Determination of phytoplankton groups from ocean color spectral measurements in the Senegalo-Mauritanian upwelling

Ymane Taoufiq[1], Ousmane Farikou[2], Séverine Alvain[3], Julien Brajard[1,4], Michel Crépon[1], Malick Ngom[1], and Sylvie Thiria[1]

[1]Sorbonne Universités (UPMC, Univ Paris 06), CNRS, IRD, MNHN, LOCEAN Laboratory, IPSL, 4 place Jussieu, F-75005, Paris, France
[2]Université Cheikh Anta Diop, Dakar, Sénégal
[3]Laboratoire d'Oceanologie et de Geosciences, CNRS-ULCO-USTL, Wimereux, France
[4]INRIA, Rocquencourt, France

20 octobre 2014

1 Introduction

Ocean color measurements have been intensively used to estimate chlorophyll-a concentration (Chl-a in abreviation) in the surface waters of the ocean, marginal seas and lakes.

Phytoplankton is the first element in the ocean food webs and consequently drives the ocean productivity. It also plays a fundamental role in climate regulation by trapping atmospheric CO2 through gas exchanges at the sea surface. With the growing interest in climate change, one may ask how the different phytoplankton populations will respond to changes in ocean characteristics (temperature, salinity) and nutrient supply.

Pigment analysis by High Performance Liquid Chormatography (HPLC) has been widely used to categorized broad Phytoplancton size classes (PSC) or phytoplancton functional types (PFT) [Hirata et al., 2011]. Each phytoplancton group (PSC/PFT) is associated with diagnostic pigments and a convertion formula can be derived to estimate the percentage of each group from the pigment measurements.

These in-situ measurements were used to build relationships between PSC/PFT and ocean properties that can be derived from satellite ocean color sensors (e.g. Chl-a concentration or water leaving-radiance), which is of fundamental interest to understand the phytoplankton behavior and to model its evolution [Uitz et al., 2006, Ciotti and Bricaud, 2006, Hirata et al., 2008, Sathyendranath et al., 2014, Alvain et al., 2005, Alvain et al., 2012].

In the present work, we propose a regional algorithm based on PHYSAT [Alvain et al., 2012], that estimates diagnostic pigments associated with PFT/PSC from satellite ocean color measurements. The region of application is the senegalo-mauritean upwelling and the results focused on the relative concentration of Fucoxanthin (Fuco) which is the main diagnostic pigment for Microplankton ($> 20\mu m$) and Diatoms.

2 Data

2.1 Satellite dataset

For this study, a satellite image archive of the senegalo-mauritean upwelling (8^oN-24^oN, $14^oW - 20^oW$) obtained from the radiometer SeaWiFS was used and the year 2003 was chosen to be a test case of the algorithm.

Each data is a daily image of the water-leaving reflectances (ρ_w) at four wavelengths (443nm, 490nm, 510nm and 555nm) and of the concentration of Chl-a during the year 2003. The radiance at 412nm was not retained because of the high sensitivity of ρ_w to colored dissolved organic matter (CDOM) at this wavelength.

Due to the presence of saharan dusts in this region, very few estimations of ρ_w and Chl-a were available and it may lead to strong over-estimations of chlorophyll-a [Gregg and Casey, 2004]. For that reason, an atmopsheric correction algorithm dedicated to saharan dust [Diouf et al., 2013] was used to obtain accurate ρ_w and chl-a data.

As in [Ben Mustapha et al., 2014], the reflectance ratio for each pixel was computed as follow :

$$Ra(\lambda) = \rho_w(\lambda)/\rho_{wref}(\lambda, chl - a) \tag{1}$$

The concentration ρ_{wref} depends on the Chl-a concentration only. ρ_{wref} was calculated for Chl-a values observed by SeaWiFS in the studied region using a multilayer perceptron which is a class of artificial neural network able to model any non linear function. This is a difference compared to [Ben Mustapha et al., 2014] who used tabulated values. This permits to have a smoother ρ_{wref} function even if the dependency between ρ_{wref} and Chl-a is not linear.

The satellite dataset made of the $Ra(\lambda)$ during the year 2003 is thereafter denoted DSAT.

2.2 The pigment dataset

Phytoplankton pigments are commonly used to discriminate PSC and PFT [Hirata et al., 2011]. The strong hypothesis made in this work is that the correlation between the satellite measurement (ρ_w, Chl-a) and pigment concentrations is not dependant on the location or the date of the measurement. It means that if a satellite measurement can be associated with a pigment concentration in one particular place, the association must stay relevant anywhere and at anytime in the ocean.

