Global Change Observation Mission-Climate (GCOM-C)/Second-Generation Global Imager (SGLI)

Use of AERONET-OC for validation of SGLI/GCOM-C products in Ariake Sea, Japan

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Abstract
A station of AErosol RObotic NETwork Ocean Color (AERONET-OC) has been set on the Ariake Observation Tower of Saga University on April, 2018, for verification of the Second generation Global Imager (SGLI)/Global Change Observation Mission-Climate (GCOM-C). Remote sensing reflectance (Rrs) observed by the AERONET-OC was used for verification of SGLI. SGLI Version 1 data underestimated the shortwave Rrs and Rrs(380) and Rrs(412) were mostly negative, while the estimation was improved by Version 2 with the correction of Rrs(412) to be positive. It was indicated that absorptive aerosol was influenced to SGLI atmospheric correction and caused the underestimation of Rrs. Simple linear correction method to improve shortwave Rrs also worked well for specifically Version 1 data. Water constituents, chlorophyll-a (Chl-a), total suspended matter (TSM) and colored dissolved organic matter (CDOM) of the SGLI were also verified by the ship observation data. All constituents were improved from Version 1 to 2 with the correction of Rrs, although Version 2 underestimated Chl-a and CDOM. Simple regression algorithms were also examined with in situ as well as SGLI Rrs data, and it indicated that more sophisticated algorithms may be required. Time series of water constituents derived from AERONET-OC and SGLI data were compared to river discharge and spring–neap tidal cycle. The results indicated that the behavior, such as the increase of Chl-a after river discharge and interaction of Chl-a and TSM with the spring–neap tidal cycles were observed, although estimations of water constituents were not completely separated by the algorithms.

Keywords Ocean color satellite · SGLI/GCOM-C · AERONET-OC · Ariake Sea · Atmospheric correction · In-water algorithm · Chlorophyll-a · TSM · CDOM

1 Introduction
Second Generation Global Imager (SGLI) on Global Change Observation Mission-Climate (GCOM-C) was launched on December 27, 2017. SGLI obtains ocean color data with 250 m resolution which is the highest for global ocean color data presently (Groom et al. 2019). Because of this high resolution, it is expected that the data is useful for coastal observation. However, the ocean color products in coastal area were not very accurate because of the difficulties of both atmospheric correction and in-water algorithms (Siegel et al. 2000; Fan et al. 2021). Therefore, it is important to verify the product in the field. Obtaining the enough data set for verification is not easy because of the limited opportunity of the ship observation and the cloud coverage, and continuous observation is desirable.

AErosol RObotic NETwork (AERONET) is the global network of optical aerosol measurement with autonomous sun-photometers (Holben et al. 1998), and AERONET-Ocean Color (AERONET-OC) expands the network to monitor the normalized water leaving radiances with the modified equipment (Zibordi et al. 2009) for the verification of ocean color satellites. We set a station of AERONET-OC on the Ariake Observation Tower of Saga University (Ito et al. 2013, http://www.ariake.civil.saga-u.ac.jp/tower.html) for verification of specifically SGLI from April 2018, and the data have been used some studies of verification of satellite
data and the algorithms (Fan et al. 2021; Feng et al. 2021; Pahlevan et al. 2021; He et al. 2021; Sekiguchi et al. 2021).

Ariake Sea is a shallow, enclosed bay in the southwest of Japan which covers fairly large tidal flat along the coast, and it has been known to be one of the most productive bays in Japan (Fig. 1). The production has been suffering from harmful algal blooms and hypoxia for the last 20 years, and the relation to the dike construction in Isahaya Bay, which is a small bay in the Ariake Sea (Ishizaka et al. 2006; Hayami et al. 2019; Hayami et al. 2021), has been discussed. Many studies focus on the relation between the harmful algal blooms with turbidity of the bay. Ishizaka et al. (2006) used ocean color satellite (Sea-viewing Wide Field-of-view Sensor: SeaWiFS) standard chlorophyll-a (Chl-a) data to detect one of the largest red tide events in the Ariake Sea in winter of 2000–2001. Yang et al. (2018) verified the problem of standard MODIS (Moderate Resolution Imaging Spectroradiometer) products of both atmospheric correction and in-water algorithm, and suggested using the linear correction method of remote sensing reflectance (Rrs) data proposed by Hayashi et al. (2015) as well as local switching algorithm to tune the OC3 in-water algorithm to obtain accurate Chl-a in Ariake Sea. Yang et al. (2020, 2021) further analyzed the variation of MODIS Chl-a and TSM data in this region. On the other hand, Feng et al. (2020, 2021) used standard MODIS and GOCI (Geostationally Ocean Color Imager) data to discriminate diatom and raphidophyte red tide in Ariake Sea avoiding the erroneous shorter-wavelength data.

In this study, with the data of AERONET-OC and ship observations in Ariake Sea, we verified ocean standard products of SGLI, including normalized water leaving radiance as well as the water constituents: Chl-a, total suspended matter (TSM), and colored dissolved organic matter (CDOM). We also verified the linear correction method to reduce the error of Rrs with AERONET-OC data and the in-water algorithms with the ship data. We further analyzed the time series of the water constituents by combining AERONET-OC and SGLI data to check the behavior.

2 Methods

2.1 AERONET-OC data

AERONET-OC Level 3 normalized water leaving radiance (Lwn) data from April 2018 to March 2019 was taken from the AERONET data distribution site (https://aeronet.gsfc.nasa.gov/new_web/data.html). The data was converted to Rrs with solar radiance at the top of the atmosphere (Thuillier et al. 2003). Rrs of 400, 510, 560, 667 nm was converted to the SGLI band (380, 530, 565 and 672 nm) with the conversion factors (0.7898, 1.134, 1.023, 0.9633) obtained by the hyperspectral Rrs data taken in Ariake Sea.

2.2 SGLI data

SGLI near-real time products around Japan from JAXA Satellite Monitoring for Environmental Studies (JASMES) were used in this study (https://www.eorc.jaxa.jp/cgi-bin/jasmes/sgli_nrt/index.cgi). Version 1 (V.1) and 2 (V.2) products of the JASMES Lwn, Chl-a, TSM, and CDOM were downloaded. V.1 products were replaced with V.2 from January 2020, and they were compared because there were some differences in algorithms. Difference of atmospheric correction

Fig. 1 Location of Ariake Sea and Ariake Tower (star). Square and triangle indicate Oura tidal gauge and Senoshita River station, respectively. Dots indicate the observation stations.
algorithm was small for Lwn V.1 and V.2 products; however, negative Lwn correction was conducted for the V.2 products (https://suzaku.eorc.jaxa.jp/GCOM_C/data/files/ATBD_ocean_ac_murakami_v2_en.pdf). Notice the atmospheric correction algorithm is slightly different from the JAXA standard products from the G-portal (https://gportal.jaxa.jp/gpr/). (Toratani et al. 2018, 2021). For the verification in this study, Lwn data were converted to Rs(565) with same factors with AERONET-OC.

Difference of in-water algorithms of V.1 and V.2 Chl-a, which were the same as the standard products, was also small and showed only slight difference of the parameter values (Murakami et al. 2018, 2020). This algorithm is based on the switching of OC3 algorithm (O’Reilly et al. 2000) with the ratio of maximum of Rs(443), Rs(490). Rs(530) normalized by Rs(565) and Color Index Algorithm (Hu et al. 2012). In the Ariake Sea where the water is fairly high turbid and has Chl-a, the algorithm used mostly normalized Rs(530) with the OC3 algorithm.

\[
\text{Log}_{10}(\text{Chl-a}) = 0.40451 - 3.42411R + 5.29717R^2 - 5.33247R^3 + 1.68959R^4,
\]

(1)

where \(R = \text{Rs}(530)/\text{Rs}(565)\).

For TSM, the difference of V. 1 and V. 2 algorithms was significant. V. 1 was used log–log regression with only one wavelength of Rs(672) (Toratani et al. 2018);

\[
\text{TSM} = \left( \frac{\text{Rrs}(672)}{0.000561} \right)^{0.89638},
\]

(2)

V. 2 used multiple regression of Rs(490) normalized by Rs(565) and Rs(565) (Toratani et al. 2021);

\[
\text{Log}_{10}(\text{TSM}) = -1.5831 \text{Log}_{10}(\text{Rrs}(490)/\text{Rrs}(565)) + 0.3626 \text{Log}_{10}(\text{Rrs}(565)) + 1.2096.
\]

(3)

The CDOM algorithm is based on inherent optical properties algorithm (Hirata et al. 2019a, b, 2020; Smyth et al. 2006), and the CDOM was calculated from the total absorption coefficients of CDOM and non-phytoplankton particle (NAP) \(a_{\text{CDOM+NAP}}\), with the relations derived by NOMAD (NASA bio-Optical Marine Algorithm Dataset, Werdell and Bailey 2005) dataset.

