Ocean carbon from space: current status and priorities for the next decade

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Abstract

The ocean plays a central role in modulating the Earth's carbon cycle. Monitoring how the ocean carbon cycle is changing is fundamental to managing climate change. Satellite remote sensing is currently our best tool for viewing the ocean surface globally and systematically, at high spatial and temporal resolutions, and the past few decades have seen an exponential growth in studies utilising satellite data for ocean carbon research. Satellite-based observations have to be combined with *in-situ* observations and models, to obtain a comprehensive view of ocean carbon pools and fluxes. To help prioritise future research in this area, a workshop was organised that assembled leading experts working on the topic, from around the world, including remote-sensing scientists, field scientists and modellers, with the goal to articulate a collective view of the current status of ocean carbon research, identify gaps in knowledge, and formulate a scientific roadmap for the next decade, with an emphasis on evaluating where satellite remote sensing may contribute. A total of 449 scientists and stakeholders participated (47 % female, 53 % male), from North and South America, Europe, Asia, Africa, and Oceania. Sessions targeted both inorganic and organic pools of carbon in the ocean, in both dissolved and particulate form, as well as major fluxes of carbon between reservoirs (e.g., primary production) and at interfaces (e.g., air-sea and land-ocean). Extreme events, blue carbon and carbon budgeting were also key topics discussed. Emerging priorities identified include: expanding the networks and quality of *in-situ* observations; improved satellite retrievals; improved uncertainty quantification; improved understanding of vertical distributions; integration with models; improved techniques to bridge spatial and temporal scales of the different data sources; and improved fundamental understanding of the ocean carbon cycle, and of the interactions between pools of carbon and light. We also report on priorities for the specific pools and fluxes studied, and highlight issues and concerns that arose during discussions, such as the need to consider the environmental impact of satellites or space activities; the role satellites can play in monitoring ocean carbon dioxide removal approaches; to consider how satellites can contribute to monitoring cycles of other important climatically-relevant compounds and elements; to promote diversity and inclusivity in ocean carbon research; to bring together communities working on different aspects of planetary carbon; and to follow an open science approach. Overall, this paper provides a comprehensive scientific roadmap for the next decade on how satellite remote sensing could help monitor the ocean carbon cycle, and its links to the other domains, such as terrestrial and atmosphere.

Keywords: Ocean, Carbon cycle, Satellite, Remote sensing

Contents

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1. Introduction

The element carbon plays a fundamental role in life on Earth. Owing to its ability to bond with other atoms, carbon allows for variability in the configuration and function of biomolecules such as DNA and RNA that control the growth and replication of organisms. Carbon is constantly flowing through every sphere on the planet, the geosphere, atmosphere, biosphere, cryosphere and hydrosphere, in liquid, solid or gaseous form. This flow of carbon is referred to as the Earth's carbon cycle. It comprises of diverse chemical species, organic and inorganic, and many processes responsible for transformations and flow of carbon between the different reservoirs. Although the total amount of carbon on Earth is relatively constant over geological time, the carbon content of the component spheres and reservoirs can change, with profound consequences for the climate of the planet. Since the establishment of the industrial revolution at the start of the 19th century, humans have been increasing the carbon content of the atmosphere through the burning of fossil fuels and land use changes, trapping outgoing long-wave radiation in the lower atmosphere and increasing the temperature of the planet.

This anthropogenic increase in atmospheric carbon (in the gaseous form of CO_2) has three principal fates: it can remain in the atmosphere, be absorbed by the ocean, or be absorbed by vegetation on land. Latest estimates for the year 2020 suggest that just under half of the anthropogenic CO_2 emissions currently released (10.2 ± 0.8 Gt C yr^{-1}) remain in the atmosphere (5.0 ± 0.2 Gt C yr^{-1}), with just over a quarter being absorbed by the land (2.9 ± 1.0 Gt C yr^{-1}) and by the ocean (3.0 ± 0.4 Gt C yr^{-1}) (Hauck et al., 2020; Friedlingstein et al., 2022). Our ocean therefore plays a major role in regulating climate change. Understanding what controls the trends and variability in the ocean carbon sink is consequently a major question in Earth Science. Recent work from the Global Carbon project suggests model estimates of this sink are not in good agreement with observational-based evidence (Friedlingstein et al., 2022). Never before has it been so urgent to improve our understanding of the ocean carbon cycle.

Monitoring the ocean carbon cycle is key to improved understanding. Historically, ocean carbon cycle reservoirs and fluxes were monitored using *in-situ* methods, collecting data from ship-based platforms (dedicated research cruises and ships of opportunity), moorings and time-series stations (Karl and Winn, 1991; Raitsos et al., 2014; Bakker et al., 2016; Olsen et al., 2016). Since the 1970's satellite observations have been used (Gordon et al., 1980; Shutler et al., 2019; Brewin et al., 2021) and recent years have seen the expansion of ocean robotic platforms for monitoring ocean carbon cycles (Williams et al., 2015, 2017; Gray et al., 2018; Chai et al., 2020; Claustre et al., 2020, 2021), both aiding the extrapolation of local *in-situ* measurements to global scale. Each of these platforms has advantages and disadvantages, and it is commonly accepted that an approach integrating data from all platforms is required. There is also a need to use coupled physical and biogeochemical modelling, with the *in-situ* and satellite data, to estimates the pools and fluxes of carbon that are difficult to measure otherwise, at the required temporal and spatial scales.

Satellites play a major role in our global carbon monitoring system. They are the only platforms capable of viewing our entire surface ocean and the air-sea boundary layer synoptically, at high temporal resolution. Consequently, the use of satellites in ocean carbon research has been expanding exponentially over the past 50 years (Fig. 1a). However, satellite instrumentation can only view the surface of the ocean (the actual depth the signal represents varies with wavelength and water composition), are constrained to operate in certain conditions (e.g., passive visible systems are limited to cloud-free conditions and low to moderate sun-zenith angles) and at certain spatial and temporal scales, and are limited to collecting information that can be contained in electromagnetic radiation. To make full use of satellite observations for ocean carbon monitoring the remote-sensing community needs to work closely with *in-situ* data experts, physical and biogeochemical modellers, Earth system scientists, climate scientists and marine policy experts.

With this in mind, the European Space Agency (ESA) with support from the US National Aeronautics and Space Administration (NASA), organised a virtual workshop called "Ocean Carbon from Space" in February 2022, building on a successful workshop organised in 2016 (Colour and Light in the ocean from Earth Observation; Sathyendranath et al., 2017a; Martinez-Vicente et al., 2020), and findings from a wide range of international initiatives (e.g., NASA EXport Processes in the Ocean from Remote Sensing (EXPORTS), ESA Ocean Science Cluster, ESA Climate Change Initiative (CCI), various European Commission Carbon Initiatives (e.g. Copernicus, such as OC TAC and MOB TAC), the Surface Ocean Lower Atmosphere Study (SOLAS), the Blue Carbon Initiative, the Global Carbon Project, International Carbon Observing System[1]). The workshop was also part of the CEOS (Committee on Earth Observation Satellites) workplan on

[1] see https://oceanexports.org/; https://eo4society.esa.int/communities/scientists/esa-

Aquatic Carbon (CEOS, 2021). The theme of the workshop was on ocean carbon, its pools and fluxes, its variability in space and time, and the understanding of its processes and interactions with the Earth system. The goal of the workshop was to bring leading experts together, including remote-sensing scientists, field scientists and modellers, to describe the current status of the field, and identify gaps in knowledge and priorities for research. In this paper, we synthesize and consolidate these discussions and produce a scientific roadmap for the next decade, with an emphasis on evaluating where and how satellite remote sensing can contribute to the monitoring of the ocean carbon cycle.

2. Workshop details and approach to capture collective view of the status of the field

2.1. Ocean Carbon from Space Workshop

The "Ocean Carbon from Space Workshop" (https://oceancarbonfromspace2022.esa.int/) was organised by a committee of 15 international scientists, led by ESA within the framework of the Biological Pump and Carbon Exchange Processes (BICEP) project (https://bicep-project.org) with support from NASA. In addition to this organising committee, a scientific committee of 31 international experts on the topic of ocean carbon were assembled, who helped structure the sessions and review abstracts. These committees initially proposed a series of sessions, targeting 16 themes, covering: the pools of carbon in the ocean (including particulate organic carbon, phytoplankton carbon, particulate inorganic carbon, dissolved organic carbon, and carbon chemistry, including dissolved inorganic carbon); the main processes (including marine primary production, export production, air-sea exchanges, and land-sea exchanges); and crosscutting themes (including the underwater light field, uncertainty estimates, freshwater carbon, blue carbon, extreme events, tipping points and impacts on carbon, climate variability and change, and the ocean carbon budget).

ocean-science-cluster/; https://climate.esa.int/en/; https://www.copernicus.eu/en https://www.thebluecarboninitiative.org/; https://www.globalcarbonproject.org/; https://www.icos-cp.eu/; https://www.solas-int.org/about/solas.html

The workshop was widely advertised, through a variety of means, including: email distribution lists; through international bodies like the International Ocean Colour Coordinating Group (IOCCG) and Surface Ocean Lower Atmosphere Study (SOLAS) networks; space agencies; and through social media platforms. Scientists and stakeholders working in the field of ocean carbon were invited to submit abstracts to the 16 themes and to participate in the workshop. The organising committee also identified key experts in the field who were invited to give keynote presentations.

A total of 98 abstracts were submitted to the workshop, and based on the topics of these abstracts, the workshop was organised into six sessions combining various themes as needed, and covering

- Primary Production (PP)
- Particulate Organic Carbon (POC)
- Phytoplankton Carbon (C-phyto)
- Dissolved Organic Carbon (DOC)
- Inorganic Carbon and fluxes at the ocean interface (IC)
- Cross-cutting themes with three sessions:
    - Blue Carbon (BC)
    - Extreme Events (EE)
    - Carbon Budget Closure (CBC)

The organisation committee identified chairs for each session, and abstracts were reviewed by the organisation and scientific committees, and assigned to oral or e-poster presentations. E-poster presentations were delivered through breakout rooms to help promote discussions. Each session included keynote speakers, oral presentations and importantly, time for discussing gaps in knowledge, priorities and challenges. There were four poster sessions covering the six themes of the workshop. Participants were encouraged to upload their presentations or e-poster (under the form of a 1-3 slides presentation) prior to the conference start to facilitate knowledge exchange and prepare for workshop discussions.

The workshop took place from 14th to 18th February 2022, following the international day of women and girls in science (Fig. 1a). Due to COVID restrictions, an online format was preferred (using the webex video conferencing software; https://www.webex.com). This resulted in a flexible schedule and programme designed to accommodate participants from different regions and time zones, and flexible working (e.g. child care responsibilities). A total of 449 people from a wide geographical spread (Fig. 1b) participated, of which 47 % were female and 53 % male (Fig. 1c), reflecting an increasing participation of female scientists in ocean carbon science.

2.2. Tools and approaches to capture collective view

A series of tools and approaches were used to capture the collective view of the community and identify the major gaps, challenges and priorities, that fed into this scientific roadmap.

Firstly, session chairs were asked to prepare statements on the main scientific challenges, gaps and opportunities of their session theme, prior to the start of the conference. All presenters (e-poster and oral) were also asked to include one slide about knowledge gaps and priorities for next steps on their work over the next decade. These statements were then used by session chairs to help structure the discussion slot organised at the end of each session. A final discussion session was held at the end of the workshop, whereby all session chairs were asked to join a panel to identify overarching themes.

All sessions were recorded through webex. Throughout the workshop, we used *Padlet* software (https://en-gb.padlet.com), a cloud-based, real-time collaborative web platform which allowed participants to interact and upload thoughts they had on the scientific challenges, gaps and opportunities for each session, comment on those suggested by the chairs and other participants, all within virtual bulletin boards called "padlets". Following the closure of the workshop, session chairs were asked to provide a written synthesis of the main outcome of their sessions.

All scientific priorities, challenges, gaps and opportunities identified and discussed during the workshop, were organised into

- Session-specific themes
- Common themes
- Emerging concerns and broader thoughts

Table 1 provides an overview of the themes of the paper and guide to navigate this scientific roadmap.

3. Session-specific theme outcomes

In the following sections, we begin by providing a brief description of each session-specific theme, then briefly highlight the current state of the art, and finally focus on the identified priorities, scientific challenges, gaps and opportunities, to be targeted over the next decade.

3.1. Primary production (PP)

Primary production (PP, photosynthesis) channels energy from sunlight into ocean life, converting dissolved inorganic carbon (DIC), in the form of CO_2, into phytoplankton tissue (e.g., C-phyto) that then fuels ocean food webs. Total PP is approximately the same on land and in the ocean ($\sim 50\,\mathrm{Gt\,C\,yr^{-1}}$; Longhurst et al., 1995; Field et al., 1998; Bar-On et al., 2018). By removing CO_2 from surrounding waters, PP lowers the ambient CO_2 concentration in surface waters. This can potentially lead to a drawdown of CO_2 from the atmosphere. In doing so, PP can influence climate. The magnitude of any climate effect of PP depends, however, on the fate of the phytoplankton produced through PP. Only when the reduction in surface ocean pCO_2 is maintained over time can it lead to a lasting drawdown of CO_2. In practice, PP can only have a long-term impact on climate when its products are removed from surface waters through the ocean's organic carbon "pumps" (Volk and Hoffert, 1985; Boyd et al., 2019). The "biological pump", whereby organic material is transported to below the permanent thermocline is largely driven by "new" production (Dugdale and Goering, 1967), i.e., PP driven by allochthonous nutrient input (which is sensitive to stoichiometry and nutrient availability). To quantify the effect of ocean PP in global carbon cycling and, thereby, climate development, there is therefore a need to develop mechanisms to differentiate between total and new PP in the ocean (Brewin et al., 2021).

3.1.1. State of the art in primary production

Satellite algorithms of primary production have a long-established history, dating back over 40-years, to the time when the first ocean-colour satellite (the Coastal Zone Color Scanner) became available (Smith et al., 1982; Platt and Herman, 1983). Some initial attempts were made to convert fields of chlorophyll-a directly into primary production (Smith et al., 1982; Brown et al., 1985; Eppley et al., 1985; Lohrenz et al., 1988), before approaches based on first principles were established, utilising in addition to information on chlorophyll-a concentration, information on bulk and spectral light availability (now available through satellite Photosynthetically Available Radiation (PAR) products), and on the response of the phytoplankton to the available light (parameters of the photosynthesis-irradiance curve) (e.g., Platt et al., 1980; Platt and Herman, 1983; Platt et al., 1990; Platt and Sathyendranath, 1988; Sathyendranath and Platt, 1989). The first global estimates were computed in the mid-1990's (Longhurst et al., 1995; Antoine et al., 1996; Behrenfeld and Falkowski, 1997a), arriving at values of around 50 $\mathrm{Gt\,C\,y^{-1}}$, consistent with current estimates (Carr et al., 2006; Buitenhuis et al., 2013; Kulk et al., 2020, 2021). Whereas many of the modern techniques can differ in implementation, they have been shown to conform to the same basic formulation, with the same set of parameters (Sathyendranath and Platt, 2007), with some going beyond total primary production, and partitioning it into different phytoplankton size-classes (e.g., Uitz et al., 2010, 2012; Brewin et al., 2017b). For a review of these approaches, the reader is referred to the classical works of Platt and Sathyendranath (1993), that of Behrenfeld and Falkowski (1997b), Sathyendranath and Platt (2007), Sathyendranath et al. (2020) and Section 4.2.1. of Brewin et al. (2021). For a review of operational satellite radiation products for ocean biology and biogeochemistry and a roadmap for improving existing products and developing new products, see Frouin et al. (2018). The reader is also referred to the huge efforts made by NASA over the past 20 years to evaluate and improve these satellite algorithms (Campbell et al., 2002; Carr et al., 2006; Friedrichs et al., 2009; Saba et al., 2010, 2011; Lee et al., 2015), which have highlighted variations in model performance with region and season (root mean square deviations of between 0.2 to 0.5 in $\log_{10}$ space, when compared with *in-situ* data), illustrated the importance of minimising the uncertainties in model inputs and parameters, and in knowing the uncertainties in the *in-situ* measurements used for validation.

Following presentations and discussions on primary production at the workshop, five key priorities were identified. These are summarised in Table 2 and include: 1) parametrisation of satellite algorithms using *in-situ* data; 2) uncertainty estimation of satellite algorithms and validation; 3) linking surface satellite measurements to the vertical distribution; 4) trends; and 5) understanding.

3.1.2. PP priority 1: Parametrisation of satellite algorithms using in-situ data

Challenges: Considering that most satellite primary production models conform to the same principles (Sathyendranath and Platt, 2007), a major challenge to the research community is to improve our understanding of the spatial and temporal variability in the model parameters. This will be key to improving accuracy of satellite primary production models (Platt et al., 1992). Although large efforts have been made in recent years to compile global *in-situ* datasets of the parameters of the photosynthesis-irradiance curve (e.g., Richardson et al., 2016; Bouman et al., 2018), relatively few measurements of photosynthesis-irradiance curve parameters exists globally, with many regions (e.g., Indian Ocean, Southern Ocean and central Pacific) being under-represented (Kulk et al., 2020). The continuation of existing sampling campaigns and expansion to under-represented regions, is subject to financial support for *in-situ* observations, particularly ship-based research cruises, considering that many primary production measurements require specialised equipment, not suitable for automation. Given the declining fleet of research vessels in many regions (e.g., Kintisch, 2013), new solutions are needed, with sustained funding.

Another challenge is that *in-situ* data on primary production and model parameters are often collected in a non-standardised way, with differing conversion factors and protocols, and differing ancillary measurements, with limited information on the light environment, for both the experimental set-ups as well as the *in-situ* data (Platt et al., 2017). There are many ways primary production can be measured (see Sathyendranath et al., 2019b; Church et al., 2019; IOCCG Protocol Series, 2021a), and to convert between methods is not straight-forward, though some studies have shown promise in this regard (e.g., Regaudie-de Gioux et al., 2014; Kovač et al., 2016, 2017; Mattei and Scardi, 2021). There is a clear challenge to develop better protocols and standards for primary production data collection. Recent efforts by the IOCCG have made some progress (IOCCG Protocol Series, 2021a).

A further challenge with developing and validating satellite algorithms stems from the fact that primary production (a time varying rate) is estimated from an instant satellite snapshot in time. The time variability of PAR, biomass and the possible variability in photosynthetic parameters must be modelled. Meanwhile these all have diurnal variability.

Gaps: Challenges to *in-situ* data collection (e.g. lack of adequate funding) and compilation have meant there are very few stations with continuous *in-situ* measurements of primary production and related parameters. As the ocean colour time-series approaches a length needed for climate change studies (~40 years; Henson et al., 2010; Sathyendranath et al., 2019a), this will impede our ability to verify climate trends in primary production detected from space (see PP priority 5). There are gaps in coordination at the international level that if filled, would greatly benefit the systematic and sustained collection of *in-situ* measurements on primary production. Many remote sensing algorithms of PP rely on a knowledge of photosynthesis-irradiance curve parameters. Consequently, the algorithms are only as accurate as the coverage (both spatial and temporal) of these *in-situ* parameters. They are also likely to be sensitive to climate change, so it is important to keep updating the *in-situ* databases.

Opportunities: By capitalising on an expanding network of novel and autonomous *in-situ* platforms, there are opportunities to improve the quantity of measurements of primary production, by harnessing active fluorescence-based methods (IOCCG Protocol Series, 2021a), such as Fast Repetition Rate (FRR) fluorometry (Kolber and Falkowski, 1993; Kolber et al., 1998; Gorbunov et al., 2000) and Fluorescence Induction and Relaxation (FIRe) techniques (Gorbunov et al., 2020). In fact, variable fluorescence techniques are increasingly being used to assess phytoplankton photosynthesis (see Gorbunov and Falkowski, 2020). There are challenges in interpreting these data (Gorbunov and Falkowski, 2020), and differences between FRR and ^{14}C PP can be large (Corno et al., 2006). However, as these are optical measurements that can be collected in real time, they are well suited to autonomous platforms (Carvalho et al., 2020). For a recent review on the topic see Schuback et al. (2021). Dissolved oxygen measurements, derived from oxygen optode sensors on autonomous platforms, can be used to estimate and quantify photosynthesis and respiration rates, as well as to quantify gross oxygen production that can be used to constrain net primary production estimates (Barone et al., 2019; Johnson and Bif, 2021). Such estimates require high temporal resolution sampling, to observe the entire daily cycle (both night and day).

A multi-platform approach to combining discrete *in-situ* measurements, with those from autonomous *in-situ* platforms and satellite data, could offer synergistic benefits, providing the different scales of the observations, and differences in measurement techniques can be bridged. There are also opportunities to encourage and support existing time-series stations (e.g., BATS, HOT, WCO-L4, CARIACO, Line P, Porcupine Abyssal Plain, Blanes Bay Microbial Observatory, LTER sites, and Stončica) to continue to make high-quality *in-situ* measurements of primary production as well as the model parameters necessary for implementation of primary production and photoacclimation models. There are opportunities to use artificial intelligence, such as machine learning, to help in this regard (e.g., see Huang et al., 2021).

There are opportunities to exploit the ability of geostationary platforms (e.g. GOCI), to resolve diurnal variability in light (PAR) and biomass. Such sensors are also able gather considerably more data for a given region than polar orbiting satellites (Feng et al., 2017). By building on the international community engagement of the "Ocean Carbon from Space" workshop, and that of other international initiatives (e.g., IOCCG), there are opportunities to formulate priorities for funding, and to create the necessary coordinating bodies, to address the challenges and gaps identified above.

3.1.3. PP priority 2: Uncertainty estimation of satellite algorithms and validation

Challenges: Assessment of satellite-based primary production estimates is currently challenging, owing to the sparsity of *in-situ* data on primary production and model parameters (limited in spatial and temporal coverage and by costs), differences in the methods used for *in-situ* data collection, differences in scales of *in situ* and satellite observations, and a lack of availability of independent *in-situ* data to those used for model tuning. Standard oceanographic cruises can be affected by extreme weather conditions, particularly during fall and winter seasons. As a result, ship-based observations are sparse and often biased towards the summer-season.

Gaps: Validation-based uncertainty estimates of satellite-derived primary production products are often not readily provided, and it is difficult to quantify model-based error propagation methods (e.g., Brewin et al., 2017c). There are gaps in our understanding of the uncertainty in key parameters and variables used for input to primary production models. Other gaps exist relating to the nature of passive ocean-colour, such as data gaps in satellite observations (e.g., cloud covered pixels, and coverage in polar regions; Stock et al., 2020).

Opportunities: We are now at a point where the computational demand of formal error propagation methods (going from errors in top-of-atmosphere reflectance through to errors in primary production model parameters) can be met, such that per-pixel uncertainty estimates in satellite primary production products could be computed (McKinna et al., 2019). There are also opportunities to constrain primary production estimates and reduce uncertainties through harnessing emerging hyperspectral, lidar and geostationary sensors, that may provide more information on the community composition of the phytoplankton and their diel cycles (day-night cycles, a requirement being increased temporal resolution), as well as information on the spectral attenuation of underwater light, crucial for deriving PP. The synergistic usage of multiple satellites can be an opportunity to improve input irradiance products to PP models. There are also opportunities to use satellite sensors measuring light in the UV to improve satellite PP estimates (Cullen et al., 2012; Oelker et al., 2022). For improved uncertainty estimation, continuous validation is crucial, as is quantifying uncertainties in model parameters. Autonomous platforms and active ocean colour remote sensing (lidar) may offer opportunities to help in this regard.

3.1.4. PP priority 3: Linking surface satellite measurements to the vertical distribution

Challenges: Considering passive ocean-colour satellites only view a portion of the euphotic zone (the first penetration depth), resolving the vertical structure of all satellite-based carbon pools and fluxes is challenging, but none more so than that of primary production. There are challenges in the requirements to know vertical variations in the phytoplankton biomass (e.g., Chlorophyll-a, hereafter denoted Chl-a), the physiological status (e.g., photoacclimation) of the phytoplankton (e.g., through the parameters of the photosynthesis-irradiance curve), and the magnitude, angular structure and spectral nature of the underwater light field. For example, due to wind-depending wave-induced light focussing, there can be extreme short-term variability in PAR near the surface, with irradiance peaks > 15 times the average (Hieronymi and Macke, 2012) in visible, ultraviolent-A and -B spectral ranges, with implications for phytoplankton photosynthesis.

