Title
Optimized Merger of Ocean Chlorophyll Algorithms of MODIS-Aqua and VIIRS

Permalink
https://escholarship.org/uc/item/6rn5657w

Authors
Kahru, M
Kudela, RM
Anderson, CR
et al.

Publication Date
2015-09-07

DOI
10.1109/LGRS.2015.2470250

Peer reviewed
Optimized Merger of Ocean Chlorophyll Algorithms of MODIS-Aqua and VIIRS


Abstract—Standard ocean chlorophyll-a (Chla) products from currently operational satellite sensors Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua and Visible Infrared Imager Radiometer Suite (VIIRS) underestimate medium and high in situ Chla concentrations and have approximately 9% bias between each other in the California Current. By using the regional optimization approach of Kahru et al., we minimized the differences between satellite estimates and in situ match-ups as well as between estimates of the two satellite sensors and created improved empirical algorithms for both sensors. The regionally optimized Chla estimates from MODIS-Aqua and VIIRS have no bias between each other, have improved retrievals at medium to high in situ Chla, and can be merged to improve temporal frequency and spatial coverage and to extend the merged time series.

Index Terms—Chlorophyll, Moderate Resolution Imaging Spectroradiometer (MODIS), ocean color, phytoplankton, Visible Infrared Imager Radiometer Suite (VIIRS).

I. INTRODUCTION

Combining or merging data from multiple sensors is required to improve the temporal resolution and spatial coverage of ocean color imagery and to construct long time series or climate data records using data from multiple sensors [2]–[5]. Currently (i.e., in mid-2015), there are two well-calibrated global ocean color sensors in operation: Moderate Resolution Imaging Spectroradiometer on Aqua (MODISA) and Visible Infrared Imager Radiometer Suite (VIIRS) on Suomi NPP. While improvements in on-orbit sensor calibration [6] have greatly improved the compatibility between data from different sensors, significant differences remain [7], [8]. Moreover, global algorithms may not be regionally optimized as significant differences exist in bio-optical properties of different oceanic provinces [9]. Standard NASA ocean chlorophyll-a (Chla) algorithms significantly underestimate in situ values in the California Current at high concentrations, often by a factor of 5 [1]. This is highly relevant for detection and monitoring of phytoplankton blooms, including harmful algal blooms [10], 11. While differences between Chla estimates from MODIS-Aqua and VIIRS have diminished after multiple reprocessings, they still exist [8].

Kahru et al. [1] created optimized empirical algorithms for the California Current for a suite of four sensors (OCTS, SeaWiFS, MERIS, and MODISA) and the time period of 1997–2011. An update to that work is currently needed as 1) MERIS stopped operating in April 2012; 2) new data from VIIRS are available from the beginning of 2012; and 3) both MODIS-Aqua and VIIRS data have been reprocessed by NASA’s 50 Ocean Biology Processing Group. The purpose of this work is to create empirical algorithms that are optimized for creating a merged Chla time series in the California Current for the period of 2012–2015 from the two currently available sensors MODISA and VIIRS.

