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Impact of inter-mission differences and drifts on chlorophyll-*a* trend estimates

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ABSTRACT

The chlorophyll-*a* (chl-*a*) concentration is an Essential Climate Variable, and the study of its variability at global scale requires a succession of satellite ocean colour missions to cover a period suitable for climate research. In the context of a multi-mission data record, inter-mission differences can introduce artefacts affecting trend evaluations, and the impact of the bias between the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) and Moderate Resolution Imaging Spectroradiometer (MODIS) chl-*a* products is shown to be significant in a substantial part of the ocean. The assessment of trends can also be directly impacted by a drift in the chl-*a* time series resulting from sensor functions. These issues are addressed by a sensitivity analysis that compares slopes of linear regression obtained for varying levels of inter-mission bias and drift with respect to a 15-year reference series built with SeaWiFS and MODIS data. The relationship, constructed for a representative set of ocean provinces, between bias and the level of significance associated with the comparison of slopes shows that a bias on the order of ±5–6% generally induces a slope that is significantly different from the reference case, while a threshold on bias values not exceeding 2% largely alleviates this effect. Moreover, the study suggests that a drift larger than 2% per decade on the chl-*a* series can result in misleading conclusions from a trend analysis. All results have a clear regional dependence that needs to be taken into account in bias-correction and merging efforts. Low chl-*a* regions, such as the oligotrophic subtropical gyres, appear particularly sensitive to perturbations and require still higher levels of consistency and stability.

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1. Introduction

Marine ecosystems are affected by various pressures of anthropogenic origin, including the input of nutrients into coastal zones (Galloway et al. 2008) and top-down effects of fisheries (Stewart et al. 2010). The release of greenhouse gases also will profoundly affect the oceans through warming and the intrusion of CO_2 leading to acidification (Fabry et al. 2008). In that context, it appears essential to monitor the evolution of the marine phytoplankton, which is the base of the marine food chain and a key component of the

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carbon cycle. As such, chlorophyll-*a* (chl-*a*) concentration is listed as an Essential Climate Variable (ECV, Bojinski et al. 2014) by the Global Climate Observing System (GCOS 2011). Preliminary results suggest that phytoplankton is and will be affected by climate forcing in different manners (e.g. Sarmiento et al. 2004; Steinacher et al. 2010; Boyce et al. 2014).

Ocean colour remote sensing is currently the only means by which a comprehensive picture of the ocean phytoplankton and its variations can emerge. But before changes in chl-*a* are to be attributed to climate change above the background of natural seasonal and inter-annual variability, long time series (i.e. on the order of decades, Henson et al. 2010; Yoder et al. 2010) are required that obviously exceed the lifetime of any one satellite mission. Indeed, changes seen in the annual cycle (Vantrepotte et al. 2011) or resulting from a strong inter-annual signal (such as that displayed by the El Niño Southern Oscillation, ENSO, Kahru and Mitchell 2000; Ryan et al. 2006) can impact a trend calculation performed over a 10-year period, which is currently the most that can be expected for the optimal operation of a space sensor. But if the study period is sufficiently long, the effect of these natural variations should no longer contribute to the long-term signal, unless their amplitude, pattern, and/or frequency are themselves affected by climate change (in the case of ENSO, see Fedorov and Philander 2000; Yeh et al. 2009; Collins et al. 2010). Several studies used the data collected by the Sea-viewing Wide Field-of-view Sensor (SeaWiFS, McClain et al. 1998) over a decade to analyse inter-annual variations in the global chl-*a* series (e.g. Behrenfeld et al. 2006; Martinez et al. 2009; Vantrepotte and Mélin 2009, 2011) but the inclusion of other subsequent missions in the overall data record is now necessary to extend the temporal basis of such analyses. Several investigations for local or global applications actually used the SeaWiFS record with data from other missions (McClain, Signorini, and Christian 2004; Mélin, Zibordi, and Djavidnia 2009, Mélin et al. 2011; Kahru et al. 2012; Bélanger, Babin, and Tremblay 2013; Coppini et al. 2013; Saulquin et al. 2013; Gregg and Casey 2010; Gregg and Roussseaux 2014; Park et al. 2015; Signorini, Franz, and McClain 2015), and various merging techniques were proposed to combine data sets from multiple missions (Kwiatkowska and Fargion 2003; Maritorena and Siegel 2005; Pottier et al. 2006; Mélin and Zibordi 2007; Mélin et al. 2011; IOCCG 2007).

On the other hand, it is well documented that ocean colour products from different missions may show significant differences (Djavidnia, Mélin, and Hoepffner 2010; Mélin 2010, 2011), and inter-mission differences, if not accounted for, may introduce artefacts in a combined data set that could modify or even invalidate the conclusions of trend analyses (Gregg and Casey 2010; Beaulieu et al. 2013). In the studies cited above, inter-mission biases were handled in a variety of ways, from ignoring them in the temporal analyses to specifically accounting for them, or correcting them. These issues have been faced by other disciplines that have developed responses adapted to the characteristics associated with the variable under study, for instance, sea level (Ablain et al. 2015), sea surface temperature (Kilpatrick, Podestà, and Evans 2001), or atmospheric ozone (Lerot et al. 2014; Pastel et al. 2014).

The treatment of inter-mission differences in the construction of an ocean colour climate data record (CDR) begs the question of how close mission-specific data sets need to be in order to allow a trend analysis with a combined data set. This study attempts to provide elements of response that should be relevant for the definition of mission requirements and merging strategies. This is done by performing analyses of chl-*a* series constructed with data from two satellite missions, SeaWiFS and the Moderate Resolution Imaging Spectroradiometer (MODIS, Esaias et al. 1998) onboard the Aqua platform. Specifically, the effects of inter-mission differences on trend estimates are analysed by investigating how trends are affected by varying levels of bias between mission-specific products. The impact of a drift on trend detection affecting the chl-*a* is also analysed. It is stressed that in the whole analysis, trend will be intended as a mathematical term resulting from a statistical calculation and does not imply an association with a particular nature of the underlying variations, such as climate change.