For that reason, it was decided to use a large in situ dataset compiled at global scale during the whole SeaWiFS period. This dataset was collocated with the ρ_w and Chl-a measured by SeaWiFS data [Ben Mustapha et al., 2014]. Some missing data was completed using a self-organizing map technics [Junninen et al., 2004].

The pigment dataset, denoted DPIG, is composed of 1068 variables. Each variable is a 10-dimensional vector defined as :

- Component 1 : chlorophyll-a concentration
- Component 2 : divinyl chlorophyll-a concentration ratio
- Component 3 : peridin concentration ratio
- Component 4 : fucoxanthin concentration ratio
- Component 5 : 19'hexanoyloxyfuxanthine concentration ratio
- Component 6 : zeaxanthin concentration ratio
- Component 7 to 10 : SeaWiFS Ra at 4 wavelengths : 443nm, 490nm, 510nm and 555nm.

The pigment ratio are defined as in [Alvain et al., 2005] by normalizing the pigment concentration by the Chl-a and divinyl chlorophyll-a concentration.

3 Method

The algorithm was divided in two phases. The first phase consists in clustering the DPIG dataset to retrieve the link between the reflectance ration Ra and the pigment concentration ratio. The second phase consists in labeling the reflectances in DSAT in term of associated pigments.

3.1 Clustering

The clustering of DPIG was done using Self-Organizing Maps (herafter denoted SOM). The SOM [Kohonen, 1994] algorithm is a powerful non-linear classifier. It aims at clustering samples of a multidimensional dataset (in our case, DPIG) into classes represented by a dedicated network (the so-called SOM map).

SOM is a neural classifier where each neuron of the map is associated with a particular referent vector V_k. The different neurons og the SOM map are connected together and determine a topological (neighbourhood) relationship between the different neurons (subset of similar data).

In the present case, the SOM map is a two-dimensional (13×12) grid that represents the partition of the DPIG dataset. Each class is associated with a so-called referent vector V_k ($k = \{1, 2, ...180\}$). V_k are calculated by a weigted mean of elements in DPIG. Therefore, V_k has the same dimension as each element of the dataset (in our case $V_k \in \mathbb{R}^{10}$) and contains 5 relative pigment concentration ratio, the remote sensing chlorophyll-a concentration and Ra at 4 wavelengths.

At the end of the clustering, each element of the dataset DPIG is associated with the referent V_k (denoted the Best Matching Unit) which is the closest in term of the euclidien distance.

3.2 Labelisation

The labelisation phase consists in associating each element of DSAT with a pigment concentration ratio.

Each pixel P_j of DSAT contains the SeaWiFS Ra at the four wavelengths (443nm, 490nm, 510nm and 555nm). These elements can be directly compared with the composants 7 to 10 of the V_k vector that represents Ra value in DPIG.

The problem is thus to determine the Best Matching Unit V_k using only four values among the 10 used in the SOM map. A truncated distance (TD) that considere only the existing values was used. The Best Matching Unit V_k was determined using the TD.

Then, the pixel P_j is directly associated with the values of the pigments concentration ratio of V_k.

With this method, each pixel P_j is associated with 5 pigment concentration ratios. The underlying assumption is that the link between reflectances and pigment ratios is the same in DPIG than for DSAT. In the following, we focus on the fucoxanthin concentration ratio which is a caracteristic of diatoms and microplanktons.