II. DATA AND METHODS

We used in situ Chla data collected by the California Cooperative Oceanic Fisheries Investigations (CalCOFI) on their quarterly cruises covering a regular grid of stations from 59 nearshore to as far as 600 km offshore for the entire coast of California [11]. In total, 3388 near-surface Chla samples from 61 2002–2014 were used to validate MODIS data, and 744 Chla samples from 2012–2014 were used to validate VIIRS data. All satellite data were acquired at level 2 (i.e., processed to surface quantities but unmapped) with approximately 1-km ground resolution. MODISA (2002–2014, version 2013.1.1) and VIIRS (2012–2014, version 2014.0.1) level-2 data were obtained from NASA’s Ocean Color Web (http://oceancolor.gsfc.nasa.gov/). The standard NASA Chla algorithm uses empirical 69 polynomial fits between satellite-derived maximum band ratio (MBR) of remote sensing reflectance (Rrs) bands and near-surface Chla [12] with the coefficient values for each sensor given at http://oceancolor.gsfc.nasa.gov/cms/abdr/chlor_a. The validation of satellite products using quasi-simultaneous 74 and spatially collocated measurements (match-ups) of satellite 75 and in situ data followed the procedures of previous studies 76 [1], [8], [13], [14]. We assumed that the following level-2 77 flags made a pixel invalid: ATMFAIL, LAND, HISATZEN, STRAYLIGHT, CLDICE, CHLFAIL, SEAICE, NAVFAIL, and HIPOL (see http://oceancolor.gsfc.nasa.gov/VALIDATION/80 flags.html for an explanation of the flags). All variables in the level-2 files were extracted from a 3 × 3-pixel window centered at the pixel nearest to the in situ sample. For statistical analysis, we accepted only those match-ups with at least five 84
For sensor-to-sensor match-ups, the choice of the observed match-ups, we assume that and between different satellite sensors. For satellite to performance of satellite products against algorithm between MODISA and VIIRS. of 2012–2014. These MODISA to VIIRS match-ups were having valid values. As a result, a total of 4060 matching with at least 99% of the pixels within each edges and coastal zones, we kept only those matching wide area along the coast extracted from daily NASA level-3 mon map. Although both MODISA and VIIRS have equatorial latitude × longitude covering an approximately 1000-km-wide area along the coast extracted from daily NASA level-3 datasets. Those daily mean $R_{rs}$ values of MODISA and VIIRS were then matched with each other. In order to eliminate cloud edges and coastal zones, we kept only those matching $R_{rs}$ pairs with at least 99% of the pixels within each $1^\circ \times 1^\circ$ subarea having valid values. As a result, a total of 4060 matching $R_{rs}$ vectors for MODISA and VIIRS were found for the period of 2012–2014. These MODISA to VIIRS match-ups were then used in the minimization of the differences in the Chla algorithm between MODISA and VIIRS.

Several statistical measures were used to assess the performance of satellite products against in situ observations and between different satellite sensors. For satellite to in situ match-ups, we assume that $O_i$ is the $i$th observation of an in situ variable and $P_i$ is the corresponding predicted satellite variable. For sensor-to-sensor match-ups, the choice of the observed versus predicted variable is arbitrary, but we used MODISA estimates as $O_i$. As an estimate of the prediction scatter, we used the median absolute percentage error (MdAPE), which was calculated as $\text{MdAPE} = 100 \times \text{median}((P_i - O_i)/O_i)$. For comparing two sensors, we used the median unbiased absolute percentage error (MdUAPE), which was calculated as $122 \text{MdUAPE} = 100 \times \text{median}((P_i - O_i)/|0.5*(P_i + O_i)|)$. As an estimate of bias, we used the median relative percentage difference (MdRPE), which was calculated as $\text{MdRPE} = 100 \times \text{median}((P_i - O_i)/O_i)$. These statistics were calculated for 126 $P_i$ and $O_i$ using untransformed values (i.e., not $\log_{10}$). We also include the coefficient of determination ($R^2$), the slope of the reduced major axis (RMA) regression, and the root-129 mean-square error (rmse), all calculated on $\log_{10}$-transformed 130 variables.

### III. Results

**A. Match-Ups With Standard chlor$_a$ Products**

Satellite to in situ match-ups of Chla using the NASA standard chlor$_a$ product over three orders of magnitude (Fig. 2 and Table I) have relatively high coefficients of determination $R^2 = 0.87$ for MODISA and 0.85 for VIIRS but also show bias. For example, all MODISA match-ups with in situ Chla $> 138$ $2 \text{mg m}^{-3}$ underestimate in situ Chla. For VIIRS, the standard chlor$_a$ product suffers from overestimation at low in situ Chla and underestimation at medium and high Chla, which causes 141 the slope of the RMA regression to be significantly less than 142 one (0.68; Table I).