2. Data

The data sets used in this work were obtained from the National Aeronautics and Space Administration (NASA) archive of Level-3 gridded data in the form of global mapped, 24th-degree, monthly chl-*a* products, associated with processing versions 2010.0 and 2013.1 for SeaWiFS and MODIS-Aqua, respectively. These data sets were handled to represent what could be considered as the typical case of two subsequent 10-year-long missions with a 5-year overlap. SeaWiFS data were considered for the period 1997–2007 and the MODIS data for the period 2002–2012. Other periods could be considered for temporal analyses, but those were chosen to represent an ideal case. After 2007, the SeaWiFS record actually showed gaps in the series, and after 2012, MODIS data started showing signs of sensor ageing. NASA's work on instruments calibration (Xiong et al. 2010; Eplee et al. 2012) supports the assumption that no significant artefact results from the instrument calibration history for each mission, an assumption that could be revised as knowledge about the instruments is further improved. It is stressed that the last years of the MODIS record are excluded to avoid artefacts that could come from an insufficiently corrected radiometric degradation of the sensor (Meister and Franz 2014). When studying trends for a combined SeaWiFS/MODIS data set, the period is 1998–2012, that is, a period of 15 years. The SeaWiFS (noted with subscript 's') and MODIS (subscript 'a') monthly 10-year chl-*a* series are referred to as $(x_s)_{i=1,N_s}$ and $(x_a)_{i=1,N_a}$, respectively (with N_s and N_a both equal to 120 months).

For a sensitivity study, chl-*a* time series representative of annual cycles found in natural waters are needed. For that purpose, the partition of the global ocean into biogeographical provinces proposed by Longhurst (2006) was adopted with minor modifications (like the addition of the Baltic and Black Seas), leading to the definition of 55 provinces. Average chl-*a* time-series associated with this ensemble of provinces are thought to display a representative set with a realistic and fairly comprehensive diversity of seasonal cycles and inter-annual variations (see Longhurst 2006). For each province, monthly geometric average values were considered for analysis if valid values covered at least 10% of the province area.

A monthly climatology was derived for both missions using the period of overlap. The climatological January value is the average of the valid January values for the 5 years from 2003 to 2007, and so on for the other months. These climatologies were computed over the period of overlap (and not over the full period) in order to correct the MODIS data for differences with respect to SeaWiFS, by computing a corrected MODIS record ($x_{a,corr}$):

$$x_{\mathrm{a,corr}}(m) = x_{\mathrm{a}}(m) + x_{\mathrm{s,clim}}(m) - x_{\mathrm{a,clim}}(m), \tag{1}$$

where the 'clim' subscript indicates the climatological chl-*a* value for the month *m*. This step, that can be termed bias correction, corrects in a simple manner the spatial and seasonal dependence in inter-mission biases that has been noticed for ocean colour products (Djavidnia, Mélin, and Hoepffner 2010; Mélin, Zibordi, and Djavidnia 2009; Mélin 2011; Mélin et al. 2016). It can be noticed that this bias correction is affected by a certain level of uncertainty that mostly results from the uncertainties associated with the two data records.

Two types of data sets combining both satellite missions were created (and noted with the subscript 'c' for 'combined'). The first type applied a concatenation (associated with the superscript 'cct') of the SeaWiFS and MODIS series, with SeaWiFS data up to a switch date and MODIS data afterwards, with the resulting series noted $x_{\mathrm{c}}^{\mathrm{cct}}$. Three switch dates were tested, placed at one-third, half, and two-thirds of the overall period (i.e. after 5, 7.5, and 10 years, respectively), with associated data sets noted $x_{\mathrm{c}}^{\mathrm{cct},1}, x_{\mathrm{c}}^{\mathrm{cct},2}$ and $x_{\mathrm{c}}^{\mathrm{cct},3}$, respectively. Another approach was to merge the two data sets, which implied combining them over a period of overlap. Here the merged data set (superscript 'mrg') was constructed by performing a simple average over the period of overlap 2003–2007 (5 complete years) which led to the series $x_{\mathrm{c}}^{\mathrm{mrg}}$. For each month *m*, the combined data can be written as:

$$x_{\mathrm{c}}(m) = \delta_{\mathrm{s}}(m)x_{\mathrm{s}}(m) + \delta_{\mathrm{a}}(m)x_{\mathrm{a}}(m). \tag{2}$$

In the case of the concatenated series $x_{\mathrm{c}}^{\mathrm{cct}}$, $\delta_{\mathrm{s}} = 1$ and $\delta_{\mathrm{a}} = 0$ ($\delta_{\mathrm{s}} = 0$ and $\delta_{\mathrm{a}} = 1$) before (after) the switch date. For the merged data, $\delta_{\mathrm{s}} = 1\,(\delta_{\mathrm{a}} = 1)$ if only the SeaWiFS (MODIS) record is available, $\delta_{\mathrm{s}} = \delta_{\mathrm{a}} = 0.5$ when both SeaWiFS and MODIS data are available.

Other series were derived in a similar way by using the corrected MODIS data instead, that is, combining the data sets x_{s} and $x_{\mathrm{a,corr}}$ with concatenation or merging (Equation (2)). These series are referred to as the reference series, $x_{\mathrm{c,corr}}$, considering that they are thought to be the least affected by any residual differences between the two original data records. For the purpose of discussion, it is assumed that these series are ideal data sets that could be constructed from fully consistent SeaWiFS and MODIS records.