Gaps: Our understanding of this vertical variability is impeded by the sparsity of *in-situ* observations on vertical structure. Ideally, we require observations at the equivalent spatial and temporal scale to that of the satellite data, for successfully extrapolating the surface fields to depth. There are also gaps in vertical physical data, and in their uncertainties, at equivalent scales to the satellite observations, such as the mixed-layer depth.

Opportunities: There are future opportunities to improve our basic understanding of vertical structure by tapping into existing and planned arrays of autonomous *in-situ* platforms, such as the global array of Biogeochemical (BGC) - Argo floats (Johnson et al., 2009; Claustre et al., 2020; Cornec et al., 2021) and also the physical Argo array for fields of mixed-layer depth, with the help of statistical modelling (e.g., Foster et al., 2021). Other technologies are also expected to improve understanding of vertical structure, such as moorings and ice tethered and towed undulating platforms (Laney et al., 2014; Bracher et al., 2020; Stedmon et al., 2021; Von Appen et al., 2021). These platforms may help us improve our understanding of the vertical distribution of parameters and variables relevant for PP modelling, such as chlorophyll (acknowledging potential vertical changes in fluorescence quantum yield efficiency), backscattering and light. Future satellite lidar systems will be capable of viewing the ocean surface up to three optical depths, improving the vertical resolution of ocean colour products.

3.1.5. PP priority 4: Trends

Challenges: Detecting trends in primary production is a major challenge to our research community. A recent report by the Intergovernmental Panel on Climate Change (IPCC, 2019) expressed low confidence in satellite-based trends in marine primary production.

Gaps: The reasons the IPCC report cited this low confidence were related to the fact that the length of satellite ocean colour record is not sufficient yet for climate change studies, and the lack of corroborating trends in *in-situ* data (see primary production priority 1) (IPCC, 2019). Additionally, there are gaps in uncertainty estimates for satellite-based products (see primary production priority 3), needed to quantity the significance of any such trends.

Opportunities: To meet these challenges, and fill these gaps, there has been significant work over the past decade to create consistent and continuous satellite records for climate research (e.g., Sathyendranath et al., 2019a). As we approach the point at which the length of satellite ocean colour record will be sufficient for climate change studies, we can build on this work and harness these systems that have been put in place (e.g., Yang et al., 2022a). There are also opportunities to bring satellite data and models together, for example, using data assimilation, to improve our confidence and understanding of primary production trends (e.g., Gregg and Rousseaux, 2019) and understand variability in primary production and photoacclimation. There are also opportunities to gain insight into the impacts of climate change on primary production, by studying short-term extreme events (see Section 3.7 and Le Grix et al., 2021).

3.1.6. PP priority 5: Understanding

Challenges: At the workshop, participants also identified some major challenges relating to our fundamental understanding of marine primary production. These included: the need to understand better the relationships between primary production, phytoplankton community structure and physical-chemical environment (e.g. nutrient availability); understand better feedbacks between physics and biology and how biology affects the carbon cycle; understand better the fate of primary production (e.g., secondary and export production); and understand better the interactions between different components of the Earth System and how they influence marine primary productivity. As stated earlier, for carbon cycle studies, there is a clear requirement to go beyond PP and strive to quantify new production and net community production (e.g., Tilstone et al., 2015; Ford et al., 2021, 2022a,b).

Gaps: There are gaps in *in-situ* observations that if filled could help meet some of these challenges (see primary production priority 1). Additionally, meeting some of these challenges may require higher spatial and temporal resolution products than currently available, for example, to study diurnal variability. The need for higher spatial and temporal resolution data also limits our ability to estimate primary production in coastal and inland waters, impeding our understanding of land-sea interactions (Regnier et al., 2021) (see Section 3.6 for links to Blue Carbon).

There are also gaps in satellite information on datasets relevant to photochemical reactions, mostly activated by UV light, impacting primary production through photodegradation of phytoplankton and the formation of UV absorbing compounds. High spectral resolution data from satellite is also needed to improve primary production modelling (Antoine and Morel, 1996). Should such datasets become available, they will require validation. Equipping autonomous platforms with hyperspectral sensors could provide help in this regard (see priority 3).

Opportunities: With greater emphasis placed on an Earth system approach, to meet the challenges of the UN Ocean Decade, there are now more opportunities for collaborative interdisciplinary research, which may help to unify the integration of primary production across interfaces, bringing together primary production on land and in the ocean. With increasing computation power, there are also opportunities to merge/nest regionally-tuned models for larger scale estimates of primary production.

There are opportunities to harness novel algorithms and satellites (e.g. S5P, S5, S4, PACE) that can provide enhanced information on the spectral composition of underwater light field (e.g., for the retrieval of diffuse underwater attenuation (K_d) of UV and short blue light for TROPOMI (S5P) see Oelker et al., 2022). There is also scope to go beyond the one waveband (490 nm) K_d products, as currently provided operationally, to multi and hyperspectral K_d products, building on the capabilities of S3-OLCI next generation missions and older generation satellites like MERIS, that have a suit of bands in the visible range. Especially considering improved data storage and transfer capabilities. There are also opportunities to use satellite instruments covering the UV spectral range to give insight on the presence of UV absorbing pigments and types of CDOM, which may provide important information on photodegradation processes. Active-based lidar systems, capable of viewing further into the water column, at day and night and at low sun angles, and geostationary platforms, may offer opportunities to fill gaps in our understanding of primary production.

3.2. Particulate Organic Carbon (POC)

Particulate Organic Carbon (POC) can be defined functionally as the organic carbon in a water sample that is above 0.2 μm in diameter (taken as the formal boundary between dissolved and particulate substances). Globally, it is thought to be in the region of 2.3-4.0 Gt C in size (Stramska, 2009; CEOS, 2014; Galí et al., 2022), with around 0.58-1.3 Gt C in the upper mixed layer (Evers-King et al., 2017; Galí et al., 2022). It is among the most dynamic pools of carbon in the ocean, and turns over at a higher rate than any organic carbon pool on Earth

(Sarmiento and Gruber, 2006). It can be separated into living (e.g., phytoplankton, zooplankton, bacteria) and non-living (e.g., detritus) organic carbon material.

3.2.1. State of the art in POC

Satellite remote-sensing of POC focuses typically on the use of ocean colour data, and is among the more mature satellite ocean carbon products, with the first satellite-based algorithm developed in the late 90's (Stramski et al., 1999). Current algorithms include those that are: based on empirical band ratio or band-differences in remote-sensing reflectance wavelengths; backscattering based; backscattering and chlorophyll based; based on estimates of diffuse attenuation (K_d); and based on a two-step relationship between diffuse attenuation and beam attenuation. It is worth acknowledging the IOP-, chlorophyll-, and K_d-based algorithms involve first deriving these inputs from remote-sensing reflectances. For a recent review of these algorithms the reader is referred to Section 4.1.3.1. of Brewin et al. (2021). The empirical algorithm that links POC in the near-surface ocean to the blue-to-green reflectance band ratio described in Stramski et al. (2008) has been used by NASA to generate the standard global POC product from multiple satellite ocean color missions, and in some ESA POC initiatives (Evers-King et al., 2017). These standard algorithms provided a tool for estimation of global and basin-scale reservoirs of POC in the upper ocean layer (e.g., Stramska and Cieszyńska, 2015). Recently, a new suite of ocean color sensor-specific empirical algorithms intended for global applications was proposed by Stramski et al. (2022) with a main goal to improve POC estimates compared to current standard algorithms in waters with very low POC (ultraoligotrophic environments) and relatively high POC (above a few hundred mg m^{-3}). Intercomparison and validation exercises have suggested the performance of satellite POC algorithms is comparable to, or even better than, satellite estimates of chlorophyll-a (Evers-King et al., 2017), among the more widely used ocean colour products. This is perhaps related to POC representing the entire pool of organic particles (rather than just phytoplankton, as with Chl-a). However, a recent study highlighted significant inconsistencies between satellite-retrieved POC and that estimated from BGC-Argo float data at high-latitudes during the winter season (Galí et al., 2022).

The POC session saw the presentation of novel algorithms for POC estimation, including a refined empirical approach to the use of blue and green bands of reflectance for global POC estimation, the algorithms based on optical classes, theoretical optical algorithms based on the backscattering signal, multi-variate empirical algorithms and those that employ machine learning methods. Intercomparisons of existing algorithms were presented, as well as plans to generate long time series of POC products, combining multiple satellite sensors. Plans for POC algorithms for future satellite sensors were also presented. Six priority areas of POC were identified, that will be discussed separately in this section, including: 1) *in-situ* measurement methodology; 2) *in-situ* data compilation; 3) satellite algorithm retrievals; 4) partitioning into components; 5) vertical profiles; and 6) biogeochemical processes and the biological carbon pump. Table 3 summarises these priorities, and their challenges, gaps and opportunities.

3.2.2. POC priority 1: In-situ measurement methodology

Challenges: The current filtration-based methodology that uses glass-fiber filters (nominal porosity typically around 0.7 μm, though the effective pore size of glass-fiber filters is though to be substantially smaller; Sheldon, 1972) for retaining particles and measuring POC does not include all POC-bearing particles, and hence does not determine the total POC. In particular, some fraction of submicrometer POC-bearing particles is missed by this method (e.g., Nagata, 1986; Taguchi and Laws, 1988; Stramski, 1990; Lee et al., 1995), and these small-sized particles can make significant contribution to total POC (e.g., Sharp, 1973; Fuhrman et al., 1989; Cho and Azam, 1990). Glass-fiber filters are also subject to cell leakage and can cause breakage of cells due to the combined effects of pressure sample loading, and needle-like microfiber ends (IOCCG Protocol Series, 2021b). Other sources of possible underestimation of total POC include the loss of POC due to the impact of pressure differential across the filters (but see Liu et al., 2005) and an underrepresentation of the contribution of relatively rare large particles associated with a limited filtration volume (e.g., Goldman and Dennett, 1985; Bishop, 1999; Gardner et al., 2003; Collos et al., 2014). Thus it is very important to report volumes filtered together with POC concentrations. Differences in filter type, particle settling in bottles, and breakage or leakage of phytoplankton and other cells, are other issues that can cause errors in filtration-based methods.

Optical remote sensing (including ocean colour measurements from space) is driven by all particles suspended in water, including particles which are missed and/or underrepresented by the current filtration-based POC methodology. Thus, there is a mismatch between *in-situ* POC measurements through filtration and optical measurements that serve as a proxy of POC. The missing portion of POC unaccounted for by the current filtration-based POC methodology is important to both the ocean biogeochemistry and ocean optics that underlies ocean colour measurements from space.

While standardisation of POC methodology is generally desirable, there are important interpretive challenges that must be recognized in the course of the standardisation process. In particular, while the recommendation to use DOC-absorption correction to the standard filtration-based method will result in correction for one known source of overestimation of the fraction of total POC that is strictly retainable on the filters (Moran et al., 1999; Gardner et al., 2003; Cetinić et al., 2012; Novak et al., 2018; IOCCG Protocol Series, 2021b), the issue of known sources of underestimation of total POC remains unresolved.

The fractional contributions to POC associated with differently-sized particles and/or different types of particles (e.g., different groups or species of microorganisms) are difficult to quantify and remain poorly known for natural polydisperse and heterogenous assemblages of suspended particles.

Gaps: The current POC standard method does not account for both the artificial gains and losses of POC during collection of particles by filtration (Gardner et al., 2003; Turnewitsch et al., 2007; IOCCG Protocol Series, 2021b). With the exception of size-based filtration (which has know limitations), no experimental capabilities exist to partition total POC of natural particulate assemblages into contributions by different size fractions and/or different types of particles which play different roles in ocean biogeochemistry and carbon cycling. Another important gap is the lack of a certified reference material (CRM) for POC. A CRM allows to estimate the accuracy of POC estimated by different laboratories and by the same laboratory in different times and locations. As a consequence, a CRM for POC, if used by the community, would allow to reduce uncertainties in POC.

Opportunities: There are opportunities to advance and standardise the measurement methodology of total POC to provide improved estimates. These advancements can be brought about by including the portion of POC that is unaccounted for by the current standard filtration-based method. This would likely involve developing measurement capabilities aiming at quantification of POC contributions associated with differently-sized particles and different particle types based on combination of single-particle measurement techniques for particle sizing, particle identification, and particle optical properties.

3.2.3. POC priority 2: In-situ data compilation

Challenges: POC algorithm development and validation depends on datasets used in these analyses. For the purposes of algorithm development or validation, the field-based datasets are commonly compiled from data collected by different investigators on many oceanographic expeditions covering a long period of time. The information content available in documentation of various individual datasets is non-uniform and does not always contain sufficient details about data acquisition and processing methodology. This creates a risk that the compiled datasets are affected by methodological inconsistencies across diverse subsets of data, including the potential presence of methodological bias in some data. The presence of methodological bias is generally difficult to identify given the range of environmental variability, especially when available details on data acquisition methods are limited and/or there is a lack of replicate measurements (a CRM would help in this regard, see POC priority 1). Thus, indiscriminate use of data for the algorithm development and validation analyses is not advisable. These issues pose significant challenges for assembling high-quality field datasets that meet the standards and objectives of algorithm development or validation analyses including, for example, the process of data quality control based on predefined set of inclusion and exclusion criteria and assurance of environmental representativeness of datasets assembled for the analysis of specific algorithms (e.g., global vs. regional; Stramski et al., 2022).

The common validation strategy that relies on comparisons of field-satellite data matchups is not by itself sufficient to ensure rigorous assessment and understanding of various sources of uncertainties in satellite-derived POC products. The deviations between field and satellite data matchups can occur for various reasons such as spatio-temporal mismatch of data, uncertainties in both satellite and *in-situ* measurements, atmospheric correction, and performance skills of the in-water algorithm itself. In addition, the number of available data matchups is often limited in various environments.

Gaps: While the documentation of data acquisition and processing methods is often limited, especially in historical datasets, there are no standardised best-practice guidelines to ensure consistency in data quality control and synthesis efforts when larger datasets are compiled from various individual subsets of data. There are also regions within the world's oceans, such as polar regions and the Indian Ocean, where concurrently collected field data of POC and optical properties are scarce, including the lack of temporal coverage over the entire seasonal cycle.

Opportunities: Further efforts related to POC algorithm development and validation can benefit from careful scrutiny of historical and future data to minimize the risk of using biased data and ensure that the analyses are conducted using data with consistently high quality and are accompanied with sufficiently detailed documentation on data acquisition and processing methods. These efforts can be facilitated through further improvements and standardisation of best practices for documentation, quality control, sharing, and submission of data into database archives. Such practices are expected to lead to better data quality, data interpretation, and uncertainty assessments (IOCCG Protocol Series, 2021b).

There is a need to continue field programs in which concurrent POC and optical data are acquired across diverse environments including those that have been severely undersampled in the past.

3.2.4. POC priority 3: Satellite algorithm retrievals

Challenges: There can be a high level of complexity and variability of water optical properties and water constituent composition including POC-bearing particles, especially in coastal regions and inland waters (where non-algal particles are more prevalent), which are highly susceptible to land effects and re-suspension of sediments from shallow bottom. This makes it very difficult to develop a unified approach to provide reliable POC retrievals from optical remote sensing along the continuum of diverse optical/biogeochemical environments from open ocean to coastal and inland water bodies.

Standard global POC products are generated indiscriminately with respect to optical water types or the optical composition of water. Hence, this product is generated for a wide range of environmental situations, including the conditions outside the intended scope of global algorithms, which implies unknown and potentially large uncertainties. An inter-mission consistency of POC satellite-based products is required to support long-term climate data records. To successfully harness new satellite sensors geostationary and hyperspectral satellite data (e.g., GLIMR, PRISMA, PACE), there are challenges associated with appropriate atmospheric correction schemes, that can deal with large solar zenith and viewing angles for geostationary sensors, and spectral consistency for hyperspectral sensors.

Gaps: The current routine process of generating standard global POC products from global empirical algorithms either lack the mechanistically-based flags associated with ocean properties or optical water types to prevent the application of algorithms beyond their intended use, or where flags do exist, their usage is often not clarified and they are often not accurate. Clear and accurate flags are needed to minimize the risk of generating a product with unknown or large uncertainty (e.g., optically complex waters with mineral-dominated particulate assemblages). The need for appropriate flags to prevent the use of algorithms outside their scope is broadly relevant, for example, it applies also to regional algorithms (McKinna et al., 2019).

There is a lack of advanced algorithms based on adaptive approaches that incorporate mechanistic principles on the interaction of light with water constituents and associated optical water typologies, but the workshop saw the emergence of such methods, which is a promising sign. For example, algorithms that discriminate the water bodies based on varying composition of organic and mineral particles are required to enable reliable POC retrievals across diverse environments including the optically-complex coastal water bodies (Loisel et al., 2007; Woźniak et al., 2010; Reynolds et al., 2016).

Opportunities: Recent development of a new suite of empirical satellite sensor-specific global POC algorithms provide the opportunity for further testing, validation, analysis of inter-mission consistency, and ultimately an implementation of next-generation algorithms for routine production of a refined global POC product (Stramski et al., 2022).

Development of new algorithmic approaches with enhancements offered by potential incorporation of mechanistic principles underlying interactions of light with water constituents will support and advance future remote sensing applications along the continuum of diverse aquatic environments.

The analysis of POC reservoir and its spatio-temporal dynamics is expected to be enhanced by increased availability and use of geostationary and hyperspectral satellite data (e.g., GLIMR, PRISMA, PACE) along with *in-situ* data.

3.2.5. POC priority 4: Partitioning into components

Challenges: The particle size distribution (PSD) is an important link between ecosystem structure and function on the one hand, and optical properties on the other, as it affects both. Phytoplankton cell size is a key trait, and size fractions are closely related to functional types (Le Quéré et al., 2005; Marañón, 2015). One of the most challenging, yet important tasks moving forward is to develop understanding of the different functional and/or size partitions of POC. Bulk POC does not give a full picture of the ecosystem or its role in biogeochemical cycles. In addition, empirical POC satellite algorithms assume certain relationships between POC and optical properties. These relationships can change if basic characteristics of the POC change, such as its particle size distribution (PSD) or the fraction of total POC due to living phytoplankton. For example, the

POC-specific backscattering coefficient can change if the PSD of POC changes, and the POC-specific absorption spectra can change if the living carbon:POC ratio changes (e.g., Stramski et al., 1999; Loisel et al., 2001; Balch et al., 2010; Woźniak et al., 2010; Cetinić et al., 2012; Reynolds et al., 2016; Kostadinov et al., 2016; Johnson et al., 2017; Koestner et al., 2021; Kostadinov et al., 2022).

Notwithstanding the operational limitations of what constitutes POC and dissolved substances within the submicrometer size range, the particle assemblages in the near surface ocean are exceedingly complex, which makes this challenge particularly difficult to address. In addition, both forward and inverse modelling of the optical properties of the ocean entirely from first principles are not feasible currently. The range from truly dissolved substances to particles such as large zooplankton and beyond span many orders of magnitude in size and are governed by different optical regimes, which makes it difficult, for example, to identify, quantify, and separate the various sources of optical backscattering in the ocean (Stramski et al., 2004; Clavano et al., 2007; Stemmann and Boss, 2012).

In terms of functional fractions, POC can be considered to consist of phytoplankton, heterotrophic bacteria, zooplankton, and organic detritus. In terms of size fractions, ideally the PSD of POC and its various functional components should be measured *in situ*. There are theoretical considerations indicating that the marine bulk PSD, spanning several orders of magnitude in size, can follow, to first approximation, a power-law with a certain slope ((e.g., Kerr, 1974; Kiefer and Berwald, 1992; Jackson, 1995; Rinaldo et al., 2002; Brown et al., 2004; Hatton et al., 2021). The power-law approximation of marine PSD was used in numerous studies involving experimental data of PSD (e.g., Bader, 1970; Sheldon et al., 1972; Jackson et al., 1997; Jonasz and Fournier, 2007; Buonassissi and Dierssen, 2010; Clements et al., 2022) and satellite-based estimation of PSD (Kostadinov et al., 2009, 2010, 2016, 2022). However, there is a challenge associated with the use of power-law approximation because marine PSDs commonly exhibit some features across different size ranges, such as distinct peaks, shoulders, valleys, and changes in slope, which can result in significant deviations of PSD from a single-slope power function. Such deviations were demonstrated in many measurements of PSD in different oceanic environments (e.g., Jonasz, 1983; Risović, 1993; Bernard et al., 2007; Reynolds et al., 2010; White et al., 2015; Organelli et al., 2020; Reynolds and Stramski, 2021).

Finally, optically complex coastal waters present an additional challenge in that allochthonous and autochthonous sources of POC may be mixed, for example, due to riverine input, making the task of separating POC by functional fractions with known or assumed optical properties or PSD more challenging.

Gaps: There is a dearth of concurrent data on POC, PSD and carbon data for the components that make up the POC (e.g., phytoplankton carbon). This is a major limiting factor for satellite algorithm development.

Opportunities: There is an opportunity to exploit upcoming hyperspectral and polarization remote-sensing data. However, to do so requires efforts directed toward progress in basic research into how POC is partitioned into its various components. It is important to include measurements of PSD in future POC field campaigns globally, and in the compilation of global, quality-controlled datasets for algorithm development. Further studies of non-parametric descriptors of PSD are desirable because they offer superior performance compared with the power law approximation for representing the contributions of different size fractions to PSD across a wide diversity of marine environments (Reynolds and Stramski, 2021). Satellite-based approaches to monitoring zooplankton (e.g. Strömberg et al., 2009; Basedow et al., 2019; Behrenfeld et al., 2019; Druon et al., 2019) could futher aid in partitioning out the contribution of zooplankton to POC.

3.2.6. POC priority 5: Vertical profiles

Challenges: Whereas vertical profiles of POC can be estimated from *in-situ* optical sensors (in particular, backscattering sensors and transmissometers) deployed on autonomous *in-situ* platforms, the performance of present optical-based POC algorithms is hampered by limited understanding and predictability of variations in the characteristics of particulate assemblages and their relationships with optical properties throughout the water column. There is a strong requirement to promote fundamental research to better quantify and understand the relationships between variable vertical profiles of POC (and characteristics of the POC such as PSD, functional and size fractions) and the optical signal detectable from satellites.

Gaps: One of the most frequently asked questions posed by users of ocean colour remote sensing data (e.g., modellers) is what the satellite sensor actually "sees", in particular how deep the satellite sensor probes the water column in terms of variable near-surface vertical profiles of retrieved data products such as POC. For passive ocean colour, due to the double trip light has to take through the water column between the ocean surface and a given depth (downwelling radiance and then upwelling radiance), the source of the water-leaving optical signal reaching the satellite is heavily weighted to the near-surface layers of the ocean. Early research from the 1970s demonstrated that 90 % of the water-leaving signal comes from one e-folding attenuation depth, i.e., the layer defined by $1/K_d$, where K_d is the wavelength-dependent diffuse attenuation coefficient for downwelling irradiance (Gordon and McCluney, 1975). There is a need to expand on this research and develop POC-specific understanding, including the effects of vertical profiles of variables going beyond just bulk POC, namely POC partitioned by functional and/or size fractions (see POC priority 4). The diurnal evolution of the characteristics of POC vertical profiles also needs careful consideration. At present, there is an uneven distribution of vertical *in-situ* profiles of POC globally, with the southern hemisphere poorly covered compared with the northern hemisphere.

Opportunities: There are opportunities to advance basic research into improving our understanding of the relationships between POC and optical properties, such as the particulate backscattering coefficient, that are potentially amenable to measurements from autonomous *in-situ* platforms such as BGC-Argo floats. Artificial Intelligence may help in this regard (Claustre et al., 2020). Such research is expected to guide development of new sensors and algorithms (e.g., scattering sensors that include polarization) which will ultimately provide more reliable estimations of POC throughout the water column from autonomous systems. There are opportunities for synergy between satellite, models and autonomous platforms to create 3D and 4D fields of POC (Claustre et al., 2020). Future active-based satellite lidar systems will penetrate further into the water column improving vertical resolution of variables like the backscattering coefficient, a proxy for POC (Jamet et al., 2019).

