Sensors for ecology

Towards integrated knowledge of ecosystems

Edited by Jean-François Le Galliard,
Jean-Marc Guarini and Françoise Gaill

CNRS
www.cnrs.fr

Chapter 3

Use of global satellite observations to collect information in marine ecology

Séverine Alvain, Vincent Vantrepotte, Julia Uitz, Lucile Duforêt-Gaurier

1. Introduction: ocean colour features, a state of the art

The term "ocean colour" encompasses the retrieval and description of parameters linked with oceanic phytoplankton from optical measurements. The remote sensing of ocean colours has been used for more than 30 years and now provides key information on the dynamics of the oceanic phytoplankton (Morel and Prieur, 1977; Mobley et al., 1993; Antoine et al., 1996; Bricaud et al., 1998; Loisel et al., 2006). Phytoplankton comprises microscopic plant-like organisms living in the illuminated surface layers of the ocean. The existence of phytoplankton is of a fundamental interest as they form the base of the aquatic food webs, providing an essential ecological function for all aquatic life. Like terrestrial plants, phytoplankton uses pigment antennae to capture the energy of photons. Among these phytoplankton pigments, total chlorophyll-a (i.e. the sum of chlorophyll-a, divinyl-chlorophyll-a, and chlorophyllide a) is a commonly used proxy of total phytoplankton biomass. Chlorophyll-a selectively modifies the flux of photons that penetrates the ocean surface layer. It absorbs the red and blue wavelengths and scatters the green ones. For this reason, the colour of the ocean changes from blue to green depending on the concentration and type of phytoplankton populations. Thus, by studying the colour of light scattered from the oceans, in other words ocean colour, optical sensors onboard satellites enable to quantify the chlorophyll concentration and observe its interactions with other constituents (Mobley et al., 1993; Antoine et al., 1996; Bricaud et al., 1998).

Visible and near-infrared passive radiometers onboard spacecrafts provide useful data on spatial and temporal scales, unattainable by shipboard sampling. This was well demonstrated by the first satellite dedicated to the observation of ocean colour, the coastal zone colour scanner (CZCS) launched in 1978. Since then, a number of advanced ocean-colour satellites have been launched, including SeaWiFS (sea viewing wide field of view sensor, from August 1997 to December 2010), Modis (moderate resolution imaging spectroradiometer) and Meris (medium-spectral resolution imaging spectrometer), which are still in activity. However, the ocean colour observation from space faces some important limitations. Indeed, the information obtained from satellite observation is restricted to the near-surface layer of the ocean (Gordon and McCluney, 1975). The thickness of this layer typically varies from a few metres to about 60m, depending on the presence of optically-significant constituents in the water and the wavelength considered (Smith and Baker, 1978). Products derived from satellite data are therefore integrated content over the first penetration depth. Another limitation is that a large part ocean colour measurements in the visible spectrum is caused by the atmosphere and aerosols that diffuse and absorb light. The atmosphere is responsible for about 90% of the blue light detected by a satellite sensor. However, the portion of the signal that carries information from the ocean and the atmosphere can be de-convoluted. This is currently done by using atmospheric correction algorithms that are still being improved. In the past few years, the analysis of ocean colour satellite data has moved beyond the estimation of chlorophyll-a concentration to include new parameters. This includes the ability to determine the dominant phytoplankton groups in the surface waters (Aiken et al., 2009; Alvain et al., 2005: Uitz et al., 2006; Raitsos et al., 2008; Kostadinov et al., 2009; Brewin et al., 2010), to obtain information on particle size distribution (Loisel et al., 2006), or to retrieve information about other biogeochemical components such as particulate organic carbon (POC) and coloured detrital matter (Stramski et al., 1999; Loisel et al., 2002; Siegel et al., 2002). This chapter presents an overview of these newly available parameters from remote sensing of ocean colour. We conclude by a synthesis of most important challenges and ongoing developments.

2. Overview of newly available parameters from remote sensing

2.1. Particulate organic carbon

Inherent optical properties (IOPs) describe the absorption and scattering properties of ocean water and its constituents. A recent method to analyse remote sensing data consists in deriving the surface content of particulate organic carbon (POC_{surf}) from the inherent optical properties, as presented in Loisel et al. (2002). The natural variations of optically-significant substances in seawater can be deduced from the measurements of the total backscattering coefficient of seawater, b_b, which is not sensitive to the presence of dissolved material. The b_b coefficient can be partitioned into two components,

$b_b = b_{bp} + b_{bw}$

where b_{bw} is the backscattering coefficient of seawater (Morel and Prieur, 1977) and b_{bp}, is the backscattering coefficient of particles. The b_{bp} variability is determined primarily by changes in the abundance of the particle assemblage and also, secondarily, by the composition of the assemblage.

In a remote-sensing context, the backscattering coefficient of seawater is not measured directly, but is derived by the inversion of the natural light field reflected back from the ocean and detected by satellite ocean colour sensors (Loisel and Stramski, 2000; Loisel and Poteau, 2006). A simple linear relationship calibrated for a study area is then used between POC_{surf} and b_{bp} (Claustre et al., 1999; Loisel et al., 2001). Previous studies at regional (Stramski et al., 1999; Loisel et al., 2001) and global scales (Loisel et al., 2002) have demonstrated the feasibility of estimating POC from b_{bp}, and figure 1 displays global maps of the near-surface concentration (POC_{surf}) for the SeaWiFS period 1997-2008 in June and January.