4 Regional Study

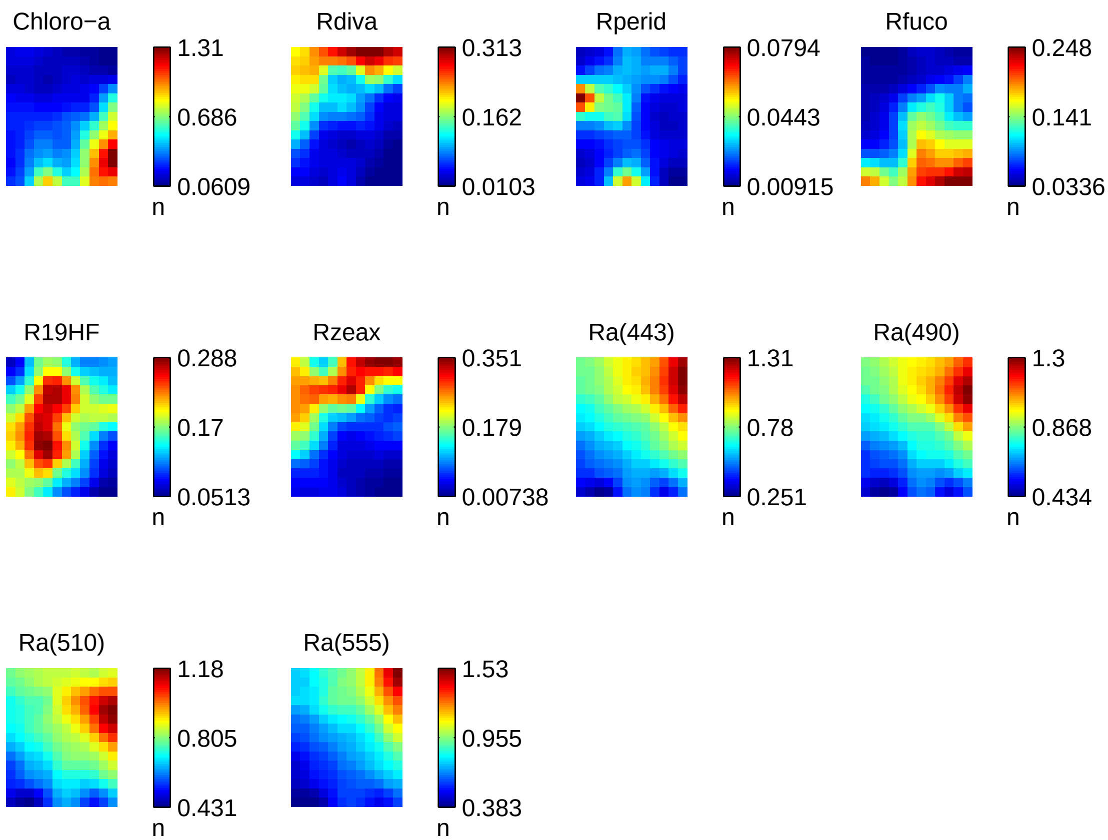

FIG. 1 – Representation of the value of the 7 composants of R_k on the Self-Organizing Map. Each image represent a composant (6 pigments and 4 Ra, each node of the image represent a class. Here the dimension of the map is 13×12

4.1 Labelisation of the reflectance spectra

In this section, the association between Ra spectra and the pigment concentration ratio are presented.

First, in Fig. 1, we show the values of all the V_k components of the 13×12 SOM map. Each component was represented by the color intensity of the grid point. It can be notice that values of the V_k components were spatially well structured on SOM. Another important remark is that the values of each component has a large range of variation of the same order as the range of variation of DPIG. It means that the SOM map has captured most of the variability of the dataset.

As each V_k contains a value for the pigment concentration ratio, it is possible to estimate several typical index of PSC or PFT. It is an important feature of this algorithm that does not estimate one particular PSC/PFT but associates directly pigment concentration ratios that can be used as proxies.

As an illustration and a validation of the approach, we can compute the percentage of microplankton (Micro) following the formula [Hirata et al., 2011] :

$$Micro = 1.41 \times (Fuco + Perid) \tag{2}$$

where $Fuco$ (resp. $Perid$) denotes the concentration ratio of Fucoxanthin (resp. Peridin).

In Fig. 2, we represent the percentage of microplankton (calculated using 2 with respect with the chlorophyll-a concentration obtained for the referent vectors V_k. The relationship between the Chl-a concentration and the Microplancton percentage is consistent with the relationship found in [Hirata et al., 2011] :

$$Micro = [a_0 + exp(a_1 log_{10}(Chl - a) + a_2)]^{-1} \tag{3}$$

where $a_0 = 0.9117$, $a_1 = -2.7330$ and $a_2 = 0.4003$.

We can notice that, in comparison with this global relationship, the regional relationship found using SOM overestimates the microplankton percentage for small value of Chl-a ($< 0.2mg/m3$). It would need further analyses to find if it is an artifact of the algorithm or a regional specificity.

This is a first validation of the correlations found in the SOM map, and it demonstrates the potentiallity of the approach. The association between remote sensing reflectance spectra and pigment concentrations is an efficient way to identify phytoplankton groups.