To study the effect of biases between mission products, synthetic combined series were built by ingesting a varying level of bias between the two missions, as follows:

$$x_{\mathrm{c},b}(m) = \delta_{\mathrm{s}}(m)x_{\mathrm{s}}(m) + \delta_{\mathrm{a}}(m)\left(1 - \frac{b(m)}{100}\right)x_{\mathrm{a,corr}}(m), \tag{3}$$

with δ_{s} and δ_{a} defined as above for the concatenated or merged cases. The bias *b* is expressed in percentage and applied to the corrected MODIS series $x_{\mathrm{a,corr}}$ so that $b = 0$ corresponds to the series $x_{\mathrm{c},0}$ equal to the reference series $x_{\mathrm{c,corr}}$. In this analysis, *b* is varied between -50% and $+50\%$ by steps of 1%. In the whole study, positive bias values correspond to higher SeaWiFS chl-*a* with respect to MODIS.

Similarly, synthetic series were built with a formula intended to mimic a drift in chl-*a* and applied to a combined series $x_{\mathrm{c,corr}}$ (where again the MODIS chl-*a* is corrected for the inter-mission bias):

$$x_{c,d}(m) = \left(1 + \frac{d}{100}\frac{m}{12}\right)x_{c,corr}(m), \tag{4}$$

where d is the drift expressed in percentage per year (year^{-1}). Trend analysis is performed from January 1998 so that $x_{c,d}$ is equal to the reference series $x_{c,corr}$ for that month. For the sensitivity analysis, d is varied between -3% and $+3\%$ year^{-1} by steps of 0.02% year^{-1}.

3. Methods

Trend analysis was conducted for any given chl-*a* time series (for any grid point of the mapped products, or for a province-based averaged series) in a manner fully described by Vantrepotte and Mélin (2009, 2011) and briefly summarized here. Each series first underwent a preprocessing step. If a month was associated with a missing value in more than 50% of the cases (i.e. the number of years), then all values for that month were excluded, in practice creating an annual cycle of varying length (≤ 12 months). If the reduced series was characterized by more than 30% of missing values, then the whole series was excluded from the analysis. For the remaining series, missing values were filled in by an eigenvectors filtering method (Ibañez and Conversi 2002).

A second step was the calculation of the linear trend (expressed in % year^{-1}) associated with a given series after removal of its annual cycle (de-seasonalized series) (Vantrepotte and Mélin 2009). If the slope value is noted β, the standard error of the slope is:

$$s_\beta = \sqrt{\frac{1}{(N-2)}\left(\frac{\sigma(y)^2}{\sigma(x)^2} - \beta^2\right)}, \tag{5}$$

where x and y represent the series associated with time and geophysical data, respectively, and σ indicates the standard deviation. The level of significance p of the trend is calculated with a t-test performed with $t = \beta/s_\beta$ and N –2 degrees of freedom.

Trend analysis was carried out on the various combined series introduced in the previous section. The focus of the present study is not the amplitude of individual trends but to compare the trend diagnostics associated with different series over a given period. Two slopes of regression lines β_1 and β_2 were compared through a t-test in order to establish if β_1 and β_2 could be considered equal (null hypothesis H_0), with a level of significance P: if P was small, then H_0 was rejected and the slopes were considered different (for the sake of clarity, P was associated with the level of significance obtained when comparing slopes, while p was used to quantify the significance of a single trend). The statistical comparison of the two slopes β_1 and β_2 (with their associated standard error $s_{\beta,1}$ and $s_{\beta,2}$) was performed with a t-test value defined as:

$$t = \frac{\beta_1 - \beta_2}{\sqrt{s_{\beta,1}^2 + s_{\beta,2}^2}}, \tag{6}$$

with a degree of freedom v equal to:

$$v = \frac{\left(s_{\beta,1}^2 + s_{\beta,2}^2\right)^2}{\frac{1}{N_1}s_{\beta,1}^4 + \frac{1}{N_2}s_{\beta,2}^4} \tag{7}$$

following Andrade and Estévez-Pérez (2014, their Equation (8)). The numbers of samples N_1 and N_2 are equal since the merged series x_c, $x_{c,corr}$, $x_{c,b}$ and $x_{c,d}$ were built over the same period 1998–2012 (15 years) and with the same sampling frequency. In the description of results, the value of P is considered as the measure of the difference between two slopes of linear trends: the smaller P is, the more the slopes differ.

4. Results

4.1. *Comparison between global distributions*

This section compares the trends obtained for the time series x_c^{mrg} and $x_{c,corr}^{mrg}$ constructed by merging (similar statistical results are obtained with concatenated series; see Section 4.2). The significant trends of these two series ($p < 0.05$, Figure 1) show a generally consistent distribution but also some differences. Some negative signals are seen in the Indian Ocean, the subtropical North Pacific, central South Pacific, or the tropical Atlantic, while positive trends are found in the Baltic Sea, the California Current, the Tasman Sea, the southwest Atlantic, and in the South Pacific with a horseshoe pattern that goes from the western equatorial Pacific to mid-latitude South America and then westward across the South Pacific. In general, the slopes obtained with the series x_c (i.e. without climatological bias correction, Figure 1(*a*)) are higher than for the $x_{c,corr}$ series, and some patterns of significant trends almost disappear after bias correction, such as in the Arabian Sea, the Caribbean Sea, the eastern Mediterranean Sea, or the equatorial Atlantic. In fact, 40.5% of the domain of analysis is associated with significant trends in the case of x_c^{mrg} versus 31.1% for $x_{c,corr}^{mrg}$.