The global distribution of POC_{surf} follows the major gyre system and other large scale circulation features of the ocean. Low surface POC concentrations are encountered in subtropical gyres, where large scale downwelling is expected. For example, POC_{surf} is less than 50mg.m^{-3} in the South Pacific gyre. Elevated near-surface POC concentration in the range 100-200mg.m^{-3} are encountered at high and temperate latitudes (e.g. Antarctic circumpolar current, subarctic gyres, or temperate North Atlantic). Compared to subtropical gyres, these areas are characterized by a high chlorophyll concentration supported by inputs of nutrients injected from below the euphotic layer by advection or vertical mixing, or from terrestrial sources.

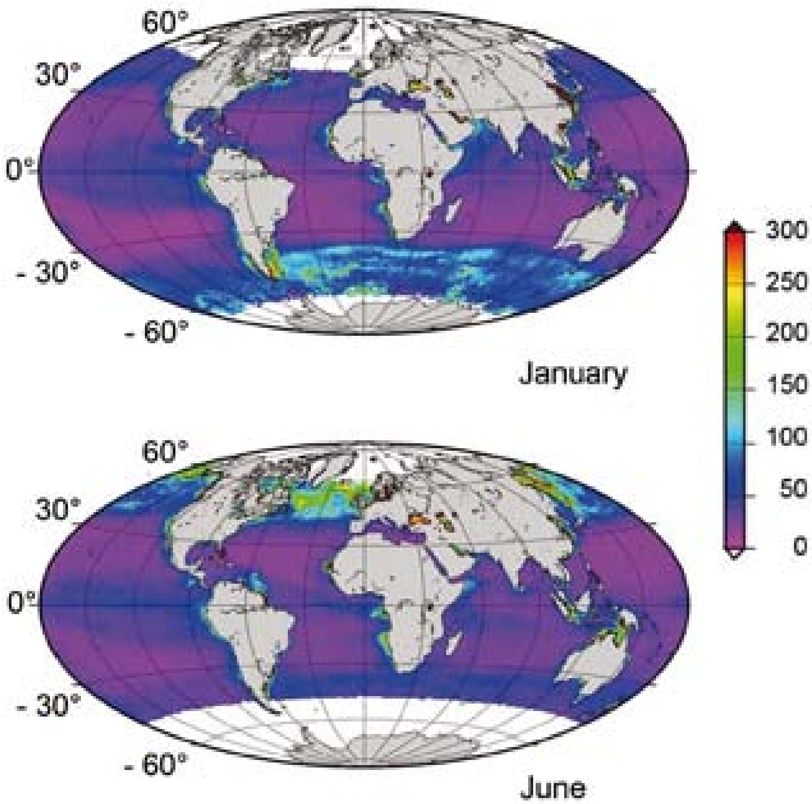

Figure 1: Global maps of the particulate organic plankton near-surface concentration calculated from SeaWiFS observations, during the period 1997-2008 in June and January using the method of Loisel et al. (2002).

2.2. Phytoplankton functional types

Phytoplankton plays an important role in many global biogeochemical cycles. However, the photosynthetic efficiency and biogeochemical impacts of phytoplankton depend strongly on the functional types of phytoplankton species. Thus, monitoring the spatial and temporal distribution of dominant phytoplankton functional groups is of critical importance. For a given chlorophyll-a concentration (Chl-a), phytoplankton groups scatter and absorb light differently according to their pigments composition, shape and size. However, the first order signal retrieved from ocean colour sensors in open oceans, the normalized water leaving radiance (nL_w), varies with Chl-a (Gordon et al., 1983; Morel et al., 1988) and cannot be easily used to extract information about phytoplankton groups present in the oceanic surface layer. To circumvent this difficulty, different approaches have been developed in the past few years. When changes in nL_w are significant enough between phytoplankton groups, they can be detected from their specific radiances measurements (Sathyendranath et al., 2004; Ciotti et al., 2006). When reflectance changes are not significant enough to separate one group from another, empirical or semi-empirical methods have to be developed. This last case is particularly relevant when the objective is to detect phytoplankton groups defined from a biogeochemical or size point of view at global scale. The Physat algorithm (Alvain et al., 2005; Alvain et al., 2008) has been developed based on an empirical relationship between coincident *in situ* phytoplankton observations and remote sensing measurements anomalies. The Physat method has been applied to the SeaWiFS satellite archive, and more recently to MODIS. Monthly Physat data have been used to retrieve the monthly climatology maps for January and June, shown in figure 2.