3.2.7. POC priority 6: Biogeochemical processes and the biological carbon pump

Challenges: It is estimated that around 80 % of the carbon that is exported through the ocean biological carbon pump (BCP) is in the form of POC, and the remainder is transported downward as DOC via vertical mixing and advection (Passow and Carlson, 2012; Legendre et al., 2015; Boyd et al., 2019). The vertical export of POC results from several biological and physical processes, of which gravitational POC sinking is the largest component (Boyd et al., 2019). For a fixed fluid viscosity and density, gravitational sinking speed is a function of particle size, composition, and structure (Laurenceau-Cornec et al., 2020; Cael et al., 2021). The distribution of these properties in the particle population results to a large extent from the functioning of the upper-ocean ecosystem. Therefore, improving the satellite retrieval of POC mass (POC priority 3), size distribution (POC priority 4), and vertical distribution (POC priority 5), as well as additional particle properties (e.g., composition), is key to understanding and predicting the operation of the BCP at various scales.

Quantifying the global vertical POC export flux is a major challenge, as the range of current estimates (ca. 5-15 Gt C yr^{-1}; Boyd et al., 2019) remains similar to the ranges quoted in the 1980s (Martin et al., 1987; Henson et al., 2022). Improved ability to estimate the concentration and fluxes of POC (gravitational sinking, but also other pathways like the migrant pumps and physical pumps) would also benefit the study of trace element cycling (Conway et al., 2021) and deep-ocean ecosystems that rely on POC export. Current methods to measure gravitational POC export are work-intensive and do not allow for high spatio-temporal coverage, nor do they cover other pathways of carbon export, such as the migrant and mixing pumps, that contribute to a large portion of carbon export (Boyd et al., 2019) and change the sequestration times of exported carbon. Moreover, they often rely on simplifying assumptions (steady-state vertical profiles, negligible effects of horizontal advection, to name just a few) whose validity is not always tested or subjected to sensitivity analyses (Buesseler et al., 2020). Therefore, empirical (e.g., remote-sensing based) and prognostic models of gravitational POC export rely on *in-situ* measurements that are inherently uncertain and have sparse spatio-temporal coverage.

Gaps: The relationship between upper-ocean biogeochemical properties and vertical POC fluxes is still very uncertain, which hampers their representation in empirical and mechanistic models of the BCP. Large-scale estimates of vertical POC export usually focus on the average (climatological) state of the ocean, but interannual variations and their drivers (e.g., the role of physical forcing) remain poorly known (Lomas et al., 2022), and because of data sparseness there is a risk of confounding spatial and temporal variability.

Although shallow seas and continental slope areas are thought to play an important role in the global POC cycle, the sources and fate of POC in these areas remain difficult to monitor and quantify owing to the presence of optically complex environments, the higher abundance of inorganic particulate materials and the potentially larger role of lateral advection (Arístegui et al., 2020). Finally, processes other than gravitational sinking, such as the role of zooplankton diel vertical migration (DVM) (e.g., Bianchi et al., 2013a,b; Boyd et al., 2019). and the associated biogenic hydrodynamic transport (BHT) (e.g., Wilhelmus et al., 2019) need to be better understood and incorporated into ocean biogeochemical models.

Opportunities: Sampling from autonomous platforms (BGC-Argo, gliders, moorings, etc.) can provide the spatial-temporal resolution needed to refine our understanding of the BCP, complementing more detailed shipborne observations and the synoptic surface view obtained from satellites. For example, "optical sediment traps" mounted on BGC-Argo floats (Bishop et al., 2004; Estapa et al., 2017) can record a nearly-continuous proxy of vertical POC fluxes in the ocean interior.

Merging of these various data streams using statistical techniques (e.g., machine learning Sauzéde et al., 2020) can allow for refined estimates of the BCP, reducing the sampling bias associated with shipborne measurements. These complementary data streams can be further used to constrain mechanistic models of the BCP, for example, through data assimilation and parameter optimization (Nowicki et al., 2022). These approaches will improve quantification of the fluxes that form the BCP, help identify knowledge gaps and eventually spur progress in process-level understanding. Ongoing efforts are aimed at improving understanding of the effects of DVM and BHT on the biological pump, through a synergy of remote-sensing (e.g., Behrenfeld et al., 2019), laboratory studies, and biogeochemical modelling.

Although the framework drafted above is conceptually valid for the study of continental shelves, these areas require higher-resolution observations and models that can resolve their larger heterogeneity and a wider array of transport and transformation processes. Therefore, such areas would benefit from dedicated regional process studies and monitoring from geostationary satellites and other airborne sensors.

3.3. Phytoplankton Carbon (C-phyto)

The living pool of POC can be partitioned into components associated with living phytoplankton cells and other types of carbon (e.g., zooplankton, detritus, fecal pellets). Phytoplankton carbon (C-phyto) is a particularly important pool of POC owing to its role in marine primary production, and providing food to the majority of the marine ecosystem. It has been estimated that the pool is around 0.78 – 1.0 Gt C in size (Falkowski et al., 1998; Le Quéré et al., 2005), but despite its small size (relative to terrestrial plants, which is in the order to 450 Gt C, see Bar-On et al., 2018) it contributes around 50 Gt C yr^{-1} in primary production (equivalent to terrestrial plants, see Section 3.1).

C-phyto is key to establishing the carbon-to-chlorophyll ratio (important for understanding phytoplankton physiology and thier adaptation to light, nutrient and temperature changes), to compute primary production using carbon-based models (Behrenfeld et al., 2005; Sathyendranath et al., 2009), and to assess the contribution of photophysiology to the phytoplankton seasonal cycle (Bellacicco et al., 2016). High temporal C-phyto data 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 has also been innovatively used to assess, at the sea-air interface, the export of organic matter towards the atmosphere in the form of aerosols (O'Dowd et al., 2004; Fossum et al., 2018).

3.3.1. State of the art in Phytoplankton Carbon

A number of algorithms have been developed to derive C-phyto from ocean color observations (see Bellacicco et al. (2020) and reference therein, and Section 4.1.3.2. of Brewin et al. (2021)). The approaches used can be grouped broadly into: i) backscattering-based (e.g., Behrenfeld et al., 2005; Martínez-Vicente et al., 2013; Graff et al., 2015); ii) Chlorophyll-a-based (e.g. Sathyendranath et al., 2009) some with use of models of photoacclimation and physiology parameters (e.g., Jackson et al., 2017; Sathyendranath et al., 2020); and iii) size-class-based (e.g., Kostadinov et al., 2016, 2022; Roy et al., 2017) approaches. These approaches can also be ground according to their product (PSD, size class or taxonomic class) or the optical properties used to derive them (Chla-abundance based, backscatter, absorption, radiance) (Mouw et al., 2017). Each approach relies on the covariation between optical properties or POC, and a proxy of phytoplankton concentration such as Chl-a, phytoplankton light absorption or size distribution.

One of the biggest challenges in retrieving C-phyto from ocean color observations is separating 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, particularly in turbid or coastal waters. It is assumed that phytoplankton (and co-varying material) control the backscattering signal in the open ocean (Dall'Olmo et al., 2009; Organelli et al., 2018), an assumption used in Case-1 water models (e.g., Morel and Maritorena, 2001). However, the variation of NAP horizontally, vertically, and temporally is considerable in many parts of the ocean (Bellacicco et al., 2019, 2020) in size and concentration (Organelli et al., 2020). Recent efforts have been made to improve C-phyto estimates from satellite-based particle backscattering by accounting for variability in NAP (e.g., Bellacicco et al., 2020).

Each of the proposed approaches have advantages and disadvantages, and can be improved with knowledge on the optics-to-carbon conversion factors (that can inform the Chl-a to C ratio), using *in-situ* C-phyto datasets (e.g., Martínez-Vicente et al., 2017), and through reduced uncertainties in satellite-derived inputs of relevant quantities (i.e., backscattering, Chl-a, and particle size distribution). Currently, no method has extended the global estimation of C-phyto to below the ocean surface where many biogeochemical interactions occur.

During the workshop, three key priority areas of C-phyto were identified, that will be discussed separately in this section, and include: 1) *in situ* data; 2) satellite algorithm retrievals; and 3) vertical structure. Table 4 summarises these priorities, and their challenges, gaps and opportunities.

3.3.2. C-phyto priority 1: In-situ data

Challenges: Measuring C-phyto *in-situ* is notoriously difficult and no standard method exists and any such measurements are likely to have high uncertainties. A major challenge for communities working in this field is to improve *in-situ* methodologies for quantifying C-phyto and to measure or estimate photoacclimation model parameters. Standardization of phytoplankton carbon data submission using emerging *in-situ* techniques (such as the Imaging FlowCytobot) is also challenging (Neeley et al., 2021).

Gaps: As a direct result of this challenge, one of the largest gaps for deriving C-phyto from space is the paucity of global *in-situ* C-phyto data (and C-phyto community composition), to develop and validate models and algorithms. A couple of methods exist to directly measure C-phyto. One of them entails the separation of living phytoplankton particles from non-living (detrital) particles and the subsequent elemental measurement of those particles (Graff et al., 2012, 2015). Another, older method (Redalje and Laws, 1981), requires incubation experiments in which the sample cells are labelled with ^{14}C, and the specific activity of Chl-a is measured at the end of the experiment as well as the total particulate ^{14}C activity. The direct measurement methodology of Graff et al. (2012, 2015) is largely biased towards nano and pico-sized phytoplankton particles detected by flow cytometry, whereas the method of Redalje and Laws (1981) depends on

Chl-a being sufficiently high for the incubation experiments. It is important that these direct methods are incorporated into existing programs. C-phyto may also be indirectly measured by applying empirical relationships that relate cell biovolume to C-phyto (Menden-Deuer and Lessard, 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. Only limited number of field data sets (e.g., NASA's EXPORTS campaign, and the Atlantic Meridional Transect Programme (AMT)) contain these coincident measurements, leading to a lack of understanding of their temporal or spatial variability. Moreover, few measurements are taken below the surface ocean (see C-phyto priority 3).

Additionally, there are very few consistent C-phyto surface time-series data sets available. Time series data sets with clear uncertainties are critical to understanding of 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, https://nes-lter.whoi.edu/).

Opportunities: There is an opportunity to enlarge and explore data collected at *in-situ* supersites. These are sites with co-located satellite data, were all the different measurements needed to tune and validate satellite C-phyto algorithms would be available (linking C-phyto to optical properties, and considering the diversity and variation of phytoplankton and other optical constituents). A strategy to achieve this could be to empower existing observatories, often also used for applications such as water quality assessment, and expand the range of data they collect to ensure all measurements needed for satellite C-phyto algorithms are available (e.g., phytoplankton taxonomy, flow cytometry, FlowCAM). These supersite measurements could even be complemented by dedicated mesocosm experiments that will help to improve the mechanistic understanding of the relationship between C-phyto and optical properties. In addition, these data sets can be used to derive reliable uncertainties in *in-situ* C-phyto data. A future network of these supersites could be established to be representative of global scales, and not only collect data at the surface but also throughout the euphotic zone.

Another opportunity is to improve the global distribution of optical property measurements used as input of C-phyto algorithms by empowering validation through continuous underway optical measurements (e.g. Slade et al., 2010; Brewin et al., 2016; Rasse et al., 2017; Burt et al., 2018) and autonomous mobile platforms such as BGC-Argo profiling floats and Lagrangian drifters (e.g., Abbott et al., 1990; Boss et al., 2008; Sauzède et al., 2016; Bisson et al.; Xing et al., 2020). For the latter, these robotic platforms allow the acquisition of optical data with limited spatial and temporal bias, as they also collect data in remote regions, even during meteorological conditions that are unfavourable for ship-based sampling (Organelli et al., 2017). Optical data from these platforms, or similar technologies, have been used to derive bulk properties, such as diffuse attenuation (K_d), Chl-a, coloured dissolved organic matter (CDOM) and POC, and are a source of sub-surface data, complementary to the surface data from satellites. As hyperspectral data can help resolve estimates on the composition (type and size) of phytoplankton (Chase et al., 2013; Liu et al., 2019), integrating instrumentation with hyperspectral capabilities (Jemai et al., 2021; Organelli et al., 2021) can provide insight into phytoplankton composition in the illuminated part of the water column (Bracher et al., 2020). Efforts to enlarge the optical multi-platform data acquisition, and to develop protocols 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 and provide information of phytoplankton photoacclimation (see C-phyto priority 3).

3.3.3. C-phyto priority 2: Satellite algorithm retrievals

Challenges: Backscattering is an optical property that has been linked to

C-phyto. However, particle backscatter includes all particles, not just phytoplankton and it is challenging to separate phytoplankton from non-living particles, without complementary information such as microscopic or flow cytometric data. Additionally, we should strive to increase the accuracy of backscattering retrievals from space. Correcting the remote sensing reflectances for Raman scattering prior to semi-analytical retrievals has shown some promise for improving quality of back-scattering retrievals (Westberry et al., 2013; Lee et al., 2013; Pitarch et al., 2019).

Chl-a, both satellite-derived and *in-situ*, is often used in models that relate particle backscatter to C-phyto through empirical relationships. However, the uncertainties within these empirical relationships are increased by the influence of phytoplankton composition and the physiological state of phytoplankton driving photoacclimation, i.e., the adjustment of Chl-a in response to light, particularly in the surface ocean, and uncertainties in Chl-a measurements. In addition, in low phytoplankton biomass regions, such as in the subtropical gyres, uncertainties in both satellite retrieved optical properties and Chl-a can be large.

Gaps: There is a gap in our mechanistic understanding of how optical properties link to C-phyto, considering the diversity of phytoplankton composition and their physiological state, and the other optically significant substances that can have an impact on the optical properties.

Each of the methods, models and algorithms, possess uncertainties, either inherent or owing to the input data, which are infrequently reported. As such, there are gaps in our knowledge of the accuracy of our models and algorithms to derive C-phyto. This includes uncertainties assoicated with direct or indirect measurements of *in-situ* C-phyto.

Opportunities: Long time-series of C-phyto data should be developed by using merged ocean-colour datasets (e.g., OC-CCI, Globcolour and Copernicus Marine Maritorena et al., 2010; Sathyendranath et al., 2019a; Kostadinov et al., 2022), or by adapting algorithms to operate on different ocean colour sensors that cover different time spans (e.g., since 1979 until today; Oziel et al., 2022). These products should include pixel-by-pixel uncertainties. C-phyto satellite algorithms may be improved by using synergistic information on the abundance and composition of the different optical components (phytoplankton, NAP, CDOM), which may lower the uncertainties in C-phyto retrievals.

There are also opportunities to improve C-phyto products by exploring the combined use of satellite data with ecosystem modelling. Directly using satellite Chl-a or phytoplankton community-specific Chl-a for evaluation or assimilation in (coupled-ocean-) biogeochemical models could be a promising avenue for deriving C-phyto (IOCCG, 2020). Other exciting avenues of research include combining models of photoacclimation with size-based approaches (Sathyendranath et al., 2020), that can be reconciled with models of primary production, meaning the carbon pools and fluxes are produced in a consistent manner.

3.3.4. C-phyto priority 3: Vertical structure

Challenges: Considering the difficulties in measuring C-phyto *in situ* (see C-phyto priority 1) is it very challenging to collect, aggregate and produce an *in-situ* dataset that is representative of entire euphotic depth and at global scale, required for understanding distributions in C-phyto.

Gaps: Since satellite data only delivers information from the first optical depth, the collection of *in-situ* C-phyto data for validation of satellite products has been largely limited to discrete water sampling at surface depths. For a complete understanding of the role of C-phyto in the ocean carbon cycle, it is imperative that we extend measurements deeper into the water column, encompassing the entire euphotic zone.

Satellite, *in-situ* and modelling data often have large discrepancies in spatial and temporal resolution, particularly in the vertical dimension. There are a few methods designed to combine these different data sets, and help extrapolate the satellite C-phyto products from the surface down through the entire euphotic zone.

Opportunities: There are potential opportunities to use autonomous platforms such as BGC-Argo floats (Claustre et al., 2020), undulating profilers (Bracher et al., 2020) and moorings (Von Appen et al., 2021), together with satellite remote-sensing and modelling (e.g. through data assimilation), to help reconstruct, via techniques like artificial intelligence, the 4D view of C-phyto, to better observe phytoplankton biomass dynamics below the ocean surface (e.g., Brewin et al., 2022).

3.4. Dissolved Organic Carbon (DOC)

Dissolved Organic Carbon (DOC) is ubiquitous in the ocean and represents a considerable reservoir of carbon, at around 662 Gt C, approximately the size of the atmospheric CO_2 pool (Hansell et al., 2009). Marine DOC is also a dynamic carbon component, that fulfills important biogeochemical and ecological functions, and connects terrestrial landscapes (Anderson et al., 2019), freshwater and marine ecosystems and the atmosphere (Carlson and Hansell, 2015; Anderson et al., 2019). Continuously and accurately quantifying DOC stocks and fluxes in the ocean is critical to our understanding of the global role of DOC and its susceptibility to change.

3.4.1. State of the art in DOC

In recent years, synoptic monitoring of DOC has been attempted using optical techniques and Earth Observation. A wide range of methods have been trialled, mainly empirical, including linear regressions, artificial neural network algorithm, random forest classification, and gradient boosting. These approaches typically estimate DOC concentration using single or multiple variables, including: remote-sensing reflectance, remotely-sensed coloured dissolved organic matter (CDOM) absorption coefficients, sea-surface salinity, SST, chlorophyll-a concentration, and modelled mixed layer depths. For an in-depth review of the status of DOC monitoring, the reader is referred Section 4.1.2. of Brewin et al. (2021) and Fichot et al. (In Prep, this issue).

Four key priorities were identified following presentations and discussions at the workshop. These are summarised in Table 5 and include: 1) temporal coverage of the coastal ocean; 2) understanding the relationship between CDOM and DOC; 3) identification of sources and reactivity; and 4) vertical measurements.

3.4.2. DOC priority 1: Spatial and temporal coverage of the coastal ocean

Challenges: The remote sensing of DOC in the surface ocean is facilitated by the optical detection of CDOM (the coloured component of dissolved matter), particularly in the coastal ocean, where DOC and CDOM can be tightly correlated (Ferrari et al., 1996; Vodacek et al., 1997; Bowers et al., 2004; Fichot and Benner, 2012; Tehrani et al., 2013). In such cases, the detection of DOC from space relies on the optical detection of CDOM absorption coefficients, $a_g(\lambda)$, from remote-sensing reflectance, followed by the estimation of DOC from $a_g(\lambda)$. However, as coastal regions are highly dynamic and heterogenous, quantifying DOC stocks and fluxes require satellite optical monitoring systems with high temporal and spatial coverage, and accurate atmospheric correction (e.g., separating the contribution of Rayleigh scattering in the atmosphere is particularly important for DOC retrievals; Juhls et al., 2019). High latitudes, where high loads of DOC are transported from rivers into the sea (e.g., Arctic rivers, Baltic) are difficult to view using passive ocean colour satellites in winter months.

Gaps: At present, accurate estimates of DOC stocks and fluxes in coastal environments are severely limited by the temporal coverage of existing ocean-color satellites. Current satellites offer revisit times of about five times per week, at best (though this depends on latitude and time of year). More appropriate revisit times for nearshore coastal waters would need to be an order of magnitude higher (e.g., ideally 3-5 times per day) to adequately capture the dynamics of DOC and facilitate the accurate estimation of DOC fluxes across the boundaries of coastal systems. This is especially important for the nearshore regions of the coastal ocean which can be strongly influenced by tides, current, and rivers.

Opportunities: With the advent of geostationary ocean-colour satellites, such as the Geostationary Ocean Color Imager (GOCI) and the upcoming hyperspectral NASA Geostationary Littoral Imaging and Monitoring Radiometer (GLIMR), capable of imaging multiple times daily, there are exciting opportunities to address these challenges and gaps at regional scales (e.g., see Huang et al., 2017). NASA's GLIMR (launch expected in 2027) will help quantify DOC stocks and fluxes in coastal environments of the continental USA and in targeted regions of coastal

South America (e.g., Amazon River outflow, Orinoco River Outflow) by providing multiple observations per day (hourly), at around 300 m resolution. Reflectances from GLIMR will also be hyperspectral (10 nm resolution) across the UV-NIR range (340 -1040 nm) and will therefore provide the opportunity for improved accuracy of DOC concentration retrievals. We recommend continuing efforts towards deploying additional geostationary and hyperspectral satellites to improve the temporal coverage of other coastal regions around the world.

3.4.3. DOC priority 2: Understanding and constraining the relationship between CDOM and DOC

Challenges: Improvements in satellite CDOM absorption retrievals are needed, with uncertainties in algorithms often higher than other inherent optical properties derived from ocean colour data (Brewin et al., 2015). The relationships between DOC and CDOM absorption, commonly used to quantify stocks of DOC in coastal regions, tends to be variable seasonally and across coastal systems (Mannino et al., 2008; Massicotte et al., 2017; Cao et al., 2018). Furthermore, the dynamics of CDOM and DOC are largely decoupled in the open ocean (Nelson and Siegel, 2013), making the accurate remote sensing of DOC concentration challenging in much of the open ocean.

Gaps: There are gaps in our understanding of the relationship between DOC and CDOM absorption coefficients that need to be addressed, for example, relationships are likely to depend on the type of river system studied, and its optical constituents. There are also gaps in our understanding of the various physical and biogeochemical processes that impact differently CDOM absorption and DOC, depending on DOC quality (e.g., Miller and Moran, 1997; Tzortziou et al., 2007; Helms et al., 2008). This will improve our understanding of regional and seasonal variability in the relationship between these variables, and consequently improve DOC estimates from space. Additionally, there is a lack satellite UV and hyperspectral data for resolving DOC and its composition.

Opportunities: We recommend the community work towards improving this understanding through a combination of the following four efforts.

1. Utilise the spectral slope of CDOM absorption, $S_{275-295}$, to constrain the variability between CDOM and DOC in the ocean and improve empirical algorithms. In river-influenced coastal systems, $S_{275-295}$ has been shown to be a useful parameter to constrain the variability between CDOM and DOC (Fichot and Benner, 2011; Cao et al., 2018). It has also been shown that this parameter can be retrieved empirically with reasonable accuracy from ocean colour, therefore providing a means to improve DOC retrievals (Mannino et al., 2008; Fichot et al., 2013, 2014; Cao et al., 2018). Future studies could look into developing similar approaches for other regions of the ocean. Retrievals of $S_{275-295}$ requires very accurate atmospheric correction, which is challenging in coastal waters.

2. Develop mechanistic models of the processes regulating the relationship between CDOM and DOC, by integrating new insight on the effects of photobleaching. Recent efforts have quantified and included in biogeochemical models (e.g., Clark et al., 2019) the effects of photobleaching on CDOM absorption coefficient spectra, which in turn, may improve our ability to constrain the relationship between CDOM and DOC (Swan et al., 2013; Zhu et al., 2020). Similar efforts should be conducted for understanding other processes such as the marine biological net production of DOC. A quantitative appreciation of these processes is also critical to understand the influence of climate-driven change on the relationship between CDOM and DOC.

3. Harness opportunities to acquire high-quality field measurements of DOC and CDOM absorption across different seasons and marine environments. This could be achieved by tapping into field campaigns that collect inherent and apparent optical properties for satellite validation, and perform additional concurrent sampling for DOC. Many field datasets include measurements of CDOM absorption coefficients but lack DOC measurements. It should be noted, however, that while many labs have the capability to measure CDOM, much fewer labs can measure DOC. Coordinated efforts

should therefore be considered to ensure that CDOM and DOC are measured together as often as possible. This could be aided by the development of semi-automative methods to measure DOC, that could be used alongside similar techniques for measuring CDOM absorption (e.g., Dall'Olmo et al., 2017). This could facilitate the development of improved satellite DOC algorithms.