To further quantify the agreement between the two distributions, a contingency matrix is created that compares the occurrence of different trend diagnostics (Table 1). Overall 81.6% of the domain of analysis are characterized by a trend slope of the same sign (adding the first two diagonal terms in Table 1), while 18.4% are characterized by

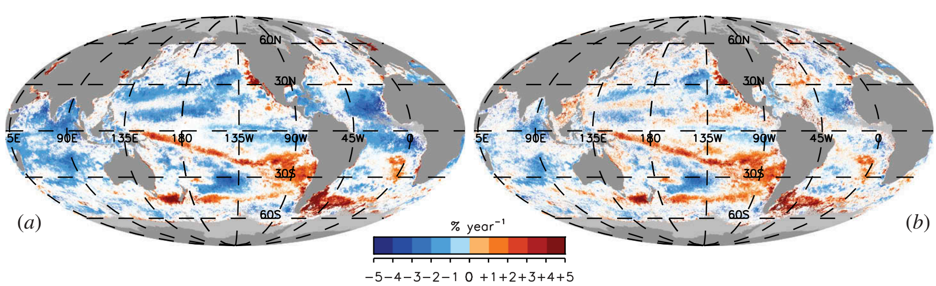

Figure 1. Trends for (*a*) the merged SeaWiFS/MODIS chl-*a* series x_c^{mrg}, and (*b*) for a similar product $x_{c,corr}^{mrg}$ where the MODIS data include a climatological correction for the bias with respect to SeaWiFS. Only significant trends ($p<0.05$) are represented.

Table 1. Matrix comparing trend estimates for the merged series combining SeaWiFS and MODIS with/without climatological bias correction.

(%)	$\beta_{corr} \geq 0$	$\beta_{corr} < 0$	n.s.	$\beta_{corr} \geq 0^*$	$\beta_{corr} < 0^*$
$\beta \geq 0$	29.8	2.7			
$\beta < 0$	15.7	51.7			
n.s.			52.3	5.3	1.7
$\beta \geq 0^*$			1.7	7.8	0.0
$\beta < 0^*$			14.8	0.1	16.1

Numbers are fractions (%) of the domain of analysis characterized by different trend diagnostics, expressed by the sign of the slope β and its level of significance. The subscript 'corr' indicates the climatologically corrected product; 'n.s.' stands for non-significant; '*' indicates significant trends ($p < 0.05$).

trends of opposite signs. Non-significant trends are obtained for both products over approximately half the domain (52.3%), while 24% of the domain is associated with significant trends ($p < 0.05$) for both products (and in this case, overwhelmingly the slopes have the same sign, Table 1). Furthermore, 16.6% of the domain area have a trend considered significant for the x_c series and not for $x_{c,corr}$, while the opposite is true for only 7.1% of the domain area.

These first results suggest that the bias between the SeaWiFS and MODIS data has a significant effect on the trend distribution, particularly at the regional level. The link between this bias and the trend diagnostics is more specifically illustrated by Figure 2. First, the bias ψ between the SeaWiFS and MODIS records is shown in Figure 2(*a*). This quantity is expressed as the mean relative difference computed as follows over the period of overlap 2003–2007:

$$\psi = \frac{1}{N}\sum_{m=1}^{N}\frac{2(x_s(m) - x_a(m))}{x_a(m) + x_s(m)}, \tag{8}$$

where N is the number of months with valid values for both products. In the metrics ψ, the numerator is divided by the average of the two products being compared, which avoids arbitrarily selecting one product as the value of reference. In general, ψ is fairly small, with its modulus ($|\psi|$) not exceeding 5% for 56% of the domain of analysis (or 10% for 83% of the domain), but some higher values can be noticed, for instance, in the

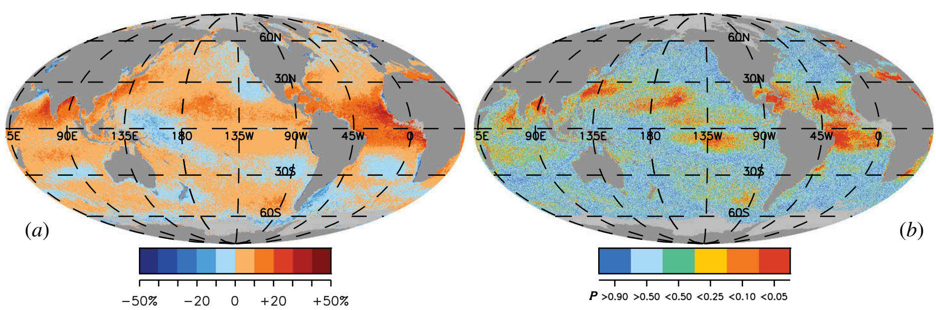

Figure 2. (*a*) Bias between SeaWiFS and MODIS chl-*a* over the period 2003–2007, expressed in %. A positive bias means that SeaWiFS chl-*a* is higher that the MODIS product. (*b*) Level of significance P of the t-test comparing the slopes of linear regression obtained for the merged series x_c^{mrg} and $x_{c,corr}^{mrg}$ (obtained with climatologically bias corrected MODIS chl-*a*) shown in Figure 1. Low values of P indicate that the slopes are significantly different.

northern Indian Ocean or in the tropical Atlantic Ocean. Over most of the globe, ψ is positive (i.e. SeaWiFS chl-*a* higher than the MODIS product).

Figure 2(*b*) is the result of comparing the slopes of linear regression associated with the series x_c and $x_{c,corr}$, expressed as the level of significance P of the H_0 hypothesis. Low values of P, typically lower than 0.1, are found in the northern Indian Ocean, the western and central subtropical North Pacific, the central equatorial Pacific (slightly south of the Equator), the Caribbean Sea, the subtropical Atlantic, the eastern Mediterranean Sea, or the Baltic Sea. Therefore for these regions, the slopes of linear regression appear significantly different $(P < 0.1)$. Over the area of analysis, $P < 0.5$ for 42.1% of the domain ($P < 0.1$ for 9.6% of the domain). All the main regions with a low P are also associated with fairly large values of $|\psi|$, mostly positive and more rarely negative (as in the Baltic Sea). Actually, for the part of the domain with $|\psi|$ larger than 10% (i.e. 17% of the domain), 59.4% of the area is characterized by $P < 0.5$ (27.4% by $P < 0.1$). Thus, over a substantial part of the ocean, the bias existing between SeaWiFS and MODIS chl-*a* could induce a significant trend artefact in the analysis of a merged series created without any correction for the bias. The next section tackles the question of how close these products need to be in order to avoid introducing such artefact.