### 2.3 Linear correction of Rs

To improve Rs of SGLI data, linear correction was conducted. This method was proposed by Hayashi et al. (2015) to improve the negative Rs of the standard products of SeaWiFS and MODIS data in Ise-Mikawa Bay, Japan. The method was based on the simple assumptions: (1) the error of MODIS Rs(547) (Rs(555) for SeaWiFS) was small, (2) Rs(412) can be calculated from the linear relation of Rs(547) derived from the field observations, so that the error of Rs(412) can be estimated from the difference of satellite Rs(412) and calculated Rs(412) from Rs(547), and (3) the error of Rs between 412 and 547 nm can be estimated as linear to the wavelength. Yang et al. (2018) applied this method for MODIS data in Ariake Sea not only for the correction for Rs with negative Rs(412), but also for overestimation of Rs(412). Tsukamoto et al. (2019) corrected the error of Rs(547) of MODIS with in situ data before the linear correction and applied it in Lake Biwa, Japan. This method worked well to reduce the influence of negative Rs in overestimating Chl-a. One of the biggest advantages of this simple correction method compared with the sophisticated atmospheric correction method is that the users do not need to go back to the atmospheric correction and can use the standard Rs products with the simple modification. To use the correction method for SGLI data, we used SGLI Rs(565) instead of MODIS Rs(547). Then Rs(412) can be estimated from the following relationship in Ariake Sea obtained from Rs dataset in Ariake Sea:

\[
\text{Rrs}_{\text{-LC}}(412) = 0.3566 \text{Rrs}_{\text{-SGLI}}(565),
\]

where \(\text{Rrs}_{\text{-LC}}\) and \(\text{Rrs}_{\text{-SGLI}}\) are the Rs from the linear correction method and from the standard SGLI products, respectively. Then \(\text{Rrs}_{\text{-LC}}(\lambda)\) can be estimated by the following equation:

\[
\text{Rrs}_{\text{-LC}}(\lambda) = \text{Rrs}_{\text{-SGLI}}(\lambda) + (\text{Rrs}_{\text{-LC}}(412) - \text{Rrs}_{\text{-SGLI}}(412)) \frac{(65 - \lambda)}{(565 - 412)},
\]

where \(\lambda\) is 443, 490, and 530 nm.

### 2.4 Verification of in-water algorithms

As simple empirical algorithms, some of the Rs data of SGLI wavelengths (443, 490, 530, 672 nm) were extracted and normalized by Rs(565) (hereafter, \(n\text{Rs}(443), n\text{Rs}(490), n\text{Rs}(530), n\text{Rs}(672)\), respectively). Type-II fitting (reduced major axis) was used to obtain the relation between the log-transformed nRs and log-transformed Chl-a, TSM, and CDOM. To check the in-water algorithms except the SGLI standard, we used only simple linear equations, although the original SGLI algorithm used fourth-order equation (OC4). This is because we only apply those algorithms mostly in the head of Ariake Sea and the range of water constituents are narrow and mostly Rs(530) > Rs(490) > Rs(443) as described in the results. Four algorithms including
SGLI V.2 were examined for Chl-a and CDOM, and nine algorithms including SGLI V.1 and V.2 were examined for TSM (cf. Table 4).

To check the performance of the relationships and to verify with coincident data of those water constituents with SGLI Rrs, correlation coefficient (r), mean error/difference (ME/MD), and root mean square error/difference (RMSE/RMSD), as well as the slope and intercept of the correlations to in situ data, were taken after log transformation.

2.5 In-situ data

To verify the SGLI products and to examine in-water algorithms, we used four data sets in Ariake Sea (Table 1, Fig. 1). One is the data of Chl-a and Rrs collected by Nagasaki University during 2001 and 2010, and another is the data of Chl-a, TSM, CDOM and Rrs collected by Nagoya University during 2015 and 2017. Those data were used for the verification of in-water algorithms. The third and fourth datasets are Chl-a, TSM and CDOM from Nagoya University and Chl-a from Saga Fisheries Research Institute, respectively, during 2018 and 2019. Those were used for the verification with SGLI data.

The Rrs data were taken by an underwater radiometer (PRR-800, Biospherical Inc.) and onboard radiometer (RAMSES, Trios Inc.). The Chl-a was measured by fluorometers after extraction (Welschmeyer 1994). The TSM was measured by weighing samples on 0.2 μm nucleopore filters. The CDOM at 412 nm were measured the absorption of samples after filtered by 0.2 mm nucleopore filters. The details of the measurement methods can be found in Yang et al. (2018).

Daily discharge information from Chikugo River, which is the largest discharge amount into the Ariake Sea, at Seno-shita station (Fig. 1) of 2018 and 2019 was downloaded from the Water Information System (http://www1.river.go.jp/), Ministry of Land, Infrastructure, Transport and Tourism. Sea level data of Oura (Fig. 1) was also downloaded from tidal data homepage (https://www.data.jma.go.jp/kaiyou/db/tide/suisan/) of Japan Metrological Agency. The daily maximum sea level difference was calculated.

3 Results

3.1 Verification of SGLI products with AERONET-OC and in situ data

Rrs values calculated from SGLI and AERONET-OC Lwn during April 2018 and March 2019 were compared (Fig. 2). Most of the Rrs from AERONET-OC showed a peak at 565 nm, indicating a high Chl-a and/or turbidity. Rrs from SGLI also showed a peak at 565 nm. V.1 Rrs of

![Figure 2](https://example.com/figure2.png)
380, 412, 443 nm was mostly negative, indicating the influence of error of atmospheric correction by the presence of the absorptive aerosol (Li et al. 2003; Toratani et al. 2007). Most of Rrs(380), Rrs(412), and Rrs(443) were negative, zero, and positive for the SGLI V.2, indicating that the Rrs was corrected to make Rrs(412) from being negative.

SGLI V.1 Rrs showed significant correlations \(r = 0.179 \sim 0.859\) to AERONET-OC data, but with high \(r = 1.09\sim2.92\) slopes and with negative intercept \((-0.00100 \sim -0.0134)\) (Fig. 3, Table 2). The Rrs of shorter wavelength showed larger error than the longer one \((-0.00529 \sim 0.00006)\), and the mean difference between the SGLI and AERONET-OC Rrs was not significant for Rrs(565). SGLI V.2 Rrs improved the correlations \(0.189 \sim 0.899\) and intercept \(-0.00079 \sim 0.00242\), although it showed mostly smaller slope \(0.257 \sim 0.912\). The mean difference between the SGLI and AERONET-OC was not significant. This indicated that on the correction of the underestimate of Rrs for V.2 clearly improved specifically the Rrs estimation of short wavelength.

Then, normalized Rrs by Rrs(565), some of which was used for estimation of constituents, also showed the improvement from V.1 to V.2. The correlation was 0.098 to 0.772 and \(-0.028 \sim 0.846\), and the slope was 10.2 to 1.17 and \(-2.48 \sim 0.962\) for V.1 and V.2, respectively (Fig. 4). Because of the underestimate of Rrs(443) and Rrs(490), the nRrs(443) and nRrs(490) were also underestimated by specifically V.1, and they were improved by V.2.

Chl-a, TSM and CDOM of SGLI were compared with the data from ship observations (Fig. 5, cf. Tables 4, 5 and 6). Chl-a was mostly overestimated by V.1, and the overestimation was reduced by V.2. However, the V.2 product generally underestimated the Chl-a. The correlation was improved from V.1 \(r = 0.283\) to V.2 \(r = 0.512\), although the slope became lower than 1 \(1.08 \sim 0.684\) for V.1 and V.2, respectively. V.2 products improved the underestimate of TSM by V.1. The correlation was also slightly improved from V.1 \(r = 0.316\) to V.2 \(r = 0.531\), and the slope was 0.670 and 0.487 for V.1 and V.2, respectively. There were few data for V.1 CDOM because of the negative values for the short wavelength, and the number increased for V.2. The correlation between SGLI and in situ CDOM was also improved from V.1 \(r = 0.325\) to V.2 \(r = 0.688\); however, they were still underestimated. Those results indicated that the V.2 products were much better than V.1, although it is required to be improved.

3.2 Linear correction of SGLI Rrs

The linear correction methods were applied to SGLI V.1 and V.2 data to obtain the corrected Rrs(443), Rrs(490), and Rrs(530) (Table 2). The V.1 SGLI Rrs(412) to Rrs(530) was improved from the original SGLI Rrs \(r = 0.179 \sim 0.768\) to \(r = 0.759 \sim 0.871\), although the mean difference between the SGLI Rrs and AERONET-OC for 412–490 nm was still significant. The V.2 SGLI Rrs data was also improved by the linear correction; however, the results were not very different from the linear correction of V.1, and the mean error of linearly corrected Rrs(530) was larger than that of the original V.2 Rrs(530). This indicated that the linear correction was effective for both V.1 and V.2 SGLI data, although the error of Rrs(530) used for the Chl-a calculation was already small for V.2 even without linear correction. The nRrs also showed that the linear correction was effective for improvement of both V.1 and V.2 nRrs in short wavelength, although the original V.2 nRrs(530) showed smaller difference than the linearly corrected data.

