# 水色学经典论文评述-6

## Band ratio to band difference for Chl of oceanic waters: broke a self-imposed no-touch zone

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**Abstract:**

There are many empirical algorithms developed for the remote sensing of chlorophyll-a concentration (Chl) from ocean color measurements, with the blue-green band-ratio type of algorithms dominating these practices. During the phase of algorithm development, which is data-driven, generally the errors of remote sensing reflectance ($R_{rs}$) from satellites are ignored until Hu et al. (2012) developed a band-difference type algorithm where $R_{rs}$ at the blue, green, and red bands were used as the input, where the errors in $R_{rs}$ were kept in mind. This band-difference algorithm generated significantly better Chl image products for oceanic waters from satellite ocean color measurements, which contributed greatly to satellite ocean color remote sensing and influenced the way of thinking in algorithm development.

## 1. Band ratio to band difference for chlorophyll concentration in the ocean: a 30-year self-imposed no-touch zone

As stated in the IOCCG Report #2, "A primary goal of ocean-colour remote sensing is to produce synoptic fields of chlorophyll pigment …" (IOCCG 1999). To achieve this, a robust algorithm for the estimation of chlorophyll-a concentration (Chl) from ocean color data is one of the key components of any processing system. Traditionally, this has been achieved through blue/green band-ratio algorithms (Hu and Campbell 2014; O'Reilly et al. 1998), because, at least conceptually, the ratio would decrease with increasing Chl. About 10 years ago, Hu et al. (2012) introduced a new concept in algorithm design, which used a 3-band difference to estimate Chl in relatively clear waters. The algorithm base of Hu et al. (2012) is the difference of remote sensing reflectance ($R_{rs}$) at the blue, green, and red bands, rather than the base of "standard" algorithms adopted by NASA and ESA for many decades, which is the blue-green ratio of $R_{rs}$. Because of the improved performance in data product accuracy and cross-sensor consistency, subsequently, NASA, NOAA, and ESA adopted a mixed algorithm to process satellite ocean color data for the generation of global Chl, with the band-difference algorithm for waters with Chl < ~0.2 mg/m$^3$ (more than 70% of the global ocean), band-ratio algorithm for waters with Chl > ~0.3 mg/m$^3$, and an empirical bridge for waters with Chl between ~0.2 and ~0.3 mg/m$^3$.

The development of algorithms for the estimation of Chl from ocean color measurements is a key aspect of research in ocean optics and ocean color remote sensing, which could be dated back to the 1970s, where nearly all algorithms took an approach based on the blue-green ratio of water color, represented either by $R_{rs}$ or the water-leaving radiance. Why did it take many decades to reach this new level, and thinking, on the processing of satellite ocean color images? Note that 30 years earlier, before Hu et al. (2012), Viollier et al. (1978; 1980) developed empirical Chl algorithms based on the difference of water-leaving radiance at two bands (which is equivalent to the difference of $R_{rs}$ at two bands).

One likely reason for this hiatus is the analyses presented in the book authored by Gordon and Morel (1983), which used a model of reflectance to demonstrate the variables related to the reflectance difference of "Case 2" waters. Gordon and Morel (1983) stated that the model "… would be a good approximation to some Case 2 waters," which "… can be used to demonstrate the dangers associated with the use of such an algorithm", i.e., band-difference type of algorithms will inherently not perform well for such waters. This statement was somehow interpreted by the community that the band difference algorithm is not a good option for all waters, thus no longer evaluated or practiced until Hu et al. (2012), resulting in a 30-year hiatus or no-touch zone. However, Gordon and Morel's analyses are about a "danger" in "Case 2" waters for such band-difference algorithms; they did not evaluate the situations of oceanic waters, and they did not state that there is such a "danger" for oceanic waters where Chl is low. It is rather that nearly all practitioners in ocean-color-algorithm development insensitively, and incorrectly, extended the interpretation to such waters, where the practitioners were not careful or rigorous enough in extending results from one environment to another. As presented in Hu et al. (2012) and below, for oceanic waters where Chl is low, actually there is no such "danger".