4.2. *Sensitivity analysis*

The consequence of the differences separating satellite products on the trend analysis and the effect of a drift are addressed using the set of data associated with the ocean provinces. For each province, a trend analysis is conducted for the series x_s, x_a, x_c, $x_{c,corr}$, and the suites $x_{c,b}$ $(b \in [-5\%, +50\%])$ and $x_{c,d}(d \in [-30\%\,\text{year}^{-1}, +3\%\,\text{year}^{-1}])$.

4.2.1. *Merging versus concatenation*

Before analysing the impact of biases, the comparison of slopes is conducted for the merged and concatenated series. Considering the data sets associated with the 55 analysed provinces, the trend for the SeaWiFS 10-year series x_s is found significant $(p < 0.01)$ for 18 provinces (for the period 1998–2007), while it is so for 24 provinces in the case of MODIS (2002–2012). For the merged series x_c^{mrg}, trends are found significant for 26 provinces, while for the concatenated cases with x_c^{cct} (with switch dates placed at one-third, half or two-third of the 15-year period), this is so for 24 to 26 provinces. If the climatological bias correction is applied, trends are found significant for 12 provinces for $x_{c,corr}^{mrg}$, and for 12 or 13 provinces for $x_{c,corr}^{cct}$. So, the merged and concatenated series provide a consistent picture at global scale from the point of view of trend detection.

The slopes obtained for merged and concatenated products can be compared for each province. Comparing the slopes associated with x_c^{mrg} and $x_c^{cct,2}$ (switch date halfway within the period), the P value is lower than 0.5 for 5 out of 55 provinces, 3 in the tropical Atlantic, the Caribbean Province, and the Boreal Polar Province (BPLR; see Longhurst 2006, for the list of provinces and related acronyms). This is true for two provinces with $x_c^{cct,1}$, the Northern Atlantic Tropical Province (NATR) and the Subantarctic Province, and for three provinces with $x_c^{cct,3}$, BPLR, NATR, and the Atlantic Arctic Province (ARCT). These provinces fall into two broad categories. The first group contains the three tropical Atlantic provinces and the Caribbean Sea, regions with a relatively large bias between the SeaWiFS and MODIS series (larger than 10% in modulus) that has an impact on the trend analysis since the average chl-*a* level varies during the overlap period according to the relative importance of the two data sets. The second group is associated with high latitudes and a restricted data coverage so that merging can significantly alter a trend analysis by improving the coverage.

If the corrected MODIS data are used to build x_c^{mrg} and x_c^{cct}, the P value is lower than 0.5 for no province in the case of $x_c^{cct,1}$, two provinces (representing 3.7% of the global ocean) for $x_c^{cct,2}$, namely BPLR ($P = 0.03$) and the Alaska Coastal Province ($P = 0.49$), and two provinces (representing 4.4% of the global ocean) for $x_c^{cct,3}$, BPLR and ARCT. Employing the bias-corrected MODIS data clearly reduces the differences in slopes that are now found significant only for high-latitude regions. Considering that results are consistent in the merged and concatenated cases, the rest of the analysis is presented only for merged series unless specified otherwise.

4.2.2. *Impact of the inter-mission bias*

Example series are shown for the Northern Atlantic Tropical Province (NATR) in Figure 3. The SeaWiFS series x_s shows a highly significant trend of $-1.55\%\,\text{year}^{-1}$ ($p<0.001$) while the trend for MODIS is not significant. The trend for the merged series x_c^{mrg} appears highly significant ($-1.84\%\,\text{year}^{-1}$) and stems from two factors: the negative trend associated with SeaWiFS for the first years, and the fact that SeaWiFS chl-*a* is on average higher than MODIS values, as is also evident for that region in Figure 2(*a*).

The slope of the merged product $x_{c,corr}^{mrg}$ including the climatological bias correction is only $-0.82\%\,\text{year}^{-1}$ albeit still highly significant ($p < 0.001$) ($-0.84\%\,\text{year}^{-1}$ for the concatenated product $x_{c,corr}^{cct,2}$ with a half-way switch date). This slope is significantly

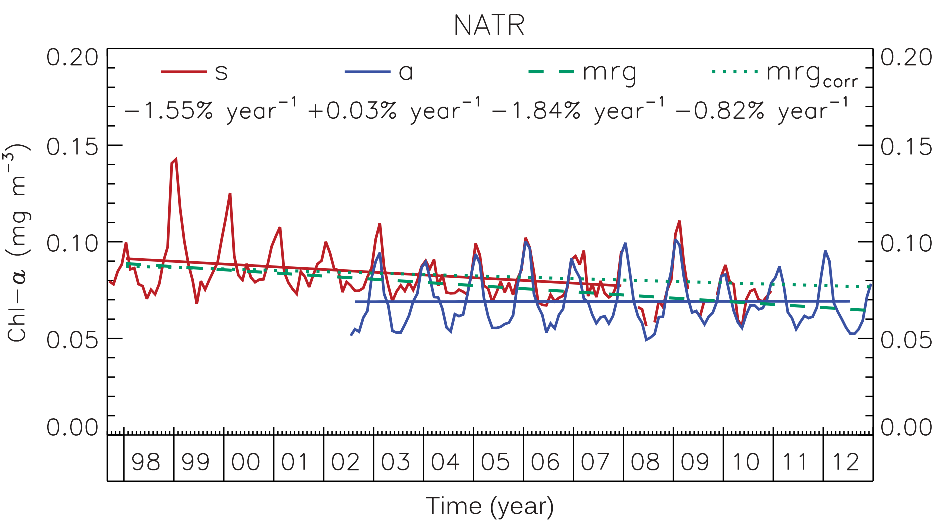

Figure 3. Time series of chl-*a* for SeaWiFS ('s', red), MODIS ('a', blue) averaged over the North Atlantic Tropical Ocean (NATR). The slopes of linear regression are also shown, together with the slopes obtained for the merged products x_c^{mrg} ('mrg', dashed green line) and $x_{c,corr}^{mrg}$ ('mrg$_{corr}$', dotted green line, obtained with climatologically corrected MODIS chl-*a*). The value of the slope in % per year is indicated in each case.

different from the slope obtained for the simple merged series x_c^{mrg} $(P < 0.001)$. The case of NATR exemplifies a more general behaviour. As anticipated above, trends are found significant for 24 to 26 provinces for x_c series (either merged or concatenated) but only for 12 or 13 provinces when the bias correction is applied to MODIS data, again highlighting the impact that biases have on combined products when studying trends.