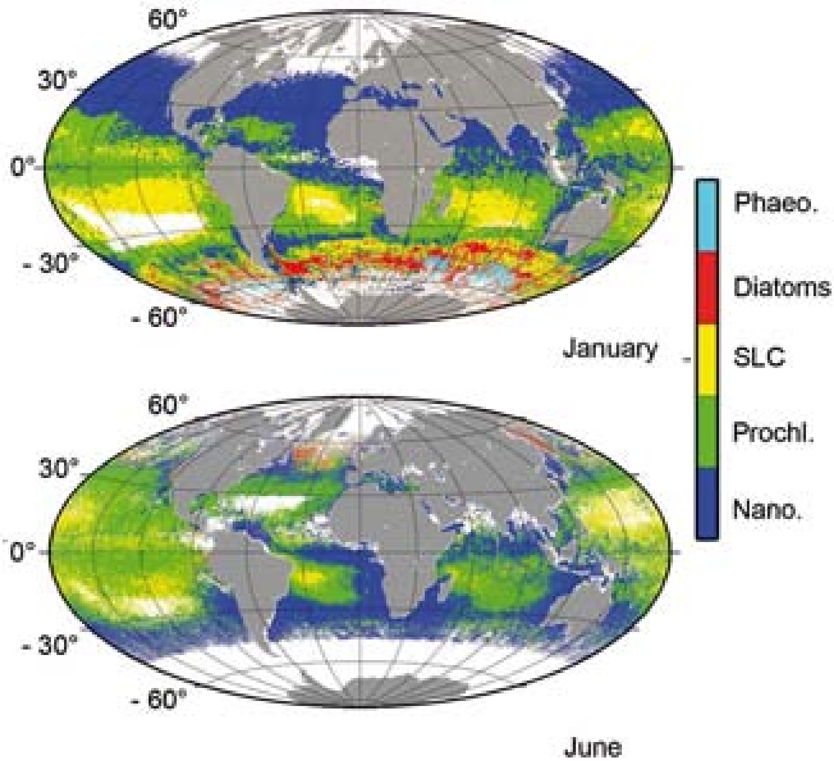

Figure 2: Dominant phytoplankton groups climatology maps over 1997-2008 period (SeaWiFS), from Physat, for June and January. Physat method allows to separate dominant phytoplankton groups from remote sensing measurements.

Physat has a domain of applicability ranging from concentrations of Chl-a higher than 0.04mg m^{-3}, so as to discard ultra-oligotrophic waters where it is unlikely that a dominant group can be found using ocean-colour data, to Chl-a lower than 3mg.m^{-3} so that waters possibly contaminated by coastal material are excluded. The Physat approach is based on the identification of specific signatures in spectra classically measured by ocean colour sensors. It has been established by comparing two kinds of simultaneous and coincident measurements: normalised SeaWiFS water leaving measurements (nL_w) and *in situ* measurements of phytoplankton biomarker pigments performed in the framework of the Gep&Co program (Dandonneau et al., 2004). Five dominant phytoplankton groups are currently identified: diatoms, nanoeukaryotes, *Synechococcus*, *Prochlorococcus* and *Phaeocystis*-like. Note that the Physat method allows the detection of these groups only when they are dominant.

The key step in the success of methods such as Physat is to associate *in situ* measurements with remote sensing measurements after having removed the first order variations due to the Chl-a concentration and classically used in previous ocean colour products. This step is done by dividing the actual nL_w by a mean nL_w model (nL_w ref) for each wavelength (λ), established from a large remote sensing dataset of $nL_w(\lambda)$ and Chl-a:

$$nL_w{}^*(\lambda) = nL_w(\lambda) \,/\, nL_w\ \mathrm{ref}(\lambda, \mathrm{Chl\ a})$$

By dividing nL_w by this reference, we obtain a new product, noted $nL_w{}^*$, which is used in Physat. Indeed, it was shown that main dominant phytoplankton groups sampled during the GeP&Co program were associated with a specific $nL_w{}^*$ spectrum. It is thus possible to define a set of criteria to characterise each group as a function of its $nL_w{}^*$ spectrum. These criteria can thus be applied to the global daily SeaWiFS archive in order to obtain global monthly maps synthesis of the most frequently detected dominant group, as shown in figure 2. Note that when no group prevails over the period of one month, the pixels are associated with an "unidentified" group. The geographical distribution and seasonal succession of major dominant phytoplankton groups were studied in Alvain et al. (2008) and are in good agreement with previous studies and *in situ* observations (Zubkov et al., 2000; DuRand et al., 2001; Marty and Chivérini, 2002; Dandonneau et al., 2004; Longhurst, 2007; Alvain et al., 2008). However, as for all empirical ocean colour methodology, validation based on in situ measurements has to be pursued every time a suitable dataset is available. *In situ* observations are indispensable in any stage of satellite development. Therefore, constructing and maintaining fully consistent coupled biogeochemical and optical records is a high priority.