3.3 Examination of in-water algorithms

For the estimation of water constituents, Chl-a, TSM and CDOM, in-water algorithms from Rrs are also important. Thus, here we examined the standard and simple empirical algorithms with in situ data.
Table 2  Correlation and differences of Rs and normalized Rs with Rs(565)(nRrs) between AERONET-OC and SGLI data (V.1 and V.2)

| SGLI data | V.1 | | | | | V.2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Rs412 | Original | 0.179 | 50 | 0.00529*** | 0.00619 | 2.92 | −0.0134 | 0.189 | 55 | −0.00405*** | 0.00426 | 2.57 | −0.0079 |
| Rs443 | Original | 0.378 | 50 | 0.00382*** | 0.00468 | 1.81 | −0.00821 | 0.744 | 55 | −0.00253*** | 0.00283 | 0.573 | −0.0016 |
| Rs490 | Original | 0.661 | 50 | 0.00196*** | 0.00294 | 1.29 | −0.00434 | 0.871 | 55 | −0.00121*** | 0.00178 | 0.705 | 0.00126 |
| Rs530 | Original | 0.768 | 50 | 0.00107*** | 0.00221 | 1.04 | −0.00146 | 0.886 | 55 | −0.00027 | 0.00151 | 0.782 | 0.00207 |
| Rs565 | Original | 0.836 | 50 | 0.00006 | 0.00164 | 1.09 | −0.00112 | 0.899 | 55 | 0.00018 | 0.00145 | 0.825 | 0.00242 |
| Rs672 | Original | 0.859 | 50 | 0.00040* | 0.00122 | 1.12 | −0.00100 | 0.850 | 55 | 0.00006 | 0.00127 | 0.912 | 0.00040 |
| nRrs412 | Original | 0.098 | 29 | −0.900*** | 0.999 | 10.2 | 3.39 | −0.028 | 55 | 1.16*** | 1.17 | −2.48 | −2.807 |
| nRrs443 | Original | 0.134 | 50 | −0.364*** | 0.491 | 5.93 | 1.43 | 0.414 | 55 | −0.278*** | 0.298 | 1.97 | 0.0815 |
| nRrs490 | Original | 0.602 | 50 | −0.149*** | 0.203 | 3.18 | 0.260 | 0.831 | 55 | −0.0728*** | 0.0796 | 1.18 | −0.0396 |
| nRrs530 | Original | 0.588 | 50 | −0.0464*** | 0.0626 | 1.19 | −0.0315 | 0.612 | 55 | −0.0146*** | 0.0372 | 0.934 | −0.0200 |
| nRrs672 | Original | 0.772 | 50 | −0.0467* | 0.0903 | 1.17 | 0.0259 | 0.846 | 55 | −0.00838 | 0.0601 | 0.962 | −0.0247 |
| Rs412 | LC | 0.759 | 50 | 0.00051*** | 0.00092 | 1.02 | 0.00043 | 0.817 | 55 | 0.00025* | 0.00084 | 0.699 | 0.00157 |
| Rs443 | LC | 0.808 | 50 | 0.00080*** | 0.00129 | 1.05 | 0.00468 | 0.846 | 55 | 0.00089*** | 0.00132 | 0.879 | 0.00156 |
| Rs490 | LC | 0.871 | 50 | 0.00089*** | 0.00150 | 1.09 | 0.00014 | 0.889 | 55 | 0.00089*** | 0.00146 | 0.852 | 0.00213 |
| Rs530 | LC | 0.849 | 50 | 0.00025 | 0.00155 | 0.997 | 0.00029 | 0.889 | 55 | 0.00071*** | 0.00161 | 0.840 | 0.00243 |
| Rs565 | LC | Same as the Original | | | | | | | | | | |
| Rs672 | LC | Same as the Original | | | | | | | | | | |
| nRrs443 | LC | Same as the Original | | | | | | | | | | |
| nRrs412 | LC | Constant | | | | | | | | | | |
| nRrs490 | LC | 0.777 | 50 | 0.0483*** | 0.0590 | 0.978 | 0.0442 | 0.832 | 55 | 0.0406*** | 0.0490 | 0.884 | 0.0187 |
| nRrs530 | LC | 0.678 | 50 | 0.0156*** | 0.0346 | 0.761 | −0.00342 | 0.609 | 55 | 0.0249*** | 0.0415 | 0.847 | 0.1220 |
| nRrs672 | LC | Same as the Original | | | | | | | | | | |

LC stands for the linear correction of the SGLI Rs. All the statistics of Rs and nRs were calculated with linear and log–log scale, respectively. Slope and intercept for Rs412 were calculated with Type II regression. *, **, and *** of MD indicate significant difference with $p<0.05$, $p<0.01$, and $p<0.001$, respectively.
3.3.1 Correlation between water constituents and in situ Rrs

Before examining the empirical algorithms, the correlation analysis between water constituents and in situ Rrs was conducted to choose the Rrs used for the algorithms (Table 3). Log-transformed Chl-a, TSM, and CDOM generally did not correlate with each other, except for Chl-a and TSM which were weakly correlated \( (r = 0.443) \). In situ Rrs values were highly correlated with each other, with higher correlation between Rrs of closer wavelength (not shown data).

After normalization by \( Rrs(565) \), in situ \( nRrs(380) \), \( nRrs(412) \), \( nRrs(443) \), \( nRrs(490) \), \( nRrs(530) \) were still highly correlated \( (p < 0.001) \) with each other, although \( nRrs(672) \) was only slightly negatively correlated with \( nRrs(443) \) and not correlated with \( nRrs \) of other wavelengths. Chl-a was negatively correlated with \( nRrs \), except \( nRrs(672) \) which showed positive correlation. This probably indicates that the influence of absorption and scattering of phytoplankton...
with other constituent correlated to Chl-a influence on nRrs of shorter wavelength and nRrs(672), respectively. TSM showed strong positive correlation with all Rrs before the normalization (not shown data), and only Rrs(672) after the normalization indicating the influence of light scattering. CDOM values were negatively correlated with nRrs(412), nRrs(443), and nRrs(530) \((r = -0.532\) to \(-0.611\)), and only slightly with nRrs(380) \((r = -0.251)\) indicating the influence of the absorption of CDOM. Those relations were in general consistent with the assumption of the ocean color algorithms, including the standard algorithms for SGLI.

### 3.3.2 Chl-a algorithm

The SGLI Chl-a algorithm (CHL-1 in Table 4) showed poorer correlation \((r = 0.563)\) with larger errors with in situ Rrs \((ME = 0.37, RMSE = 0.45)\) compared with algorithms fitted to the in situ data (CHL-2-4 in Table 4). The Chl-a algorithm was also examined by the SGLI V.2 Rrs data without (original) and with the linear correction for checking of influence of atmospheric correction error. The SGLI algorithms with the SGLI Rrs data showed almost similar performance with the in situ Rrs \((r = 0.512\) to \(0.530, ME = 0.19\) to \(-0.34, RMSE = 0.37\) to \(-0.46)\). Those results indicated that performance of SGLI Chl-a algorithm was not best for Ariake Sea. However, the performance was better than the standard MODIS algorithm (Yang et al. 2018) because of the use of Rrs(530) avoiding the error in the short wavelength.

Because the SGLI Chl-a algorithm used nRrs(530) for the high Chl-a/turbid Ariake water, simple linear fitting with nRrs(530) (CHL-2) was examined. Fitting the simple linear equations with nRrs(530) to the in situ dataset showed only slightly better correlation \((r = 0.583)\) and smaller errors \((ME = 0.25, RMSE = 0.32)\) than the original SGLI algorithm for the in situ Rrs. The small improvement may indicate the requirement of addition of other wavelengths.

Yang et al. (2018) found the shift of the relation between Chl-a and Rrs(490)/Rrs(547) for MODIS for high and low turbidity, indicated by the magnitude of Rrs(667), respectively. The correlation analysis also indicated a positive correlation between the Rrs(672) with Chl-a and TSM (Table 3). Therefore, we also constructed switching algorithm of linear relationship of Chl-a and nRrs(530) with the threshold of Rrs(672) \(= 0.005\) \(sr^{-1}\) (CHL-3). The performance was much better than the original SGLI algorithm for the in situ Rrs \((r = 0.695, ME = 0.22, RMSE = 0.28)\). Multiple regression algorithms with nRrs(530) and nRrs(672) was also tested (CHL-4), and the performance was much better than the SGLI and linear nRrs(530) algorithms (CHL-1 and 2) and equivalent to the switching algorithm (CHL-3) for the in situ data \((r = 0.693, ME = 0.20, RMSE = 0.20)\). This indicated that the Rrs(672) as an indicator of turbidity may be required for the good performance of the Chl-a algorithm in Ariake Sea.