For each province, the trend analysis is then conducted for each element of the suite $x_{c,b}(b \in [-50\%, +50\%])$, and the slope compared with that obtained for the reference series $x_{c,corr}$. This is done by computing P_b, the level of significance quantifying to what degree the two slopes are statistically different for the bias b. The derived relationship between the bias b and the level of significance P_b can be inverted by finding, for any P_b, the bias that would entail a slope of linear regression statistically different with that level of significance. For instance, for the example of NATR, a level of significance P_b<0.05 is reached if b exceeds $\pm 5\%$. For each level of significance and using all provinces, the average and standard deviation of the associated bias are computed, as well as a weighted average, where the weights are the areal surface of the various provinces. These relationships P_b versus b are displayed in Figure 4. Coloured symbols illustrate single realizations of that relationship by showing the bias between SeaWiFS and MODIS chl-*a* and the level of significance P associated with the comparison of the slopes obtained for x_c^{mrg} and $x_{c,corr}^{mrg}$. Out of 55 provinces, 21 are characterized by a bias between SeaWiFS and MODIS chl-*a* exceeding 5%, and for 15 of these, $P < 0.05$.

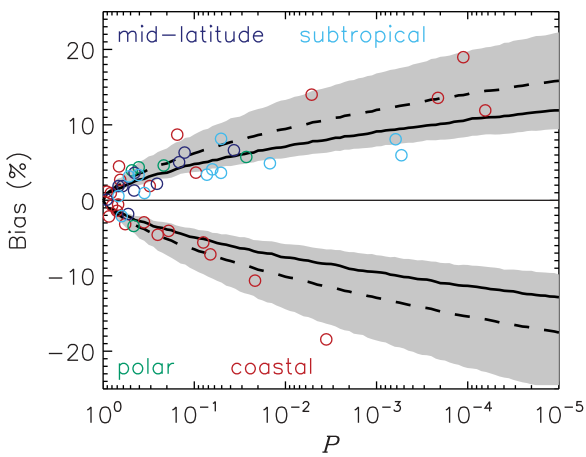

Figure 4. Relationship linking the bias (in %) between SeaWiFS and MODIS and the level of significance P quantifying to what degree the slopes of linear regression are statistically different when comparing a merged series x_c^{mrg} (where the MODIS data are affected by a given bias) and the reference series $x_{c,corr}^{mrg}$ with MODIS chl-*a* including a climatological bias correction. P is increasing from right to left. The dashed line (with grey envelope) shows the average relationship between bias and P (with its standard deviation) for the global set of ocean provinces (see text); the black line is the average relationship with a weighting by the areal surface of each province. Coloured circles are associated with a global distribution of biogeographic provinces and compare the actual bias between SeaWiFS and MODIS and P obtained analysing the slopes for x_c^{mrg} and $x_{c,corr}^{mrg}$ (the bias is positive if SeaWiFS chl-*a* is higher than MODIS chl-*a*). Different colours have been used for the provinces associated with the polar, coastal, mid-latitude and subtropical biomes. The point obtained for the Baltic Sea is out of the graph, with a bias of -53.8% and P of 1.2×10^{-7}.

Figure 4 shows that the relationship between P_b and b is almost symmetric. For a given bias b, P is lower for the weighted average than for the simple average, which is explained by the fact that the weighted average is influenced by the largest provinces that are associated with open ocean oligotrophic conditions (Longhurst 2006). For these regions of low chl-*a*, the variability is usually small with respect to coastal regions or marginal seas (Esaias, Iverson, and Turpie 2000), with the consequence that trends may be more easily detected. Considering a threshold level P, Figure 4 indicates the bias that needs to be enforced in order to respect that threshold. Hence, if considering the merged case (x_c^{mrg} series), a P value of 0.05 is associated with a bias of approximately 7.5% (b of -7.7% or $+7.4\%$) if the relationship obtained with the simple average is used, and approximately 5.6% (b of -5.8% or $+5.5\%$) if the relationship obtained with the weighted average is used. For concatenated series $(x_c^{cct,2})$, these values are slightly smaller, approximately 6.7% and 5.0% for the average and weighted average cases, respectively. So, if the bias is on the order of $\pm 5\%$, there is a significant risk that the trend associated with a combined product be affected, that is, the slope of the combined product be significantly different $(P<0.05)$ from the slope obtained with the bias-corrected series. If the more conservative threshold P of 0.5 is selected as an objective (to avoid that the slopes be significantly different), the corresponding bias when analysing merged series is $\pm 2.9\%$ and $\pm 2.2\%$ considering the relationships with the average and weighted average, respectively. If working with concatenated series $(x_c^{cct,2})$, these values are $\pm 2.7\%$ and $\pm 2.0\%$.

Provinces can be grouped into four biomes following Longhurst (2006): coastal, polar, westerlies mid-latitude, and trades regime subtropical provinces. Considering the merged series, a threshold P of 0.5 is associated with biases of $\pm 3.6\%$, $\pm 3.4\%$, $\pm 2.6\%$, and $\pm 2.1\%$ on average for the four biomes. Again, the oligotrophic low-variability conditions typically associated with subtropical waters are more conducive to trend detection, with the implication that small inter-mission biases are easily interpreted as trends. Enforcing a P value of 0.5 in the three large southern subtropical gyres (in the Pacific, Atlantic, and Indian Oceans) requires biases as low as 1–2%.