4. Harnessing new satellite sensors for CDOM and DOC retrievals. For example, consideration in the allocation and characteristics of spectral wavebands for DOC studies has also gone into the development of NASA's PACE mission (Werdell et al., 2019). Harnessing optical water type frameworks for algorithm selection and merging for better separation of NAP-CDOM effects.

3.4.4. DOC priority 3: Identification of source and reactivity

Challenges: To quantify the cycling, fate, and impacts of DOC in the ocean, requires identifying specific pools of DOC of different sources and reactivity. This is particularly true for the coastal ocean. There is likely to be large gradients in the sources and reactivity of DOC as we transition from inland waters to coasts and the open ocean.

Gaps: Although fluorescence excitation-emission matrix methods have been used as an *in-situ* optical indicator of dissolved organic matter (DOM) origin and reactivity (Mopper and Schultz, 1993; Kowalczuk et al., 2013), there has been few studies assessing whether the DOM fluoresced signal can be detected from remote-sensing reflectance.

Opportunities: We recommend the community puts efforts towards assessing whether the fluorescence of DOC and CDOM, originating from specific sources (e.g., riverine, effluent), can have a measurable influence on remote-sensing reflectance. Recent and upcoming hyperspectral sensors (e.g., TROPOMI, GLIMR, PRISMA, PACE, see Table 10) have (or will have) improved signal-to-noise ratio, as well as enhanced spectral information in the UV-visible range, and adequate spatial resolution, that could facilitate detection of the fluorescence signature of certain pools of DOC and CDOM (Wolanin et al., 2015; Oelker et al., 2022; Harringmeyer et al., 2021). Such efforts can be facilitated with radiative transfer simulations (e.g., Hydrolight, www.hydrolight.info, and SCIATRAN, https://www.iup.uni-bremen.de/sciatran/). However, fluorescence signature of DOC is currently not well understood, and we require a better quantitative knowledge of the fluorescence quantum yield matrix of DOC and CDOM and how it varies with specific DOM sources (Wünsch et al., 2015).

Active remote-sensing approaches based on laser-induced fluorescence could also potentially facilitate the sourcing of DOM in the surface ocean. Airborne laser-based measurements of DOM have been used in the past, but these only used a single excitation-emission wavelength pair and were used to specifically measure DOC (Hoge et al., 1993; Vodacek, 1989). The use of multiple, carefully chosen excitation-emission wavelength combinations could potentially help identify specific pools of DOM with unique fluorescence signatures.

3.4.5. DOC priority 4: Vertical measurements

Challenges: The remote sensing of CDOM and DOC is limited to surface measurements. Accurately extrapolating these measurements to depth requires understanding of vertical variability. At present, depth variability is generally assumed or estimated using empirical or statistical approaches (e.g., neural networks) trained with field observations (Mannino et al., 2016).

Gaps: Approaches that extrapolate surface DOC and CDOM to depth require extensive *in-situ* datasets (vertical profiles) of DOC and CDOM, representative of a wide range of conditions. Though efforts have been made in this regard (Nelson and Siegel, 2013; Hansell, 2013), gaps exist for many regions and seasons.

Opportunities: *In-situ* measurements from autonomous platforms like BGC-Argo equipped with DOM-fluorescence sensors can provide valuable information about the depth-dependency of DOM in the ocean (Claustre et al., 2020). BGC-Argo radiometric measurements in the UV can also be used to get CDOM absorption proxies (Organelli et al., 2017; Organelli and Claustre, 2019). Recently, projects such as AEOLUS COLOR (CDOM-proxy retrieval from aeOLus ObseRvations), have focused on developing UV-lidar-based techniques to retrieve sub-surface information about CDOM in the ocean (Dionisi et al., 2021). The ESA AEOLUS mission is a UV-lidar (355 nm) mission originally designed for the retrieval of atmospheric properties, but the UV capabilities of this active sensor provides an opportunity to retrieve in-water properties of CDOM. Within ESA project S5POC, K_d at three wavelengths (UVAB, UVA and short blue) were developed (Oelker et al., 2022), which could help provide insight on the sources of CDOM. Additionally, there is potential to exploit the high spectral resolution of TROPOMI (e.g. the filling of the Fraunshofer lines by FDOM) to acquire information on the sources of DOM. We recommend that the community continue to explore original ideas to improve the detection of CDOM and DOC below the surface. There are also opportunities to harness mechanistic modelling approaches (physical and biogeochemical modelling) to improve estimation of DOC dynamics at depth (Mannino et al., 2016).

3.5. Inorganic carbon and fluxes at the ocean interface (IC)

Inorganic carbon in the ocean can be partitioned into dissolved (DIC) and particulate (PIC) form. Relative to DIC, PIC is a small pool of carbon at around 0.03 Gt C (Hopkins et al., 2019), but annual production is considered highly variable and estimated to be of the order 0.8-1.4 Gt C y^{-1} (Feely et al., 2004). This PIC is present in the form of particulate calcium carbonate ($CaCO_3$), with coccolithophores, pteropods and foraminifera thought to be the main sources of PIC in the ocean (Schiebel, 2002; Feely et al., 2004; Buitenhuis et al., 2019). Despite its biological growth the formation of PIC has the net-effect of shifting the carbonate chemistry towards higher CO_2 in the water and decreasing its pH (Zeebe and Wolf-Gladrow, 2001; Rost and Riebesell, 2004; Zeebe, 2012).

In contrast, DIC constitutes the largest pool of carbon in the ocean, at around 38,000 Gt C (Hedges, 1992), and connects carbon in the ocean with the atmosphere and with the land. CO_2 dissolves in seawater and reacts with water to form carbonic acid (H_2CO_3). Carbonic acid is unstable and dissociates into bicarbonate (HCO_3^-), carbonate (CO_3^{2-}) and protons (H^+). The equilibrium between these forms controls ocean pH. From a biological viewpoint the gaseous quantity of CO_2 in seawater, $p$$CO_2$, is modulated by photosynthesis (primary production) and respiration (mineralization) which is captured within net community production estimates.

The flux or movement of CO_2 between ocean and atmosphere is often described using a formation first described by Liss and Slater (1974), which can be expressed as Flux= $kK_0(pCO_{2,w} - pCO_{2,a})$ (Wanninkhof, 2014); where k is the gas transfer velocity (equivalent to the inverse of the resistance to gas transfer), K_0 is the constant of solubility of gas, and $(pCO_{2,w}-pCO_{2,a})$ is the difference between the CO_2 partial pressures in the ocean and the atmosphere (ΔCO_2), respectively (see Woolf et al., 2016, for discussion on how best to derive ΔCO_2). Ocean temperature, and to a less extent salinity, is a strong modulator of the solubility of CO_2 in seawater (Takahashi et al., 2009) and is thus an important parameter for determining the ΔCO_2. k is often parameterised as a function of wind speed and temperature (e.g., Schmidt number; Wanninkhof, 2014).

3.5.1. State of the art in inorganic carbon and air-sea fluxes

Methods to remotely sense PIC have focused on individual or multi-spectral band optical detection of coccolithophores (Gordon et al., 2001; Balch et al., 2005; Mitchell et al., 2017), with some using time series to improve data consistency (Shutler et al., 2010). Due to their unique optical signature (when the plankton dies coccoliths are detached causing the water to appear spectrally white), coccolithophore blooms have been mapped via satellite ocean colour since the launch of NASA's CZCS satellite sensor in 1978 (Holligan et al., 1983; Brown and Yoder, 1994). The challenges of detection include: detecting coccolithophores and their associated PIC at low concentrations (or prior to their coccoliths becoming detached), during bloom events, in the presence of bubbles (e.g. in the Southern Ocean), and to remove the effects of suspended particulates that exhibit similar spectral properties in shelf seas (Shutler et al., 2010). Laboratory and field observations (Voss et al., 1998; Balch et al., 1999, 1996; Smyth et al., 2002) have informed PIC algorithm development for determining calcite concentrations by relating coccolithophore abundance and morphology to PIC concentrations. Currently NASA Ocean Biology DAAC distributes a PIC concentration product that merges Balch et al. (2005) and Gordon et al. (2001), and there is also a developmental PIC product available (Mitchell et al., 2017).

DIC and other key carbonate system parameters (e.g., total alkalinity (TA), pH, and pCO_2) are more challenging to determine from satellite observations as they don't have a unique spectral signature. However, alkalinity is strongly conservative with salinity so this has led to the development of many regional relationships to predict TA from salinity (e.g., Cai et al., 2010; Lefévre et al., 2010) and DIC from salinity and temperature (e.g. Lee et al., 2006), as well as global relationships using a suite of physical and chemical parameters (e.g., Sasse et al., 2013) and their application to satellite remote sensing has been identified (Land et al., 2015). For example, total alkalinity has been estimated using the strong relation with sea surface salinity (SSS) which in the last decade has been measured by different satellites, such as ESA's Soil Moisture and Ocean Salinity satellite (SMOS; Reul et al., 2012), NASA/CONAE Aquarius (Lagerloef et al., 2013), and NASA's Soil Moisture Active Passive satellite (SMAP Tang et al., 2017). More recently, efforts to combine physical and optical satellite ocean observations with climatological and re-analysis data products has opened the door to remote estimation of the complete marine carbonate system via regional and global relationships as well as new machine learning methods and carbonate system calculation packages (e.g., Land et al., 2019; Gregor and Gruber, 2021).

Large scale air/sea flux estimates typically make use of the Surface Ocean CO_2 ATlas (SOCAT, https://www.socat.info/index.php/data-access/; Bakker et al., 2016) and/or global climatologies of surface seawater pCO_2 using data interpolation/extrapolation and neural network techniques (e.g., Takahashi et al., 2009; Rödenbeck et al., 2013; Landschützer et al., 2020) to produce spatially and temporally complete fields. These pCO_2 fields can be coupled with satellite retrievals of SST, wind speed, and other variables, to calculate the air-sea CO_2 flux (e.g., as demonstrated with the FluxEngine toolbox; Shutler et al., 2016). A key parameter for the calculation of the air-sea CO_2 fluxes is the xCO_2 fraction in air. Global coverage of atmospheric CO_2 estimates is available from multiple satellite missions (e.g., GOSAT 2009-present, OCO-2 2014-present, OCO-3 2019-present). Satellite observations have also been combined with model output to estimate

pCO$_2$ and air-sea flux (e.g., Arrigo et al., 2010). Whilst estimates of pCO$_2$ and air-sea flux have been achieved solely from satellite observations (e.g., Ono et al., 2004; Borges et al., 2009; Lohrenz et al., 2018). It is also possible to calculate seawater pCO$_2$ from observations of TA and DIC and using marine carbonate system calculations (e.g., Humphreys et al., 2022). For a more in-depth review of status of using satellite remote sensing for determining inorganic carbon and fluxes at the ocean interface, the reader is refereed to Shutler et al. (Submitted).

Modelling studies can also help inform satellite approaches. They have been used to evaluate the drivers of the marine carbonate system (e.g., Lauderdale et al., 2016) and examine potential impacts of extreme and compound events (e.g., Salisbury and Jönsson, 2018; Burger et al., 2020; Gruber et al., 2021). Seawater pCO$_2$ and air-sea CO_2 fluxes can also be estimated using dynamic ocean biogeochemical models (Hauck et al., 2020) and data-assimilation-based models (e.g., Verdy and Mazloff, 2017). ECCO-Darwin (Carroll et al., 2020, 2022) is one such example which is initialised with a suite of physical variables, biogeochemical properties and also TA, DIC and pCO$_2$ from datasets such as SOCAT and GLODAP. It assimilates a combination of physical and biogeochemical data in order to produce physically-conserved properties. As such models continue to evolve, it will be increasingly possible to use them to assess regional and global scale carbon inventories as well as fluxes, and evaluate them with satellite-based products.

At the workshop, four priorities were identified in relation to the detection of inorganic carbon and the air-sea flux of CO_2 from space (summarised in Table 6), including: 1) *in-situ* data; 2) satellite retrievals and mapping uncertainty; 3) models and data integration; and 4) mechanistic understanding of gas transfer.

3.5.2. IC priority 1: In-situ data

Challenges: Considering many components of inorganic carbon are not directly observable from space, there is a strong reliance on *in-situ* data. Integrating *in-situ* data products with satellite data is challenging, owing to large differences in spatial and temporal resolution. Furthermore, it can be challenging to integrate *in-situ* datasets from different sources and collaborators, without community consensus on best practices and consistent use of traceable reference materials and consistent standards.

Gaps: Improved spatial and temporal coverage of field observations in key regions and times, not only at the surface but also the full water column, is a key requirement for the development and validation and use of satellite-based IC approaches. Air-sea CO_2 flux assessments will always be spatially and temporally limited by the extent and number of the *in-situ* data that underpin them. Additionally, our understanding of long-term changes in pCO_2 and fluxes, in key ocean regions (e.g., the Southern Ocean), is limited by a lack of *in-situ* data time-series stations (Sutton et al., 2019). At present, there is no dedicated framework for sustained, long-term monitoring of seawater pCO_2 (particularly in South Ocean which contributes around 40 % of the anthropogenic carbon uptake) which is concerning as without these no satellite methods can be used.

There are also gaps in our ability to assure consistent quality of these *in-situ* observations. For example, TA and DIC observations require a certified reference material (Dickson, 2010), that needs to be sustained into the future (at present there is only one laboratory able to produce it). Community-wide agreement on best practices and approaches is needed for measurements that enable accurate estimation of air-sea CO_2 fluxes.

Opportunities There are opportunities to improve the spatial and temporal resolution of *in-situ* data through autonomous platforms, such as BGC-Argo floats (Williams et al., 2017; Bittig et al., 2018; Claustre et al., 2020) and autonomous surface vehicles or saildrones (Sabine et al., 2020; Chiodi et al., 2021; Sutton et al., 2021). There may be opportunities to extend recent efforts to develop Fiducial Reference Measurements (FRM) for satellite products (e.g., Le Menn et al., 2019; Banks et al., 2020; Mertikas et al., 2020) to *in-situ* measurements of inorganic carbon. This could help towards generating robust, community-accepted processes and protocols, needed to satisfy issues related to integrating *in-situ* datasets from different sources.

3.5.3. IC priority 2: Satellite retrievals and mapping uncertainty

Challenges: Estimating some components of the inorganic carbon cycle in optically-complex water is challenging. For example, current PIC satellite products are global and are not as accurate in environments where other highly scattering materials are present (e.g., coastal shelf seas, but see Shutler et al., 2010, who used of machine learning and computer vision approaches), and can be flagged as clouds. For all inorganic products (including TA and , ΔCO_2) there are also trade-offs related to retaining the use of satellite algorithms based on theoretical understanding, and harnessing new powerful empirical (blackbox) approaches, such as machine learning.

Gaps: The lack of pixel-by-pixel uncertainty estimates in the satellite products, for all components of the inorganic carbon cycle and carbonate system, is a major gap that needs to be addressed. There is a crucial lack of coincident *in-situ* observations of PIC concentrations and other highly scattering materials, along with full spectral measurements of specific inherent optical properties for PIC, needed to improve PIC concentration estimates in optically-complex water.

Opportunities: Plans for improved spatial, spectral and temporal resolution of satellite sensors will likely lead to improvements in IC satellite products. For example, in optically complex waters, hyperspectral satellite data may help differentiate among particles that scatter light with high efficiency, and lead to improved PIC products. There may be opportunities to harness and build on recent techniques used to map uncertainty in satellite organic carbon products (e.g., Evers-King et al., 2017; Martínez-Vicente et al., 2017; Brewin et al., 2017a; IOCCG, 2019) for the mapping of uncertainty in satellite inorganic carbon products and flux estimates.

3.5.4. IC priority 3: Models and data integration

Challenges: Bridging the differences in spatial and temporal scales in data products and models, and differences in units (e.g. what is measured versus what is represented in the models), is a major challenge in producing accurate inorganic carbon and flux products. There are also challenges in extrapolating $p\mathrm{CO}_2$ observations to the surface and horizontally (see Woolf et al., 2016).

Gaps: Closer collaboration between data generators and modellers is required to improve the development of satellite-based inorganic carbon products for integration into Earth System Models.

Opportunities: Enhanced computer processing power, and the development of new statistical tools for big data (e.g., machine learning), offer opportunities to improve model and data integration. There are opportunities to improve model products by reconciling model carbon budgets with both satellite and *in-situ* observations, for example, by constraining the different terms within the budget. Increases in the amount of data produced from a range of sources (models, satellites, ships, autonomous platforms, etc.) mean that improved links between biogeochemical, physical, optical and biological data could help improve data products (e.g., Bittig et al., 2018). Additionally, assimilation of these large dataset into models could improve reanalysis products, providing accurate, high resolution pCO$_2$, DIC and TA estimations on local, regional and global scales (Verdy and Mazloff, 2017; Rosso et al., 2017; Carroll et al., 2020, 2022).

There is a key opportunity to pursue a full and routine integration of *in-situ*, model, and satellite observations to enable routine assessment of the surface water pCO$_2$, air-sea exchange and the net integrated air-sea flux (or ocean sink) of carbon. This potential has been highlighted and is needed to support policy decisions for reducing emissions (Shutler et al., 2019).

3.5.5. IC priority 4: Mechanistic understanding of gas transfer

Challenges: Air-sea gas transfer remains a controlling source of uncertainty within global assessments of the oceanic sink of CO_2 (Woolf et al., 2019). Despite significant progress in our ability to measure gas exchange, our mechanistic understanding of gas transfer is incomplete (see Yang et al., 2022b).

Gaps: There is a need to move away from wind speed as a proxy for air-sea transfer (Shutler et al., 2019) as many other processes control the transfer including wave breaking, surfactants and bubbles and new advances in understanding are now being made (e.g. Bell et al., 2017; Blomquist et al., 2017; Pereira et al., 2018). The carbon dynamics and air-sea CO_2 fluxes within mixed sea ice regions provides further complexities and are poorly understood (see Gupta et al., 2020; Watts et al., 2022) and these regions are expected to grow with a warming climate which illustrates a major gap in understanding.

There are large uncertainties surrounding the influence of near surface temperature gradients on air-sea CO_2 fluxes (see Watson et al., 2020; Dong et al., 2022), and the role of wave breaking, bubbles and turbulence (see Bell et al., 2017; Blomquist et al., 2017). Carbon dynamics and air-sea CO_2 fluxes in mixed sea ice regions are poorly understood (see Watts et al., 2022), which is a major gap in understanding, given that climate at the poles is changing rapidly, affecting sea ice melt and freeze processes and timings.

Opportunities: State-of-the-art flux measurement techniques, such as eddy covariance (see Dong et al., 2021), need to be established as FRM. There are then opportunities to exploit these techniques on novel platforms and to use novel autonomous technologies to improve understanding of air-sea CO_2 fluxes. The novel tools should be applied in a range of environments (e.g. low winds, high winds, marginal ice zones) to understand specific processes. For example, the influence of near surface temperature gradients on air-sea CO_2 fluxes is currently only theoretical, and needs to be quantified/verified by direct observations. Improvements in wind speed products could aid in better gas transfer (Taboada et al., 2019; Russell et al., 2021), although satellite-derived gas transfer estimates could also be improved if measures other than wind speed are exploited that provide more direct observations of surface structure and turbulence (e.g., sea state or sea surface roughness using radar backscattering observations, see Goddijn-Murphy et al., 2013).

3.6. Cross-cutting activities: Blue Carbon (BC)

Tidal marshes, mangroves, macroalgae and seagrass beds, collectively referred to as Blue Carbon (BC) ecosystems, are some of the most carbon-dense habitats on Earth. Despite occupying only 0.2 % of the ocean surface, they are thought to contribute around 50 % of carbon burial in marine sediments, with a global stock size in the region of 10 to 24 Gt C (Duarte et al., 2013). In addition to providing many essential services, such as coastal storm and sea level protection, water quality regulation, wildlife habitat, biodiversity, shoreline stabilization, and food security, they are highly productive ecosystems that have the capacity to sequester vast amounts of carbon and store it in their biomass and their soils (Mcleod et al., 2011). However, their carbon sequestration capacity, carbon storage, and carbon export, depend on many critical processes, including inundation dynamics, sea level rise, air- and water pollution, changes in salinity regimes, and rising temperatures. All of which are sensitive to human impacts and climate change (Macreadie et al., 2019) with coastal ecosystems being a highly active interface between human and natural infrastructures and a complex mix of natural and anthropogenic processes.

The role that blue carbon habitats play in regional and global carbon budgets and fluxes is a big focus in carbon research (Mcleod et al., 2011). One of the biggest unknowns and largest sources of uncertainty in quantifying the role these systems play in global carbon budgets and fluxes, is mapping the spatial extent of BC and how it is changing. Satellites can play a major role in this, but an important distinction compared to green carbon, is that the carbon is primarily stored below rather than above ground.

3.6.1. State of the art in Blue Carbon

Remote sensing technologies are increasingly used for studying BC ecosystems, owing to their synoptic capabilities, repeatability, accuracy and low cost (Hossain et al., 2015; Pham et al., 2019b; Campbell et al., 2022). Various techniques have been utilised for this purpose, including spectral optical imagery, synthetic aperture radar (SAR), lidar and aerial photogrammetry (Pham et al., 2019a; Lamb et al., 2021). Of these technologies, high spatial resolution, multi-spectral and hyper-spectral optical imagery are used more commonly, with the Landsat time-series thought to be the most widely-used dataset for studying changes in BC remotely over the past decade (Giri et al., 2011; Pham et al., 2019a; Yang et al., 2022c).

In recent years, there has been an increasing use of high resolution Sentinel-2 and Landsat-8/9 imagery for mapping coastal BC, such as tidal marshes (e.g., Sun et al., 2021; Cao and Tzortziou, 2021) and mangroves (e.g., Castillo et al., 2017). High frequency and high spatial resolution commercial satellites are also increasingly being used for BC research. For example, the PlanetScope constellation, DigitalGlobe's WorldView-2, and Planet's RapidEye satellites, are offering new insights into seagrass mapping (Wicaksono and Lazuardi, 2018; Traganos and Reinartz, 2018; Coffer et al., 2020). Despite being challenged by the optical complexity of nearshore coastal waters, and accurate nearshore atmospheric correction (Ibrahim et al., 2018; Tzortziou et al., 2018), submerged aquatic vegetation habitats are now being studied remotely. For example, Huber et al. (2021) used Sentinel-2 data, together with machine learning techniques and advanced data processing, to map and monitor submerged aquatic vegetation habitats, including kelp forests, eelgrass meadows and rockweed beds, in Denmark and Sweden. Optical satellite remote sensing has been increasingly used for mapping benthic and pelagic macroalgae (e.g., Gower et al., 2006; Hu, 2009; Cavanaugh et al., 2010; Hu et al., 2017; Wang et al., 2018; Schroeder et al., 2019; Wang and Hu, 2021), and has highlighted that macroalgae blooms are increasing in severity and frequency (Gower et al., 2013; Smetacek and Zingone, 2013; Qi et al., 2016, 2017; Wang et al., 2019), with implications for carbon fixation and sequestration (Paraguay-Delgado et al., 2020; Hu et al., 2021).

International efforts have focused on translating science into policy, management and finance tools for conservation and restoration of blue carbon ecosystems, for example, through the Blue Carbon Initiative (https://www.thebluecarboninitiative.org). Large scale mapping of ecosystem extent, change, and attributes such as carbon, is essential for blue carbon prioritisation and implementation at global to local scales, and remote sensing plays a key role in this. For example, Goldberg et al. (2020) used satellite observations to help map mangrove coverage and change, and understand anthropogenic drivers of loss. The Global Mangrove Watch global mangrove forest baseline (taken as the year 2010) was recently updated (v2.5) and has resulted in an additional of 2,660 km^2, yielding a revised global mangrove extent of 140,260 km^2 (Bunting et al., 2022). However, this needs to be built upon for BC as different species will have different below-ground biomass. Therefore, the carbon trapping efficiency and carbon uptake needs to be measured and used to calibrate maps of habitat extent. The development of similar tools and baselines for seagrass, salt marsh, and kelp ecosystems is needed. For a recent review on the topic of remote sensing of BC, the reader is referred to Pham et al. (2019a).