Those algorithms were also used to examine SGLI data without (original) and with linearly corrected SGLI data. As expected, the correlation and errors were lower and larger, respectively, than the in situ Rrs which was used for fitting of the algorithms. The performance for the SGLI data with linear correction was better \((r = 0.523\) to \(0.583, ME = -0.05\) to \(-0.17, RMSE = 0.32\) to \(0.49)\) than the original data \((r = 0.522\) to \(0.586, ME = 0.17\) to \(-0.34, RMSE = 0.41\) to \(0.69)\). This indicated that the linear correction of Rrs reduced the atmospheric correction error of Rrs(530) used for Chl-a estimation.
3.3.3 TSM algorithm

Next, we evaluated TSM algorithms of SGLI V.1 with only Rrs(672) (TSM-1 in Table 5) and SGLI V.2 with Rrs(565) and nRrs(490) (TSM-5 in Table 5), and of similar simple equations (TSM-2-4, 6-9 in Table 5) fitted to the in situ data. The V.2 algorithm (TSM-5) showed the poorest performance ($r=0.535$, ME = −0.18, RMSE = 0.36) for the in situ data set, and V.1 algorithm (TSM-1) showed better performance ($r=0.877$, ME = −0.21, RMSE = 0.27). Other algorithms (TSM-2-4, 6-9) tuned to the in situ data showed similarly better performance ($r=0.806–0.887$, ME = 0.00–1.29, RMSE = 0.17–0.22).

Those algorithms were also evaluated with SGLI Rrs. The V.2 algorithm (TSM-5) with original and linearly corrected SGLI data was not very different from in situ data ($r=0.531–0.535$, ME = −0.07 to −0.29, RMSE = 0.29–0.41). The tuned algorithms with two wavelengths with or without normalization (TSM-6-9) were much worse than with the in situ data, and slightly worse ($r=0.370–0.511$, ME = −0.22 to 0.22, RMSE = 0.34–0.42) than the V.2 algorithm (TSM-5). Because of the assumption of the linear correction, the results of algorithms with only Rrs(565) and Rrs(672) (TSM-2-4) were the same for the original. The performances of single wavelength algorithms (TSM-2-4) were much poorer ($r=0.283–0.316$, ME = −0.26 to 0.23, RMSE = 0.36–0.46) than the V.2 algorithm (TSM-5).

Table 3 Correlation between in situ water constituents and nRrs

|          | log(Chl-a) | log(TSM) | log(CDOM) | nRrs(380) | nRrs(412) | nRrs(443) | nRrs(490) | nRrs(530) | nRrs(672) |
|----------|------------|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| log(Chl-a) | 1          | 0.443**  | 0.094     | −0.381*** | −0.413*** | −0.419*** | −0.521*** | −0.583*** | 0.389***  |
| log(TSM)  | 1          | −0.164   | −0.215    | 0.056     | 0.177     | 0.115     | 0.093     | 0.881***  |           |
| log(CDOM) | 1          | 0.251*   | −0.532*** | −0.611*** | −0.559*** | −0.225    | −0.054    |           |           |
| nRrs(380) | 1          | 0.918*** | 0.717***  | 0.547***  | 0.414***  | 0.161     |           |           |           |
| nRrs(412) | 1          | 0.909*** | 0.762***  | 0.566***  | 0.029     |           |           |           |           |
| nRrs(443) | 1          | 0.919*** | 0.695***  | 0.178*    |           |           |           |           |           |
| nRrs(490) | 1          |          |           | 0.847***  | 0.071     |           |           |           |           |
| nRrs(530) | 1          |          |           |           |           |           |           | 0.033     |           |
| nRrs(672) | 1          |          |           |           |           |           |           |           | 1         |

$n = 126$ (Chl-a and nRrs), $n = 75$ (CDOM and nRrs), $n = 66$ (Chl-a and CDOM), $n = 43$ (Chl-a and TSM; TSM and nRrs)

Table 4 Comparison of performances of different algorithms for Chl-a

| Inputs and algorithms | Equation | $r$ | $n$ | ME | RMSE | Slope | Intercept |
|-----------------------|----------|-----|-----|----|------|-------|-----------|
| In situ Rrs           |          |     |     |    |      |       |           |
| CHL-1 SGLI V.2        | Equation (1) | 0.563 | 126 | 0.37 | 0.45 | 0.386 | 0.327     |
| CHL-2 nRrs(530)       | $\text{Log(Chl-a)} = 0.071–11.7\times\text{Log(nRrs(530))}$ | 0.583 | 126 | 0.25 | 0.32 | 0.583 | 0.448     |
| CHL-3 Switching       | $\text{Log(Chl-a)} = 0.135–10.1\times\text{Log(nRrs(530))}$ for Rrs(672)<0.005, $\text{Log(Chl-a)} = 0.381–20.6\times\text{Log(nRrs(530))}$ for Rrs(672)>0.005 | 0.695 | 126 | 0.22 | 0.28 | 1.01 | −0.002    |
| CHL-4 Multiple Regression | $\text{Log(Chl-a)} = 0.893–6.96\times\text{Log(nRrs(530))} + 0.907\times\text{Log(nRrs(672))}$ | 0.693 | 126 | 0.20 | 0.20 | 0.70 | 0.341     |
| Original SGLI V.2 Rrs |          |     |     |    |      |       |           |
| CHL-1 SGLI V.2        |          | 0.512 | 116 | −0.19 | 0.37 | 0.684 | 0.118     |
| CHL-2 nRrs(530)       |          | 0.522 | 116 | 0.20 | 0.56 | 1.70 | −0.492    |
| CHL-3 Switching       |          | 0.586 | 116 | 0.34 | 0.69 | 2.04 | −0.691    |
| CHL-4 Multiple Regression |          | 0.528 | 116 | 0.17 | 0.41 | 1.16 | 0.009     |
| Linearly Corrected SGLI V.2 Rrs |          | 0.530 | 116 | −0.34 | 0.46 | 0.543 | 0.111     |
| CHL-1 SGLI V.2        |          | 0.523 | 116 | −0.17 | 0.49 | 1.51 | −0.662    |
| CHL-2 nRrs(530)       |          | 0.556 | 116 | −0.14 | 0.50 | 1.62 | −0.752    |
| CHL-4 Multiple Regression |          | 0.583 | 116 | −0.05 | 0.32 | 0.945 | 0.003     |
and similar to the performance of the original V.1 algorithm (TSM-1) \((r=0.316, \text{ME}=-0.20, \text{RMSE}=0.39)\).

Those results indicated that the atmospheric correction errors of \(R_{rs}(565)\) and \(R_{rs}(672)\) were probably the source of the larger error with the single wavelength regression, and improvement of \(R_{rs}\) of those long wavelength is necessary for further improvement of the TSM estimation. The results also indicated that it was not very clear that \(R_{rs}\) of short wavelength was necessary as V.2 rather than single wavelength as V.1. This is consistent with the results that the correlations of TSM with \(nR_{rs}\) at short wavelength was not significant, although the correlation was significant with Chl-\(a\) (Table 3).

3.3.4 CDOM algorithm

Finally, we evaluated SGLI V.2 CDOM algorithms (CDOM-1-2 in Table 6) and simple regression algorithms (CDOM-3-5 in Table 6) with log-transformed \(nR_{rs}(412)\), \(nR_{rs}(443)\) and \(nR_{rs}(490)\). We realized that the input bands of V.2 CDOM was mistakenly shifted from the six bands of 380–565 nm (CDOM-1) to the six bands of 412–670 nm (CDOM-2) for the SGLI products (https://www.eorc.jaxa.jp/JASMES/docs/20220301_About_Bugs_in_CDOM_of_SGLI_NRT.pdf), so we also checked the results from the shifted bands and the original bands.