2.3. Phytoplankton size classes and associated primary production

Another approach to discriminating phytoplankton groups from space consists in using the surface Chl-a concentration (Chl-a_{surf}) retrieved from ocean colour measurements as an index of phytoplankton community composition. Chlorophyll-based approaches typically rely on the general knowledge that, in open oceans, large phytoplankton cells (mostly diatoms) develop in eutrophic regions (e.g. upwelling systems) where new nutrients are available, whereas small phytoplankton are preferentially associated with the presence of regenerated forms of nutrients and dominate phytoplankton assemblage in oligotrophic environments. On the basis of such trends, Uitz et al. (2006) proposed a method for deriving the contributions of three pigment-based size classes (micro-, nano-, and picophytoplankton) to depth-resolved chlorophyll-a biomass using Chl-a_{surf} as input parameter. This method was developed through the statistical analysis of an extensive phytoplankton pigment database (2419 sampling stations) obtained from high performance liquid chromatography (HPLC) analysis of samples from a variety of oceanic regions. Using an improved version of the diagnostic pigment criteria of Vidussi et al. (2001), Uitz et al. (2006) computed phytoplankton class-specific vertical profiles of Chl-a for each station included in the pigment database, from which the desired statistical relationships were established. Essentially, seven pigments were selected as biomarkers of specific taxa, which were then assigned to one of the three size classes according to the average size of the organisms.

Some limitations of this method were recognised in the past (Vidussi et al., 2001; Uitz et al., 2006). For example, certain diagnostic pigments are shared by various phytoplankton taxa and some taxa may have a wide range of cell size. Yet, this method enables characterising the taxonomic composition of the entire phytoplankton assemblage while providing relevant information on its size structure (Bricaud et al., 2004). For example, microphytoplankton essentially include diatoms, nanophytoplankton include primarily prymnesiophytes, and picophytoplankton are often prokaryotes (cyanobacteria) and small eukaryotic species. The approach of Uitz et al. (2006) provides quantitative information on the composition of phytoplankton community within the entire upper water column rather than just the surface layer accessible to ocean colour satellites. In addition, this approach can be extended to the estimation of primary production associated with the pigment-based size classes, using a bio-optical model (Morel, 1991) coupled to class-specific photo-physiological properties (Uitz et al., 2008). In a nutshell, Uitz et al. (2008) investigated relationships between phytoplankton photo-physiology and community composition by analysing a large database of HPLC pigment determinations and measurements of phytoplankton absorption spectra and photosynthesis vs. irradiance curve parameters collected in various open ocean waters. An empirical model that describes