**B. Optimized MBR Algorithm**

Standard empirical ocean color algorithms OC3 and OC4 [12] use polynomial fits between $\log_{10}$-transformed in situ Chla (Cins) and $\log_{10}$-transformed MBR of $R_{rs}$ measured 147 in situ. MBR is calculated as the maximum of $R_{rs}$ at two or 148 more wavelengths (e.g., $R_{rs}443$ and $R_{rs}488$ for MODISA or 149 $R_{rs}443$ and $R_{rs}486$ for VIIRS) to the $R_{rs}$ of the green band 150 ($R_{rs}547$ for MODISA and $R_{rs}551$ for VIIRS). In order to 151 remove the bias evident in Fig. 2, we created our own best 152 fits to the match-up points. The distribution of match-up points 153 is highly uneven as there are more points in the middle of the 154 range than at both ends of the distribution. To reduce the effect 155 of the uneven distribution, the match-up points were aggregated 156 into bins by using the median values of small brackets of 157 $\log_{10}$(Cins) and the corresponding medians of $\log_{10}$(MBR) 158 following [3] and binning interval of 0.04 in $\log_{10}$(MBR) units. 159

### Table I

<table>
<thead>
<tr>
<th>Sensor</th>
<th>$N$</th>
<th>$R^2$</th>
<th>MdAPE</th>
<th>MdRPE</th>
<th>RMSE</th>
<th>RmaSlope</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODISA</td>
<td>306</td>
<td>0.87</td>
<td>22.5</td>
<td>$-0.1$</td>
<td>0.15</td>
<td>0.88</td>
</tr>
<tr>
<td>VIIRS</td>
<td>74</td>
<td>0.85</td>
<td>31.0</td>
<td>8.0</td>
<td>0.21</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Fig. 1. Locations of the MODIS-Aqua Chla match-ups (black dots with white circles) within 3-h time difference overlaid on the April 2012 Chla composite.
Fig. 2. Chlorophyll-a match-ups with (a) MODISA and (b) VIIRS using standard NASA chlor_a products. The red line is the one-to-one line, and the blue line is the RMA linear regression.

Fig. 3. Optimized Chla algorithm (red) compared to standard NASA OC3 (blue) and bracket points of in situ Chla match-ups (black diamonds) as a function of the MBR of remote sensing reflectance for (a) MODISA and (b) VIIRS.

Table II

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$R^2$</th>
<th>MdAPE, %</th>
<th>MdRPE, %</th>
<th>RMSE</th>
<th>RmaSlope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard</td>
<td>0.95</td>
<td>13.7</td>
<td>-9.4</td>
<td>0.105</td>
<td>1.04</td>
</tr>
<tr>
<td>In situ fit</td>
<td>0.94</td>
<td>14.0</td>
<td>-6.8</td>
<td>0.125</td>
<td>1.12</td>
</tr>
<tr>
<td>Optimized</td>
<td>0.95</td>
<td>10.3</td>
<td>-0.1</td>
<td>0.113</td>
<td>1.04</td>
</tr>
</tbody>
</table>

The resulting “bracket” points (24 for MODISA and 20 for VIIRS) were then used in algorithm development (Fig. 3).

Ideally, by “tuning” the algorithms of multiple sensors to the same set of in situ data, the resulting estimates by different sensors should be compatible between each other. In reality, as the Chla high end is poorly constrained due to few scattered match-ups, the resulting empirical algorithms do not improve the intersensor consistency and may even make it worse [1]. Indeed, as the main difference of the empirical fits compared to the standard OC3 algorithms is their increased predicted Chla Chla at high end (Fig. 3), the intersensor variability (MdAPE) between MODISA and VIIRS is slightly increased from 13.7% to 14.0% when using the coefficients fitted to in situ data (Table II). In order to improve the consistency between satellite sensors and at the same time keep them consistent with in situ datasets, we need an optimization that minimizes not only the differences between satellite and in situ match-ups but also the differences between the satellite estimates of different sensors [1]. The matching Rs pairs of MODISA and VIIRS in $1^\circ \times 1^\circ$ subareas were further binned according to the corresponding $\log_{10}(\text{MBR})$ value, which resulted in 89 “bracket points” of MODISA and VIIRS $\log_{10}(\text{MBR})$ values. The differences in the derived Chla estimates were then minimized for the input vector consisting of 24 MODISA bracket points of MBR and Cins, 20 VIIRS bracket points of MBR and Cins, and 89 bracket points of MBR from MODISA and VIIRS. For this optimization, we used the trust-region method, a variant of the Levenberg–Marquardt method as implemented in the NMath numerical libraries (http://www.centerspace.net/). As a result, we produced two sets of polynomial coefficients (for both MODISA and VIIRS) of the MBR OC3 model called CALFIT2015 (Table III).