The V.2 algorithm (CDOM-2) with original bands showed the highest correlation \((r=0.676)\) compared with

### Table 5 Comparison of performances of different algorithms for TSM

| Inputs and algorithms | Equation | \(r\) | \(n\) | ME  | RMSE | Slope | Intercept |
|-----------------------|----------|-------|-------|-----|------|--------|-----------|
| **In situ \(R_{rs}\)** |          |       |       |     |      |        |           |
| TSM-1 SGLI V.1 (Eq. 2) | \(\log(TSM) = 2.91 + 0.896*\log(\text{Rrs}(672))\) | 0.877 | 43   | −0.21 | 0.27 | 0.804 | −0.031   |
| TSM-2 \(R_{rs}(565)\) | \(\log(TSM) = 1.80 + 4.71*\log(\text{Rrs}(565))\) | 0.806 | 43   | 0.00  | 0.22 | 1.00  | 0.000     |
| TSM-3 \(R_{rs}(672)\) | \(\log(TSM) = 3.66 + 1.12*\log(\text{Rrs}(672))\) | 0.877 | 43   | 0.00  | 0.17 | 1.00  | −0.001    |
| TSM-4 \(nR_{rs}(672)\) | \(\log(TSM) = 1.84 + 2.60*\log(\text{nRrs}(672))\) | 0.881 | 43   | 1.29  | 0.17 | 2.60  | 1.84      |
| TSM-5 SGLI V.2 (Eq. 3) | \(\log(TSM) = 1.21 + 1.58*\log(\text{nRrs}(490)) + 0.363*\log(\text{Rrs}(565))\) | 0.535 | 43   | −0.18 | 0.36 | 0.258 | 0.514     |
| TSM-6 \(nR_{rs}(490), R_{rs}(565)\) | \(\log(TSM) = 3.96 + 0.42*\log(\text{nRrs}(490)) + 1.47*\log(\text{Rrs}(565))\) | 0.808 | 43   | 0.02  | 0.21 | 0.652 | 0.349     |
| TSM-7 \(nR_{rs}(530), R_{rs}(565)\) | \(\log(TSM) = 3.98 + 2.44*\log(\text{nRrs}(530)) + 1.53*\log(\text{Rrs}(565))\) | 0.819 | 43   | 0.02  | 0.20 | 0.819 | 0.191     |
| TSM-8 \(nR_{rs}(530), R_{rs}(672)\) | \(\log(TSM) = 3.27 + 2.08*\log(\text{nRrs}(530)) + 1.01*\log(\text{Rrs}(672))\) | 0.887 | 43   | 0.01  | 0.17 | 0.886 | 0.120     |
| TSM-9 \(nR_{rs}(530), nR_{rs}(672)\) | \(\log(TSM) = 1.70 + 0.714*\log(\text{nRrs}(530)) + 2.30*\log(\text{Rrs}(672))\) | 0.882 | 43   | 0.01  | 0.17 | 0.881 | 0.126     |
| **Original SGLI V.2 \(R_{rs}\)** |          |       |       |     |      |        |           |
| TSM-1 SGLI V.1 (Eq. 2) | Same as the original |       |       |     |      |        |           |
| TSM-2 \(R_{rs}(565)\) | Same as the original |       |       |     |      |        |           |
| TSM-3 \(R_{rs}(672)\) | Same as the original |       |       |     |      |        |           |
| TSM-4 \(nR_{rs}(672)\) | Same as the original |       |       |     |      |        |           |
| TSM-5 SGLI V.2 (Eq. 3) | \(\log(TSM) = 0.531 + 0.07*\log(\text{nRrs}(530)) + 2.44*\log(\text{Rrs}(565))\) | 0.369 | 31   | 0.23  | 0.39 | 0.636 | 0.588     |
| TSM-6 \(nR_{rs}(490), R_{rs}(565)\) | \(\log(TSM) = 0.511 + 0.22*\log(\text{nRrs}(530)) + 0.38*\log(\text{Rrs}(672))\) | 0.480 | 31   | 0.05  | 0.34 | 0.976 | 0.073     |
| TSM-7 \(nR_{rs}(530), R_{rs}(672)\) | \(\log(TSM) = 0.370 + 0.22*\log(\text{nRrs}(530)) + 0.42*\log(\text{Rrs}(672))\) | 0.373 | 31   | −0.22 | 0.42 | 0.937 | −0.156    |
| **Linearly Corrected SGLI V.2 \(R_{rs}\)** |          |       |       |     |      |        |           |
| TSM-1 SGLI V.1 (Eq. 2) | Same as the original |       |       |     |      |        |           |
| TSM-2 \(R_{rs}(565)\) | Same as the original |       |       |     |      |        |           |
| TSM-3 \(R_{rs}(672)\) | Same as the original |       |       |     |      |        |           |
| TSM-4 \(nR_{rs}(672)\) | Same as the original |       |       |     |      |        |           |
| TSM-5 SGLI V.2 (Eq. 3) | \(\log(TSM) = 0.535 + 0.09*\log(\text{nRrs}(530)) + 0.42*\log(\text{Rrs}(565))\) | 0.392 | 31   | 0.16  | 0.35 | 0.600 | 0.562     |
| TSM-6 \(nR_{rs}(490), R_{rs}(565)\) | \(\log(TSM) = 0.532 + 0.15*\log(\text{nRrs}(530)) + 0.33*\log(\text{Rrs}(672))\) | 0.498 | 31   | −0.01 | 0.32 | 0.904 | −0.080    |
| TSM-7 \(nR_{rs}(530), R_{rs}(672)\) | \(\log(TSM) = 0.373 + 0.24*\log(\text{nRrs}(530)) + 0.43*\log(\text{Rrs}(672))\) | 0.373 | 31   | −0.24 | 0.43 | 0.912 | −0.154    |
the linear regressions (CDOM-3-5) \(r = 0.532–0.611\) for in situ data, although the ME and RMSE of the V.2 algorithm were higher (ME = −0.20, RMSE = 0.23) and showed negative intercept (−0.331) indicating the underestimation. The V.2 CDOM was estimated by \(a_{\text{CDOM+NAP}}\) from the IOP algorithm and by simple relationship between CDOM and \(a_{\text{CDOM+NAP}}\). The estimation of CDOM from \(a_{\text{CDOM+NAP}}\) could induce overestimation because of the high turbidity with high \(a_{\text{NAP}}\) in Ariake Bay (not shown data). Thus, \(a_{\text{CDOM+NAP}}\) was probably underestimated by the IOP algorithm. This indicated that further development of the IOP algorithm as well as the conversion from \(a_{\text{CDOM+NAP}}\) to CDOM is necessary for the accurate CDOM estimation in Ariake Bay, although the statistics of CDOM estimation was not bad. The V.2 algorithm (CDOM-1) with the shifted bands showed the lowest performance \(r = 0.411, \text{ME} = -0.32, \text{RMSE} = 0.35\) with larger underestimation.

With the original SGLI V.2 Rsrs, the V.2 algorithm with shifted bands (CDOM-1) showed a higher correlation \(r = 0.688\) compared with all other linear algorithms (CDOM-3-5) \(r = 0.123–0.597\). The regression algorithm with \(n_{\text{Rrs}}(412)\) (CDOM-3) showed poor results \(r = 0.123, \text{ME} = 1.97, \text{RMSE} = 2.22\) with the original SGLI Rsrs because of the poor atmospheric correction. The results became better \(r = 0.530, \text{ME} = 0.33, \text{RMSE} = 0.47\) with \(n_{\text{Rrs}}(443)\) (CHL-4) and further better with \(n_{\text{Rrs}}(490)\) (CHL-5) \(r = 0.597, \text{ME} = -0.11, \text{RMSE} = 0.29\). The V.2 algorithm with the original bands (CDOM-2) showed the highest correlation \(r = 0.803\); however, it should be noticed that the sample number was significantly smaller \(n = 5\). This is because the original algorithm requires a positive value of Rsrs(380), and a large number of SGLI V.2 Rsrs(380) were negative as described previously.

With linearly corrected SGLI V.2 Rsrs, SGLI V.2 algorithm with shifted band (CDOM-1) showed much worse result than the original SGLI Rsrs. The algorithm with \(n_{\text{Rrs}}(412)\) (CDOM-3) was not calculated because of the assumption of constant \(n_{\text{Rrs}}(412)\). The results of the regression algorithms with the linearly corrected Rsrs(443) (CDOM-4) and Rsrs(490) (CDOM-5) became better, and the linear correction improved the performance of the simple regression algorithms \(n_{\text{Rrs}}(443)\) (CDOM-4) best. Rsrs(380) was calculated from Rsrs(565) similar to the Rsrs(412) for the linear correction of Rsrs and used with the SGLI V.2 algorithm (CDOM-2). The correlation of the estimated CDOM with the in situ CDOM was high \(r = 0.714\), although the estimated values were underestimated (ME = −0.55, RMSE = 0.56). This indicated that the SGLI V.2 algorithm could be the best algorithm with the simple linear correction for the SGLI Rsrs.