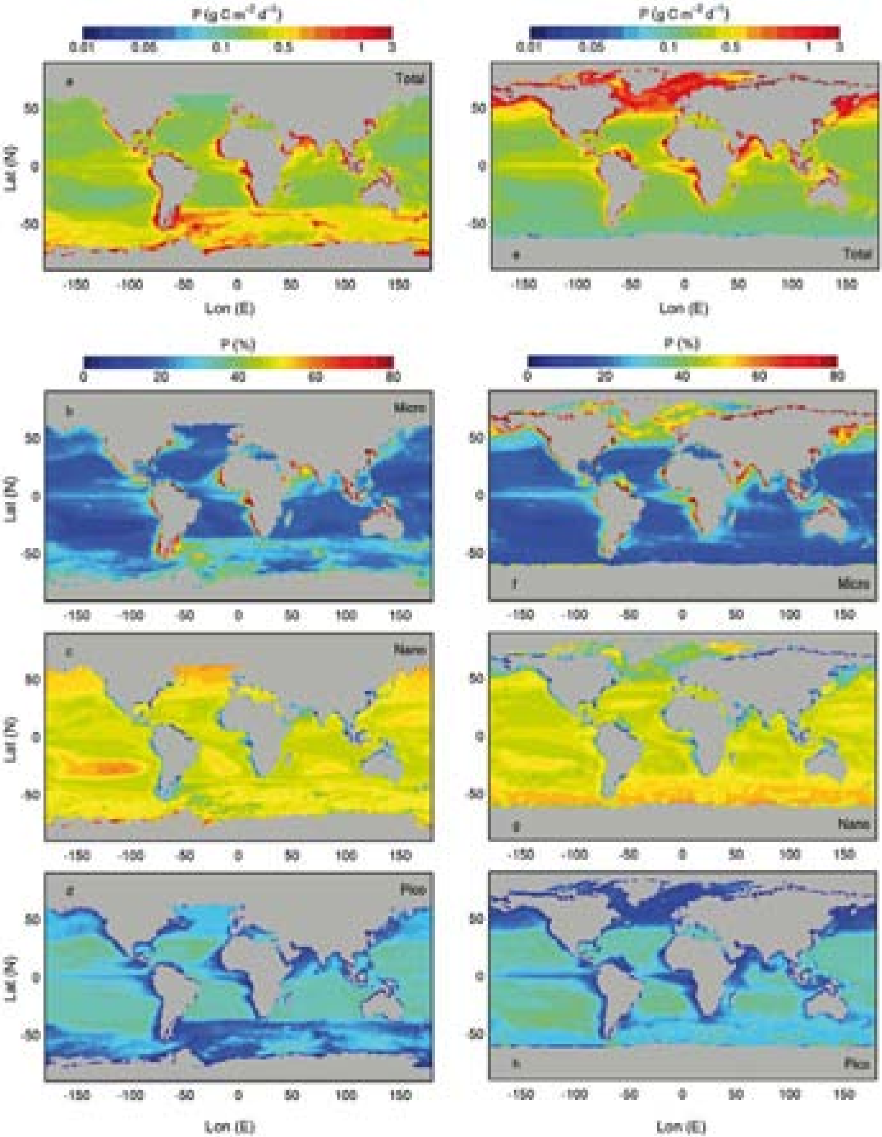

Figure 3: Seasonal climatology (1998-2007) of total and phytoplankton class-specific primary production for the December-February period (boreal winter/austral summer; left-hand side panels) and for the June-August period (boreal summer/austral winter; right-hand side panels). (a, e) Total primary production in absolute units of $gC.m^{-2}.d^{-1}$. (b-d) and (f-h) percent contribution of class-specific production to total primary production. Total primary production, attributed to the entire algal biomass, was obtained by summing the contributions of each class. (adapted from Uitz et al., 2010).

the dependence of algal photo-physiology on the community composition and depth within the water column, essentially reflecting photo-acclimation, was proposed. The application of the model to the set of *in situ* data enabled the identification of vertical profiles of photo-physiological properties for each phytoplankton size class.

Figure 3 illustrates the seasonal climatology of phytoplankton class-specific and total primary production obtained by applying the class-specific approach to a 10-year time series of Chl-a_{surf} data from SeaWiFS (Uitz et al., 2010). Temperate and subpolar latitudes in each hemisphere exhibit high total primary production values in summer, especially in the North Atlantic Ocean. In contrast, oligotrophic subtropical gyres are associated with low values and show weak seasonality. Microphytoplankton appear as a major contributor to primary production in temperate and subpolar latitudes in spring-summer, especially in the North Atlantic (more than 50%) and in the Southern Ocean (30-50%). Their contribution reaches a maximum of about 70% in near-coastal upwelling systems year-round, but is reduced drastically in subtropical gyres. Nanophytoplankton appear ubiquitous and account for a significant fraction of total primary production (30-60%). The relative contribution of picophytoplankton to primary production represents up to 40-45% in subtropical gyres and decreases to 15% in the northernmost latitudes in summer. The proposed approach enabled to produce ocean colour-derived climatology of primary production at a phytoplankton class-specific level in the world's open oceans (Uitz et al., 2010). Such information represents a significant contribution to our ability to understand and quantify marine carbon cycle. It also provides a benchmark for monitoring the responses of oceanic ecosystems to climate change in terms of modifications of phytoplankton biodiversity and associated carbon fluxes.

3. Challenges posed by current developments

3.1. Dissolved organic matter (DOM)

Besides the latter parameters, new developments in ocean colour remote sensing are needed especially for studying the dynamics of the dissolved organic matter. The dissolved organic carbon (DOC) is operationally defined as the fraction of organic carbon smaller than 0.2µm. It accounts for almost all the organic carbon of the ocean (Chen and Borges, 2009) being equivalent in magnitude to the atmospheric CO_2 stock. DOC can be degraded by microbial activity and sunlight action and converted into CO_2. Hedges (2002) reported that an increase of 1% in the DOC degradation rates would lead to a source of CO_2 equivalent or greater than that represented by the fossil fuel combustion. Therefore it appears crucial, for understanding the global carbon cycle, to investigate the dynamics of this biogeochemical compartment, which is still poorly constrained. This is particularly true for the coastal ocean, where DOC fluxes are potentially large and highly variable in time and space, due to numerous driving factors taking effect on these very heterogeneous ecosystems, such as biological activity, land-sea interactions, and strong hydrodynamic forcing. In that context, efforts are needed to develop research activities aiming to estimate DOC concentrations and fluxes from space.

Recent studies have emphasised the potential of satellite imagery for retrieving DOC concentrations with a satisfying accuracy (Mannino et al., 2008; Del Castillo et al., 2008; Fichot and Benner, 2011). The current main limitation for estimating DOC concentrations from radiative measurements stands in the crucial need of a relevant correlation between DOC concentration, which is uncoloured, and CDOM (coloured dissolved organic matter), which represents the coloured part of the marine dissolved material and is therefore measurable from space. Significant DOC-CDOM relationships were documented for various coastal ecosystems, especially those influenced by rivers discharges (e.g. Ferrari, 2000; Mannino et al., 2008; Del Castillo et al., 2008). However, the diversity in the origin of the dissolved material as well as the potential decoupling in the sensitivity of DOC and CDOM to various environmental factors (e.g. biological activity, photo-degradation processes…) induces regional and seasonal variations in the CDOM-DOC relationships. Environmental effects can significantly alter or preclude the establishment of a significant link between CDOM and DOC, for example, in the oceanic waters and coastal ecosystems not influenced by terrestrial inputs. Therefore, our ability to derive dissolved organic carbon contents from satellite measurements is still limited. The understanding of environmental effects through dedicated *in situ* or laboratory studies represents the major challenge for developing DOC inversion algorithms in the next years. These algorithms will provide, in a near future, relevant insights for global ocean carbon cycle study.