The optimization reduced the bias (MdRPE) between Chla derived with MODISA and VIIRS from $-9.4\%$ to practically zero (Table II and Fig. 4). It also reduced somewhat the scatter (MdUAPE) between MODISA and VIIRS from $\sim14\%$ to $10\%$. However, the other statistical indicators ($R^2$, rmse, and RmaSlope) were not improved.

### IV. Discussion

The resulting optimized Chla algorithm shows improved performance compared to the standard OC3 algorithm and 200
in situ Chla and produced updated versions of the regionally optimized Chla algorithms. The new Chla estimates from MODISA and VIIRS are similar to standard chlor_a estimates at low Chla but have improved retrievals at medium to high in situ Chla and have no bias between one another. The 231 improved algorithms (CALFIT2015) have been applied to MODISA and VIIRS imagery from 2012 to the present (2015). The merged satellite time series (available at http://spg.ucsd.edu/Satellite_Data/CC4km/CC4km.htm) have improved spatial and temporal coverage compared to a single sensor and improved correspondence to in situ data. Improved detection of high biomass events is crucial for running harmful algal bloom 236 predictive models in coastal California that require accurate Rrs and chlorophyll values [10] and is also necessary to enhance our understanding of coastal biology and provide long-term continuity of ocean data records.

Acknowledgment

The authors would like to thank the CalCOFI program and Dr. R. Goericke for providing the in situ Chla data. Satellite data were provided by the NASA Ocean Color Processing Group.

References


V. Conclusion

We have extended the optimization approach of [1] to current MODISA and VIIRS satellite data using a large database of
AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

Please be aware that authors are required to pay overlength page charges ($200 per page) if the paper is longer than 3 pages. If you cannot pay any or all of these charges please let us know.

This pdf contains 2 proofs. The first half is the version that will appear on Xplore. The second half is the version that will appear in print. If you have any figures to print in color, they will be in color in both proofs.

The “Open Access” option for your paper expires when the paper is published on Xplore in an issue with page numbers. Papers in “Early Access” may be changed to “Open Access.”

AQ1 = Please provide publication update in Ref. [14].

END OF ALL QUERIES
Optimized Merger of Ocean Chlorophyll Algorithms of MODIS-Aqua and VIIRS


Abstract—Standard ocean chlorophyll-a (Chla) products from currently operational satellite sensors Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua and Visible Infrared Imager Radiometer Suite (VIIRS) underestimate medium and high in situ Chla concentrations and have approximately 9% bias between each other in the California Current. By using the regional optimization approach of Kahru et al., we minimized the differences between satellite estimates and in situ match-ups as well as between estimates of the two satellite sensors and created improved empirical algorithms for both sensors. The regionally optimized Chla estimates from MODIS-Aqua and VIIRS have no bias between each other, have improved retrievals at medium to high in situ Chla, and can be merged to improve temporal frequency and spatial coverage and to extend the merged time series.

Index Terms—Chlorophyll, Moderate Resolution Imaging Spectroradiometer (MODIS), ocean color, phytoplankton, Visible Infrared Imager Radiometer Suite (VIIRS).