3.4 Time Series of Chl-\(a\), TSM and CDOM

Time series of Chl-\(a\), TSM and CDOM during April 2018 and March 2019 at the location of AERONET-OC position were examined with both AERONET-OC and linearly

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### Table 6 Comparison of performances of different algorithms for CDOM

| Inputs and algorithms | Equation | \(r\) | \(n\) | ME | RMSE | Slope | Intercept |
|-----------------------|---------|-------|-------|-----|------|-------|-----------|
| **In situ Rsrs**      |         |       |       |     |      |       |           |
| CDOM-1                | SGLI V.2 IOP (Shifted Bands) | 0.411 | 75    | −0.32 | 0.35 | 0.645 | −0.493    |
| CDOM-2                | SGLI V.2 IOP (Original Bands) | 0.676 | 75    | −0.20 | 0.23 | 0.730 | −0.331    |
| CDOM-3                | \(n_{\text{Rrs}}(412)\) \(\text{Log(CDOM)} = -1.56–2.16*\text{Log(nRrs(412))}\) | 0.532 | 75    | 0.00  | 0.14 | 1.00  | 0.000     |
| CDOM-4                | \(n_{\text{Rrs}}(443)\) \(\text{Log(CDOM)} = -1.25–2.05*\text{Log(nRrs(443))}\) | 0.611 | 75    | 0.00  | 0.13 | 1.00  | 0.000     |
| CDOM-5                | \(n_{\text{Rrs}}(490)\) \(\text{Log(CDOM)} = -1.00–2.53*\text{Log(nRrs(490))}\) | 0.558 | 75    | 0.00  | 0.13 | 1.00  | −0.001    |
| **Original SGLI V.2 Rsrs** |         |       |       |     |      |       |           |
| CDOM-1                | SGLI V.2 IOP (Shifted Bands) | 0.688 | 30    | −0.40 | 0.40 | 1.07  | −0.348    |
| CDOM-2                | SGLI V.2 IOP (Original Bands) | 0.803 | 5     | 0    | 0.22 | 0.26  | 0.523     |
| CDOM-3                | \(n_{\text{Rrs}}(412)\) | 0.123 | 30    | 1.97  | 2.22 | 6.23  | 3.96      |
| CDOM-4                | \(n_{\text{Rrs}}(443)\) | 0.530 | 30    | 0.33  | 0.47 | 2.36  | 0.854     |
| CDOM-5                | \(n_{\text{Rrs}}(490)\) | 0.597 | 30    | −0.11 | 0.29 | 1.21  | −0.033    |
| **Linearly Corrected SGLI V.2 Rsrs** |         |       |       |     |      |       |           |
| CDOM-1                | SGLI V.2 IOP (Shifted Bands) | 0.484 | 30    | −0.39 | 0.42 | 0.970 | −0.399    |
| CDOM-2                | SGLI V.2 IOP (Original Bands) | 0.714 | 30    | −0.55 | 0.56 | 0.836 | −0.611    |
| CDOM-3                | \(n_{\text{Rrs}}(412)\) | Not available |       |       |     |       |           |
| CDOM-4                | \(n_{\text{Rrs}}(443)\) | 0.654 | 30    | −0.25 | 0.28 | 0.903 | −0.284    |
| CDOM-5                | \(n_{\text{Rrs}}(490)\) | 0.604 | 30    | −0.26 | 0.35 | 1.08  | −0.233    |

See text for the detail explanation of the SGLI V.2 algorithm
Fig. 6 Time series of Chl-α with CHL-1 (a) and CHL-4 (b), TSM with TSM-1 (c) and TSM-5 (d), and CDOM with CDOM-2 (e) and CHL-4 (f). The Rs data was taken by AERONET-OC (open) and SGLI (fill). SGLI Rs data were V.2 and corrected with LC and adjusted to the value of Rs from AERONET-OC. The line indicates the running mean with 31 days of both data corrected SGLI data (Fig. 6). In this analysis, Chl-α was calculated with SGLI V.2 (CHL-1) and nRrs(530) and nRrs(672) multiple regression (CHL-4) algorithms. TSM was calculated with the SGLI V.1 (TSM-1) and V.2 (TSM-5) algorithms. CDOM was calculated by the SGLI V.2 algorithm with the original band (CDOM-2) and tuned nRrs(443) algorithm (CDOM-4). As described earlier, the comparisons of Rs and nRs showed significant difference between SGLI and AERONET-OC for most of the wavelength (Table 2). Thus, we first compared each water constituent derived from SGLI and AERONET-OC (Table 7). Chl-α, TSM and CDOM were significantly different between the one derived
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from SGLI and from AERONET-OC Rs. To obtain a consistent time series between SGLI and AERONET-OC, the SGLI Rs were transformed with the linear relationship shown in Table 2 after linear correction. The transformation made the difference of water constituents from SGLI and AERONET-OC not significant (Table 7). However, the CDOM with SGLI V.2 algorithm showed poorer statistics with the adjustment and estimation of a few large values.

Chl-a with SGLI V.2 algorithm (CHL-1) varied from 2.94 to 16.4 mg m\(^{-3}\) and from 1.86 to 40.3 mg m\(^{-3}\) for AERONET-OC and SGLI data, respectively (Fig. 6a). SGLI Chl-a data showed larger variation than the one of AERONET-OC, although the matched data indicate small mean differences (cf. Table 7). For both data, the variation within each month was fairly large, and the monthly averaged Chl-a was high in July and August 2018 and March 2019.

Chl-a with regression of nRrs(530) and nRr(672) (CHL-4) varied from 3.60 to 62.7 mg m\(^{-3}\) and from 1.72 to 91.3 mg m\(^{-3}\) for AERONET-OC and SGLI data, respectively (Fig. 6b). Generally, this tuned algorithm Chl-a from both AERONET-OC and SGLI Rs was more than twice higher than the Chl-a with the SGLI V.2 algorithm, although the correlation was high (r = 0.941). The time variation of this algorithm was similar to Chl-a with SGLI algorithm, and higher in July to August, November 2018 and March 2019 with large variation within a month.

TSM from SGLI V.1 algorithm (TSM-1) varied from 1.87 to 21.3 g m\(^{-3}\) for AERONET-OC data and 2.21 to 19.2 g m\(^{-3}\) for SGLI data, and the variation were very similar to each other (Fig. 6c). The time variation was high in April, July, and October 2018 and January 2019 and different from Chl-a. It showed weak negative correlation with Chl-a from SGLI V.2 algorithm (CHL-1) (r = −0.221, p < 0.05) and no correlation with Chl-a from tuned algorithm (CHL-4) (r = 0.087).

On the other hand, TSM derived from V.2 algorithm (TSM-5) with AERONET-OC data was from 4.07 to 10.0 g m\(^{-3}\), and both magnitude and variation were smaller than V.1 TSM (Fig. 6d). V.2 TSM from SGLI data was from 4.32 to 35.9 g m\(^{-3}\), and the variation was also slightly lower than the V.1 TSM. V.2 TSM was high in July and August 2018 and March 2019. This time variation was different from V.1 TSM, and it was similar to Chl-a. The V.2 TSM showed positive correlation with V.2 Chl-a (r = 0.636) and tuned Chl-a (r = 0.624). Correlation between TSM from V.1 and V.2 algorithms was not significant (r = −0.125).

Those results may indicate that V.2 TSM was influenced by absorption of Chl-a or associated organic matter, although V.1 TSM was mostly detected by the scattering of inorganic matter.

The time series of CDOM by SGLI V.2 algorithm with original band (CDOM-2) varied from 0.165 to 0.275 m\(^{-1}\) for AERONET-OC data and 0.186 to 0.304 m\(^{-1}\) for SGLI data, and the variation were very similar to each other (Fig. 6c).

| Table 7 | Correlations and differences between AERONET-OC and SGLI data for Chl-a with CHL-1 and CHL-4, TSM with TSM-1 and TSM-5, and CDOM with CDOM-2 and CDOM-4 |
|---------|---------------------------------|
|          | r     | n    | MD         | RMSD | Slope   | Intercept |
| Chl-a V.2 | Original | 0.616 | 55 | 0.0649*** | 0.171 | 0.972 | 0.0856 |
|          | LC     | 0.613 | 55 | −0.110*** | 0.184 | 0.778 | 0.0527 |
|          | LC adjust | 0.626 | 55 | 0.00336 | 0.179 | 1.22 | −0.155 |
| Chl-a nRrs(530), nRr(672) | Original | 0.637 | 55 | 0.0939*** | 0.264 | 0.955 | 0.142 |
|          | LC     | 0.633 | 155 | −0.181*** | 0.301 | 0.881 | −0.0513 |
|          | LC adjust | 0.65 | 55 | −0.00212 | 0.277 | 1.20 | −0.214 |
| TSM V.1 | Original | 0.884 | 55 | 0.00214 | 0.0860 | 0.901 | 0.0831 |
|          | LC     | Same as Original |
|          | LC adjust | 0.884 | 55 | −0.00012 | 0.0881 | 0.992 | 0.00646 |
| TSM V.2 | Original | 0.836 | 55 | 0.119*** | 0.129 | 1.19 | −0.0339 |
|          | LC     | 0.830 | 55 | −0.0603*** | 0.0745 | 0.921 | 0.00446 |
|          | LC adjust | 0.809 | 55 | 0.00354 | 0.0563 | 1.24 | −0.189 |
| CDOM V.2 | Original | 0.417 | 48 | −0.0251*** | 0.0348 | 0.8865 | −0.0029 |
|          | LC     | 0.289 | 48 | 0.00439 | 0.0736 | 3.25 | −0.436 |
| CDOM   | Original | 0.414 | 55 | 0.571*** | 0.610 | 1.97 | 1.04 |
| nRrs(443) | LC | 0.391 | 55 | −0.131*** | 0.179 | 0.818 | −0.220 |
|          | LC adjust | 0.423 | 55 | 0.00191 | 0.142 | 1.20 | 0.0971 |
AERONET-OC and 0.132 to 0.292 m\(^{-1}\) for SGLI (Fig. 6e). The time variation showed high in July and August 2018 and February 2019, and it was similar to the variation of V.2 TSM. It does not show correlation with Chl-a from SGLI (\(r = 0.025\)) and tuned (\(r = -0.065\)) algorithms. It also showed weak negative correlation with V.1 TSM (\(r = -0.331, p < 0.005\)) and positive correlation with V.2 TSM (\(r = 0.409\)).