4.2 Labelisation of images

Using the truncated distance (TD) described in the previous section, it is possible to associate a pixel of an image to a referent V_k and thus to all the pigment concentration ratios. In this work, we present results of this association with the Fucoxanthin. All pixels from DSAT were associated with the Fucoxanthin concentration ratio. In fig 3, the mean ratio for each sequence of 3 months is presented (January to March JFM, April to June AMJ, July to Septembre JAS and finally October to December OND).

We can observe the seasonal variability of the associated Fucoxanthin concentration ratio, with a maximum concentration and a southernmost extent at the beginning of the year. Knowing that high Fucoxanthin concentration ratio are characteristic of the presence of diatoms, this seasonal variability is consistent with previous studies of the senegalo-mauritanean upwelling variability [Farikou

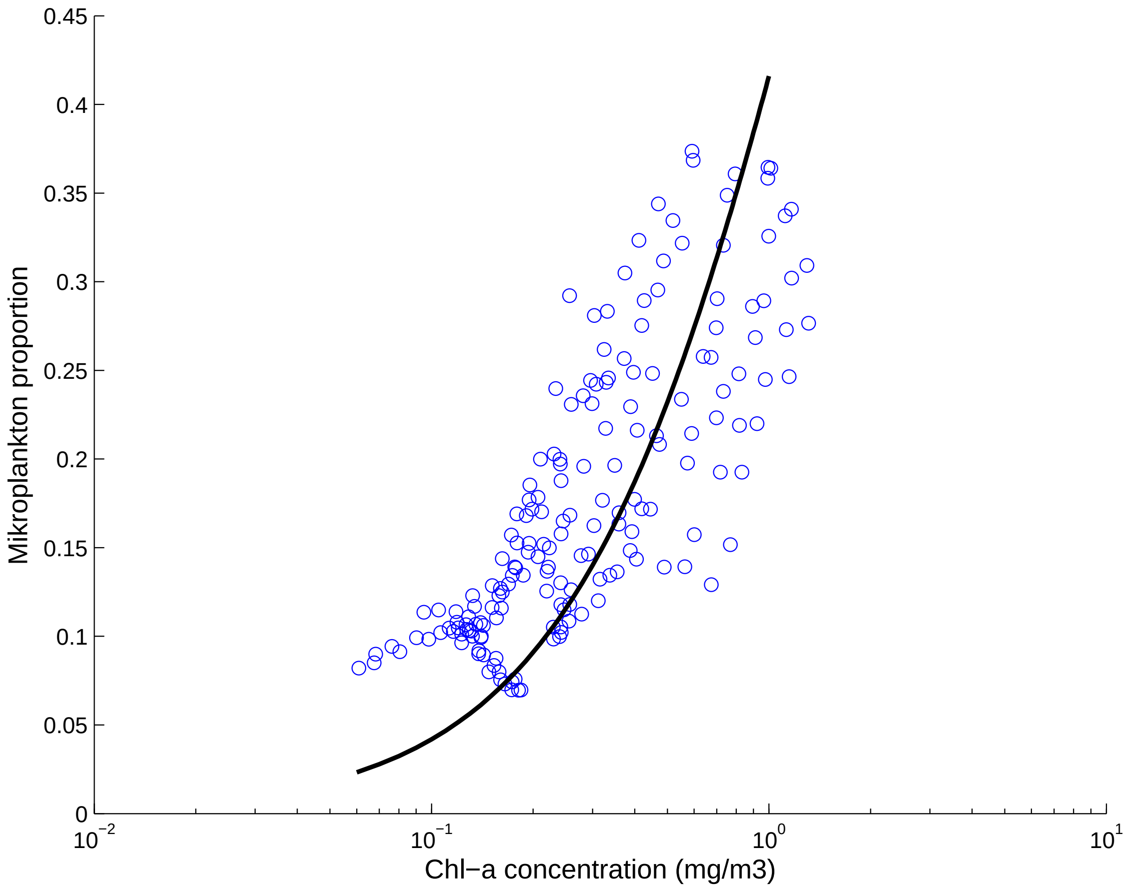

FIG. 2 – Percentage of Microplankton following Eq. 2 with respect with the chlorophyll-a concentration. Each circle represents a referent vector of the SOM map and the solid black-line represents the relationship in Eq. 3

et al., 2013, Lathuilière et al., 2008], and the observations done during the EUMELI cruises [Claustre and Marty, 1995] and the Atlantic Meridional Transec (AMT) [Aiken et al., 2009].