At the workshop, three priorities were identified in relation to the remote sensing of BC, these are summarised in Table 7 and include: 1) satellite sensors; 2) algorithms, retrievals and model integration; and 3) data access and accounting.

3.6.2. BC priority 1: Satellite sensors

Challenges: Owing to the high temporal variability and heterogeneity of many BC ecosystems (tidal or otherwise), there is a requirement for monitoring at high temporal (hourly) and spatial (tidal) scales. This is challenging with the current fleet of Earth Observing satellites.

Gaps: Although Landsat has proven vital for the long-term monitoring of some BC ecosystems (e.g., Ha et al., 2021), there is a lack of long-term satellite datasets for change detection in many BC ecosystems.

Opportunities: New sensors and techniques are leading to significant advancements in the spatial and temporal characterization and monitoring of BC ecosystems. New hyperspectral observations (e.g., PACE, GLIMR, PRISMA; DESIS, EnMAP; SBG; CHIME) at high to medium resolution and global scale, have the potential to distinguish differences between mangrove, seagrass, salt marsh species, and estimate satellite products relevant to carbon quality. High spatial resolution (3-5 m) imagery from constellations of satellite sensors (e.g., PlanetScope) provides an unprecedented dataset to study vegetation characteristics in BC ecosystems (Warwick-Champion et al., 2022). Multiple images per day from new geostationary satellite instruments (e.g., GLIMR), will allow to capture tidal dynamics in BC ecosystems, and monitor them (e.g., seagrass meadows) under optimum conditions. Additionally, there is scope to build on efforts to develop satellite climate records (e.g., through ESA's CCI) with a focus on BC, to help develop the long-term data records needed.

3.6.3. BC priority 2: Algorithms, retrievals and model integration

Challenges: Considering many BC remote sensing approaches are regional, they are not easily applied (or have been tested) at global scale. Owing to the complexity of some of the techniques, uncertainty estimation for carbon fluxes in

BC ecosystems is particularly challenging. For detecting subaquatic vegetation (and some other BC ecosystems), there are large uncertainties in the impact of the atmosphere and water depth on the signal. Considering large quantities of carbon are stored in the sediments of BC habitats, there are challenges to develop direct or indirect satellite techniques to monitor the dynamics of sediment carbon. The lack of models that link carbon storage and cycling in terrestrial and aquatic ecosystems, further challenges our understanding of carbon fluxes and stocks in BC habitats. Sub-pixel variability poses a challenge when monitoring macroalgae using courser resolution satellite data.

Gaps: A major gap to improving algorithms and methods, is the limited availability of *in-situ* data for development and validation. For example, the lack of measurements on rates (e.g., *Sargassum* carbon fixation and sequestration efficiency) severely limits our ability to quantify large scale BC budgets (e.g., for pelagic macroalgae, see Hu et al., 2021). The lack of basic ecosystem mapping and change detection for seagrasses and kelp forests, limits our ability to extrapolate these measurements to large scales using remote sensing. The lack of BC ecosystem models limits our ability to quantify full BC carbon budgets (including soil) globally.

Opportunities: With improvements in computation power and statistical analysis of big data (e.g., techniques like machine learning) there is scope to improve satellite algorithms and methods of BC carbon quantification (e.g., Huber et al., 2021). Additionally, fusion of hyperspectral optical and SAR data provides a promising approach for characterization of tidal wetland interfaces, including wetland vegetation characteristics, inundation regimes, and their impact on carbon fluxes. New *in-situ* monitoring techniques (e.g., drones) are becoming useful to bridge the scales between satellites and *in-situ* BC monitoring (e.g., Duffy et al., 2018).

3.6.4. BC priority 3: Data access and accounting

Challenges: Existing products and approaches are not easily accessible by users who have limited remote sensing expertise. With the increasing use of commercial satellites, there are challenges to ensure cost-effective monitoring using remote sensing techniques to track the progress of rehabilitation and restoration of blue carbon ecosystems.

Gaps: There are a lack of products suited to project development and carbon accounting. The remote-sensing science community must work directly with policy-makers, conservationists and others, to ensure advances in such products are tailored to applications and that the tools developed are available broadly and equitably. Products are also now needed on global scales, at higher spatial and temporal resolutions, and in a broader range of ecosystems, to support BC integration into national carbon accounts and to expand the application of carbon financing.

Opportunities: There is increasing momentum towards efforts to develop BC habitat mapping portals that are user friendly, for example, see Huber et al. (2021). These developments are needed to support blue-carbon based conservation and restoration and have been instrumental in the recent development of blue carbon policy and financing by supporting prioritisation, assessment, and monitoring. There are also potential opportunities to link OMICS with satellite data, as a way to monitor BC ecosystems and their production/export efficiency.

3.7. Cross-cutting activities: Extreme Events (EE)

Extreme events (EE) can be defined as events that occur in the upper or lower end of the range of historical measurements (Katz and Brown, 1992). Such events occur in the atmosphere (e.g., tropical cyclones, dust storms), ocean (e.g., marine heatwaves, tsunami's), and on land (e.g., volcanic eruption, extreme bushfires), affecting marine carbon cycling at multiple spatio-temporal scales (Bates et al., 1998; Jickells et al., 2005; Gruber et al., 2021). With continued global warming in the coming decades, many EE are expected to intensify, occur more frequently, last longer and extend over larger regions (Huang et al., 2015; Diffenbaugh et al., 2017; Frölicher et al., 2018). Extreme events and their effects on marine ecosystems and carbon cycling can be observed, to some extent, by various methods, including: ships, buoys, autonomous platforms and satellite sensors (e.g., Di Biagio et al., 2020; Hayashida et al., 2020; Le Grix et al., 2021;

Wang et al., 2022). Here, we first provide a broad overview of the current state of the art in the topic, before highlighting the priorities identified at the workshop.

3.7.1. State of the art in Extreme Events

Extremely high temperatures and droughts due to global warming are expected to result in more frequent and intense wildfires and dust storm events in some regions (Huang et al., 2015; Abatzoglou et al., 2019; Harris and Lucas, 2019). Aerosols emitted from wildfire and dust storms can significantly impact marine biogeochemistry through wet and dry deposition (Gao et al., 2019), by supplying soluble nutrients (Schlosser et al., 2017; Barkley et al., 2019), especially essential trace metals such as iron (Jickells et al., 2005; Mahowald et al., 2005, 2011) which can also enhance the export of carbon from the photic zone to depth (Pabortsava et al., 2017). The record-breaking Australian wildfire that occurred between September 2019 and March 2020 was evaluated using a combination of satellite, BGC-Argo float, *in-situ* atmospheric sampling and primary productivity estimation (Li et al., 2021; Tang et al., 2021; Wang et al., 2022). The wildfire released aerosols that contained essential nutrients such as iron for growth of marine phytoplankton. These aerosols were transported by westerly winds over the South Pacific Ocean and the deposition resulted in widespread phytoplankton blooms. Severe dust storms, observable from space, in arid or semi-arid regions can also transport aerosols to coastal and open ocean waters increasing ocean primary productivity (Gabric et al., 2010; Chen et al., 2016; Yoon et al., 2017).

Volcanic eruptions can also fertilise the ocean. The solubility and bioavailability of volcanic ash is thought to be much higher than mineral dust (Achterberg et al., 2013; Lindenthal et al., 2013), and can act as the source of nutrients and/or organic carbon for microbial plankton, and influence aggregation processes (Weinbauer et al., 2017). The first multi-platform observation (using SeaWiFS images and *in-situ* data) of the impact of a volcano eruption was provided by Uematsu et al. (2004), who observed the enhancement of primary productivity caused by the additional atmospheric deposition from the Miyake-jima Volcano in the nutrient-deficient region south of the Kuroshio. Lin et al. (2011) observed abnormally high phytoplankton biomass from satellite and elevated concentrations of limiting nutrients, from laboratory experiments, caused by aerosol released by the Anatahan Volcano in 2003. The eruption of Kīlauea volcano triggered a diatom-dominated phytoplankton bloom near Hawaii (Wilson et al., 2019). More recently, the eruption of Hunga Tonga–Hunga Ha'apai ejected about 400,000 tonnes of SO_2, threw ash high into the stratosphere, and caused a catastrophic tsunami on Tonga's nearby islands (Witze, 2022). Detailed observations on its biochemical effects have yet to be reported.

Marine heatwaves (MHWs) (and cold spells) are defined as prolonged periods of anomalously high (low) ocean temperatures (Hobday et al., 2016), which can have devastating impacts on marine organisms and socio-economics systems (Cavole et al., 2016; Wernberg et al., 2016; Couch et al., 2017; Frölicher and Laufkötter, 2018; Hughes et al., 2018; Smale et al., 2019; Cheung et al., 2021). MHWs and cold spells are caused by a combination of local oceanic and atmospheric processes, and modulated by large-scale climate variability and change (Holbrook et al., 2019; Vogt et al., 2022). As a consequence of long-term ocean warming, MHWs have become longer-lasting and more frequent, and have impacted increasingly large areas (Frölicher et al., 2018; Oliver et al., 2018). Satellite and autonomous platforms have been used to study MHWs in many regions, including: the Mediterranean Sea (Olita et al., 2007; Bensoussan et al., 2010), the East China Sea (Tan and Cai, 2018), NE Pacific (Bif et al., 2019), the Atlantic (Rodrigues et al., 2019), Western Australia (Pearce and Feng, 2013) and the Tasman Sea (Oliver et al., 2017; Salinger et al., 2019). Using satellite data with *in-situ* observations, and profiling floats, recent research showed remarkable changes during marine heatwaves in the oceanic carbon system (Long et al., 2021; Gruber et al., 2021; Burger et al., Accepted) and phytoplankton structures (Yang et al., 2018; Le Grix et al., 2021), that are linked to background nutrient concentrations (Hayashida et al., 2020).

Tropical cyclones (called hurricanes or typhoons in different regions) are defined as non-frontal, synoptic scale, low-pressure systems over tropical or sub-tropical waters with organized convection (Lander and Holland, 1993). They can bring deep nutrients up into the photic zone and lead to changes in the local carbon system by cooling the sea surface (Li et al., 2009; Chen et al., 2017; Osburn et al., 2019). Satellite data are often used for studying tropical cyclones, however, it is difficult to obtain clear images shortly after typhoons due to extensive cloud cover (Naik et al., 2008; Hung et al., 2010; Zang et al., 2020). Combining satellite observations with Argo float and biogeochemical models is increasingly being used to understand biological impacts of tropical cyclones (Shang et al., 2008; Chai et al., 2021). D'Sa et al. (2018) have reported intense changes in dissolved organic matter dynamics after Hurricane Harvey in 2017 and then reported changes in particulate and dissolved organic matter dynamics and fluxes after Hurricane Michael in 2018 (D'Sa et al., 2019), highlighting the importance of using multiple satellite data with different resolutions as well as hydrodynamic models. Using the constellation of Landsat-8 and Sentinel-2A/2B sensors, Cao and Tzortziou (2021) showed strong carbon export from the Blackwater National Wildlife Refuge marsh into the Chesapeake Bay and increase in estuarine DOC concentrations by more than a factor of two after the passage of Hurricane Matthew compared to pre-hurricane levels under similar tidal conditions.

The impacts of marine compound events, defined as extremes in different hazards that occur simultaneously or in close spatio-temporal sequence, are being increasingly studied (Gruber et al., 2021). The dual or even triple compound extremes such as ocean warming, deoxygenation and acidification, could lead to particularly high biological and ecological impacts (Gruber, 2011; Zscheischler et al., 2018; Le Grix et al., 2021; Burger et al., Accepted). The increasing prevalence of extreme Harmful Algae Blooms (HABS) have have been linked with extreme events, and satellites play a major role in their monitoring and management (IOCCG, 2021). Although EE have emerged as a topic of great interest over the past decade, our understanding of their impacts on the marine ecosystems and ocean carbon cycle remains limited.

At the workshop, three priorities (summarised in Table 8) were identified in relation to understanding impacts of EE on the ocean carbon cycle: 1) *in-situ* data; 2) satellite sensing technology; and 3) model synergy and transdisciplinary research.

3.7.2. EE priority 1: In-situ data

Challenges: *In-situ* observations are essential to monitor EE events, especially considering some EE are hard to monitor from space (e.g., clouds with tropical cyclones or volcanic eruptions) and require ground truthing, owing to challenges around satellite retrievals (e.g., atmospheric aerosols with dust events and volcanic eruptions). In some cases EEs can be close to the valid range of measurements retrieved by satellites. Considering the temporal scales of EEs, their sporadic occurrence, and hazardous environments, they are extremely challenging and sometimes dangerous to monitor *in-situ* using ship-based techniques.

Gaps: At present there are major gaps in the availability of *in-situ* observations of EE events. This severely limits our understanding of their impact on the ocean carbon cycle. Gaps are even greater in subsurface waters. Long time-series measurements with high frequency resolution are also essential to provide robust baselines against which extremes can be detected and attributed.

Opportunities: With an expanding network of autonomous *in-situ* platforms (Chai et al., 2020), we are becoming better positioned to monitor EEs. It will be important that these networks of autonomous *in-situ* platforms have fast response protocols that can be implemented soon after an extreme event takes place, so valuable data are collected and not missed. It is also essential that funding continues, at the international level, to support these expanding networks of autonomous platforms.

3.7.3. EE priority 2: Satellite sensing technology

Challenges: Monitoring EE from space requires suitable temporal and spatial coverage to track the event. This varies depending on the nature and location of the event. Some events require high temporal and spatial coverage, which challenges current remote sensing systems. Other challenges exist, for example, dealing with cloud coverage during tropical cyclones, or retrievals in the presence of complex aerosols (e.g., volcanic eruptions).

Gaps: High temporal and spatial resolution data is required for monitoring some EE. There are gaps in satellite data for some EE (e.g., clouds). Algorithms for satellite retrievals during some EE (e.g., volcanic eruptions) require detailed knowledge on the optical properties of the aerosols present. Long time-series remote sensing data are needed for baselines against which extremes can be monitored.

Opportunities: Synergistic use of different long-term, high-frequency and high-resolution, remote sensing data may allow better insight into extreme events and their development. For example, combining ocean colour products from ESA's OC-CCI (e.g., Sathyendranath et al., 2019a) and NOAA's Climate Data Record Programme (e.g., Bates et al., 2016). The increased spectral, spatial and temporal resolution of the satellite sensors and platforms would help to improve understanding of the response of phytoplankton community (Losa et al., 2017) and their diel cycles to extreme events, and HAB detection, for example, with NASA's PACE mission (Werdell et al., 2019) and the Korean geostationary GOCI satellite platform (Choi et al., 2012). There are opportunities to derive indicators of EE for determining good environmental status of our seas and oceans, for example, for use in the EU Marine Strategy Framework Directive and OSPAR EE and pollution monitoring.

3.7.4. EE priority 3: Model synergy and transdisciplinary research

Challenges: Owing to gaps in observational platforms (both satellite and *in-situ* observations) and the transdisciplinary nature of EE, there is a need to utilise Earth System Models (ESMs) for understanding EE and projecting future scenarios, and to bring together communities from multiple fields.

Gaps: Reliable projections of extreme events require higher spatial resolution ESMs, with improved representation of marine ecosystems. ESMs ideally need to include prognostic representations of EE processes, and improvements are needed in coupling with land via aerosol emissions and deposition due to fires or due to dust. Transdisciplinary research on the impact of extremes on marine organisms and ecosystem services is needed to close knowledge gaps.

Opportunities: With enhancements in computation power and improvements in ESMs and data assimilation techniques, there is likely to be an increasing use of ESMs for understanding EE, and especially marine compound events. To promote cross-disciplinary research, support is needed for collaborative projects and digital platforms, to make data digestible to non-experts (e.g., Giovanni, MyOcean).

3.8. Cross-cutting activities: Carbon Budget Closure (CBC)

Quantifying the ocean carbon budget and understanding how it is responding to anthropogenic forcing is a major goal in climate research. It is widely accepted that the ocean has absorbed around a quarter of CO_2 emissions released anthropogenically, and that the ocean uptake of carbon has increased in proportion to increasing CO_2 emissions (Aricò et al., 2021). Yet, our understanding of the pools of carbon in the ocean, the processes that modulate them, and how they interact with the land and atmosphere, is not satisfactory enough to make confident predictions of how the ocean carbon budget is changing. Improving our understanding requires a holistic and integrated approach to ocean carbon cycle research, with monitoring systems capable of filling the gaps in our understanding (Aricò et al., 2021). Satellites can play a major role in this (Shutler et al., 2019).

3.8.1. State of the art in Carbon Budget Closure

Each year, the international Global Carbon project produces a budget of the Earth's carbon cycle (https://www.globalcarbonproject.org/about/index.htm), based on a combination of models and observations. In the most recent report (Friedlingstein et al., 2022), for the year 2020, and for a total anthropogenic CO_2 emission of $10.2\,\mathrm{Gt\,C\,y^{-1}}$ (±0.8 $\mathrm{Gt\,C\,y^{-1}}$), the oceans were found to absorb $3.0\,\mathrm{Gt\,C\,y^{-1}}$ (±0.4 $\mathrm{Gt\,C\,y^{-1}}$), similar to that of the land at $2.9\,\mathrm{Gt\,C\,y^{-1}}$ (±1.0 $\mathrm{Gt\,C\,y^{-1}}$). Building on earlier reports (e.g., Hauck et al., 2020), this latest report highlighted an increasing divergence, in the order of $1.0\,\mathrm{Gt\,C\,y^{-1}}$, between different methods, on the strength of the ocean sink over the last decade (Friedlingstein et al., 2022), with models reporting a smaller sink than observation-based data-products (acknowledging that observation-based data-products are heavily extrapolated). Results from this report suggest our ability to predict the ocean sink could be deteriorating. Understanding the causes of this discrepancy is undoubtedly a major challenge. Possible causes include: uncertainty in the river flux adjustment that needs to be added to the data-products in order to account for different flux components being represented in models and data-products; data sparsity; methodological issues in the mapping of methods used in data-products; underestimation of wind speeds in the climate reanalyses (Verezemskaya et al., 2017), model physics biases; possible issues in air-sea gas exchange calculations; and underestimation of the role of biology in air-sea gas exchange. Or possibly some compound effects of these causes.

It is clear satellite data can help in addressing this issue. For example, through assimilation of physical data (temperature, salinity, altimeter) into high resolution physical models, to improve model physics (e.g., Verdy and Mazloff, 2017; Carroll et al., 2020) or ocean colour data assimilation to improve the representation of biology (e.g., Gregg, 2001, 2008; Rousseaux and Gregg, 2015; Gregg et al., 2017; Ciavatta et al., 2018; Skákala et al., 2018). A recent budget analysis using ECCO-Darwin successfully managed to close the global carbon budget "gap" between observation-based products and biogeochemical models (see Carroll et al., 2022). Other ways satellites could help include: by improving observation-based data-products (e.g. using direct SST skin measurements Watson et al., 2020), through improved estimates or river-induced carbon outgassing and deposition in the sediments, and even through better understanding of the way ocean biology is responding to climate (Kulk et al., 2020; Li et al., 2021; Tang et al., 2021; Wang et al., 2022). On this latter point, whereas it is accepted that biology is critical to maintaining the surface to depth gradient of DIC (estimated to be responsible for around 70 % of it; Sarmiento and Gruber, 2006), which creates a surface air-sea CO_2 disequilibrium promoting ocean carbon uptake, the role of biology in ocean anthropogenic CO_2 update has been thought to be minor, based on a lack of evidence that the biological carbon pump has changed over the recent (industrial) period, or that any change is sufficient to impact anthropogenic CO_2 uptake. An assumption that is now being challenged. It has been shown in ocean models that with a future reduced buffer factor, the CO_2 uptake may increase during the phytoplankton growth season (Hauck and Völker, 2015). This 'seasonal ocean carbon cycle feedback' leads to an increase of ocean carbon uptake by 8 % globally in a high-emission scenario RCP8.5 by 2100 (Fassbender et al., 2022). Increasing amplitudes of the seasonal cycle of *p*CO2 can already be determined in $p\text{CO}_2$-based data-products (Landschützer et al., 2018).

Satellite ocean carbon products have expanded in recent years (CEOS, 2014; Brewin et al., 2021), to the point where some satellite-based carbon budgets maybe feasible in the surface mixed layer. For example, we are now in a position to use satellite data to improve our understanding of how organic carbon is partitioned into particulate carbon (PC = PIC + POC) and dissolved carbon (DOC), how particulate carbon (PC) is partitioned into organic (POC) and inorganic (PIC) contributions, how POC is partitioned into algal (C-phyto) and non-algal portions, and the relationship between phytoplankton carbon (C-phyto), primary production (PP and net community production), which can give information on turnover times for marine phytoplankton. Considering the continuous ocean-colour record started in 1997, we can begin to develop an understanding how these budgets are changing. This could be extremely useful for evaluating models.

Notwithstanding the potential and use of satellite-based carbon budgets, it is clear that many carbon pools and fluxes are still not amenable from satellite remote sensing, that satellite ocean observations are limited to the surface ocean, to cloud-free conditions and low to moderate sun-zenith angles (for some systems), have difficulties in coastal regions, and in spatial and temporal resolution. Thus to quantify ocean carbon budgets, an integrated approach is required, combining satellite data with other observations (*in situ*) and with models. A nice demonstration of this is a recent study by Nowicki et al. (2022), who assimilated satellite and *in-situ* data into an ensemble numerical model of the ocean's biological carbon pump, to quantify global and regional carbon export and sequestration, and the contributions from three key pathways to export: gravitational sinking of particles, vertical migration of organisms, and physical mixing of organic material. Their analysis demonstrated large regional variations in the export of organic carbon, the pathways that control export, and the sequestration timescales of the export.

It also suggested ocean carbon storage will weaken as the oceans stratify, and the subtropical gyres expand due to anthropogenic climate change.

Three priorities were identified at the workshop in relation to carbon budget closure (CBC). These are summarised in Table 9 and include: 1) *in-situ* data; 2) satellite algorithms, budgets and uncertainties; and 3) model and satellite integration.

3.8.2. CBC priority 1: In-situ data

Challenges: As emphasised throughout previous sections, *in-situ* data is central to algorithm development and validation of ocean carbon products. Some carbon pools and fluxes are easier to measure *in situ* than others. As a consequence, the quality, quantity and spatial distribution of *in-situ* measurements vary depending on the pool or flux being studied. This makes it challenging for budget computations.

Gaps: Very few, if any, datasets exist (or are accessible) on concurrent and co-located *in-situ* measurements of all the key pools and fluxes required to evaluate satellite or model budgets. Some remote regions that are thought to play a critical role in global budgets, such as the Southern Ocean, are severely under-sampled. There are gaps in some key measurements in many regions (e.g., for organic carbon budgets, photosynthesis irradiance parameters, see Bouman et al., 2018; Sathyendranath et al., 2020).

Opportunities: As technology develops, improved methods are being developed to measure pools and fluxes of carbon in the ocean. Some of these methods (e.g., Williams et al., 2017; Estapa et al., 2017; Bresnahan et al., 2017; Sutton et al., 2021; Bishop et al., 2022) have the potential to be (or have already been) integrated into networks of autonomous platforms, such as gliders and BGC-Argo floats. New methods are also being developed to quantify carbon pools and fluxes from standard biogeochemical measurements on autonomous platforms (e.g., Dall'Olmo et al., 2016; Claustre et al., 2020; Giering et al., 2020; Claustre et al., 2021; Johnson and Bif, 2021). As *in-situ* data grow with time, it is feasible to quantify properties of carbon budgets from *in-situ* compilations that can be used to check and constrain satellite or model budgets. For example, empirical relationships between POC, C-phyto, and Chl-a (Sathyendranath et al., 2009), have proven useful in model evaluations of emergent carbon budgets (de Mora et al., 2016).

3.8.3. CBC priority 2: Satellite algorithms, budgets and uncertainties

Challenges: When closing the ocean carbon budget, it is critical that there is coherence in the satellite data fields we input into the different satellite algorithms, and that uncertainties are available for model propagation. Additionally, and as identified in previous sections, some of the pools and fluxes of carbon require satellite data with higher spatial, temporal and spectral resolution. There need for consistency in algorithms used to quantify budgets (see Sathyendranath et al., 2020), and these algorithms must respect properties of the ecosystem known from *in-situ* data.