I. INTRODUCTION

COMBINING or merging data from multiple sensors is required to improve the temporal resolution and spatial coverage of ocean color imagery and to construct long time series or climate data records using data from multiple sensors [2]–[5]. Currently (i.e., in mid-2015), there are two well-calibrated global ocean color sensors in operation: Moderate Resolution Imaging Spectroradiometer on Aqua (MODISA) and Visible Infrared Imaging Radiometer Suite (VIIRS) on Suomi NPP. While improvements in on-orbit sensor calibration and Visible Infrared Imager Radiometer Suite (VIIRS) on Suomi NPP. While improvements in on-orbit sensor calibration and spatial collocation measurements (match-ups) of satellite data from different sensors, significant differences remain [7], [8]. Moreover, global algorithms may not be regionally optimal as significant differences exist in bio-optical properties of different oceanic provinces [9]. Standard NASA ocean chlorophyll-a (Chla) algorithms significantly underestimate in situ values in the California Current at high concentrations, often by a factor of 5 [1]. This is highly relevant for detection and monitoring of phytoplankton blooms, including harmful algal blooms [10]. While differences between Chla estimates from MODIS-Aqua and VIIRS have diminished after multiple reprocessings, they still exist [8].

Kahru et al. [1] created optimized empirical algorithms for the California Current for a suite of four sensors (OCTS, 45 SeaWiFS, MERIS, and MODISA) and the time period of 1997–2011. An update to that work is currently needed as 1) MERIS stopped operating in April 2012; 2) new data from VIIRS are available from the beginning of 2012; and 3) both MODISA and VIIRS data have been reprocessed by NASA’s Ocean Biology Processing Group. The purpose of this work is to create empirical algorithms that are optimized for creating a merged Chla time series in the California Current for the 53 period of 2012–2015 from the two currently available sensors MODISA and VIIRS.

II. DATA AND METHODS

We used in situ Chla data collected by the California Cooperative Oceanic Fisheries Investigations (CalCOFI) on their quarterly cruises covering a regular grid of stations from nearshore to as far as 600 km offshore for the entire coast of California [11]. In total, 3388 near-surface Chla samples from 61 fields of view of 5 [1]. This is highly relevant for detection and monitoring of phytoplankton blooms, including harmful algal blooms [10]. While differences between Chla estimates from MODIS-Aqua and VIIRS have diminished after multiple reprocessings, they still exist [8].

Kahru et al. [1] created optimized empirical algorithms for the California Current for a suite of four sensors (OCTS, 45 SeaWiFS, MERIS, and MODISA) and the time period of 1997–2011. An update to that work is currently needed as 1) MERIS stopped operating in April 2012; 2) new data from VIIRS are available from the beginning of 2012; and 3) both MODISA and VIIRS data have been reprocessed by NASA’s Ocean Biology Processing Group. The purpose of this work is to create empirical algorithms that are optimized for creating a merged Chla time series in the California Current for the 53 period of 2012–2015 from the two currently available sensors MODISA and VIIRS.

All satellite data were acquired at level 2 (i.e., processed to surface quantities but unmapped) with approximately 1-km 65 ground resolution. MODISA (2002–2014, version 2013.1.1) 66 and VIIRS (2012–2014, version 2014.0.1) level-2 data were obtained from NASA’s Ocean Color Web (http://oceancolor.gsfc.nasa.gov/). The standard NASA Chla algorithm uses empirical polynomial fits between satellite-derived maximum band ratio (MBR) of remote sensing reflectance (Rrs) bands and near-surface Chla [12] with the coefficient values for each sensor 72 given at http://oceancolor.gsfc.nasa.gov/cms/atbd/chlor_a.

The validation of satellite products using quasi-simultaneous 74 and spatially collocated measurements (match-ups) of satellite 75 and in situ data followed the procedures of previous studies 76 [1], [8], [13], [14]. We assumed that the following level-2 77 flags made a pixel invalid: ATFAIL, LAND, HISATZEN, STRAYLIGHT, CLDICE, CHLFAIL, SEAICE, NAVFAIL, and HIPO (see http://oceancolor.gsfc.nasa.gov/VALIDATION/80 flags.html for an explanation of the flags). All variables in the level-2 files were extracted from a 3 × 3-pixel window 82 centered at the pixel nearest to the in situ sample. For statistical analysis, we accepted only those match-ups with at least five 84
used the median absolute percentage error (MdAPE), which was calculated as $\text{MdAPE} = 100 \times \text{median} (\left|\frac{P_i - O_i}{O_i}\right|)$. For comparing two sensors, we used the median unbiased absolute percentage error (MdUAPE), which was calculated as $\text{MdUAPE} = 100 \times \text{median} (\left|\frac{P_i - O_i}{0.5^* (P_i + O_i)}\right|)$. As an estimate of bias, we used the median relative percentage difference (MdRPE), which was calculated as $\text{MdRPE} = 100 \times \text{median} (\frac{(P_i - O_i)}{O_i})$. These statistics were calculated for MODISA or VIIRS using untransformed values (i.e., not $\log_{10}$). We also include the coefficient of determination ($R^2$), the slope of the reduced major axis (RMA) regression, and the root-mean-square error (rmse), all calculated on $\log_{10}$-transformed variables.