5 Conclusion

A regional classification technique derived from [Ben Mustapha et al., 2014] that associates reflectance spectra with pigment concentration ratio was developped and tested during the year 2003 int he senegalo-mauritanian and the Fucoxanthin concentration ratio. It was shown that results was coherent with relations found in literature. It also allows to retrieve the seasonal variability of the associated Fucoxanthin concentration ratio. It is thus possible to have significant

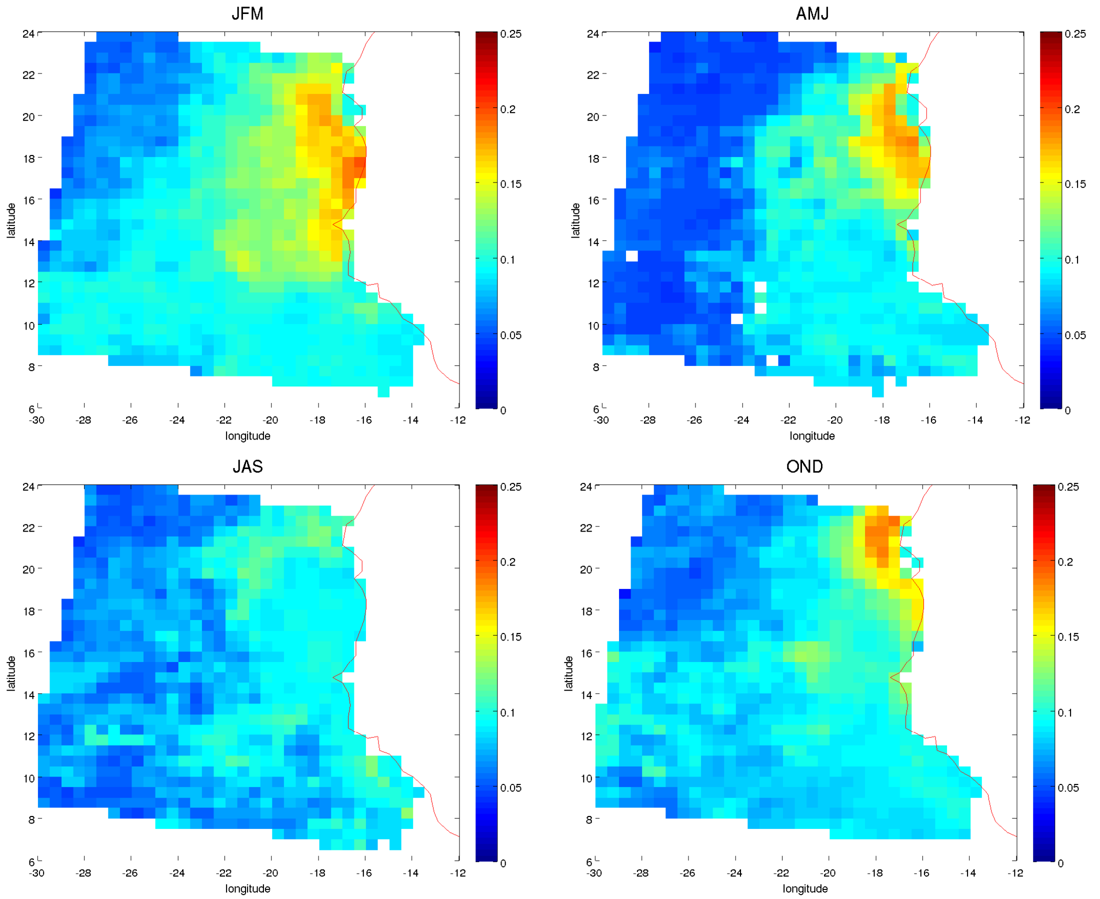

FIG. 3 – Mean value of associated Fucoxanthin concentration ratio in 2003 for the several period : January to March JFM, April to June AMJ, July to Septembre JAS and finally October to December OND

quantitative indices (concentration ratio) of phytoplankton groups.

This approach gives a lot of opportunity to study variability of pytoplankton groups (PSC or PFT) in the region of the senegal-mauritanean upwelling. This study could be continued for other classification groups and validated using in-situ data in this region.

Acknowledgement

The authors acknowledge NASA/GSFC/DAAC for providing access to daily L2 SeaWiFS products. This work was funded by the french space agency CNES/Tosca program.

Références

[Aiken et al., 2009] Aiken, J., Pradhan, Y., Barlow, R., Lavender, S., Poulton, A., Holligan, P., and Hardman-Mountford, N. (2009). Phytoplankton pigments and functional types in the atlantic ocean : a decadal assessment, 1995–2005. *Deep Sea Research Part II : Topical Studies in Oceanography*, 56(15) :899–917.

