu\text{m}^{-1} \) in 10 m vs 30 m (see Fig. 9(d)) and \( \text{RMSE} = 13.2 \, \text{W m}^{-2} \, \text{sr}^{-1} \, \mu\text{m}^{-1} \) in 10 m vs 500 m (See Fig. 9(e)). Meanwhile, the degraded resolution also reduces the correlation with the original data, especially in the low CV region (see Fig. 9(g)). In addition, details of the satellite image are quickly lost when the resolution degrades. The CV values in regions I, I’, and I” change from 22.27% for the image at 10 m resolution to 16.57% for the image at 500 m resolution, which is characterized by increased horizontal striping [3] as well as decreased linear regression slopes in the scatterplots (see Figs. 9(d, e)). As a result, different spatial resolutions certainly impact the precision of the cross-comparisons of data/products, e.g., between multi-sensor data/products in fine and coarse resolutions or between satellite and \textit{in situ} data.

6. Conclusions

In this work, data from different product levels, such as \( P_{TOA} \) and atmospherically corrected \( R_a \) data, and products, e.g., SPM, that were derived separately from three in-orbit high-resolution satellite sensors, i.e., L8/OLI, S2A/MSI and GF-1/WFV, against corresponding data from GOCI, were utilized for cross-comparison. Satellite data from the GOCI ocean color sensor and \textit{in situ} data from autonomous observation stations were used to validate
high-resolution data and derived products. In this study, high-resolution land observation satellites are applied for ocean color applications in medium- and small-scale estuaries.

The results of the cross-comparison indicated that the $\rho_{\text{TOA}}$ derived from the three high-resolution remote sensing sensors, i.e., S2/MSI, L8/OLI and GF-1/WFV, is consistent with the $\rho_{\text{TOA}}$ of GOCI in the visible bands. The $\rho_{\text{TOA}}$ at 660 nm from the three high-resolution sensors against the $\rho_{\text{TOA}}$ of GOCI all display excellent linear functions with $R^2 > 0.95$ and RMSE $< 0.03$. After performing atmospheric correction, the $R_n$ values at 660 nm separately from the three high-resolution sensors are in perfect correspondence with GOCI data and follow the 1:1 line.

The SPM data separately derived from the high-resolution sensors show good consistency with the SPM data derived from GOCI, except for the slight underestimation from L8/OLI for extremely turbid waters. However, some deviations between satellite- and OBS-derived SPM data still exist, which may be caused by the limited spatial resolution of remotely sensed data, the accuracy of the OBS measurements and the imperfect radiometric calibration and atmospheric correction.

The analysis of the impact of the SNR of the sensors on the satellite products reveals that the radiometric sensitivities of GF-1/WFV and L8/OLI are relatively high, with minimally detectable variations greater than 0.06% in reflectance and 0.5 mg/L in SPM for solar zenith angles $< 30^\circ$. The radiometric sensitivity of S2/MSI is slightly lower than that of the other sensors, with a detectable variation in SPM of 1.5 mg/L in moderately turbid water for solar zenith angles $< 30^\circ$. In regard to the impact of satellite spatial resolution, the details and variances (defined as CV) of satellite imagery can be lost when the spatial resolution is downscaled. Importantly, the spatial characteristics of the SPM distribution and pattern will be lost at coarse resolutions, e.g., from CV = 22.27% at 10 m to CV = 16.57% at 500 m. Moreover, a coarse spatial resolution can lead to a decline in precision, e.g., RMSE = 7.1 W m$^{-2}$ sr$^{-1}$ $\mu$m$^{-1}$ at 10 m vs 30 m (a variation of approximately 0.013 g/L in the SPM) and RMSE = 13.2 W m$^{-2}$ sr$^{-1}$ $\mu$m$^{-1}$ at 10 m vs 500 m (a variation of approximately 0.026 g/L in the SPM) for the high CV regions, which also means that the impacts from the spatial resolution on the SPM are larger than those from the SNR.

As a result, our confidence in ocean color applications in medium- and small-scale waters using high-resolution satellites that were initially developed for terrestrial applications is therefore enhanced because of these sensors have advantages of high spatial resolution, acceptable SNR and radiometric sensitivity. Cross-comparisons of sensor-measured data and derived products from multi-source satellite can promote improvements to sensor calibration, and they can also be used to examine the consistency of algorithms for atmospheric corrections and water component inversions. This method will also allow for the production of merged multi-source high-resolution satellite products with high frequency time series in the future, which are required for port and waterway traffic and maintenance in estuaries.

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