In the context of quantifying the ocean carbon budget, the pools and fluxes have to fit together in a consistent way. Therefore, it is important to not only consider the uncertainties in individual products, but to analyse uncertainties in multiple products to identify any discrepancies. This requires that we analyse each of the products in relation to all the other products, and see whether they hold together in a coherent fashion. This can also help to constrain those components which are impossible to observe or that are more uncertain.

Gaps: Many satellite carbon products lack associated estimates of uncertainty. The uncertainties for individual products are also needed when combining multiple products to assess carbon budgets. Considering the importance of model parameters in satellite algorithms, more work is needed to improve estimates of uncertainties in model parameters and look towards dynamic, rather than static, assignment of parameters in carbon algorithms. From an Earth's system perspective, increasing emphasis needs to be placed on harmonising satellite carbon products across different planetary domains, and evaluating the impact of using different input climate data records.

Opportunities: With the development of consistent and stable climate data records, with associated estimates of uncertainty (e.g., ESA CCI), we are now in a good position to utilise coherent satellite data fields as input to ocean carbon algorithms. The development of new satellite sensors, with higher spatial, temporal and spectral resolution, will lead to improved satellite algorithms and more confident carbon budgets. New approaches and statistical techniques (e.g., machine learning) are becoming available, and offer potential to get at pools and fluxes of carbon from satellite that were previously not feasible to monitor from space.

3.8.4. CBC priority 3: Model and satellite integration

Challenges: A major challenge in bringing satellite observations together with models, is dealing with the contrasting spatial scales in the two types of datasets. Quantifying carbon budgets through data integration also requires appreciation of the different temporal scales that the pools and fluxes operate on. This is particularly true from an Earth system approach, considering the timescales of carbon cycling differ between the ocean, land and atmosphere.

Gaps: Successful integration of satellite carbon products with models requires accurate uncertainties in the satellite observations and model simulations. These are often not available. Greater emphasis is needed on model diversity, which should help increase confidence in carbon budgets and improve understanding.

Opportunities: There are opportunities to harness new developments in data assimilation to help constrain carbon budgets, through the use of new satellite biological products (e.g. community structure, Ciavatta et al., 2018; Skákala et al., 2018) and advancements in optical modules for autonomous platforms (Terzić et al., 2019, 2021), or through combined physical and biological data assimilation (Song et al., 2016; IOCCG, 2020). There is scope to harness developments in machine learning to help combine data and models, for example, bridging different spatial scales in the satellite and model products. Future enhancements in computation power should lead to better representations of spatial scales in models (e.g., sub-mesoscale processes), improving carbon budgets.

3.9. Common themes

Figure 2 shows a word cloud produced using all the priorities identified across the nine themes of the workshop. It illustrates the dominant themes and subthemes emerging from all priorities identified. Commonalities among the nine themes of the workshop, include:

- ***In-situ* data**. It is strikingly clear from this analysis the importance of *in-situ* data, for algorithm development and validation, for extrapolation of surface satellite fields to depth, for parametrisation and validation of ESMs, and for constraining estimates of the carbon budget. It is critical that the international community continues investing in the collection of *in-situ* data, in better data protocols and standards, community-agreed upon data structure and metadata, more intercomparison and intercalibration exercises, the development of new *in-situ* methods for measurement of carbon, and in the expanding networks of autonomous observations, that have the potential to radically improve the spatial and temporal coverage of *in-situ* data. There are clear challenges with respect to compiling large *in-situ* datasets from different sources, using different methods and protocols, for algorithm development and validation, that need to be addressed. It is important that the *in-situ*, satellite and modelling community communicates prior to collecting data, to ensure the data collected will be useful for the entire community.

- **Satellite algorithm retrievals**. For all pools and fluxes of carbon, continued development of satellite algorithms and retrieval techniques is critical to maximise the use of satellite data in carbon research. New satellites are being launched in the near future, with new capabilities and improved spatial, temporal and spectral resolution (see Table 10). Micro- and nano-satellites (CubeSats; Schueler and Holmes, 2016; Vanhellemont, 2019) have potential to be launched cheaply into low Earth orbit, in large swarms improving spatial and temporal coverage. New advanced statistical methods are emerging (e.g., advancements in artificial intelligence). New satellite data records are appearing, that will provide the much needed coherence for input to multiple satellite carbon algorithms for budget calculations. Over the coming decades existing missions like Sentinel-3 OLCI, Sentinel-2 MSI and VIIRS, will provide better carbon products with real operational usage. Our community needs to be positioned to harness these opportunities. Satellite retrievals of carbon products critically rely on accurate atmospheric correction, and there are challenges around developing new atmospheric correction schemes for emerging sensors (Table 10). Additionally, continued investment is required into basic and mechanistic understanding of the retrieval process, and improvements in retrievals in coastal and shelf sea environments and other optically complex waters. This is crucial for monitoring trends in satellite-based carbon products (e.g., Sathyendranath et al., 2017b).

- **Uncertainty in data**. There is a clear requirement across all themes to provide uncertainty estimates with satellite, *in-situ* and model products. Continued investment in methods to quantify uncertainty is vital for quantifying carbon budgets and change (IOCCG, 2019; McKinna et al., 2019).

- **Vertical distributions**. One of the major limitations of satellites, is that they only view the surface layer of the ocean. Sub-surface measurements are required to extrapolate the surface fields to depth. Synergy between satellite surface passive fields, satellite active-based sensors (e.g. lidar) that can penetrate further into the water column (Jamet et al., 2019), and the expanding networks of autonomous and *in-situ* observations, that are viewing the subsurface with ever-increasing coverage, for example, the global network of BGC-Argo floats (Roemmich et al., 2019; Claustre et al., 2020) and Bio-GO-SHIP (https://biogoship.org), is a clear focus for future ocean carbon research.

- **Ocean models**. Many components of the ocean carbon cycle are not directly observable through satellite, and some are even inherently difficult or expensive to measure *in situ*. To target these hidden pools and fluxes we must turn to models. Models can also help tackle the low temporal and spatial resolution of *in situ* data and issues around gaps in satellite data. Exploring synergy between satellite observations and models is clear priority for future ocean carbon research (IOCCG, 2020). New developments in data assimilation may help (not only satellites, but growing data sources from autonomous platforms), and integration of radiative transfer into models, such that the models themselves become capable of simulating fields of electromagnetic energy (e.g., Jones et al., 2016; Gregg and Rousseaux, 2017; Dutkiewicz et al., 2018, 2019; Terzić et al., 2019, 2021). We must continue to identify processes poorly represented in models, that can be subsequently improved in future model design. Observing System Simulation Experiments (OSSE) can be used to evaluate the impact of undersampled observing systems on obtained results, or evaluate the value of new observing systems design for optimal sampling strategies.

- **Integration of data**. It is challenging to find an optimal way of combining satellites, models and *in-situ* observations, to produce best-quality data products. Integrated carbon products are required for near real-time forecasting of the biogeochemical ocean carbon cycle. Additionally, they are required for regional or global impact assessments, to assess the multiple stressors (e.g., temperature change, ocean acidification) acting upon the marine ecosystem, and subsequent downstream effects on the carbon cycle (e.g., natural food web, fisheries, etc.). Continued efforts are required to develop methods to bridge the spatial and temporal scales of the different datasets, and statistical methods like machine learning may help in this regard.

- **Understanding**. Continued investment is required into improving our fundamental understanding of the ocean carbon cycle, and on the interaction between pools of carbon and light. The latter is critical for the development of satellite carbon products.

3.10. Emerging concerns and broader thoughts

In addition to the common themes, during workshop discussions, other emerging concerns and broader thoughts materialised, including:

- **Bringing carbon communities together**. Considering the need to take a holistic, integrated approach to ocean carbon science (Aricò et al., 2021), there is a strong requirement to bring different communities together working on different aspects of the ocean carbon cycle, that can often operate in a disparate fashion, including those working in different zones of the ocean (e.g., pelagic, mesopelagic, bathypelagic and abyssopelagic), on the inorganic and organic sides, field and laboratory scientists, remote sensing scientists and modellers. Furthermore, and taking an Earth system view, this should also be extended to those working on carbon in other planetary domains (Campbell et al., 2022). We need to improve our understanding of the connectivity between coastal and open-ocean ecosystems, for example, the potential impact of (large) rivers on oceanic carbon dynamics.

- **The need to maximise use of limited resources**. Current funding levels make it challenging to support adequate monitoring of core ocean carbon variables in addition to supporting innovative blue skies science. Increasing overall funding and separating the funding pots for the two activities could help to maximise monitoring and achieve key priorities for blue skies research.

- **Improved distribution of satellite and model carbon products**. Although satellite-based carbon products are becoming available, more emphasis is needed to integrate satellite carbon products, as well as model products, into operational satellite services to ensure end-user access, and make products more user friendly. This requires close dialogue with the user communities.

- **Working with satellite carbon experts in different planetary domains**. More emphasis should be placed on harmonising satellite carbon products across different planetary domains (ocean, land, ice and air). This involves working closer with scientific communities working in the different spheres of the planet (Earth System approach).

- **Carbon and environmental footprints of research.**. Our communities need to start taking more responsibility to monitor and minimise the carbon and environmental footprints of scientific research, and improve how this is managed and controlled (e.g., Achten et al., 2013; Shutler, 2020). Greater stewardship is needed to document and track the carbon and environmental footprints of researchers, ideally within a transparent and traceable framework (e.g., Mariette et al., 2021). The benefits of the priorities identified (e.g., launching of new satellites and collection of more *in-situ* measurements etc.) need to be balanced against their environmental footprint, with a view to identify means by which it can be reduced and mitigated.

- **Carbon and environmental footprints of space technology**. There is an increasing number of satellites being launched into space. Although much of this growth is for internet services, Earth Observation satellites are also increasing in numbers, with increasing amounts of space junk. This raises questions on the environmental impacts of satellites and space technologies more generally throughout their complete lifetimes that have previously not been a concern (from construction, to rocket launch and being placed into orbit and use, de-orbiting and removal).

- **Use of satellite products for informing ocean carbon dioxide removal (CDR) studies**. Satellites can play a role in future monitoring of potential implementations of CDR, for understanding the consequences that some of these proposed mechanism would have on the marine ecosystem (Boyd et al., 2022; National Academies of Sciences, Engineering, and Medicine, 2022).

- **Need to consider how satellites can be used to help monitor cycles of other important climatically-relevant compounds and elements**. For example, methane (CH_4) emissions have contributed almost one quarter of the cumulative radiative forcings for CO_2, CH_4, and N_2O (nitrous oxide) combined since 1750 (Etminan et al., 2016), and absorbs thermal infrared radiation much more efficiently than CO_2.

- **Open Science**. It is essential that our community follows an open science approach, promoting data sharing and knowledge transfer, and committing to FAIR principles (https://www.go-fair.org/fair-principles/). Supporting open-access repositories for publications, data and code, and openly available education resources, for the next generations of scientists.

- **Promote diversity and inclusivity**. Geosciences are one of the least diverse branches of STEM. And while it was positive to see the high gender diversity at this meeting (Figure 1), more is needed to promote the position of the underrepresented minorities in our field. System wide changes need to be implemented, where diversity, inclusion, cohesion, and equality across the ocean research (with special emphasis on field safety) are a priority.

4. Summary

We organised a workshop on the topic of ocean carbon from space with the aim to produce a collective view of status of the field and to define priorities for the next decade. Leading experts were assembled from around the world, including those working with remote-sensing data, with field data and with models. Inorganic and organic pools of carbon (in dissolved and particulate form) were targeted, as well fluxes between pools and at interfaces. Cross-cutting activities were also discussed, including blue carbon, extreme events and carbon budgets. Common priorities should focus on improvements in: *in-situ* observations, satellite algorithm retrievals, uncertainty quantifying, understanding of vertical distributions, collaboration with modellers, ways to bridge spatial and temporal scales of the different data sources, fundamental understanding of the ocean carbon cycle, and on carbon and light interactions. Priorities were also reported for the specific pools and fluxes studied, and we highlight emerging concerns that arose during discussions, around the carbon footprint of research and space technology, the role of satellites in CDR approaches, to consider how satellites can be used to help monitor the cycles of other climatically-relevant compounds and elements, the need to promote diversity and inclusivity, bringing communities working on different aspects of ocean carbon together, and open science.

Competing Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

This paper represents a large collaborative effort. R. J. W. Brewin, S. Sathyendranath, G. Kulk, M.-H. Rio and J. A. Concha led the work. R. J. W. Brewin produced an initial draft of the paper with written input from the chairs of the workshop sessions (A. Bracher, A. R. Neeley, E. Organelli, C. Fichot, D. A. Hansell, C. Mitchell, T.G. Bell, M. Galí, T. S. Kostadinov, D. Stramski, K. Richardson, C. Rousseaux, T. Frölicher, F. Shen, E. Pidgeon, M. Tzortziou, and A. Watson), following discussions at the workshop. All authors contributed to subsequent versions of the paper.

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References

Abatzoglou, J.T., Williams, A.P., Barbero, R., 2019. Global emergence of anthropogenic climate change in fire weather indices. Geophysical Research Letters 46, 326–336. doi:10.1029/2018GL080959.

Abbott, M.R., Brink, K.H., Booth, C.R., Blasco, D., Codispoti, L.A., Niiler, P.P., Ramp, S.R., 1990. Observations of phytoplankton and nutrients from a Lagrangian drifter off northern California. Journal of Geophysical Research: Oceans 95, 9393–9409. doi:10.1029/JC095iC06p09393.

Achten, W.M.J., Almeida, J., Muys, B., 2013. Carbon footprint of science: More than flying. Ecological Indicators 34, 352–355. doi:10.1016/j.ecolind.2013.05.025.

Achterberg, E.P., Moore, C.M., Henson, S.A., Steigenberger, S., Stohl, A., Eckhardt, S., Avendano, L.C., Cassidy, M., Hembury, D., Klar, J.K., 2013. Natural iron fertilization by the Eyjafjallajökull volcanic eruption. Geophysical Research Letters 40, 921–926. doi:10.1002/grl.50221.

Anderson, T.R., Rowe, E.C., Polimene, L., Tipping, E., Evans, C.D., Barry, C.D.G., Hansell, D.A., Kaiser, K., Kitidis, V., Lapworth, D.J., Mayor, D.J., Monteith, D.T., Pickard, A.E., Sanders, R.J., Spears, B.M., Torres, R., Tye, A.M., Wade, A.J., Waska, H., 2019. Unified concepts for understanding and modelling turnover of dissolved organic matter from freshwaters to the ocean: The UniDOM model. Biogeochemistry 146, 105–123. doi:10.1007/s10533-019-00621-1.

Antoine, D., André, J.M., Morel, A., 1996. Ocean primary production. 2 Estimation at global scale from satellite (coastal zone color scanner) chlorophyll. Global Biogeochemical Cycles 10, 57–69.

Antoine, D., Morel, A., 1996. Oceanic primary production: I. Adaptation of a spectral light-photosynthesis model in view of application to satellite chlorophyll observations. Global Biogeochemical Cycles 10, 43–55. doi:10.1029/95GB02831.

Aricò, S., Arrieta, J.M., Bakker, D.C.E., Boyd, P.W., Cotrim da Cunha, L., Chai, F., Dai, M., Gruber, N., Isensee, K., Ishii, M., Jiao, N., Lauvset, S.K., McKinley, G.A., Monteiro, P., Robinson, C., Sabine, C., Sanders, R., Schoo, K.L., Schuster, U., Shutler, J.D., Thomas, H., Wanninkhof, R., Watson, A.J., Bopp, L., Boss, E., Bracco, A., Cai, W., Fay, A., Feely, R.A., Gregor, L., Hauck, J., Heinze, C., Henson, S., Hwang, J., Post, J., Suntharalingam, P., Telszewski, M., Tilbrook, B., Valsala, V., Rojas Aldana, A., 2021. Integrated Ocean Carbon Research: A Summary of Ocean Carbon Research, and Vision of Coordinated Ocean Carbon Research and Observations for the Next Decade. doi:10.25607/h0gj-pq4.

Arístegui, J., Montero, M.F., Hernández-Hernández, N., Alonso-González, I.J., Baltar, F., Calleja, M.L., Duarte, C.M., 2020. Variability in water-column respiration and its dependence on organic carbon sources in the Canary Current upwelling region. Frontiers in Earth Science 8, 349. doi:10.3389/feart.2020.00349.

Arrigo, K.R., Pabi, S., van Dijken, G.L., Maslowski, W., 2010. Air-sea flux of CO_2 in the Arctic Ocean, 1998-2003. Journal of Geophysical Research: Biogeosciences 115, G04024. URL: https://doi.org/10.1029/2009JG001224, doi:10.1029/2009JG001224.

Bader, H., 1970. The hyperbolic distribution of particle sizes. Journal of Geophysical Research 75, 2822–2830. doi:10.1029/JC075i015p02822.

Bakker, D.C.E., Pfeil, B., Landa, C.S., Metzl, N., O'Brien, K.M., Olsen, A., Smith, K., Cosca, C., Harasawa, S., Jones, S.D., Nakaoka, S., Nojiri, Y., Schuster, U., Steinhoff, T., Sweeney, C., Takahashi, T., Tilbrook, B., Wada, C., Wanninkhof, R., Alin, S.R., Balestrini, C.F., Barbero, L., Bates, N.R., Bianchi, A.A., Bonou, F., Boutin, J., Bozec, Y., Burger, E.F., Cai, W.J., Castle, R.D., Chen, L., Chierici, M., Currie, K., Evans, W., Featherstone, C., Feely, R.A., Fransson, A., Goyet, C., Greenwood, N., Gregor, L., Hankin, S., Hardman-Mountford, N.J., Harlay, J., Hauck, J., Hoppema, M., Humphreys, M.P., Hunt, C.W., Huss, B., Ibánhez, J.S.P., Johannessen, T., Keeling, R., Kitidis, V., Körtzinger, A., Kozyr, A., Krasakopoulou, E., Kuwata, A., Landschützer, P., Lauvset, S.K., Lefèvre, N., Lo Monaco, C., Manke, A., Mathis, J.T., Merlivat, L., Millero, F.J., Monteiro, P.M.S., Munro, D.R., Murata, A., Newberger, T., Omar, A.M., Ono, T., Paterson, K., Pearce, D., Pierrot, D., Robbins, L.L., Saito, S., Salisbury, J., Schlitzer, R., Schneider, B., Schweitzer, R., Sieger, R., Skjelvan, I., Sullivan, K.F., Sutherland, S.C., Sutton, A.J., Tadokoro, K., Telszewski, M., Tuma, M., van Heuven, S.M.A.C., Vandemark, D., Ward, B., Watson, A.J., Xu, S., 2016. A multi-decade record of high-quality fCO_2 data in version 3 of the Surface Ocean CO_2 atlas (SOCAT). Earth System Science Data 8, 383–413. URL: https://doi.org/10.5194/essd-8-383-2016, doi:10.5194/essd-8-383-2016.

Balch, W. M. amd Bowler, B.C., Drapeau, D.T., Poulton, A.J., Holligan, P.M., 2010. Biominerals and the vertical flux of particulate organic carbon from the surface ocean. Geophysical Research Letters 37, L22605. doi:10.1029/2010GL044640.

Balch, W.M., Drapeau, D.T., Cucci, T.L., Vaillancourt, R.D., Kilpatrick, K.A., Fritz, J.J., 1999. Optical backscattering by calcifying algae: Separating the contribution of particulate inorganic and organic carbon fractions. Journal of Geophysical Research: Oceans 104, 1541–1558. doi:10.1029/1998JC900035.

Balch, W.M., Gordon, H.R., Bowler, B.C., Drapeau, D.T., Booth, E.S., 2005. Calcium carbonate measurements in the surface global ocean based on Moderate-Resolution Imaging Spectroradiometer data. Journal of Geophysical Research 110, C0700. doi:10.1029/2004JC002560.

Balch, W.M., Kilpatrick, K.A., Trees, C.C., 1996. The 1991 coccolithophore bloom in the central North Atlantic. 1. Optical properties and factor affecting their distribution. Limnology and Oceanography 41, 1669–1683. doi:10.4319/lo.1996.41.8.1669.

Banks, A.C., Vendt, R., Alikas, K., Bialek, A., Kuusk, J., Lerebourg, C., Ruddick, K., Tilstone, G., Vabson, V., Donlon, C., Casal, T., 2020. Fiducial reference measurements for satellite ocean colour (FRM4SOC). Remote Sensing 12, 1322. doi:10.3390/rs12081322.

Bar-On, Y.M., Phillips, R., Milo, R., 2018. The biomass distribution on earth. Proceedings of the National Academy of Sciences 115, 6506–6511. doi:10.1073/pnas.1711842115.

Barkley, A.E., Prospero, J.M., Mahowald, N., Hamilton, D.S., Popendorf, K.J., Oehlert, A.M., Pourmand, A., Gatineau, A., Panechou-Pulcherie, K., Blackwelder, P., 2019. African biomass burning is a substantial source of phosphorus deposition to the Amazon, Tropical Atlantic Ocean, and Southern Ocean. Proceedings of the National Academy of Sciences 116, 16216–16221. doi:10.1073/pnas.1906091116.

Barone, B., Nicholson, D., Ferrón, S., Firing, E., Karl, D., 2019. The estimation of gross oxygen production and community respiration from autonomous time-series measurements in the oligotrophic ocean. Limnology and Oceanography: Methods 17, 650–664. doi:10.1002/lom3.10340.

Basedow, S.L., McKee, D., Lefering, I., Gislason, A., Daase, M., Trudnowska, E., Egeland, E.S., Choquet, M., Falk-Petersen, S., 2019. Remote sensing of zooplankton swarms. Scientific Reports 9, 686. URL: https://doi.org/10.1038/s41598-018-37129-x, doi:10.1038/s41598-018-37129-x.

Bates, J.J., Privette, J.L., Kearns, E.J., Glance, W., Zhao, X., 2016. Sustained production of multidecadal climate records: lessons from the NOAA Climate Data Record Program. Bulletin of the American Meteorological Society 97, 1573–1581. doi:10.1175/BAMS-D-15-00015.1.

Bates, N.R., Knap, A.H., Michaels, A.F., 1998. Contribution of hurricanes to local and global estimates of air-sea exchange of co_2. Nature 395, 58–61. doi:10.1038/25703.

Behrenfeld, M., Boss, E., Siegel, D.A., Shea, D.M., 2005. Carbon-based ocean productivity and phytoplankton physiology from space. Global Biogeochemical Cycles 19, 1–14. doi:10.1029/2004GB002299.

Behrenfeld, M.J., Boss, E.S., 2014. Resurrecting the ecological underpinnings of ocean plankton blooms. Annual Review of Marine Science 6. doi:10.1146/annurev-marine-052913-021325.

Behrenfeld, M.J., Falkowski, P.G., 1997a. Photosynthetic rates derived from satellite-based chlorophyll concentration. Limnology and Oceanography 42, 1–20.

Behrenfeld, M.J., Falkowski, P.J., 1997b. A consumer's guide to phytoplankton primary production. Limnology and Oceanograophy 42, 1479–1491. doi:10.4319/lo.1997.42.7.1479.

Behrenfeld, M.J., Gaube, P., Della Penna, A., O'Malley, R.T., Burt, W.J., Hu, Y., Bontempi, P.S., Steinberg, D.K., Boss, E.S., Siegel, D.A., Hostetler, C.A., 2019. Global satellite-observed daily vertical migrations of ocean animals. Nature 576, 257–261.

Bell, T.G., Landwehr, S., Miller, S.D., de Bruyn, W.J., Callaghan, A.H., Scanlon, B., Ward, B., Yang, M., Saltzman, E.S., 2017. Estimation of bubble-mediated air-sea gas exchange from concurrent DMS and CO_2 transfer velocities at intermediate–high wind speeds. Atmospheric Chemistry and Physics 17, 9019–9033. doi:10.5194/acp-17-9019-2017.

