Contribution to Ocean Carbon from Space

# PHYTOPLANKTON CARBON FROM SPACE: SCIENTIFIC CHALLENGES, GAPS & OPPORTUNITIES

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## 1. State of the art

Understanding the ocean carbon cycle requires disentangling the pool of organic carbon associated with living phytoplankton cells from other types of carbon (e.g., zooplankton, detritus, fecal pellets). Phytoplankton carbon (C-phyto) is key to establish the carbon-to-chlorophyll (C-Chla) ratio and compute primary production (Behrenfeld et al., 2005; Sathyendranath et al., 2009), and assess the contribution of photophysiology in the phytoplankton seasonal cycle (Bellacicco et al., 2016). It allows for determination of carbon-based growth and loss rates in phytoplankton (e.g., Sathyendranath et al., 2009; Zhai et al., 2010; Behrenfeld and Boss, 2014). C-phyto is also innovatively used to assess, at the sea-air interface, the export of organic matter towards the atmosphere in the form of aerosols (Fossum et al., 2018).

To assess C-phyto from space is not a trivial task as the C-Chla ratio is influenced by both phytoplankton composition as well as by its photophysiological state. A number of algorithms have been developed to derive C-phyto from ocean color observations (see Bellacicco et al., 2020 and reference therein). The approaches used by these algorithms can be grouped into: i) backscattering-based (e.g., Behrenfeld et al., 2005; Martinez-Vicente et al., 2013; Graff et al., 2015); ii) Chla-based (e.g., Sathyendranath et al., 2009; Sathyendranath et al., 2020); and iii) size-class-based (e.g., Kostadinov et al., 2016: Roy et al., 2017) approaches. Each approach relies on the covariation between optical properties or POC, and a proxy of phytoplankton concentration such as Chla, phytoplankton light absorption or size distribution. One of the largest challenges in retrieving C-phyto from ocean color observations is that the contributions of organic detritus, or non-algal particles (NAP), and living phytoplankton cells to the optical properties such as the particle backscattering and to the particle size distributions cannot easily be separated, particularly in turbid or coastal waters. It is assumed that phytoplankton dominates the backscattering signal in the open ocean (Dall'Olmo et al., 2009; Organelli et al., 2018), which is used in Case-1 water models (e.g., Morel and Maritorena, 2001) to approximate the NAP contribution from Chla. However, the variation of NAP horizontally, vertically, and temporally is considerable in many parts of the ocean both in units of optical contribution with respect to Chla (Bellacicco et al., 2019; Bellacicco et al., 2020) as well as in size and concentration (Organelli et al., 2020).

When considering the optical variability of NAP in space and time, C-phyto is best estimated with a relative error of 20% at the global scale (Bellacicco et al., 2020). However, all approaches to detect C-phyto are tremendously perfectible as soon as optics-to-carbon (e.g., Chla to C) conversion factors, global in situ C-phyto data coverage, and reduced uncertainties in satellite-derived inputs of algorithms (i.e., backscattering, Chla, and particle size distribution) are better achieved. Currently, no method aims to expand the global estimation of C-phyto below the ocean surface where most of biogeochemical interactions occur.

The following sections will describe the scientific challenges we face with respect to measuring and deriving phytoplankton carbon, gaps in data availability and methods to measure and derive phytoplankton carbon and the future opportunities we could utilise to fill these data gaps.

## 2. Scientific challenges

A number of scientific challenges exists for the derivation of C-phyto from bio-optical measurements, such as particle backscatter, when direct measurements of C-phyto are not available:

I. Particle backscatter includes all particles, not just phytoplankton; the ability to separate living from non-living particles without microscopic or flow cytometric data is limiting. Moreover, the accuracy of backscattering retrievals from space must be increased. Application of a correction to remote sensing reflectances for the Raman scattering prior to semi-analytical retrievals has shown a way to follow (Pitarch et al., 2020).

II. Chla, both satellite-derived and in situ, is often used in models to relate particle backscatter to C-phyto using empirical relationships. However, the uncertainties within these empirical relationships are increased by the influence of phytoplankton composition and physiological state of phytoplankton driving photoacclimation, i.e., the adjustment of Chla in response to light particularly in the surface ocean. In addition, at low phytoplankton biomass such as in the subtropical gyres, uncertainties both of satellite retrieved optical properties and Chla can be large. With all these challenges, we have not been able to develop standardized methods (models or algorithms) to derive C-phyto.

III. We have a very limited understanding of C-phyto for the entire euphotic depth on global scale from observations.

IV. Directly using satellite Chla or specific phytoplankton community Chla for evaluation or assimilation in (coupled-ocean-) biogeochemical models could more accurately derive C-phyto since for these satellite products uncertainties are lower (IOCCG, 2020). But this requires further exploration.

## 3. Method and data gaps

In this section we will highlight the major existing method and data gaps that prohibit accurate retrievals of C-phyto:

I. **Gap of mechanistic understanding** of how the optical properties link to C-phyto considering the diversity of phytoplankton composition and physiological state and other optically significant substances.