## 2. The essence of blue-green-red difference of $R_{rs}$

The band difference algorithm for Chl proposed by Hu et al. (2012) can be written as

$$BD_{Rrs} = R_{rs}(\lambda_G) - \left[R_{rs}(\lambda_B) + \frac{\lambda_G-\lambda_B}{\lambda_R-\lambda_B}\left(R_{rs}(\lambda_R) - R_{rs}(\lambda_B)\right)\right] \tag{1a}$$

$$Chl = f(BD_{Rrs}) \tag{1b}$$

where $BD_{Rrs}$ is the difference of $R_{rs}$ at the blue ($\lambda_B$), green ($\lambda_G$) and red ($\lambda_R$) bands. $R_{rs}$ is in general a function of water's inherent optical properties (Gordon et al. 1988), and to the first order it can be expressed as

$$R_{rs} = G\frac{b_b}{a+b_b} \tag{2}$$

Here, $b_b$ and $a$ are the backscattering and absorption coefficients, respectively, with $G$ ($sr^{-1}$) a model coefficient. For $b_b$, commonly it is divided into two terms

$$b_b = b_{bw} + b_{bp} \tag{3}$$

with subscripts "w, p" representing pure (sea)water and particles. For $BD_{Rrs}$, based on Eq. 2, considering $a >> b_b$ and ignoring $b_b(\lambda_R)/a(\lambda_R)$ for low Chl waters, there is

$$BD_{Rrs} \approx G\frac{\left(a(\lambda_B)b_{bw}(\lambda_G)-\beta\, a(\lambda_G)b_{bw}(\lambda_B)\right)+\left(a(\lambda_B)b_{bp}(\lambda_G)-\beta\, a(\lambda_G)b_{bp}(\lambda_B)\right)}{a(\lambda_B)a(\lambda_G)} \tag{4a}$$

$$= -G\frac{\Delta_{water}+\Delta_{particle}}{a(\lambda_B)a(\lambda_G)} \tag{4b}$$

Here $\beta$ is $(\lambda_R-\lambda_G)/(\lambda_R-\lambda_B)$. $\Delta_{water}$ and $\Delta_{particle}$ represent the contributions to $BD_{Rrs}$ related to the backscattering coefficient of pure seawater and particles, respectively. As demonstrated in Hu et al. (2012), for waters with Chl less than about 0.2 mg/m$^3$ (more than 70% of the global ocean), with $\lambda_B$ = 443 nm, $\lambda_G$ = 555 nm and $\lambda_R$ = 670 nm, $|\Delta_{water}|$ is significantly greater than $|\Delta_{particle}|$ (see Fig. 1), thus $BD_{Rrs}$ can be approximated as

$$BD_{Rrs} \approx -G\frac{a(\lambda_B)b_{bw}(\lambda_G)-\beta\, a(\lambda_G)b_{bw}(\lambda_B)}{a(\lambda_B)a(\lambda_G)} \tag{5}$$

Further, considering $a(\lambda_G)$ is nearly a constant for oceanic waters, the variation of $BD_{Rrs}$ is thus mainly driven by $a(\lambda_B)$. Because Chl is a major contributor to $a(\lambda_B)$, thus a change of $BD_{Rrs}$ represents a change of Chl, and $BD_{Rrs}$ can be used as an index to infer Chl as showing by Eq. 1b.

This scheme, however, as presented in Gordon and Morel (1983), will not work for waters with high loads of particles (waters with high Chl), where $|\Delta_{water}|$ could be significantly less than $|\Delta_{particle}|$ (see Fig. 1). For such waters, the variation of $BD_{Rrs}$ is driven by both $b_{bp}$ and $a(\lambda_B)$, consequently large uncertainties will be resulted in the estimated Chl if $BD_{Rrs}$ is used as the input, which is the "danger" warned in Gordon and Morel (1983).