Bellacicco, M., Cornec, M., Organelli, E., Brewin, R.J.W., Neukermans, G., Volpe, G., Barbieux, M., Poteau, A., Schmechtig, C., D'Ortenzio, F., Marullo, S., Claustre, H., Pitarch, J., 2019. Global variability of optical backscattering by non-algal particles from a biogeochemical-Argo data set. Geophysical Research Letters 46, 9767–9776. URL: https://doi.org/10.1029/2019GL084078, doi:10.1029/2019GL084078.

Bellacicco, M., Pitarch, J., Organelli, E., Martinez-Vicente, V., Volpe, G., Marullo, S., 2020. Improving the retrieval of carbon-based phytoplankton biomass from satellite ocean colour observations. Remote Sensing 12, 3640. URL: https://doi.org/10.3390/rs12213640, doi:10.3390/rs12213640.

Bellacicco, M., Volpe, G., Colella, S., Pitarch, J., Santoleria, R., 2016. Influence of photoacclimation on the phytoplankton seasonal cycle in the Mediterranean Sea as seen by satellite. Remote Sensing of Environment 184, 595–604. URL: https:

//doi.org/10.1016/j.rse.2016.08.004, doi:10.1016/j.rse.2016.08.004.
Bensoussan, N., Romano, J.C., Harmelin, J.G., Garrabou, J., 2010. High resolution characterization of northwest Mediterranean coastal waters thermal regimes: to better understand responses of benthic communities to climate change. Estuarine, Coastal and Shelf Science 87, 431–441. doi:10.1016/j.ecss.2010.01.008.
Bernard, S., Shillington, F.A., Probyn, T.A., 2007. The use of equivalent size distributions of natural phytoplankton assemblages for optical modeling. Optics Express 15, 1995–2007. doi:10.1364/OE.15.001995.
Bianchi, D., Galbraith, E.D., Carozza, D.A., Mislan, K.A.S., Stock, C.A., 2013a. Intensification of open-ocean oxygen depletion by vertically migrating animals. Nature Geoscience 6, 545–548. doi:10.1038/ngeo1837.
Bianchi, D., Stock, C.A., Galbraith, E.D., Sarmiento, J.L., 2013b. Diel vertical migration: Ecological controls and impacts on the biological pump in a one-dimensional ocean model. Global Biogeochemical Cycles 27, 478–491. doi:10.1002/gbc.20031.
Bif, M.B., Siqueira, L., Hansell, D.A., 2019. Warm events induce loss of resilience in organic carbon production in the northeast Pacific Ocean. Global Biogeochemical Cycles 33, 1174–1186. doi:10.1029/2019GB006327.
Bishop, J.K.B., 1999. Transmissometer measurement of POC. Deep Sea Research Part I: Oceanographic Research Papers 46, 353–369. doi:10.1016/S0967-0637(98)00069-7.
Bishop, J.K.B., Amaral, V.J., Lam, P.J., Wood, T.J., Lee, J.M., Laubach, A., Barnard, A., Derr, A., Orrico, C., 2022. Transmitted cross-polarized light detection of particulate inorganic carbon concentrations and fluxes in the ocean water column: Ships to ARGO floats. Frontiers in Remote Sensing 3. doi:10.3389/frsen.2022.837938.
Bishop, J.K.B., Wood, T.J., Davis, R.E., Sherman, J.T., 2004. Robotic observations of enhanced carbon biomass and export at 55°S during SOfeX. Science 304, 417–420. doi:10.1126/science.1087717.
Bisson, K.M., Boss, E., Westberry, T.K., Behrenfeld, M.J., . Evaluating satellite

estimates of particulate backscatter in the global open ocean using autonomous profiling floats. Optics Express 27, 30191–30203.

Bittig, H.C., Steinhoff, T., Claustre, H., Fiedler, B., Williams, N.L., Sauzéde, R., Körtzinger, A., Gattuso, J.P., 2018. An alternative to static climatologies: Robust estimation of open ocean CO_2 variables and nutrient concentrations from T, S, and O_2 data using bayesian neural networks. Frontiers in Marine Science 5, 328. doi:10.3389/fmars.2018.00328.

Blomquist, B.W., Brumer, S.E., Fairall, C.W., Huebert, B.J., Zappa, C.J., Brooks, I.M., Yang, M., Bariteau, L., Prytherch, J., Hare, J.E., Czerski, H., Matei, A., Pascal, R.W., 2017. Wind speed and sea state dependencies of air-sea gas transfer: Results from the high wind speed gas exchange study (HiWinGS). Journal of Geophysical Research: Oceans 122, 8034–8062. doi:10.1002/2017JC013181.

Borges, V., Ruddick, K., Lacroix, G., Nechad, B., Asteroca, R., Rousseau, V., Harlay, J., 2009. Estimating pco_2 from remote sensing in the Belgian coastal zone. ESA Special Publication SP-686 1, 2–7.

Boss, E., Swift, D., Taylor, L., Brickley, P., Zaneveld, R., Riser, S., Strutton, P.G., 2008. Observations of pigment and particle distributions in the western North Atlantic from an autonomous float and ocean color satellite. Limnology and Oceanography 53. doi:10.4319/lo.2008.53.5_part_2.2112.

Bouman, H.A., Platt, T., Doblin, M., Figueiras, F.G., Gudmundsson, K., Gudfinnsson, H.G., Huang, B., Hickman, A., Hiscock, M., Jackson, T., Lutz, V.A., Mélin, F., Rey, F., Pepin, P., Segura, V., Tilstone, G.H., van Dongen-Vogels, V., Sathyendranath, S., 2018. Photosynthesis-irradiance parameters of marine phytoplankton: synthesis of a global data set. Earth System Science Data 10, 251–266. URL: https://doi.org/10.5194/essd-10-251-2018, doi:10.5194/essd-10-251-2018.

Bowers, D.G., Evans, D., Thomas, D.N., Ellis, K., Williams, P.L.B., 2004. Interpreting the colour of an estuary. Estuarine, Coastal and Shelf Science 59, 13–20. URL: https://doi.org/10.1016/j.ecss.2003.06.001, doi:10.1016/j.ecss.2003.06.001.

Boyd, P., Claustre, H., Levy, M., Siegel, D.A., Weber, T., 2019. Multi-faceted particle pumps drive carbon sequestration in the ocean. Nature 568, 327–335. doi:10.1038/s41586-019-1098-2.

Boyd, P.W., Bach, L.T., Hurd, C.L., Paine, E.P., Raven, J.A., Tamsitt, V., 2022. Potential negative effects of ocean afforestation on offshore ecosystems. Nature Ecology and Evolution 6, 675–683. doi:10.1038/s41559-022-01722-1.

Bracher, A., Bouman, H., Brewin, R.J.W., Bricaud, A., Brotas, V., Ciotti, A.M., Clementson, L., Devred, E., Di Cicco, A., Dutkiewicz, S., Hardman-Mountford, N., Hickman, A.E., Hieronymi, M., Hirata, T., Losa, S., Mouw, C.B., Organelli, E., Raitsos, D.E., Uitz, J., Vogt, M., Wolanin, A., 2017. Obtaining Phytoplankton Diversity from Ocean Color: A Scientific Roadmap for Future Development. Frontiers in Marine Science 4, 1–15. doi:10.3389/fmars.2017.00055.

Bracher, A., Xi, H., Dinter, T., Mangin, A., Strass, V.H., von Appen, W.J., Wiegmann, S., 2020. High resolution water column phytoplankton composition across the Atlantic Ocean from ship-towed vertical undulating radiometry. Frontiers in Marine Science 7, 235. doi:10.3389/fmars.2020.00235.

Bresnahan, P., Martz, T., de Almeida, J., Ward, B., Maguire, P., 2017. Looking ahead: A profiling float Micro-Rosette. Oceanography 30, 32. URL: https://doi.org/10.5670/oceanog.2017.215, doi:10.5670/oceanog.2017.215.

Brewin, R.J.W., Ciavatta, S., Sathyendranath, S., Jackson, T., Tilstone, G., Curran, K., Airs, R.L., Cummings, D., Brotas, V., Organelli, E., Dall'Olmo, G., Raitsos, D.E., 2017a. Uncertainty in ocean-color estimates of chlorophyll for phytoplankton groups. Frontiers in Marine Science 4, 104. URL: https://www.frontiersin.org/article/10.3389/fmars.2017.00104, doi:10.3389/fmars.2017.00104.

Brewin, R.J.W., Dall'Olmo, G., Gittings, J., Sun, X., Lange, P.K., Raitsos, D.E., Bouman, H.A., Hoteit, I., Aiken, J., Sathyendranath, S., 2022. A conceptual approach to partitioning a vertical profileof phytoplankton biomass into contributions from two communities. Journal of Geophysical Researech: Oceans 127, e2021JC018195. doi:10.1029/2021JC018195.

Brewin, R.J.W., Dall'Olmo, G., Pardo, S., van Dongen-Vogel, V., Boss, E.S.,

2016. Underway spectrophotometry along the Atlantic Meridional Transect reveals high performance in satellite chlorophyll retrievals. Remote Sensing of Environment 183, 82–97. doi:10.1016/j.rse.2016.05.005.

Brewin, R.J.W., de Mora, L., Billson, O., Jackson, T., Russell, P., Brewin, T.G., Shutler, J., Miller, P.I., Taylor, B.H., Smyth, T., Fishwick, J.R., 2017b. Evaluating operational AVHRR sea surface temperature data at the coastline using surfers. Estuarine, Coastal and Shelf Sciences 196, 276–289. doi:10.1016/j.ecss.2017.07.011.

Brewin, R.J.W., Sathyendranath, S., Müller, D., Brockmann, C., Deschamps, P.Y., Devred, E., Doerffer, R., Fomferra, N., Franz, B.A., Grant, M., Groom, S., Horseman, A., Hu, C., Krasemann, H., Lee, Z.P., Maritorena, S., Mélin, F., Peters, M., Platt, T., Regner, P., Smyth, T., Steinmetz, F., Swinton, J., Werdell, J., White III, G.N., 2015. The Ocean Colour Climate Change Initiative: III. A round-robin comparison on in-water bio-optical algorithms. Remote Sensing Environment 162, 271–294. doi:10.1016/j.rse.2013.09.016.

Brewin, R.J.W., Sathyendranath, S., Platt, T., Bouman, H., Ciavatta, S., Dall'Olmo, G., Dingle, J., Groom, S., Jönsson, B., Kostadinov, T.S., Kulk, G., Laine, M., Martínez-Vicente, M., Psarra, S., Raitsos, D.E., Richardson, K., Marie-Hélène, R., Rousseaux, C.S., Salisbury, J., Shutler, J.D., Walker, P., 2021. Sensing the ocean biological carbon pump from space: A review of capabilities, concepts, research gaps and future developments. Earth-Science Reviews 217, 103604. URL: https://www.sciencedirect.com/science/article/pii/S0012825221001045, doi:https://doi.org/10.1016/j.earscirev.2021.103604.

Brewin, R.J.W., Tilstone, G., Jackson, T., Cain, T., Miller, P., Lange, P.K., Misra, A., Airs, R., 2017c. Modelling size-fractionated primary production in the Atlantic Ocean from remote sensing. Progress in Oceanography 158, 130–149. URL: https://doi.org/10.1016/j.pocean.2017.02.002, doi:10.1016/j.pocean.2017.02.002.

Brown, C.W., Yoder, J.A., 1994. Coccolithophorid blooms in the global ocean. Journal of Geophysical Research: Oceans 99, 7467–7482.

Brown, J.H., Gillooly, J.F., Allen, A.P., Savage, V.M., West, G.B., 2004. Towards a metabolic theory of ecology. Ecology 85, 1771–1789. doi:10.1890/03-9000.

Brown, O.B., Evans, R.H., Brown, J.W., Gordon, H.R., Smith, R.C., Baker, K.S., 1985. Phytoplankton blooming off the US east coast: A satellite description. Science 229, 163–167. doi:10.1126/science.229.4709.163.

Buesseler, K.O., Boyd, P.W., Black, E.E., Siegel, D.A., 2020. Metrics that matter for assessing the ocean biological carbon pump. Proceedings of the National Academy of Sciences 117, 9679–9687. doi:10.1073/pnas.1918114117.

Buitenhuis, E.T., Hashioka, T., Le Quéré, C., 2013. Combined constraints on global ocean primary production using observations and models. Global Biogeochemical Cycles 27, 847–858. doi:10.1002/gbc.20074.

Buitenhuis, E.T., Le Quéré, C., Bednaršek, N., Schiebel, R., 2019. Large contribution of pteropods to shallow $CaCO_3$ export. Global Biogeochemical Cycles 33, 458–468. doi:10.1029/2018GB006110.

Bunting, P., Rosenqvist, A., Hilarides, L., Lucas, R.M., Thomas, N., 2022. Global Mangrove Watch: Updated 2010 mangrove forest extent (v2.5). Remote Sensing 14, 1034. doi:10.3390/rs14041034.

Buonassissi, C.J., Dierssen, H.M., 2010. A regional comparison of particle size distributions and the power law approximation in oceanic and estuarine surface waters. Journal of Geophysical Research: Oceans 115, C10028. doi:10.1029/2010JC006256.

Burger, F., Terhaar, J., Frölicher, T.L., Accepted. Compound marine heatwaves and ocean acidity extremes .

Burger, F.A., John, J.G., Frölicher, T.L., 2020. Increase in ocean acidity variability and extremes under increasing atmospheric CO_2. Biogeosciences 17, 4633–4662. doi:10.5194/bg-17-4633-2020.

Burt, W.J., Westberry, T.K., Behrenfeld, M.J., Zeng, C., Izett, R.W., Tortell, P.D., 2018. Carbon: Chlorophyll ratios and net primary productivity of Subarctic Pacific surface waters derived from autonomous shipboard sensors. Global Biogeochemical Cycles 32, 267–288. URL: https://doi.org/10.1002/2017GB005783, doi:10.1002/2017GB005783.

Cael, B.B., Cavan, E.L., Britten, G.L., 2021. Reconciling the size-dependence of marine particle sinking speed. Geophysical Research Letters 48, e2020GL091771. doi:10.1029/2020GL091771.

Cai, W.J., Hu, X., Huang, W.J., Jiang, L.Q., Wang, Y., Peng, T.H., Zhang, X., 2010. Alkalinity distribution in the western North Atlantic Ocean margins. Journal of Geophysical Research: Oceans 115. doi:10.1029/2009JC005482.

Campbell, A.D., Fatoyinbo, T., Charles, S.P., Bourgeau-Chavez, L.L., Goes, J., Gomes, H., Halabisky, M., Holmquist, J., Lohrenz, S., Mitchell, C., Moskal, L.M., Poulter, B., Qiu, H., De Sousa, C.H.R., Sayers, M., Simard, M., Stewart, A.J., Singh, D., Trettin, C., Wu, J., Zhang, X., Lagomasino, D., 2022. A review of carbon monitoring in wet carbon systems using remote sensing. Environmental Research Letters 17, 025009. doi:10.1088/1748-9326/ac4d4d.

Campbell, J.W., Antoine, D., Armstrong, R.A., Arrigo, K.R., Balch, W., Barber, R., Behrenfeld, M., Bidigare, R., Bishop, J., Carr, M.E., Esaias, W., Falkowski, P., Hoepffner, N., Iverson, R., Kiefer, D.A., Lohrenz, S., Marra, J., Morel, A., Ryan, J., Vedernikov, V., Waters, K., Yentch, C., Yoder, J., 2002. Comparison of algorithms for estimating ocean primary production from surface chlorophyll, temperature, and irradiance. Global Biogeochemical Cycles 16, 1035. doi:10.1029/2001GB001444.

Cao, F., Tzortziou, M., 2021. Capturing dissolved organic carbon dynamics with Landsat-8 and Sentinel-2 in tidally influenced wetland-estuarine systems. Science of the Total Environment 777, 145910. doi:10.1016/j.scitotenv.2021.14591.

Cao, F., Tzortziou, M., Hu, C., Mannino, A., Fichot, C.G., del Vecchio, R., Najjar, R.G., Novak, M., 2018. Remote sensing retrievals of colored dissolved organic matter and dissolved organic carbon dynamics in North American estuaries and their margins. Remote Sensing of Environment 205, 151–165. doi:10.1016/J.RSE.2017.11.014.

Carlson, C.A., Hansell, D.A., 2015. Chapter 3 - DOM Sources, Sinks, Reactivity, and Budgets. chapter 3. pp. 65–126. doi:10.1016/B978-0-12-405940-5.00003-0.

Carr, M.E., Friedrichs, M.A., Schmeltz, M., Aita, M.N., Antoine, D., Arrigo, K.R., Asanuma, I., Aumont, O., Barber, R., Behrenfeld, M., Bidigare, R., Buitenhuis, E.T., Campbell, J.W., Ciotti, A.M., Dierssen, H.M., Dowell, M., Dunne, J., Esaias, W., Gentili, B., Gregg, W.W., Groom, S., Hoepffner, N., Ishizaka, J., Kameda, T., Le Quéré, C., Lohrenz, S., Marra, J., Mélin, F., Moore, K., Morel, A., Reddy, T.E., Ryan, J., Scardi, M., Smyth, T., Turpie, K., Tilstone, G., Waters, K., Yamanaka, Y., 2006. A comparison of global estimates of marine primary production from ocean color. Deep Sea Research Part II: Topical Studies in Oceanography 53, 741–770. doi:10.1016/j.dsr2.2006.01.028.

Carroll, D., Menemenlis, D., Adkins, J.F., Bowman, K.W., Brix, H., Dutkiewicz, S., Fenty, I., Gierach, M.M., Hill, C., Jahn, O., Landschützer, P., Lauderdale, J.M., Liu, J., Manizza, M., Naviaux, J.D., Röenbeck, C., Schimel, D.S., Van der Stocken, T., Zhang, H., 2020. The ECCO-Darwin data-assimilative global ocean biogeochemistry model: Estimates of seasonal to multidecadal surface ocean pCO_2 and air-sea CO_2 flux. Journal of Advances in Modeling Earth Systems 12, e2019MS001888. doi:10.1029/2019MS001888.

Carroll, D., Menemenlis, D., Dutkiewicz, S., Lauderdale, J.M., Adkins, J.F., Bowman, K.W., Brix, H., Fenty, I., Gierach, M.M., Hill, C., Jahn, O., Landschützer, P., Manizza, M., Mazloff, M.R., Miller, C.E., Schimel, D.S., Verdy, A., Whitt, D.B., Zhang, H., 2022. Attribution of space-time variability in global-ocean dissolved inorganic carbon. Global Biogeochemical Cycles 36, e2021GB007162. doi:10.1029/2021GB007162.

Carvalho, F., Gorbunov, M.Y., Oliver, M.J., Haskins, C., Aragon, D., Kohut, J.T., Schofield, O., 2020. FIRe glider: Mapping in situ chlorophyll variable fluorescence with autonomous underwater gliders. Limnology and Oceanography: Methods 19, 531–545. doi:10.1002/lom3.10380.

Castillo, J.A.A., Apan, A.A., Maraseni, T.N., Salmo, S.G., 2017. Estimation and mapping of above-ground biomass of mangrove forests and their replacement land uses in the Philippines using Sentinel imagery. ISPRS Journal of Photogrammetry and Remote Sensing 134, 70–85. doi:10.1016/j.isprsjprs.2017.10.016.

Cavanaugh, K.C., Siegel, D.A., Kinlan, B.P., Reed, D.C., 2010. Scaling giant kelp field measurements to regional scales using satellite observations. Marine Ecology Progress Series 403, 13–27. doi:10.3354/meps08467.

Cavole, L.M., Demko, A.M., Diner, R.E., Giddings, A., Koester, I., Pagniello, C.M.L.S., Paulsen, M.L., Ramirez-Valdez, A., Schwenck, S.M., Yen, N.K., Zill, M.E., Franks, P.J.S., 2016. Biological impacts of the 2013–2015 warm-water anomaly in the Northeast Pacific: Winners, losers, and the future. Oceanography 29, 273–285. doi:10.5670/oceanog.2016.32.

CEOS, 2014. CEOS strategy for carbon observations from space. The Committee on Earth Observation Satellites (CEOS) response to the Group on Earth Observations (GEO) carbon strategy. September 30th 2014, printed in Japan by JAXA and I&A Corporation.

CEOS, 2021. Committee on Earth Observtaion Satellites 2021-2023 Work Plan – March 2021 v1.0. Technical Report. CEOS. URL: https://ceos.org/document_management/Publications/CEOS_Work-Plans/CEOS_2021-2023-Work-Plan_Mar2021.pdf.

Cetinić, I., Perry, M.J., Briggs, N.T., Kallin, E., D'Asaro, E.A., Lee, C.M., 2012. Particulate organic carbon and inherent optical properties during 2008 North Atlantic Bloom Experiment. Journal of Geophysical Research: Oceans 117, C06028. doi:10.1029/2011JC007771.

Chai, F., Johnson, K.S., Claustre, H., Xing, X., Wang, Y., Boss, E., Riser, S., Fennel, K., Schofield, O. .and Sutton, A., 2020. Monitoring ocean biogeochemistry with autonomous platforms. Nature Reviews Earth and Environment 1, 315–326. doi:10.1038/s43017-020-0053-y.

Chai, F., Wang, Y., Xing, X., Yan, Y., Xue, H., Wells, M., Boss, E., 2021. A limited effect of sub-tropical typhoons on phytoplankton dynamics. Biogeosciences 18, 849–859. doi:10.5194/bg-18-849-2021.

Chase, A., Boss, E., Zaneveld, J.R.V., Bricaud, A., Claustre, H., Ras, J., Dall'Olmo, G., Westberry, T.K., 2013. Decomposition of in situ particulate absorption spectra. Methods in Oceanography 7, 110–124. doi:10.1016/j.mio.2014.02.002.

Chen, D., He, L., Liu, F., Yin, K., 2017. Effects of typhoon events on chlorophyll and carbon fixation in different regions of the East china sea. Estuarine, Coastal and Shelf Science 194, 229–239. doi:10.1016/j.ecss.2017.06.026.

Chen, S., Zhang, T., Chen, W., Shi, J., Hu, L., Song, Q., 2016. Instantaneous influence of dust storms on the optical scattering property of the ocean: a case study in the Yellow Sea, China. Optics Express 24, 28509–28518. doi:10.1364/OE.24.028509.

Cheung, W.W., Frölicher, T.L., Lam, V.W., Oyinlola, M.A., Reygondeau, G., Sumaila, U.R., Tai, T.C., Teh, L.C., Wabnitz, C.C., 2021. Marine high temperature extremes amplify the impacts of climate change on fish and fisheries. Science Advances 7, eabh0895. doi:10.1126/sciadv.abh0895.

Chiodi, A.M., Zhang, C., Cokelet, E.D., Yang, Q., Mordy, C.W., Gentemann, C.L., Cross, J.N., Lawrence-Slavas, N., Meinig, C., Steele, M., Harrison, D.E., Stabeno, P.J., Tabisola, H.M., Zhang, D., Burger, E.F., O'Brien, K.M., Wang, M., 2021. Exploring the Pacific Arctic seasonal ice zone with saildrone USVs. Frontiers in Marine Science, 8, 640690.

Cho, B.C., Azam, F., 1990. Biogeochemical significance of bacterial biomass in the ocean's euphotic zone. Marine Ecology Progress Series 63, 253–259. doi:10.3354/meps063253.

Choi, J.K., Park, Y.J., Ahn, J.H., Lim, H.S., Eom, J., Ryu, J.H., 2012. GOCI, the world's first geostationary ocean color observation satellite, for the monitoring of temporal variability in coastal water turbidity. Journal of Geophysical Research 117, C09004. doi:10.1029/2012JC008046.

Church, M., Cullen, J., Karl, D., 2019. Approaches to measuring primary production, in: Cochran, J.K., Bokuniewicz, J.H., Yager, L.P. (Eds.), Encyclopedia of Ocean Sciences, 3rd Edition. Elsevier. volume 1, pp. 484–492.

Ciavatta, S., Brewin, R.J.W., Skákala, J., Polimene, L., de Mora, L., Artioli, Y., Allen, J.I., 2018. Assimilation of ocean-color plankton functional types to improve marine ecosystem simulations. Journal of Geophysical Research Oceans 123, 834–854. doi:10.1002/2017JC013490.