The time series of CDOM with tuned nRrs(443) algorithm (CDOM-4) varied from 0.209 to 0.591 m\(^{-1}\) for AERONET-OC and 0.178 to 0.876 m\(^{-1}\) for SGLI (Fig. 6f). The time variation was high in July, August, November 2018 and March 2019, and it was similar to the variations of Chl-a and V.2 TSM. It showed high positive correlation with Chl-a from SGLI (\(r = 0.815\)) and tuned (\(r = 0.739\)) algorithms. It also showed negative correlation with V.1 TSM (\(r = -0.372\)) and positive correlation with V.2 TSM (\(r = 0.579\)). Because in situ data of Chl-a and CDOM did not show significant correlation (Table 3), there may be a problem of interference of estimations of Chl-a and CDOM.

### 3.5 Comparison to river discharge and sea level variation

The time series of Chl-a, TSM and CDOM were also analyzed and compared with the two possible main controlling factors, river discharge and sea level variation (Fig. 7). The 31-day running means and the anomalies were calculated for those parameters to separate the different time scales for longer (month to seasonal) river discharge and shorter (2 weeks spring–neap tidal cycle) sea level variation.

Chl-a from two algorithms (CHL-1, 4) indicated similar variation after running mean, and showed slight peak in late May, July–August, late November 2018 and March 2019 (Fig. 7a, b). The river discharge with 31-day running mean showed a large peak in June–July 2018, and smaller peaks in April–May 2018, September–October 2018, and February–March 2019. The lagged correlations of the 31-day running mean of the 1-year time series of SGLI V.2 and tuned algorithms peaked at 44 days (\(r = 0.288, p < 0.01\) for more than 15 days) and 48 days (\(r = 0.326, p < 0.01\) for more than 17 days), respectively.

The time series of SGLI V.1 TSM (TSM-1) with 31-day running mean showed peaks in May, June–July 2018, December 2018 to January 2019, and the lagged correlations of the 31-day running mean showed weak correlation peak with no time lag (\(r = 0.114, p < 0.05\)), and significant negative correlation after 15 days and peak at 32-day time lag (\(r = -0.288\)) (Fig. 7c). This was different for the time series of SGLI V.2 TSM (TSM-5) with 31-day running mean with slight peak in early June, July–August, and late November 2018, and March 2019, and the highest correlation was a time lag of 24 days (\(r = 0.595, p < 0.01\) even without time lag (Fig. 7d). This may indicate that V.1 TSM was more influenced by the direct discharge of sediments, while V.2 TSM was more related to the phytoplankton abundance corresponding to Chl-a.

The time series of CDOM by the SGLI V.2 algorithm with original band (CDOM-2) with 31-day running mean peaked slightly higher in June–August 2018 and February 2019 (Fig. 7e). The time series showed correlation with river discharge with a time lag of 12 days (\(r = 0.459, p < 0.01\)) without time lag). The time series of CDOM by tuned nRrs(443) algorithm (CDOM-4) with 31-day running mean peaked in July–August 2018 and March 2019 (Fig. 7f). The time series showed correlation with river discharge with time lag of 46 days (\(r = 0.554, p < 0.01\) for more than 10 days). The variation was similar to Chl-a, and probably the estimation of CDOM was contaminated by Chl-a as described previously.

The time series of residuals of each parameter were compared with the residual of maximum sea level difference in one day. Residual of Chl-a from both algorithms (CHL-1, 4) and the daily sea level difference showed no significance, but the highest correlations with time lag of 8 days (\(r = 0.074\)) and 11 days (\(r = 0.130\)), respectively (Fig. 7a, b).

Correlation of residual of V.1 TSM (TSM-1) was significantly (\(p < 0.01\)) negative for the time lag of 2—5 days (\(r = -0.347\) to \(-0.285\)) and positive for time lag of 11–13 days (\(r = 0.323–0.288\)) (Fig. 7c). The correlation of residual of V.2 TSM (TSM-5) also showed negative and positive correlation for the time lag of 5–6 days (\(r = 0.192\) to \(-0.183\)) and 14 days (\(r = 0.209\)), respectively, although it was not significant (\(p < 0.1\)) (Fig. 7d). Those correlations indicate that the short-term Chl-a and TSM variations seem to be consistent with the previous finding that TSM increases during spring tide with higher sea level difference, whereas Chl-a increased during neap tide with lower sea level difference.

The residual of CDOM by SGLI V.2 algorithm with original band (CDOM-2) and sea level difference was positive (\(r = 0.109\)) and negative (\(r = -0.138\)) for 1- and 6-day time lag, although those were not significant (Fig. 7e). The residual of CDOM by tuned nRrs(443) algorithm (CDOM-4) and sea level difference was positive (\(r = -0.081\)) and negative (\(r = -0.067\)) for the 3- and 10-day time lag, although those were not significant (Fig. 7f).

### 4 Discussion

#### 4.1 Atmospheric correction

Comparison of AERONET-OC and SGLI Rrs data showed a larger error in short wavelength than longer wavelength. Specifically, Rrs(380) and Rrs(412) often became negative
for SGLI Rrs, indicating the possibility of the presence of absorptive aerosol (Li et al. 2003; Toratani et al. 2007). High suspended sediment in the shallow area of Ariake Sea may also be one of the causes of the error (Siegel et al. 2000).

The error of Rrs can directly influence the error of the water constituent. Specifically, CDOM used the short wavelength (i.e. 412 nm) and the influence is large. Chl-$\alpha$ algorithm used 443 and/or 490 nm is also influenced by the error. However,

Fig. 7 Time series with 31-day running mean (blue lines in upper panels) and the anomaly (blue dots in lower panels) of Chl-$\alpha$ with CHL-1 (a) and CHL-4 (b), TSM with TSM-1 (c) and TSM-5 (d), and CDOM with CDOM-2 (e) and CDOM-4 (f). The Rrs data were taken by AERONET-OC (open) and SGLI data (fill). Black solid and dotted lines in the upper panels indicate river discharge and the one with time lag with the maximum correlation to the parameters, respectively. Black solid line in the lower panels indicates daily sea level differences.
SGLI Chl-α algorithm uses 530 nm for high Chl-α area, such as Ariake Sea, and the influence was minimized. This result was consistent with the conclusion of Isada et al. (2021, this volume), who showed that SGLI Chl-α was better than other satellites which used longer wavelength algorithm in the coastal water of Hokkaido, Japan.

AERONET-OC in Ariake Sea was already used for the verification of atmospheric correction of ocean color sensors and algorithms. For example, Feng (2021) verified standard GOCI processed by GOCl Data Processed System (GDPS) and indicated Rs from 490 to 555 nm was better than the Rs of shorter wavelength even in turbid water in Ariake Sea, while He et al. (2021) showed that standard GOCI was better than the data processed by Sea-Viewing Wide Field-of-View Sensor Data Analysis System (SeaDAS). Pahlevan et al. (2021) introduced the results of global assessment of Atmospheric Correction Intercomparison Exercise (ACIX-Aqua) with eight algorithms for Landsat-8 and Sentinel-2 data and indicated the large error in blue wavelength.

Simple linear correction method to improve standard Rs was examined for SGLI. This method was applied in Japanese coastal and inland waters, including Ariake Sea, and they showed good performance with SeaWiFS and MODIS data (Hayashi et al. 2015; Yang et al. 2018; Tsukamoto et al. 2019). The method also performed well for SGLI data, and comparison to AERONET-OC showed the improvement of Rs. The method clearly improved the SGLI V.1 Rs data, which was large negative for short wavelength. For SGLI V.2 Rs for which the negative Rs correction of Rs(412) was already applied, Rs(443) and Rs(490) were still improved by the linear correction, although the improvement of Rs(530) was not clear.