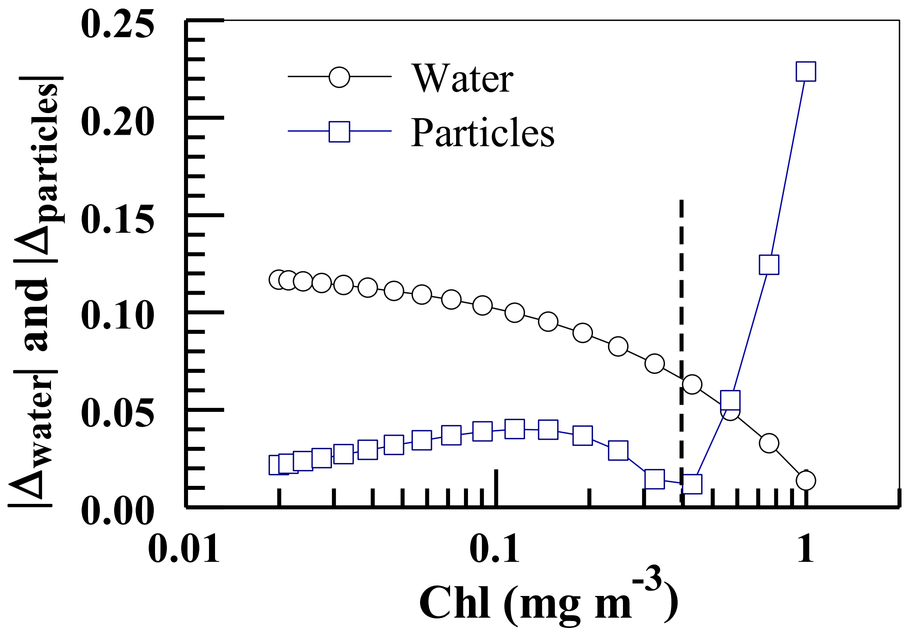


Fig. 1. Contrast between $\Delta_{water}$ and $\Delta_{particle}$ for different Chl. To show their relative significance, the absolute values (x 1000) are shown here. (From Hu et al. 2012).

More importantly, the uniqueness of the blue-green-red $BD_{Rrs}$ of Hu et al. (2012) is that it is nearly immune to residual errors in $R_{rs}$. Due to reasons from sensor's calibration to atmospheric correction, $R_{rs}$ from satellite measurements always contains some residual errors (represented as $\delta$), which generally can be considered as a linear function of wavelength (Hu et al. 2013), thus satellite remote sensing reflectance ($R_{rs}^{Sat}$) could be expressed as

$$R_{rs}^{Sat}(\lambda) = R_{rs}(\lambda) + \delta(\lambda) = R_{rs}(\lambda) + y\lambda + x \quad (6)$$

with $x$ and $y$ empirical parameters to model the wavelength dependence of $\delta$. Through simple algebra, it can be shown that the blue-green-red band difference of $R_{rs}^{Sat}(\lambda)$ equals to the blue-green-red band difference of $R_{rs}$, i.e.,

$$BD(R_{rs}^{Sat}) = BD_{Rrs} \quad (7)$$

This feature is very important for processing ocean color images, i.e., $BD(R_{rs}^{Sat})$ is simply driven by bio-optics, not affected by $\delta$ when the residual error is a linear function of wavelength. Even for the value of $y$ slightly changes for different ranges of wavelength (Chen et al. 2016), Hu et al. (2012) showed that uncertainties in the retrieved Chl due to the variation of $y$ are still < 2%, indicating the algorithm's strong tolerance to input $R_{rs}$ errors.

Such a feature is not available if simply taking a difference of $R_{rs}^{Sat}$ between two bands, as the slope term in Eq. 6 could not be cancelled out, and this slope could vary for different pixels in the same satellite image. This limitation is likely another reason that the band-difference approach was not continued in those decades.