3.2. Scaling down and up from regional scales to global scale

Coastal oceans have fast changing and contrasted optical properties, which prevents the development of a "simple", general algorithm to derive in-water bio-optical and biogeochemical parameters for the whole ocean from satellite information. Therefore, open ocean or coastal algorithms are usually developed to focus on an area-specific range of optical variability. However, these algorithms have some limitations related to their high dependency upon the data set used for their development, as well as to the difficulty to capture the numerous high frequency processes affecting regional bio-optical relationships. Moreover, the scaling-up of such regional approaches to derive biogeochemical parameters at large scale (i.e. global) would require to consider a patchwork of algorithms developed on a mosaic of regions. This seems to be difficult to set up in practice. Another approach consists in taking explicitly into account the optical diversity of the marine environment within the algorithms development procedure. This was shown to be crucial for explaining the dispersion found around the bio-optical relationships (Loisel et al., 2010). In practice, this original approach aims to classify the different regions according to their optical properties as described by the marine reflectance spectra. Further, region-specific algorithms (empirical or semi-analytical) are developed and applied to the defined optical regions. The main advantage of this classification-based approach is that it is independent of the location and time period, being thus more universal than classical approaches and potentially applicable to large-scale studies. The potential of this classification-based approach for improving the performance of the inversion procedure has been recently emphasised for the retrieval of the Chl-a (Mélin et al., 2011) and SPM concentrations (Vantrepotte et al., submitted).

3.3. Theoretical studies

If the last years have seen the development of different approaches to distinguish phytoplankton groups from space, the current techniques are usually based on empirical methods (see above). Despite the fact that remotely sensed measurements are generally well matched with *in situ* measurements, the underlying theoretical foundation is still to be addressed. In a recent study published by Alvain et al. (2011), a radiative transfer model called Hydrolight (Mobley et al., 1993) was used to reconstruct the signals used in Physat. A sensitivity analysis of the method to the following three model parameters was conducted: the specific phytoplankton absorption, the dissolved organic matter absorption, and the particle backscattering coefficients. This last parameter explained the largest part of the variability in the radiative anomalies. Our results also showed that specific environments associated with each group must be considered imperatively. This study represents a first step toward a better understanding and future improvement of phytoplankton groups detection methods based on specific signal identification. In a near future, further advances are expected from the improvement of the optical sensors themselves, especially their spectral and spatial resolution. This may also pave the way for the development of new algorithm based on both phytoplankton groups and their environmental conditions (such as the content in dissolved organic matter).

3.4. Geostationary sensors

The recent development of geostationary ocean colour sensors will increase the precision of the remote sensing measurements and will provide relevant insights for the study of marine biogeochemical cycles. Geostationary satellites continuously view the same region of the Earth's surface. The size of the observed region depends on the spacecraft specification. It thus allows obtaining high quality and frequent observations of a defined area. Such an instrument is therefore useful in order to follow the response of marine ecosystems to short-term variations in the environmental conditions. In particular, it is of interest for monitoring the effects of rivers plumes, tidal front, and mixing on the biotic and abiotic material present in coastal areas or assessing the effects of exceptional events (storms, red tides, dissemination of sediments or pollutants). Data derived from geostationary satellites will also provide relevant information for biogeochemical modelling purposes as well as for research activities related to the biogeochemical cycles at daily scales. The South Korean instrument on board the COMS-1 satellite (GOCI, geostationary ocean colour imager), launched in 2010, is the first ocean-colour sensor in a geostationary orbit. The target area of GOCI covers a large region (2500 × 2500km) around the Korean peninsula. It resolution is of 500 m while it acquires data at a 1-hour frequency. The other ocean colour geostationary missions that are currently planned (OCAPI-CNES, GEOCAPE-NASA) will increase the spatial coverage and the number of information delivered by such sensors.

3.5 Cross-using remote sensing data

Considering the recent variety of new ocean colour products, cross using studies will open a large range of new applications. For example, information on dominant phytoplankton groups could be analysed concomitantly with maps of POC and particle size distribution, hence providing new insights into biogeochemical or ecological processes. An illustration is shown in figure 1 and 2 for a Northern area (45°N-52°N, 30°W-15°W) and a Southern area (47°S-40°S, 65°E-80°E). The two areas are almost identical in terms of Chl-a concentration but distinct in terms of POC concentration. This difference also exists in terms of phytoplankton groups. The region in the Southern Ocean is dominated by diatoms whereas the region in the northern Atlantic is dominated by nanoeukaryotes. The comparison of the spatial distribution of Chl-a, POC and dominant phytoplankton groups prompts the following question. Is it possible to identify from space, and at a global scale, some differences in the "POC vs Chl-a" relationship based on the dominant phytoplankton group as detected by the Physat tool? Further investigations are required to fully answer this question but our simple example illustrates how much cross-using of remote sensing data will be necessary and useful in a near future.

Authors' references

Séverine Alvain, Vincent Vantrepotte, Lucile Duforet-Gaurier:
Université du Littoral de la Côte d'Opale-Lille Nord, Laboratoire d'Océanologie et Géosciences, Lille1-ULCO-CNRS UMR 8187, Lille, France

Julia Uitz:
Université Pierre et Marie Curie, Laboratoire d'Océanographie de Villefranche, UPMC-CNRS UMR 7093, Villefranche-sur-Mer, France

Corresponding author: Séverine Alvain, severine.alvain@univ-littoral.fr

Acknowledgement

The authors would like to thank the NASA SeaWiFS project and the NASA/GSFC/DAAC for the production and distribution of the SeaWiFS data.