4.2.3. *Impact of a drift*

A similar analysis is conducted with the case of a drift applied to the reference merged time series $x_{c,corr}^{mrg}$, where the MODIS data are first corrected for the bias with respect to SeaWiFS chl-*a*. For each province, the trend analysis is performed for each element of the suite $x_{c,d}^{mrg}$ (Equation (4), $d \in [-3\%\,\text{year}^{-1}; +3\%\,\text{year}^{-1}]$), and the slope compared with that obtained for $x_{c,corr}^{mrg}$. Again this is done by computing P_d, the level of significance quantifying to what degree the two slopes are statistically different given the drift d. Conversely, for any P_d threshold, the corresponding drift can be found for each province.

Figure 5 shows the relationship between P_d and d obtained by averaging and weighted averaging over all provinces. The GCOS requirements for the chl-*a* ECV call for a stability of $0.3\%\,\text{year}^{-1}$ (GCOS 2011) (identified as dotted lines in Figure 5). For that level of drift, 45 provinces (amounting to 93% of the domain area) yield $P < 0.5$. For five provinces representing 24% of the domain (southern Atlantic and Pacific subtropical gyres, Caribbean Sea, Subantarctic Province, and East Australian Coastal Province),

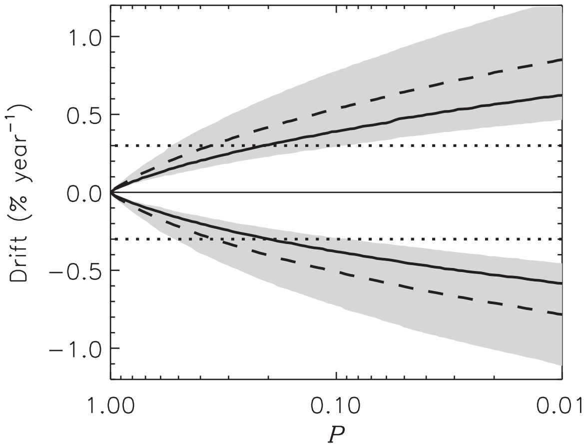

Figure 5. Relationship obtained between a drift affecting a merged SeaWiFS/MODIS time series and the level of significance P quantifying to what degree the slope of linear regression differs with respect to the case of the reference series $x^{mrg}_{c,corr}$ with MODIS chl-*a* including a climatological bias correction. P is increasing from right to left. The dashed line (with grey envelope) shows the average relationship between drift and P (with its standard deviation) for the global set of ocean provinces (see text); the black line is the average relationship with a weighting by the areal surface of each province. The dotted lines represent the GCOS requirements of $\pm 0.3\%\,\mathrm{year}^{-1}$.

$P<0.05$, which means that the difference in slopes obtained with and without drift is highly significant for a large part of the ocean. Based on the relationship between P_d and d, a threshold of 0.5 for P corresponds to a drift of $\pm 0.22\%\,\mathrm{year}^{-1}$ if the average over provinces is considered, $\pm 0.17\%\,\mathrm{year}^{-1}$ if the weighted average is used. With the average relationship, the drift associated with P of 0.5 is $\pm 0.28\%$, $\pm 0.27\%$, $\pm 0.20\%$, and $\pm 0.16\%\,\mathrm{year}^{-1}$ for polar, coastal, mid-latitude, and subtropical provinces, respectively. Again, oligotrophic regions appear as the most sensitive to perturbations of their time series. For a drift of $\pm 0.15\%\,\mathrm{year}^{-1}$, 52% of the ocean is characterized by $P<0.5$ including the Mediterranean Sea, the Caribbean Sea, the Northern Atlantic Tropical Province (NATR), the southern Atlantic subtropical gyre, the northern and southern Pacific subtropical gyres, and the southern Indian Ocean. Furthermore, three provinces are still associated with $P<0.5$ for a drift of $\pm 0.1\%\,\mathrm{year}^{-1}$, the southern Atlantic and Pacific subtropical gyres and the Subantarctic Province.

5. Conclusions and discussion

This study first showed that the trends obtained with a combined series built with SeaWiFS and MODIS chl-*a* differed from those observed with the corresponding bias-corrected series even though these two products are close to each other (Figure 1). Specifically, trends differed in regions where the bias between the SeaWiFS and MODIS chl-*a* was characterized by relatively large amplitudes (Figure 2). Quantifying how two slopes differed by the level of significance P of a *t*-test, P was found lower than 0.5 for 42.1% of the ocean domain, and lower than 0.1 for 9.6% of the domain.

This aspect was further addressed through a sensitivity analysis, where the level of bias was systematically varied and its impact on the trend detection quantified. In practice, slopes of linear regression were compared for two time series: (1) a series of reference created by combining SeaWiFS and MODIS data where the MODIS data were corrected for the bias with respect to SeaWiFS on a climatological basis, and (2) a series where a constant relative bias was applied to the climatologically bias-corrected MODIS data before combining them with the SeaWiFS data. This was performed on average chl-*a* series derived from a set of provinces that amount to a template of the world ocean and therefore provide a representative ensemble of chl-*a* annual and inter-annual variability (Longhurst 2006). Relationships were constructed that linked any level of significance with the bias between the two products (Figure 4). Results were similar if the combined SeaWiFS/MODIS data record was built by merging or concatenation, albeit some differences might appear in regions of scarce coverage such as at high latitudes. In general, a bias on the order of ±5–6% (considering results averaged over all provinces weighted by their surface) corresponds to a level of significance *P* of 0.05, that is, slopes that are different in a significant manner. Conversely, the objective of *P* equal to 0.5 would require bias values of approximately 2%. Considering uncertainties on chl-*a* in situ data (Claustre et al. 2004), results of algorithms evaluations (Brewin et al. 2015), chl-*a* satellite products validation analyses (Gregg and Casey 2004; Mélin, Zibordi, and Berthon 2007) or inter-comparison (Zhang et al. 2006; Mélin 2010, and Figure 2(*a*)), uncertainties associated with the satellite-derived remote-sensing reflectance (Mélin and Franz 2014), and limitations inherent to the calibration of radiometers in space (Zibordi et al. 2015), it is unlikely that, in the current state of technology and algorithm development, these levels of biases will be achieved by merely applying a fully consistent processing chain for the various missions (even though this is highly desirable). This study suggests that bias correction methods should become an integral part of the strategy to create ocean colour multi-mission CDRs. A corollary is that the results of trend analyses that do not specifically address inter-mission biases are questionable.