Further, when Chl is calculated from $R_{rs}^{Sat}$ with a band-ratio algorithm, it becomes

$$Chl = f\left(\frac{R_{rs}(\lambda_B)+\delta(\lambda_B)}{R_{rs}(\lambda_G)+\delta(\lambda_G)}\right) \quad (8)$$

where the residual error ($\delta(\lambda)$) could not be cancelled out. Especially, when $R_{rs}(\lambda_G)$ is small (for most oceanic waters), $\delta(\lambda_G)$ could significantly impact this ratio, which then results in noisy and speckled images (see Fig. 2). Comparing Eq. 7 with Eq. 8, it shows the fundamental reason why the blue-green-red difference is superior to the blue-green ratio for processing satellite ocean color images of oceanic waters.

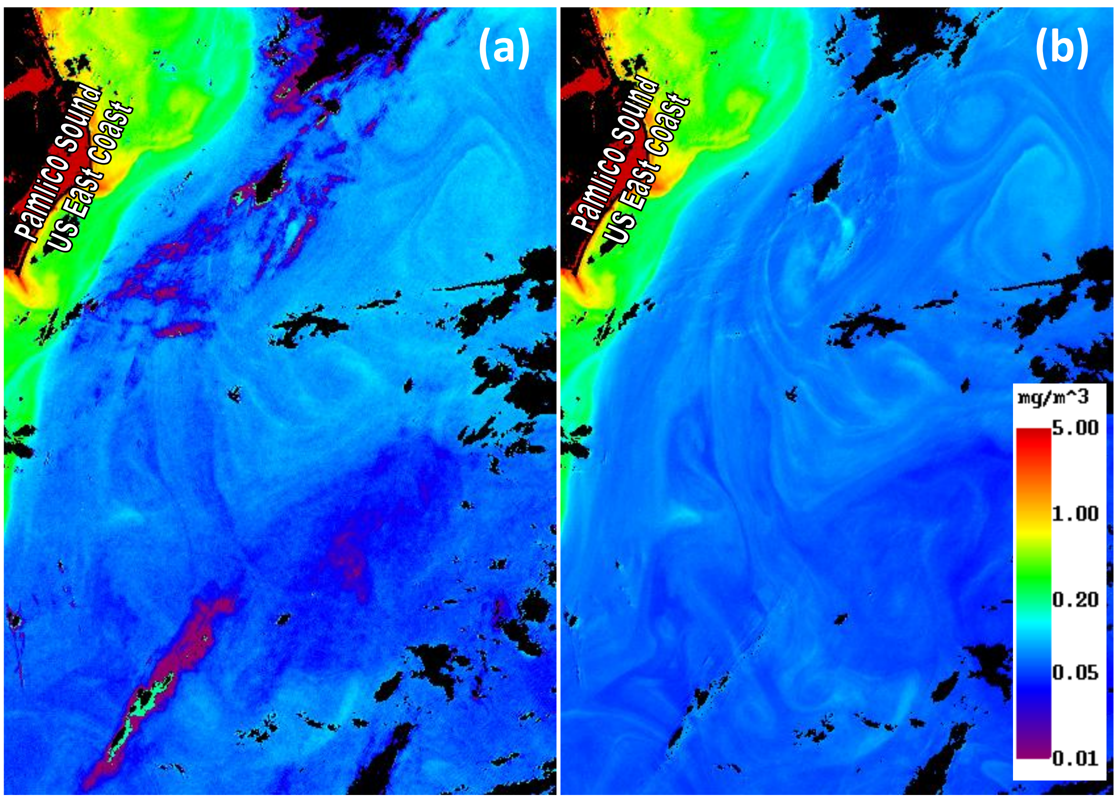


Fig. 2. Contrast of Chl image product obtained from band ratio (a) and band difference (b) algorithms. Note that some eddy features are clearly revealed in the band-difference image but absent in the band-ratio image due to noise and residual errors in atmospheric correction and other corrections. (From Hu et al. 2012).