The advantage of this linear correction method was that it is possible to improve standard Rs with simple calculation without recalculation of complex atmospheric correction algorithm, especially the region with many pixels with large errors of Rs, such as negative Rs caused by absorptive aerosols. The method requires the a priori knowledge of the relationship between green (i.e., 565 nm) and blue (i.e., 412 nm) with small and large satellite error, respectively, from in situ data. Once the relationship can be assumed, it is easy to improve the Rs of short wavelength.

More sophisticated atmospheric correction method coupled with ocean optics is also becoming available. Fan et al. (2021) showed the verification of Ocean Color-Simultaneous Marine and Aerosol Retrieval Tool (OC-SMART), which is a machine learning inversion of the atmosphere–ocean model, with many AERONET-OC data, including from Ariake Sea, to show the good performance. Sekiguchi et al. (2021) also verified Lwn retrieved from SIRAW (SIMultaneous Retrieval of Aerosol and Water-leaving radiance) by Shi et al (2019) and compared with SGLI standard V.2 algorithms with AERONET-OC data in Ariake Sea and found the retrieval of SIRAW was better. It is also expected that those coupled atmosphere–ocean optical models may be promising.

### 4.2 Verification of water constituents and in-water algorithms

In this study, water constituents (Chl-α, TSM and CDOM) of SGLI were verified in Ariake Sea. Chl-α was generally overestimated by the V.1 product, and it was improved by V.2 products (Table 4). This was mostly caused by the improvement of Rs(530) because the in-water algorithms were not very different. However, the V.2 product slightly underestimated the Chl-α, and this was mostly caused by the in-water algorithm. We also fitted some simple in-water algorithms, including nRrs(530) (CHL-2), nRrs(530) with switching with nRrs(672) (CHL-3), and multiple regression of nRrs(530) and nRrs(672) (CHL-4), to the in situ data and obtained slightly better results. The results indicated that nRrs(672) was important to improve the fitting, indicating that the correction of the influence of suspended matter is necessary. This is consistent with the result of Yang et al. (2018) and reasonable for this fairly turbid water of Ariake Sea. We also verified the algorithms with the different in situ data with original SGLI V.2 Rs data as well as linearly corrected V.2 Rs, and the results indicated that the nRrs(672) was still important, although the results were not as good as with the fitting data. The statistics indicated that the further improvement of the in-water Chl-α algorithm is required.

The correlations of both V.1 (Rs(672))(TSM-1) and V.2 (nRrs(490) and Rrs(565))(TSM-5) products of TSM with in situ data was similar to the ones of Chl-α, and the underestimation of V.1 product was improved by V.2 (Table 5). The fitting of single regressions with Rs(565)(TSM-2), Rs(672)(TSM-3), and nRrs(672)(TSM-4) as well as the multiple regressions with nRrs(490) and Rs(565)(TSM-6), nRrs(530) and Rrs(565)(TSM-7), nRrs(530) and Rs(672) (TSM-8), and nRrs(530) and nRrs(672)(TSM-9), improved the results. However, the use of SGLI Rs data degrades the performance of all the algorithms, and those results indicated that the algorithms were also sensitive to the small error of Rs.

It is also interesting to see the different behavior of TSM calculated from the time series of Rs with the V.1 and V.2 algorithm (Fig. 6). V.1 TSM showed mostly the influence of suspended sediment, whereas V.2 TSM also had the influence of Chl-α. In situ data showed significant correlation between TSM and Chl-α, and V.2 TSM algorithm was reasonable to estimate TSM in Ariake Sea, where there was correlation between TSM and Chl-α, although the V.1 TSM showed better results with in situ Rs.
Many data of V.1 CDOM were missing because of the negative Rs(380) and Rs(412), and data number and correlation of V.2 CDOM increased from V.1. However, both V.1 and V.2 SGLI CDOM underestimated the in situ CDOM. Band shift for the implementation of V.2 algorithm (CDOM-1) was found for the JASMES product (https://www.eorc.jaxa.jp/JASMES/docs/20220301_About_Bugs_in_CDOM_of_SGLI_NRT.pdf), and this seems to be one of the reasons of the underestimation, although the verification of the algorithm indicates that the estimation of $a_{CDOM+NAP}$ by the original IOP algorithm also caused the underestimation. Proper implementation of the bands made this algorithm (CDOM-2) show the best correlation compared with simple regressions of nRs(412), nRs(443), and nRs(490) (CDOM-3–5), although the correction of negative Rs(380) is necessary for satellite data. The results of the V.2 CDOM algorithm showed no correlation with Chl-$a$, although CDOM from the regression algorithms showed correlation with Chl-$a$. This indicated that the simple regression algorithms cannot separate CDOM from the influences of Chl-$a$, and sophisticated IOP algorithm is necessary.

4.3 Time series of AERONET-OC

The data of AERONET-OC was mostly used for verification of the satellite ocean color data. However, the time series of AERONET-OC should be also useful for the understanding of variations of the optical and water constituents. In this study, AERONET-OC with SGLI Rrs data, time series of water constituents were derived to see the relation to river discharge and spring–neap tidal cycle.

The time series of both Chl-$a$ with SGLI and two wavelengths were correlated with river discharge after taking 31-day running mean and more than 31-day time lag with the maximum of 41–44 days time lag. Ishizaka et al. (2006) showed high monthly Chl-$a$ for the month of high precipitation. Tsutsumi (2012) also reported that low salinity water after river discharge is important for high phytoplankton bloom in Ariake Bay. More than 1 month seems to be long for phytoplankton response to river discharge, but probably the variation caused by the accumulation of nutrients loaded into the bay was shown after the 31-day running mean.

V.1 TSM showed that the time lag was shorter than the ones of Chl-$a$. This indicates the different behavior of Chl-$a$ and V.1 TSM, although V.2 TSM seems to show mixed characteristics. It is expected that V.1 TSM was mostly influenced by only inorganic sediments which dominated by scattering, while V.2 TSM included the Chl-$a$ influence by the absorption. Therefore, the different behaviors of the different estimations of TSM may indicate the different behavior of sediments and Chl-$a$: more input of sediment by the river discharge and growth of phytoplankton by the accumulated nutrients.

The tidal cycle was also suggested to influence to phytoplankton growth, because high turbidity caused by the tidal mixing in spring tide may inhibit the light. Tanaka et al. (2004) reported the high turbidity and low Chl-$a$ during spring tide in the Chikugo River estuary, near the Ariake Tower, during winter 2002–2003. Ito et al. (2013) also showed similar variation of turbidity and Chl-$a$ at the Ariake Tower. Yang et al. (2020) analyzed Chl-$a$ and TSM derived from MODIS with switching and Rs(667)/Rrs(547) algorithms, respectively, in Ariake Sea. The spatially averaged Chl-$a$ and TSM in this study indicated high TSM and low Chl-$a$ during spring and low TSM and high Chl-$a$ during neap tide. Chl-$a$ tend to show nearly negative correlation with sea level difference, while TSM showed more positive correlation. This seems to be a similar behavior to that reported in Tanaka et al. (2004), Ito et al. (2013) and Yang et al. (2020).

Those differences of the behavior derived from the optical algorithm clearly showed the further possibility to use the time series of AERONET-OC with ocean color satellite data to understand the behavior the water constituents as well as the optical characteristics. In this study, only a rough analysis was conducted for the seasonal and neap–tidal cycle; however, it is promising that the data will provide more detailed information, including the change within a daytime since AERONET-OC including several data within a daytime. It is also worth noting that the remote optical measurement is stable for long-time observation with little maintenance compared with the equipment in the water with possible biofouling, once a good platform is found.

5 Conclusion

In this study, SGLI V.1 and V.2 products from JASMES were verified with AERONET-OC and in situ data in Ariake Sea. SGLI V.1 and V.2 products underestimated the short wavelength bands, and Rs(380) and Rs(412) were mostly negative by V.1, and Rs(412) became nearly 0 while Rs(380) was still negative by V.2. Therefore, the differences of SGLI and AERONET-OC Rrs were significant for the short wavelength, and not significant for Rrs(565) and Rrs(672). The presence of the absorptive aerosol may be the reason of the underestimation for the short wavelength Rrs. The simple linear correction method of Rs suggested by Hayashi et al. (2015) also significantly improved SGLI V.1 data. Because of the improvement of short wavelength Rrs from V.1 to V.2, Chl-$a$, TSM and CDOM were also improved from V.1 to V.2. In-water algorithms were also examined with in situ data, and the results indicated that there was limitation for the simple regression-type algorithms. Use of more accurate
atmospheric correction algorithm with more sophisticated in-water algorithms are required for the further improvement of the water constituents in the turbid coastal bay, like Ariake Sea. Furthermore, time series data of AERONET-OC with a combination of ocean color satellite data should be useful to understand the dynamics of water constituents coupling with the optical condition.

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Use of AERONET-OC for validation of SGLI/GCOM-C products in Ariake Sea, Japan

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