### III. RESULTS

#### A. Match-Ups With Standard chlor_a Products

Satellite to in situ match-ups of Chla using the NASA standard chlor_a product over three orders of magnitude (Fig. 2 and Table I) have relatively high coefficients of determination ($R^2 = 0.87$ for MODISA and 0.85 for VIIRS) but also show bias. For example, all MODISA match-ups with in situ Chla > 2 mg m$^{-3}$ underestimate in situ Chla. For VIIRS, the standard chlor_a product suffers from overestimation at low in situ Chla and underestimation at medium and high Chla, which causes the slope of the RMA regression to be significantly less than one (0.68; Table I).

#### B. Optimized MBR Algorithm

Standard empirical ocean color algorithms OC3 and OC4 [12] use polynomial fits between $\log_{10}$-transformed in situ Chla (Cins) and $\log_{10}$-transformed MBR of $Rrs$ measured in situ. MBR is calculated as the maximum of $Rrs$ at two or 148 more wavelengths (e.g., $Rrs_{443}$ and $Rrs_{488}$ for MODISA or $Rrs_{443}$ and $Rrs_{486}$ for VIIRS) to the $Rrs$ of the green band 150 ($Rrs_{547}$ for MODISA and $Rrs_{551}$ for VIIRS). In order to 151 remove the bias evident in Fig. 2, we created our own best 152 fits to the match-up points. The distribution of match-up points 153 is highly uneven as there are more points in the middle of the 154 range than at both ends of the distribution. To reduce the effect 155 of the uneven distribution, the match-up points were aggregated 156 into bins by using the median values of small brackets of 157 $\log_{10}$ (Cins) and the corresponding medians of $\log_{10}$ (MBR) 158 following [3] and binning interval of 0.04 in $\log_{10}$ (MBR) units.
IEEE Proof
KAHRU et al.: OPTIMIZE DMERGER OF OCEAN CHLOROPHYLL ALGORITHMS OF MODIS-AQUA AND VIIRS

Fig. 2. Chlorophyll-a match-ups with (a) MODISA and (b) VIIRS using standard NASA chlor_a products. The red line is the one-to-one line, and the blue line is the RMA linear regression.

Fig. 3. Optimized Chla algorithm (red) compared to standard NASA OC3 (blue) and bracket points of in situ Chla match-ups (black diamonds) as a function of the MBR of remote sensing reflectance for (a) MODISA and (b) VIIRS.

The resulting “bracket” points (24 for MODISA and 20 for VIIRS) were then used in algorithm development (Fig. 3).

Ideally, by “tuning” the algorithms of multiple sensors to the same set of in situ data, the resulting estimates by different sensors should be compatible between each other. In reality, as the Chla high end is poorly constrained due to few scattered match-ups, the resulting empirical algorithms do not improve the intersensor consistency and may even make it worse [1]. Indeed, as the main difference of the empirical fits compared to the standard OC3 algorithms is their increased predicted Chla at high end (Fig. 3), the intersensor variability (MdAPE) between MODISA and VIIRS is slightly increased from 13.7% to 14.0% when using the coefficients fitted to in situ data (Table II). In order to improve the consistency between satellite sensors and at the same time keep them consistent with in situ datasets, we need an optimization that minimizes not only the differences between satellite and in situ match-ups but also the differences between the satellite estimates of different sensors [1]. The matching Rrs pairs of MODISA and VIIRS in 1° × 1° subareas were further binned according to the corresponding log_{10}(MBR) value, which resulted in 89 “bracket points” of MODISA and VIIRS log_{10}(MBR) values. The differences in the derived Chla estimates were then minimized for the input vector consisting of 24 MODISA bracket points of MBR and Cins, 20 VIIRS bracket points of MBR and Cins, and 89 bracket points of MBR from MODISA and VIIRS. For this optimization, we used the trust-region method, a variant of the Levenberg-Marquardt method as implemented in the NMath numerical libraries (http://www.centerspace.net/). As a result, we produced two sets of polynomial coefficients (for 189 both MODISA and VIIRS) of the MBR OC3 model called CALFIT2015 (Table III).