However, no matter if it is band ratio or band difference of $R_{rs}$, it is necessary to keep in mind that the variation of $a(\lambda_B)$ is not simply driven by Chl alone, as $a(\lambda_B)$ in general is

$$a(\lambda_B) = a_w(\lambda_B) + a_{ph}^*(\lambda_B)Chl + a_{dg}(\lambda_B) \tag{9}$$

Here, $a_w$ is the absorption coefficient of pure seawater, with $a_{dg}$ the contributions from detritus and gelbstoff. $a_{ph}^*$ is the Chl-specific absorption coefficient, which is defined as the ratio of phytoplankton absorption coefficient ($a_{ph}$) to Chl. Thus, to accurately infer Chl from $BD_{Rrs}$, it is either required that $a_{ph}^*$ and $a_{dg}$ co-vary with Chl, or these two properties are determined separately. In short, the uncertainties introduced by the variations of $a_{ph}^*(\lambda_B)$ and $a_{dg}$ in the estimated Chl could not be avoided regardless of using band ratio or band difference of $R_{rs}$. Understanding and estimating the spatial and temporal changes of $a_{ph}^*(\lambda_B)$ of global ocean is still one of the biggest challenges in ocean color remote sensing.

## 3. A few extensions

### 3.1 Band difference for the remote sensing of other bio-optical variables

The concept of band difference is not new but has been used to estimate fluorescence line height (FLH, Abbott and Letelier 1999) and maximum chlorophyll index (MCI, Gower et al. 2005) from satellite measurements. Likewise, a three-band difference floating algae index (FAI) algorithm has been designed to detect and quantify floating algae (Hu 2009), with several alternative forms developed for different purposes (Xing and Hu 2016). The algorithm concept has also been applied to the red-green-blue bands using satellite-derived Rayleigh-corrected reflectance data (Rrc), which showed success in deriving relative ocean color patterns even if Rrc contains contributions from sun glint and aerosols (Hu 2011).

In view of the tolerance to atmospheric correction errors of the band-difference algorithm, the concept has also been extended to other bio-optical variables, including particulate inorganic carbon (PIC, Mitchell et al. 2017) and particulate organic carbon (POC, Le et al. 2018). In these efforts, the same 3-band difference concept has been used, but the three bands were selected to optimize the algorithm performance (e.g., 547-667-748 nm for PIC and 488-547-667 nm for POC). Improvements in both accuracy and cross-sensor consistency over the earlier empirical algorithms (mostly based on band ratios) have been demonstrated. The success of band difference might also be attributed to the fact that this approach effectively exploits both absorption and backscattering properties in the algorithm design, whereas the band-ratio algorithms focus mainly on the absorption properties.

### 3.2 Correction of the residual error

Clearly, the residual error in $R_{rs}$ is a significant source of uncertainty, resulting in a non-smooth image product from satellite ocean color remote sensing. While $BD_{Rrs}$ cleverly solved this issue for the estimation of Chl, PIC, POC and other properties separately and empirically, it is also of great interest to correct $\delta(\lambda)$ in $R_{rs}^{Sat}$, where the resulted $R_{rs}$ can then be applied in semi-analytical algorithms for the inversion of inherent optical properties and other variables. For this objective, Chen et al. (2016) developed an algebraic system based on Eq. 6 to solve the residual error pixel-by-pixel. While much smoother image products of $R_{rs}$ were presented in Chen et al. (2016), more practice and evaluations are deserved.

## 4. Concluding remarks

Developing a remote sensing algorithm is an on-going process, where better and more robust algorithms will emerge with the pass of time. However, the blue-green-red band-difference algorithm developed by Hu et al. (2012) ***completely*** changed the way of thinking in developing ocean color algorithms for the estimation of Chl and other bio-optical variables, especially its unique approach in handling residual errors in $R_{rs}$. The hiatus, or no-touch, of practicing band difference for Chl estimation, on the other hand, highlights a common and implicit "danger" of automatically extending results from one scenario to another, thus hinder the progresses in science and technology.