References

Aiken J., Pradhan Y., Barlow R., Lavender S., Poulton A., Holligan P., Hardman-Mountford N. J., 2009. Phytoplankton pigments and functional types in the Atlantic Ocean: a decadal assessment, 1995-2005. DeepSea Research Part II: Topical Studies in Oceanography, 56, pp. 899-917.

Alvain S., Moulin C., Dandonneau Y., Breon F. M., 2005. Remote sensing of phytoplankton groups in case 1 waters from global SeaWiFS imagery. DeepSea Research Part I: Oceanographic Research Papers, 52, pp. 1989-2004.

Alvain S., Moulin C., Dandonneau Y., Loisel H., 2008. Seasonal distribution and succession of dominant phytoplankton groups in the global ocean: a satellite view. Global Biogeochemical Cycles, 22, pp. 1-15.

Alvain S., Loisel H., Dessailly D., 2011. Theoretical analysis of ocean color radiances anomalies and implications for phytoplankton groups detection in case 1 waters. Optics Express, 20, pp. 1070-1083.

Antoine D., André J. M., Morel A., 1996. Oceanic primary production: II-Estimation at global scale from satellite (Coastal Zone Color Scanner) chlorophyll. Global Biogeochemical Cycles, 10, pp. 57-69.

Brewin R., Sathyendranath S., Hirata T., Lavender S., Barciela R. M., Hardman-Mountford N.J., 2010. A three-component model of phytoplankton size class for the Atlantic Ocean. Ecological Modelling, 221, pp. 1472-1483.

Bricaud A., Morel A., Babin M., Allali K., Claustre H., 1998. Variations of light absorption by suspended particles with chlorophyll a concentration in oceanic (case 1) waters: analysis and implications for bio-optical models. Journal of Geophysical Research, 103, pp. 31033-31044.

Bricaud A., Claustre H., Ras J., Oubelkheir K., 2004. Natural variability of phytoplankton absorption in oceanic waters: influence of the size structure of algal populations. Journal of Geophysical Research, 109, C11010.

Chen C. T. A., Borges A.V., 2009. Reconciling opposing views on carbon cycling in the coastal ocean: continental shelves as sinks and near-shore ecosystems as sources of atmospheric CO2. Deep Sea Research Part II: Topical Studies in Oceanography, 56, pp. 578-590.

Ciotti A. M., 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, pp. 237–253.

Claustre H., Morel A., Babin M., Cailliau C., Marie D., Marty J.-C., Talliez D., Vaulot D., 1999. Variability in particle attenuation and chlorophyll fluorescence in the tropical Pacific: scales, patterns and biogeochemical implications. Journal of Geophysical Research, 104, pp. 3401-3422.

Dandonneau Y., Deschamps P.-Y., Nicolas J. M., Loisel H., Blanchot J., Montel Y., Thieuleux F., Bécu G., 2004. Seasonal and interannual variability of ocean color and composition of phytoplankton communities in the North Atlantic, Equatorial Pacific and South Pacific. Deep Sea Research Part II: Topical Studies in Oceanography, 51, pp. 303-318.

Del Castillo C. E., Miller R. L., 2008. On the use of ocean color remote sensing to measure the transport of dissolved carbon by the Mississippi River Plume. Remote Sensing of the Environment, 11, pp. 836-844.

DuRand M. D., Olson R. J., Chisholm, S. W., 2001. Phytoplankton population dynamics at the Bermuda Atlantic time-series station in the Sargasso Sea. Deep Sea Research, Part II: Topical Studies in Oceanography, 48, pp. 1983-2003.

Ferrari G.M., 2000. The relationship between chromophoric dissolved organic matter and dissolved organic carbon in the European Atlantic coastal area and in the West Mediterranean Sea (Gulf of Lions). Marine Chemistry, 70, pp. 339-357.

Fichot C. G., Benner R., 2011. A novel method to estimate DOC concentrations from CDOM absorption coefficients in coastal waters. Geophysical Research Letters, 38, L03610.

Gordon H. R., McCluney M. R., 1975. Estimation of the depth of the sunlight penetration in the sea for remote sensing. Applied Optics, 14, pp. 413-416.

Gordon H. R., Morel A., 1983. Remote assessment of ocean color for interpretation of satellite visible imagery. A review. Springer-Verlag, Berlin, Germany.

Hedges J. I., 2002. Why dissolved organic matter, in: Hansell D. A., Carlson C. A. (Eds.) Biogeochemistry of Marine Dissolved Organic Matter., Academic Press, San Diego, pp. 1-33.

Kostadinov T. S., Siegel D. A., Maritorena S., 2009. Retrieval of the particle size distribution from satellite ocean color observations. Journal of Geophysical Research, 114, CO9015.