A similar analysis was conducted by ingesting a drift of varying amplitude into the reference merged series. The relationship between drift value and the level of significance associated with the comparison of slopes with and without drift showed that on average a drift of $\pm 0.3\%\,\mathrm{year}^{-1}$ associated with the GCOS requirements corresponds to *P* values of approximately 0.3. This suggests that this requirement, representing approximately 10% of a typical statistically significant trend in chl-*a* (Figure 1(*b*), Vantrepotte and Mélin 2009), should be further reduced. To enforce *P* values larger than 0.5 requires drift below approximately $0.2\%\,\mathrm{year}^{-1}$, or even $0.1\%\,\mathrm{year}^{-1}$ if subtropical gyres are concerned. Indeed, in both types of analysis (effects of a bias or a drift), regions of low variability such as the oligotrophic subtropical gyres are particularly sensitive to any perturbation of their time series and require a special attention, all the more so that they show signs of inter-annual variability (Polovina, Howell, and Abecassis 2008; Vantrepotte and Mélin 2011; Signorini and McClain 2012). It is worth mentioning that the drift selected here is a multiplicative term (Equation (4)) expressed in % per unit of time, with the consequence that the drift modifies the amplitude of the annual cycle. Other mathematical formula for the drift could be tested, for instance, modifying chl-*a* more strongly towards the end of a mission record as can be envisaged with an ageing sensor.

It is also not clear how a drift affecting a sensor can manifest itself in terms of chl-*a* variability, and a simple linear drift is unlikely to apply in the case of a time series based on successive missions. Equation (4) was adopted as an ideal case merely because it refers to the GCOS requirement expressed in % per decade.

These conclusions are mostly the result of a sensitivity study based on regional chl-*a* time series associated with a set of provinces deemed representative of the annual and inter-annual variability that can be observed in the global ocean. They should be somewhat independent of the reprocessing activities that the different data sets regularly undergo, insofar as these updates do not significantly change the main properties of these patterns of variability. The issue is different when it comes to obtaining quantitative estimates of trend. Indeed, some reprocessing updates might have an impact on trend detection, for instance, through the reduction of noise in the series. The most direct impact is likely to occur through a revision of the calibration history of a sensor (with effects that could be compared to those of a drift), which is a recurrent event affecting particularly the latest years of an active mission as the knowledge on the sensor characterization is updated. In that respect, the last years of the MODIS record, which suffer from radiometric degradation (Meister and Franz 2014), were cautiously excluded from the current analysis. Clearly, the effect of a data update depends on the nature of the reprocessing and its impact on the quantity of interest (such as chl-*a*). For the sake of illustration, the trend obtained with the newly reprocessed SeaWiFS data (version R2014.0) was compared over the period 1998–2007 with the trend associated with the version R2010.0 data used here. For that update, the reprocessing entailed various changes including a revised calibration history (NASA 2015) and an update of the chl-*a* algorithm in oligotrophic conditions (Hu, Lee, and Franz 2012). The P value comparing the two trend estimates is less than 0.1 for only 1.8% of the global ocean (75% have P>0.5) with isolated features mostly in oligotrophic waters, including the eastern Mediterranean Sea. In that case, the change in trend estimates is rather limited but still relevant.

This study relies on a fairly simple statistical method applied to monthly data, but this approach appears commensurate to introduce an objective framework that illustrates the effects of bias and drift on trend analyses and provides information relevant for the definition of requirements for multi-mission CDRs and merging strategies. Moreover, similar approaches were actually used for typical studies of time series (McClain, Signorini, and Christian 2004; Vantrepotte and Mélin 2009; Yoder et al. 2010; Kahru et al. 2012; Signorini, Franz, and McClain 2015). In any case, the objective of the study was not to derive accurate estimates of actual chl-*a* trends in the ocean, for which more advanced statistical methods are desirable (e.g. Beaugrand, Ibañez, and Lindley 2003; Henson and Thomas 2007; Vantrepotte and Mélin 2011; Saulquin et al. 2013), but to illustrate how significant bias or drift can be for trend detection. This being said, the trend map (Figure 1(*b*)) obtained for the period 1998–2012 with the reference merged series (combining SeaWiFS and bias-corrected MODIS data) is very coherent with the results of Gregg and Roussseaux (2014) who also used a bias correction approach and data assimilation in a biogeochemical model (see their Figure (6)). Some trends are more significant in the current study, like the positive horseshoe-shaped pattern in the southern Pacific; on the other hand, some trend amplitudes appear higher in Gregg and

Roussseaux (2014) like in the northern tropical Atlantic, which might indicate residual effects of inter-mission biases.

The current study has worked with the realistic setting of two successive satellite missions with a lifetime of 10 years and an overlap of 5 years. While a similar condition is not guaranteed in the future, further developments of this kind should take place to properly handle more complex cases, for example, with more coincident missions and varying periods of overlap. The longer periods necessary to study climate change issues require a series of successive missions, a situation that needs to be properly accommodated by the techniques called to combine and analyse the corresponding data records. In that respect, bias quantification and bias correction techniques will take a growing importance, as heralded by some current projects such as the Ocean Colour Climate Change Initiative (Sathyendranath et al. 2016). Finally, this study recalls the importance of the efforts deployed to monitor the stability of space sensors and of the consistency in calibration and processing strategies.

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Disclosure statement

No potential conflict of interest was reported by the author.

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