[Alvain et al., 2005] Alvain, S., Moulin, C., Dandonneau, Y., and Bréon, F.-M. (2005). Remote sensing of phytoplankton groups in case 1 waters from global seawifs imagery. *Deep Sea Research Part I : Oceanographic Research Papers*, 52(11) :1989–2004.

[Alvain et al., 2012] Alvain, S., Vantrepotte, V., Uitz, J., and Duforêt-Gaurier, L. (2012). Use of global satellite observations to collect information in marine ecology. *Sensors for ecology*, page 227.

[Ben Mustapha et al., 2014] Ben Mustapha, Z., Alvain, S., Jamet, C., Loisel, H., and Dessailly, D. (2014). Automatic classification of water-leaving radiance anomalies from global seawifs imagery : Application to the detection of phytoplankton groups in open ocean waters. *Remote Sensing of Environment*, 146 :97–112.

[Ciotti and Bricaud, 2006] Ciotti, A. M. and Bricaud, A. (2006). Retrievals of a size parameter for phytoplankton and spectral light absorption by colored detrital matter from water-leaving radiances at seawifs channels in a continental shelf region off brazil. *Limnology and Oceanography : Methods*, 4 :237–253.

[Claustre and Marty, 1995] Claustre, H. and Marty, J.-C. (1995). Specific phytoplankton biomasses and their relation to primary production in the tropical north atlantic. *Deep Sea Research Part I : Oceanographic Research Papers*, 42(8) :1475–1493.

[Diouf et al., 2013] Diouf, D., Niang, A., Brajard, J., Crepon, M., and Thiria, S. (2013). Retrieving aerosol characteristics and sea-surface chlorophyll from satellite ocean color multi-spectral sensors using a neural-variational method. *Remote Sensing of Environment*, 130 :74–86.

[Farikou et al., 2013] Farikou, O., Sawadogo, S., Niang, A., Brajard, J., Mejia, C., Crépon, M., and Thiria, S. (2013). Multivariate analysis of the senegalo-mauritanian area by merging satellite remote sensing ocean color and sst observations. *Research Journal of Environmental and Earh Sciences*, 5(12) :756–768.

[Gregg and Casey, 2004] Gregg, W. W. and Casey, N. W. (2004). Global and regional evaluation of the seawifs chlorophyll data set. *Remote Sensing of Environment*, 93(4) :463–479.

[Hirata et al., 2008] Hirata, T., Aiken, J., Hardman-Mountford, N., Smyth, T., and Barlow, R. (2008). An absorption model to determine phytoplankton size classes from satellite ocean colour. *Remote Sensing of Environment*, 112(6) :3153–3159.

[Hirata et al., 2011] Hirata, T., Hardman-Mountford, N., Brewin, R., Aiken, J., Barlow, R., Suzuki, K., Isada, T., Howell, E., Hashioka, T., Noguchi-Aita, M., et al. (2011). Synoptic relationships between surface chlorophyll-a and diagnostic pigments specific to phytoplankton functional types. *Biogeosciences*, 8(2) :311–327.

[Junninen et al., 2004] Junninen, H., Niska, H., Tuppurainen, K., Ruuskanen, J., and Kolehmainen, M. (2004). Methods for imputation of missing values in air quality data sets. *Atmospheric Environment*, 38(18) :2895–2907.

[Kohonen, 1994] Kohonen, T. (1994). *Self-organizing map*. Springer-Verlag.

[Lathuilière et al., 2008] Lathuilière, C., Echevin, V., and Lévy, M. (2008). Seasonal and intraseasonal surface chlorophyll-a variability along the northwest african coast. *Journal of Geophysical Research : Oceans (1978–2012)*, 113(C5).

[Sathyendranath et al., 2014] Sathyendranath, S., Aiken, J., Alvain, S., Barlow, R., Bouman, H., Bracher, A., Brewin, R., Bricaud, A., Brown, C., Ciotti, A., et al. (2014). Phytoplankton functional types from space. *(Reports of the International Ocean-Colour Coordinating Group (IOCCG) ; 15)*, pages 1–156.

[Uitz et al., 2006] Uitz, J., Claustre, H., Morel, A., and Hooker, S. B. (2006). Vertical distribution of phytoplankton communities in open ocean : An assessment based on surface chlorophyll. *Journal of Geophysical Research : Oceans (1978–2012)*, 111(C8).