Loisel H., Stramski D., 2000. Estimation of the inherent optical properties of natural waters from the irradiance attenuation coefficient and reflectance in the presence of Raman scattering. Applied Optics, 39, pp. 3001-3011.

Loisel H., Bosc E., Stramski D., Oubelkheir K., Deschamps P.-Y., 2001. Seasonal variability of the backscattering coefficient in the Mediterranean Sea based on Satellite SeaWiFS imagery. Geophysical Research Letters, 28, pp. 4203-4206.

Loisel H., Nicolas J. M., Deschamps P.-Y., Frouin R., 2002. Seasonal and inter-annual variability of particulate organic matter in the global ocean. Geophysical Research Letters, 29, pp. 2196-2200.

Loisel H., Nicolas J.-M., Sciandra A., Stramski D., Poteau A., 2006. Spectral dependency of optical backscattering by marine particles from satellite remote sensing of the global ocean. Journal of Geophysical Research, 111, C09024.

Loisel H., Poteau, A., 2006. Inversion of IOP based on Rrs and remotely retrieved Kd. IOCCG. Remote sensing of inherent optical properties: fundamentals, tests of algorithms, and applications, in: Lee Z. P. (Ed.) Reports of the International Ocean-Colour Coordinating Groups, n° 5, IOCCG, Dartmouth, Canada, pp. 35-41.

Longhurst A., 2007. Ecological Geography of the Sea, second ed. Academic Press, San Diego, USA.

Mannino A., Russ M. E., Hooker S. B., 2008. Algorithm development and validation for satellite-derived distributions of DOC and CDOM in the U.S. Middle Atlantic Bight. Journal of Geophysical Research, 113, C07051.

Marty J.-C., Chiavérini J., Pizay M. D., Avril B., 2002. Seasonal and interannual dynamics of nutrients and phytoplankton pigments in the western Mediterranean Sea at the DYFAMED time series station (1991-1999). Deep Sea Research Part II: Topical Studies in Oceanography, 49, pp. 2017-2030.

Mélin F., Vantrepotte V., Clerici M., D'Alimonte D., Zibordi G., Berthon J.-F., Canuti E. 2011. Multi-sensor satellite time series of optical properties and chlorophyll a concentration in the Adriatic Sea. Progress in Oceanography, 91, pp. 229-244.

Mobley C.D., Gentili B., Gordon H. R., Zhonghai J., Kattawar G. W., Morel A., Reinersman P., Stamnes K., Stavn R. H., 1993. Comparison of numerical models for computing underwater light fields. Applied Optics, 32, pp. 7484-7504.

Morel A., Prieur L., 1977. Analysis of variations in ocean color. Limnology and Oceanography, 22, pp. 709-722.

Morel A., 1988. Optical modeling of the upper ocean in relation to its biogenous matter content (case 1 waters). Journal of Geophysical Research, 93, pp. 10749-10768.

Morel A., 1991. Light and marine photosynthesis: A spectral model with geochemical and climatological implications. Progress in Oceanography, 26, pp. 263-306.

Raitsos D., Lavender S. J., Maravelias C. D., Haralabous J., Richardson A. J., Reid P. C., 2008. Identifying four phytoplankton functional types from space: An ecological approach. Limnology and Oceanography, 53, pp. 605-613.

Sathyendranath S., Watts L., Devred E., Platt T., Caverhill C., Maass H., 2004. Discrimination of diatoms from other phytoplankton using ocean-colour data. Marine Ecology Progress Series, 272, pp. 59-68.

Siegel D. A., Maritorena S., Nelson N. B., 2002. Global distribution and dynamics of colored dissolved and detrital organic materials. Journal of Geophysical Research, 107, pp. 3228-3242.

Smith R. C., Baker K. S., 1978. The bio-optical state of ocean waters and remote sensing. Limonology and Oceanography, 23, pp. 247-259.

Stramski D., Reynolds R. A, Kahru M., Mitchell, B.G., 1999. Estimation of particulate organic carbon in the ocean from satellite remote sensing. Science, 285, pp. 239-242.

Uitz J., Claustre H., Morel A., Hooker S. B., 2006. Vertical distribution of phytoplankton communities in open ocean: an assessment based on surface chlorophyll. Journal of Geophysical Research, 111, CO8005.

Uitz J., Huot Y., Bruyant F., Babin M., Claustre H., 2008. Relating phytoplankton photophysiological properties to community structure on large scale. Limnology and Oceanography, 53, pp. 614-630.

Uitz J., Claustre H., Gentili B., Stramski D., 2010. Phytoplankton class-specific primary production in the world's oceans: seasonal and interannual variability from satellite observations. Global Biogeochemical Cycles, 24, pp. 3016-3035.

Vidussi F., Claustre H., Manca B. B., Luchetta A., Marty J.-C., 2001. Phytoplankton pigment distribution in relation to upper thermocline circulation in the eastern Mediterranean Sea during winter. Journal of Geophysical Research, 106, pp. 19939-19956.

Zubkov M. V., Sleigh M. A., Burkill P. H., Leakey R. J. G., 2000. Picoplankton community structure on the Atlantic meridional transect: a comparison between seasons. Progress in Oceanography, 45, pp. 369-386.