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## References:


Abbott, M.R., & Letelier, R.M. (1999). Algorithm theoretical basis document; Chlorophyll Fluorescence (MODIS ATBD 20). In (p. http://modis.gsfc.nasa.gov/data/atbd/atbd_mod22.pd)

Chen, J., Lee, Z., Hu, C., & Wei, J. (2016). Improving satellite data products for open oceans with a scheme to correct the residual errors in remote sensing reflectance. *Journal of Geophysical Research: Oceans, 121*, 3866–3886

Gordon, H.R., Brown, O.B., Evans, R.H., Brown, J.W., Smith, R.C., Baker, K.S., & Clark, D.K. (1988). A semianalytic radiance model of ocean color. *J. Geophys. Res., 93*, 10,909-910,924

Gordon, H.R., & Morel, A. (1983). *Remote assessment of ocean color for interpretation of satellite visible imagery: A review*. New York: Springer-Verlag

Gower, J., King, S., Borstad, G., & Brown, L. (2005). Detection of intense plankton blooms using the 709 nm band of the MERIS imaging spectrometer. *International Journal of Remote Sensing, 26*, 2005-2012

Hu, C. (2011). An empirical approach to derive MODIS ocean color patterns under severe sun glint. *Geophysical Research Letters, 38*

Hu, C., & Campbell, J. (2014). Oceanic Chlorophyll-a Content. In J. Hanes (Ed.), *Biophysical Applications of Satellite Remote Sensing*. Berlin, Heidelberg: Springer

Hu, C., Feng, L., & Lee, Z. (2013). Uncertainties of SeaWiFS and MODIS remote sensing reflectance: Implications from clear water measurements. *Remote Sens. Env., 133*, 168-182

Hu, C., Lee, Z., & Franz, B. (2012). Chlorophyll a algorithms for oligotrophic oceans: A novel approach based on three-band reflectance difference. *J. Geophys. Res., 117*, C01011, doi:01010.01029/02011JC007395

Hu, C.M. (2009). A novel ocean color index to detect floating algae in the global oceans. *Remote Sensing of Environment, 113*, 2118-2129

IOCCG (1999). Status and plans for satellite ocean-color missions: Considerations for complementary missions. In J.A. Yoder (Ed.), *Reports of the International Ocean-Colour Coordinating Group, No.2*. Halifax, Canada: IOCCG

Le, C., Zhou, X., Hu, C., Lee, Z., Li, L., & Stramski, D. (2018). A color-index-based empirical algorithm for determining particulate organic carbon concentration in the ocean from satellite observations. *Journal of Geophysical Research: Oceans, 123*, 7407–7419.

Mitchell, C., Hu, C., Bowler, B., Drapeau, D., & Balch, W.M. (2017). Estimating particulate inorganic carbon concentrations of the global ocean from ocean color measurements using a reflectance difference approach. *Journal of Geophysical Research: Oceans, 122*, 8707–8720

O'Reilly, J.E., Maritorena, S., Mitchell, B.G., Siegel, D.A., Carder, K.L., Garver, S.A., Kahru, M., & McClain, C. (1998). Ocean color chlorophyll algorithms for SeaWiFS. *Journal of Geophysical Research-Oceans, 103*, 24937-24953

Viollier, M., Deschamps, P.Y., & Lecomte, P. (1978). Airborne remote sensing of chlorophyll content under cloudy sky as applied to the tropical waters in the Gulf of Guinea. *Remote Sens. Environ., 7*, 235–248

Viollier, M., Tanre, D., & Deschamps, P.Y. (1980). An algorithm for remote sensing of water color from space. *Boundary-Layer Meteorology, 18*, 15

Xing, Q., & Hu, C. (2016). Mapping macroalgal blooms in the Yellow Sea and East China Sea using HJ-1 and Landsat data: application of a virtual baseline reflectance height technique. *Remote Sens. Environ., 178*, 113–126