II. **Gap of accurate in situ C-phyto data**: Undoubtedly the largest gap for deriving C-phyto from space is the paucity of global in situ phytoplankton community composition and C-phyto data to develop and validate models and algorithms. One method exists to directly measure C-phyto, which entails the separation of living phytoplankton particles from non-living (detrital) particles and the subsequent elemental measurement of those particles. These direct measurements are largely biased towards nano and pico-sized phytoplankton particles detected by flow cytometry. C-phyto may also be indirectly ‘measured’ by applying empirical relationships that relate cell biovolume to C-phyto (Menden-Deuer and Lassard, 2000; Lomas et al. 2019). These empirical relationships are largely attributed to micro-sized phytoplankton (diatoms and dinoflagellates) and are limited to either a select number of laboratory cultures or a specific region in the global ocean.

Coincident in situ observations of both phytoplankton community composition, by flow cytometry, microscopy or the more recent method of imaging-in-flow cytometry (e.g., Imaging Flow Cytobot, FlowCAM) with bio-optical and radiometric measurements are critical for establishing relationships between phytoplankton type, size, pigments and optical signatures. A limited number of field data sets (e.g., NASA’s EXPORTS campaign, the Atlantic Meridional Transect Programme (AMT)) contain these coincident measurements, but are regional driven, leading to a lack of understanding of their spatio-temporal variability. Moreover, few measurements are taken below the surface ocean, assuming the satellite only sees the first few meters.

III. **Gap of consistent C-phyto surface time series data sets**: so far C-phyto satellite data sets are experimental. Time series data sets with clear uncertainties are critical to understanding spatio-temporal variability in C-phyto, community composition and coincident optical properties. Existing time series studies that include these measurements are limited (e.g., Martha’s Vineyard Coastal observatory).

IV. **Gap of global C-phyto data below the surface ocean**: Since satellite data only deliver information for the first optical depth, the collection of in situ C-phyto data has been largely limited to discrete water sampling at surface depths. Because the ocean color properties of the surface ocean may be influenced by particles and phytoplankton cells below the surface, it is imperative that we extend measurements deeper into the water column, encompassing the euphotic zone. This will bring also to a better estimation of C-phyto along the water column where most of biogeochemical interactions occur.

V. **Gap of synergistic methods** that combines different data sets (e.g., satellite observations, in situ autonomous and ship-based observations) with different coverage in space and time for the entire euphotic zone. Satellite data only provide information for the surface water often and it is challenging to extrapolate those ocean color properties for the entire euphotic zone.

VI. **Gap of uncertainties**: Each method, model or algorithm possesses inherent uncertainties, either systematic or owing to the input data. Uncertainties are infrequently reported with these data. As such, there are gaps in our knowledge of the accuracy of our models and algorithms to derive C-phyto. This includes uncertainties in our direct or indirect measurements of in situ C-phyto.

## 4. Opportunity

The method and data gaps described leave open many opportunities. Here we elaborate on few:

I. The enlargement and exploration of data analysis of **in situ super sites**: These are sites were the different measurements taken ensure the “complete” coverage of linking the C-phyto to optical properties, considering the diversity and variation of phytoplankton and other optical constituents (should also enable frequent collocation to ocean color satellite data). The strategy is to empower existing observatories, often also used for water quality assessment, by connecting them with other research communities (e.g., phytoplankton taxonomy, flow cytometry). These super sites measurements could be complemented by dedicated mesocosm experiments that will help to improve the mechanistic understanding retrieved from the super sites. In addition, these data sets can be used to verify/develop the best protocol to derive reliable (clear uncertainties) in situ C-phyto data. In situ C-phyto data then must be collected on global scale not only at surface but also through the euphotic zone.

II. **Long-time series C-phyto data** usable for climate research should be developed by adapting algorithms to different ocean color sensor data covering different time spans (since 1997 until today) and with including pixel by pixel uncertainties. C-phyto satellite data algorithms may be improved by using the synergistic information on the abundance and composition of the different optical components (phytoplankton, NAP, CDOM). This opportunity should be explored since these data could provide an opportunity to lower the uncertainties in C-phyto retrievals.

III. Accuracy of optical quantities used as input of C-phyto algorithms can be improved by empowering validation through **autonomous mobile platforms** such as Biogeochemical-Argo profiling floats and drifters (e.g., Boss et al., 2008; Sauzède et al., 2016; Bisson et al., 2019; Xing et al., 2020). These robotic platforms allow the acquisition of optical measurements with limited spatial and temporal bias, as they collect data also in remote regions during unfavorable meteorological conditions for ship-based sampling (Organelli et al., 2017). Optical data from these platforms have been used to derive bulk parameters, such as $K_d$, Chla, CDOM and POC and by this are a source for complementing satellite data beneath surface. Recently, it has been demonstrated that introducing hyperspectral instrumentation on these platforms enables resolved for the light-lit water column estimates on the composition (type and size) of optical constituents, especially phytoplankton (Chase et al. 2013, Liu et al. 2019, Bracher et al. 2020, Jemai et al. 2021, Organelli et al. 2021). Efforts to enlarge the optical multiplatform data acquisition and development of protocol for the derivation of high-quality C-phyto data sets must be taken since these have the potential to fill the gap of C-phyto information below the first optical depth.

IV. Autonomous platforms such as BGC-Argo floats (Claustre et al., 2020) or moorings (von Appen et al., 2021) also offer the opportunity to establish strong synergies with remote sensing of ocean colour to reconstruct, via artificial intelligence, the 4-dimensional view of particulate organic carbon in open ocean. Such a synergy can be expanded towards reconstruction of the **4D view of C-phyto** to better observe phytoplankton biomass dynamics and calculate primary production below the ocean surface.

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