The optimization reduced the bias (MdRPE) between Chla derived with MODISA and VIIRS from −9.4% to practically zero (Table II and Fig. 4). It also reduced somewhat the scatter (MdUAPE) between MODISA and VIIRS from ∼14% to 10%. However, the other statistical indicators (R^2, rmse, and RmaSlope) were not improved.

IV. DISCUSSION

The resulting optimized Chla algorithm shows improved performance compared to the standard OC3 algorithm and...
MODISA and VIIRS satellite data using a large database of sensor zenith angle, distance from the coast, etc. This has been between sensors related to factors such as sun zenith angle, removed just the mean bias, and there may still exist bias and VIIRS by simple arithmetic averaging of the gridded data eliminated, we can now merge Chla estimates from MODISA As the median bias between MODISA and VIIRS has been are noisy [8]. Therefore, the scatter at high Chla was boosted, the increase in Chla estimates at high Chla levels (Figs. 3 and 5), but the main effect of fitting to Chla was reduced, and the bias between Chla estimates by the fact that the main effect of fitting to in situ data was the increase in Chla estimates at high Chla levels (Figs. 3 and 5), but $R_{rs}$ estimates corresponding to medium and high Chla are noisy [8]. Therefore, the scatter at high Chla was boosted, which inevitably made some of the statistics worse (e.g., rmse). As the median bias between MODISA and VIIRS has been eliminated, we can now merge Chla estimates from MODISA and VIIRS by simple arithmetic averaging of the gridded data and increase the frequency and spatial coverage and reduce uncertainty. However, we have to keep in mind that we have removed just the mean bias, and there may still exist bias between sensors related to factors such as sun zenith angle, sensor zenith angle, distance from the coast, etc. This has been discussed in [5] in the context of satellite-derived water clarity.

V. CONCLUSION

We have extended the optimization approach of [1] to current MODISA and VIIRS satellite data using a large database of in situ Chla and produced updated versions of the regionally optimized Chla algorithms. The new Chla estimates from MODISA and VIIRS are similar to standard chlor_a estimates at low Chla but have improved retrievals at medium to high Chla and have no bias between one another. The improved algorithms (CALFIT2015) have been applied to MODISA and VIIRS imagery from 2012 to the present (2015). The merged satellite time series (available at http://spg.ucsd.edu/Satellite_Data/CC4km/CC4km.htm) have improved spatial temporal coverage compared to a single sensor and improved correspondence to in situ data. Improved detection of high biomass events is crucial for running harmful algal bloom predictive models in coastal California that require accurate $R_{rs}$ and chlorophyll values [10] and is also necessary to enhance our understanding of coastal biology and provide long-term continuity of ocean data records.

ACKNOWLEDGMENT

The authors would like to thank the CalCOFI program and Dr. R. Goericke for providing the in situ Chla data. Satellite data 2015 were provided by the NASA Ocean Color Processing Group.

REFERENCES

AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

Please be aware that authors are required to pay overlength page charges ($200 per page) if the paper is longer than 3 pages. If you cannot pay any or all of these charges please let us know.

This pdf contains 2 proofs. The first half is the version that will appear on Xplore. The second half is the version that will appear in print. If you have any figures to print in color, they will be in color in both proofs.

The “Open Access” option for your paper expires when the paper is published on Xplore in an issue with page numbers. Papers in “Early Access” may be changed to “Open Access.”

AQ1 = Please provide publication update in Ref. [14].

END OF ALL QUERIES