Clark, J.B., Neale, P., Tzortziou, M., Cao, F., Hood, R.R., 2019. A mechanistic model of photochemical transformation and degradation of colored dissolved organic matter. Marine Chemistry 214, 103666. doi:10.1016/j.marchem.2019.103666.

Claustre, H., Johnson, K.S., Takeshita, Y., 2020. Observing the global ocean with Biogeochemical-Argo. Annual Review of Marine Science 12, 23–48. URL: https://doi.org/10.1146/annurev-marine-010419-010956, doi:10.1146/annurev-marine-010419-010956.

Claustre, H., Legendre, L., Boyd, P.W., Levy, M., 2021. The oceans' biological carbon pumps: framework for a research observational community approach. Frontiers in Marine Science 8, 780052. doi:10.3389/fmars.2021.780052.

Clavano, W.R., Boss, E., Karp-Boss, L., 2007. Inherent optical properties of non-spherical marine-like particles – from theory to observation. volume 45. pp. 1–38. doi:10.1201/9781420050943.

Clements, D.J., Yang, S., Weber, T., McDonnell, A.M.P., Kiko, R., Stemmann, L., Bianchi, D., 2022. Constraining the particle size distribution of large marine particles in the global ocean with in situ optical observations and supervised learning. Global Biogeochemical Cycles 36, e2021GB007276. doi:10.1029/2021GB007276.

Coffer, M.M., Schaeffer, B.A., Zimmerman, R.C., Hill, V., Li, J., Islam, K.A., Whitman, P.J., 2020. Performance across WorldView-2 and RapidEye for reproducible seagrass mapping. Remote Sensing of Environment 250, 112036. doi:10.1016/j.rse.2020.112036.

Collos, Y., Jauzein, C., Hatey, E., 2014. Particulate carbon and nitrogen determinations in tracer studies: The neglected variables. Applied Radiation and Isotopes 94, 14–22. doi:10.1016/j.apradiso.2014.06.015.

Conway, T.M., Horner, T.J., Plancherel, Y., Gonzálezd, A.G., 2021. A decade of progress in understanding cycles of trace elements and their isotopes in the oceans. Chemical Geology 580, 120381. doi:10.1016/j.chemgeo.2021.120381.

Cornec, M., Claustre, H., Mignot, A., Guidi, L., Lacour, L., Poteau, A., D'Ortenzio, F., Gentili, B., Schmechtig, C., 2021. Deep Chlorophyll Maxima in the Global Ocean: Occurrences, drivers and characteristics. Global Biogeochemical Cycles 35, e2020GB006759. doi:https://doi.org/10.1029/2020GB006759.

Corno, G., Letelier, R.M., Abbott, M.R., Karl, D. M., .., 2006. Assessing primary production variability in the North Pacific subtropical gyre: A comparison of fast repetition rate fluorometry and ^{14}c measurements. Journal of Phycology 42, 51–60. doi:10.1111/j.1529-8817.2006.00163.x.

Couch, C.S., Burns, J.H., Liu, G., Steward, K., Gutlay, T.N., Kenyon, J., Eakin, C.M., Kosaki, R.K., 2017. Mass coral bleaching due to unprecedented marine heatwave in Papahānaumokuākea Marine National Monument (Northwestern Hawaiian Islands). PloS One 12, e0185121. doi:10.1371/journal.pone.0185121.

Cullen, J.J., Davis, R.F., Huot, Y., 2012. Spectral model of depth-integrated water column photosynthesis and its inhibition by ultraviolet radiation. Global Biogeochemical Cycles 26, GB1011. doi:10.1029/2010GB003914.

Dall'Olmo, G., Dingle, J., Polimene, L., Brewin, R.J.W., Claustre, H., 2016. Substantial energy input to the mesopelagic ecosystem from the seasonal mixed-layer pump. Nature Geoscience 9, 820–823. doi:10.1038/ngeo2818.

Dall'Olmo, G., Westberry, T.K., Behrenfeld, M.J., Boss, E., Slade, W.H., 2009. Significant contribution of large particles to optical backscattering in the open ocean. Biogeosciences 6, 947–967. doi:10.5194/bg-6-947-2009.

Dall'Olmo, G., Brewin, R.J.W., Nencioli, F., Organelli, E., Lefering, I., McKee, D., Röttgers, R., Mitchell, C., Boss, E., Bricaud, A., Tilstone, G., 2017. Determination of the absorption coefficient of chromophoric dissolved organic matter from underway spectrophotometry. Optics Express 25, A1079–A1095. doi:10.1364/OE.25.0A1079.

Di Biagio, V., Cossarini, G., Salon, S., Solidoro, C., 2020. Extreme event waves in marine ecosystems: an application to Mediterranean Sea surface chlorophyll. Biogeosciences 17, 5967–5988. doi:10.5194/bg-17-5967-2020.

Dickson, A.G., 2010. Standards for ocean measurements. Oceanography 23, 34–47. doi:10.5670/oceanog.2010.22.

Diffenbaugh, N.S., Singh, D., Mankin, J.S., Horton, D.E., Swain, D.L., Touma, D., Charland, A., Liu, Y., Haugen, M., Tsiang, M., 2017. Quantifying the influence of global warming on unprecedented extreme climate events. Proceedings of the National Academy of Sciences 114, 4881–4886. doi:10.1073/pnas.1618082114.

Dionisi, D., Liberti, G.L., Organelli, E., Colella, S., Di Paolantonio, M., Cesarini, C., Santoleri, R., D'Alimonte, D., Kajiyama, T., Di Girolamo, P., Franco, N., Di Erasmo, D., 2021. COLOR: CDOM-proxy retrieval from aeOlus Observations, in: EGU General Assembly 2021, online, 19–30 Apr 2021, EGU21-8687. doi:10.5194/egusphere-egu21-8687.

Dong, Y., Bakker, D.C.E., Bell, T.G., Huang, B., Landschützer, P., Liss, P.S., Yang, M., 2022. Update on the temperature corrections of global air-sea CO_2 flux estimates. Earth and Space Science Open Archive , 26doi:10.1002/essoar.10510573.1.

Dong, Y., Yang, M., Bakker, D.C.E., Kitidis, V., Bell, T.G., 2021. Uncertainties in eddy covariance air-sea CO_2 flux measurements and implications for gas transfer velocity parameterisations. Atmospheric Chemistry and Physics 21, 8089–8110. doi:10.5194/acp-21-8089-2021.

Druon, J.N., Hélaouët, P., Beaugrand, G., Fromentin, J.M., Palialexis, A., Hoepffner, N., 2019. Satellite-based indicator of zooplankton distribution for global monitoring. Scientific Reports 9, 1–13. URL: https://doi.org/10.1038/s41598-019-41212-2, doi:10.1038/s41598-019-41212-2.

D'Sa, E.J., Joshi, I., Liu, B., 2018. Galveston Bay and coastal ocean optical-geochemical response to hurricane Harvey from VIIRS ocean color. Geophysical Research Letters 45, 10,579–10,589. doi:10.1029/2018GL079954.

D'Sa, E.J., Joshi, I.D., Liu, B., Ko, D.S., Osburn, C.L., Bianchi, T.S., 2019. Biogeochemical response of Apalachicola Bay and the shelf waters to hurricane Michael using ocean color semi-analytic/inversion and hydrodynamic models. Frontiers in Marine Science 6, 523. doi:10.3389/fmars.2019.00523.

Duarte, C.M., Losada, I.J., Hendriks, I.E., Mazarrasa, I., Marbá, N., 2013. The role of coastal plant communities for climate change mitigation and adaptation.

Nature Climate Change 3, 961–968. doi:10.1038/nclimate1970.

Duffy, J.P., Pratt, L., Anderson, K., Land, P.E., Shutler, J.D., 2018. Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone. Estuarine, Coastal and Shelf Science 200, 169–180. doi:10.1016/j.ecss.2017.11.001.

Dugdale, R.C., Goering, J.J., 1967. Uptake of new and regenerated forms of nitrogen in primary productivity. Limnology and Oceanography 12, 196–206. doi:10.4319/lo.1967.12.2.0196.

Dutkiewicz, S., Hickman, A.E., Jahn, O., 2018. Modelling ocean colour derived Chlorophyll-a. Biogeoscience 15, 613–630. doi:10.5194/bg-15-613-2018.

Dutkiewicz, S., Hickman, A.E., Jahn, O., Henson, S., Beaulieu, C., Moneir, E., 2019. Ocean colour signature of climate change. Nature Communications 10, 578. doi:10.1038/s41467-019-08457-x.

Eppley, R.W., Stewart, E., Abbott, M.R., Heyman, U., 1985. Estimating ocean primary production from satellite chlorophyll. introduction to regional differences and statistics for the southern california bight. Journal of Plankton Research 7, 57–70. URL: https://doi.org/10.1093/plankt/7.1.57, doi:10.1093/plankt/7.1.57.

Estapa, M., Durkin, C., Buesseler, K., Johnson, R., Feen, M., 2017. Carbon flux from bio-optical profiling floats: Calibrating transmissometers for use as optical sediment traps. Deep Sea Research Part I: Oceanographic Research Papers 120, 100–111. doi:10.1016/j.dsr.2016.12.003.

Etminan, M., Myhre, G., Highwood, E.J., Shine, K.P., 2016. Radiative forcing of carbon dioxide, methane, and nitrous oxide: A significant revision of the methane radiative forcing. Geophysical Research Letters 43, 12,614–12,623. doi:10.1002/2016GL071930.

Evers-King, H., Martinez-Vicente, V., Brewin, R.J.W., Dall'Olmo, G., Hickman, A.E., Jackson, T., Kostadinov, T.S., Krasemann, H., Loisel, H., Röttgers, R., Roy, S., Stramski, D., Thomalla, S., Platt, T., Sathyendranath, S., 2017. Validation and intercomparison of ocean color algorithms for estimating particulate organic carbon in the oceans. Frontiers in Marine Science 4, 251.

doi:10.3389/fmars.2017.00251.

Falkowski, P.G., Barber, R.T., Smetacek, V., 1998. Biogeochemical controls and feedbacks on ocean primary production. Science 281, 200–206. doi:10.1126/science.281.5374.200.

Fassbender, A.J., Schlunegger, S., Rodgers, K.B., Dunne, J.P., 2022. Quantifying the role of seasonality in the marine carbon cycle feedback: An ESM2M case study. Global Biogeochemical Cycles 36, e2021GB007018. doi:10.1029/2021GB007018.

Feely, R.A., Sabine, C.L., Lee, K., Berelson, W., Kleypas, J., Fabry, V.J., Millero, F.J., 2004. Impact of anthropogenic CO_2 on the $CaCO_3$ system in the oceans. Science 305, 362–366. doi:10.1126/science.1097329.

Feng, L., Hu, C., Barnes, B.B., Mannino, A., Heidinger, A.K., Strabala, K., Iraci, L.T., 2017. Cloud and sun-glint statistics derived from GOES and MODIS observations over the intra-americas sea for GEO-CAPE mission planning. Journal of Geophysical Research: Atmospheres 122, 1725–1745. doi:10.1002/2016JD025372.

Ferrari, G.M., Dowell, M.D., Grossi, S., Targa, C., 1996. Relationship between the optical properties of chromophoric dissolved organic matter and total concentrations of dissolved organic carbon in the southern Baltic Sea region. Marine Chemistry 55, 299–316. URL: https://doi.org/10.1016/S0304-4203(96)00061-8, doi:10.1016/S0304-4203(96)00061-8.

Fichot, C., Kaiser, K., Hooker, S.B., Amon, R., Babin, M., Belanger, S., Walker, S., Benner, R., 2013. Pan-arctic distributions of continental runoff in the arctic ocean. Scientific Reports 3, 1053. URL: https://doi.org/10.1038/srep01053, doi:10.1038/srep01053.

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. doi:10.1029/2010GL046152.

Fichot, C.G., Benner, R., 2012. The spectral slope coefficient of chromophoric dissolved organic matter ($s_{275-295}$) as a tracer of terrigenous dissolved organic carbon in river-influenced ocean margins. Limnology and Oceanography 57,

1453–1466.
Fichot, C.G., Lohrenz, S.E., Benner, R., 2014. Pulsed, cross-shelf export of terrigenous dissolved organic carbon to the Gulf of Mexico. Journal of Geophysical Research: Oceans 119, 1176–1194. doi:10.1002/2013JC009424.
Field, C.B., Behrenfeld, M.J., Randerson, J.T., Falkowski, P.G., 1998. Primary production of the biosphere: integrating terrestrial and oceanic components. Science 281, 237–240.
Ford, D.J., Tilstone, G.H., Shutler, J.D., Kitidis, V., 2022a. Derivation of seawater pco_2 from net community production identifies the south atlantic ocean as a co_2 source. Biogeosciences 19, 93–115. doi:10.5194/bg-19-93-2022.
Ford, D.J., Tilstone, G.H., Shutler, J.D., Kitidis, V., 2022b. Identifying the biological control of the interannual and long-term variations in South Atlantic air-sea co_2 flux. Biogeosciences Discuss doi:10.5194/bg-2022-54.
Ford, D.J., Tilstone, G.H., Shutler, J.D., Kitidis, V., Lobanova, P., Schwarz, J., Poulton, A.J., Serret, P., Lamont, T., Chuqui, M., Barlow, R., Lozano, J., Kampel, M., Brandini, F., 2021. Wind speed and mesoscale features drive net autotrophy in the South Atlantic Ocean. Remote Sensing of Environment 260, 112435. doi:10.1016/j.rse.2021.112435.
Fossum, K.N., Ovadnevaite, J., Ceburnis, D., Dall'Osto, M., Marullo, S., Bellacicco, M., Simó, R., Liu, D., Flynn, M., Zuend, A., O'Dowd, C., 2018. Summertime primary and secondary contributions to southern ocean cloud condensation nuclei. Scientific Reports 8, 13844. doi:10.1038/s41598-018-32047-4.
Foster, D., Gagne II, D.J., Whitt, D.B., 2021. Probabilistic machine learning estimation of ocean mixed layer depth from dense satellite and sparse in situ observations. Journal of Advances in Modeling Earth Systems 13, e2021MS002474. doi:10.1029/2021MS002474.
Friedlingstein, P., Jones, M.W., O'Sullivan, M., Andrew, R.M., Bakker, D.C.E., Hauck, J., Le Quéré, C., Peters, G.P., Peters, W., Pongratz, J., Sitch, S., Canadell, J.G., Ciais, P., Jackson, R.B., Alin, S.R., Anthoni, P., Bates, N.R., Becker, M., Bellouin, N., Bopp, L., Chau, T.T.T., Chevallier, F., Chini, L.P., Cronin, M., Currie, K.I., Decharme, B., Djeutchouang, L., Dou, X., Evans,

W., Feely, R.A., Feng, L., Gasser, T., Gilfillan, D., Gkritzalis, T., Grassi, G., Gregor, L., Gruber, N., Gürses, O., Harris, I., Houghton, R.A., Hurtt, G.C., Iida, Y., Ilyina, T., Luijkx, I.T., Jain, A.K., Jones, S.D., Kato, E., Kennedy, D., Klein Goldewijk, K., Knauer, J., Korsbakken, J.I., Körtzinger, A., Landschützer, P., Lauvset, S.K., Lefèvre, N., Lienert, S., Liu, J., Marland, G., McGuire, P.C., Melton, J.R., Munro, D.R., Nabel, J.E.M.S., Nakaoka, S.I., Niwa, Y., Ono, T., Pierrot, D., Poulter, B., Rehder, G., Resplandy, L., Robertson, E., Rödenbeck, C., Rosan, T.M., Schwinger, J., Schwingshackl, C., Séférian, R., Sutton, A.J., Sweeney, C., Tanhua, T., Tans, P.P., Tian, H., Tilbrook, B., Tubiello, F., van der Werf, G., Vuichard, N., Wada, C., Wanninkhof, R., Watson, A., Willis, D., Wiltshire, A.J., Yuan, W., Yue, C., Yue, X., Zaehle, S., Zeng, J., 2022. Global carbon budget 2021. Earth System Science Data 14, 1917–2005. doi:10.5194/essd-14-1917-2022.

Friedrichs, M.A.M., Carr, M.E., Barber, R.T., Scardi, M., Antoine, D., Armstrong, R.A., Asanuma, I., Behrenfeld, M., Buitenhuis, E.T., Chai, F., Christian, J.R., Ciotti, A.M., Doney, S.C., Dowell, M., Dunne, J., Gentili, B., Gregg, W.W., Hoepffner, N., Ishizaka, J., Kameda, T., Lima, I., Marra, J., Mélin, F., Moore, J.K., Morel, A., O'Malley, R.T.O., O'Reilly, J.E., Saba, V.S., Schmeltz, M., Smyth, T.J., Tjiputraw, J., Waters, K., Westberry, T.K., Winguth, A., 2009. Assessing the uncertainties of model estimates of primary productivity in the tropical Pacific Ocean. Journal of Marine Systems 76, 113–133. doi:10.1016/j.jmarsys.2008.05.010.

Frölicher, T.L., Fischer, E.M., Gruber, N., 2018. Marine heatwaves under global warming. Nature 560, 360–364. doi:10.1038/s41586-018-0383-9.

Frölicher, T.L., Laufkötter, C., 2018. Emerging risks from marine heat waves. Nature Communications .

Frouin, R., Ramon, D., Boss, E., Jolivet, D., Compiègne, M., Tan, J., Bouman, H., Jackson, T., Franz, B., Platt, T., Sathyendranath, S., 2018. Satellite radiation products for ocean biology and biogeochemistry: Needs, state-of-the-art, gaps, development priorities, and opportunitie. Frontiers in Marine Science 5, 3. URL: https://www.frontiersin.org/article/10.3389/fmars.2018.00003, doi:10.

3389/fmars.2018.00003.

Fuhrman, J.A., Sleeter, T.D., Carlson, C.A., Proctor, L.M., 1989. Dominance of bacterial biomass in the Sargasso Sea and its ecological implications. Marine Ecology Progress Series 57, 207–217. doi:10.3354/meps057207.

Gabric, A.J., Cropp, R.A., McTainsh, G.H., Johnston, B.M., Butler, H., Tilbrook, B., Keywood, M., 2010. Australian dust storms in 2002-2003 and their impact on Southern Ocean biogeochemistry. Global Biogeochemical Cycles 24, GB2005. doi:10.1029/2009gb003541.

Galí, M., Falls, M., Claustre, H., Aumont, O., Bernardello, R., 2022. Bridging the gaps between particulate backscattering measurements and modeled particulate organic carbon in the ocean. Biogeosciences 19, 1245–1275. doi:10.5194/bg-19-1245-2022.

Gao, Y., Marsay, C.M., Yu, S., Fan, S., Mukherjee, P., Buck, C.S., Landing, W.M., 2019. Particle-size variability of aerosol iron and impact on iron solubility and dry deposition fluxes to the Arctic Ocean. Scientific Reports 9, 16653. doi:10.1038/s41598-019-52468-z.

Gardner, W.D., Richardson, M.J., Carlson, C.A., Hansell, D., Mishonov, A.V., 2003. Determining true particulate organic carbon: bottles, pumps and methodologies. Deep Sea Research Part II: Topical Studies in Oceanography 50, 655–674. doi:10.1016/S0967-0645(02)00589-1.

Giering, S.L.C., Cavan, E.L., Basedow, S.L., Briggs, N., Burd, A.B., Darroch, L.J., Guidi, L., Irisson, J.O., Iversen, M.H., Kiko, R., Lindsay, D., Marcolin, C.R., McDonnell, A.M.P., Möller, K.O., Passow, U., Thomalla, S., Trull, T.W., Waite, A.M., 2020. Sinking organic particles in the ocean–Flux estimates from in situ optical devices. Frontiers in Marine Science 6, 834. URL: https://www.frontiersin.org/article/10.3389/fmars.2019.00834, doi:10.3389/fmars.2019.00834.

Regaudie-de Gioux, A., Lasternas, S., Agustí, S., Duarte, C.M., 2014. Comparing marine primary production estimates through different methods and development of conversion equations. Frontiers in Marine Science 1, 19. doi:10.3389/fmars.2014.00019.

Giri, C., Ochieng, E., Tieszen, L.L., Zhu, Z., Singh, A., Loveland, T., Masek, J., Duke, N., 2011. Status and distribution of mangrove forests of the world using earth observation satellite data. Global Ecology and Biogeography 20, 154–159. doi:10.1111/j.1466-8238.2010.00584.x.

Goddijn-Murphy, L., Woolf, D.K., Chapron, B., Queffeulou, P., 2013. Improvements to estimating the air-sea gas transfer velocity by using dual-frequency, altimeter backscatter. Remote Sensing of Environment 139, 1–5. doi:10.1016/j.rse.2013.07.026.

Goldberg, L., Lagomasino, D., Thomas, N., Fatoyinbo, T., 2020. Global declines in human-driven mangrove loss. Global Change Biology 26, 5844–5855. doi:10.1111/gcb.15275.

Goldman, J.C., Dennett, M.R., 1985. Susceptibility of some marine phytoplankton species to cell breakage during filtration and post-filtration rinsing. Journal of Experimental Marine Biology and Ecology 86, 47–58. doi:10.1016/0022-0981(85)90041-3.

Gorbunov, M.Y., Falkowski, P.G., 2020. Using chlorophyll fluorescence kinetics to determine photosynthesis in aquatic ecosystems. Limnology and Oceanography 66, 1–13. doi:10.1002/lno.11581.

Gorbunov, M.Y., Falkowski, P.G., Kolber, Z., 2000. Measurement of photosynthetic parameters in benthic organisms in situ using a SCUBA-based fast repetition rate fluorometer. Limnology and Oceanography 45, 242–245. doi:10.4319/lo.2000.45.1.0242.

Gorbunov, M.Y., Shirsin, E., Nikonova, E., Fadeev, V.V., Falkowski, P.G., 2020. The use of multi-spectral Fluorescence Induction and Relaxation technique for physiological and taxonomic analysis of phytoplankton communities. Marine Ecology Progress Series 644, 1–13. doi:10.3354/meps13358.

Gordon, H.R., Boynton, G.C., Balch, W.M., Groom, S.B., Harbour, D.S., Smyth, T.J., 2001. Retrieval of coccolithophore calcite concentration from SeaWiFS imagery. Geophysical Research Letters 28, 1587–1590. URL: https://doi.org/10.1029/2000GL012025, doi:10.1029/2000GL012025.

Gordon, H.R., Clark, D.K., Mueller, J.L., Hovis, W.A., 1980. Phytoplankton pigments from the Nimbus-7 Coastal Zone Color Scanner: Comparisons with surface measurements. Science 210, 63–66. doi:10.1126/science.210.4465.63.

Gordon, H.R., McCluney, W.R., 1975. Estimation of the depth of sunlight penetration in the sea for remote sensing. Applied Optics 14, 413–416. doi:10.1364/AO.14.000413.

Gower, J., Young, E., King, S., 2013. Satellite images suggest a new Sargassum source region in 2011. Remote Sensing Letters 4, 764–773. doi:10.1080/2150704X.2013.796433.

Gower, J.F.R., Hu, C., Borstad, G.A., King, S., 2006. Ocean color satellites show extensive lines of floating sargassum in the gulf of mexico. IEEE Transactions on Geoscience and Remote Sensing 44, 3619–3625.

Graff, J.R., Milligan, A.J., Behrenfeld, M.J., 2012. The measurement of phytoplankton biomass using flow-cytometric sorting and elemental analysis of carbon. Limnology and Oceanography: Methods 10, 910–920. doi:10.4319/lom.2012.10.910.

Graff, J.R., Westberry, T.K., Milligan, A.J., Brown, M.B., Dall'Olmo, G., van Dongen-Vogels, V., Reifel, K.M., Behrenfeld, M.J., 2015. Analytical phytoplankton carbon measurements spanning diverse ecosystems. Deep Sea Research Part I: Oceanographic Research Papers 102, 16–25. doi:10.1016/j.dsr.2015.04.006.

Gray, A.R., Johnson, K.S., Bushinsky, S.M., Riser, S.C., Russell, J.L., Talley, L.D., Wanninkhof, R., Williams, N.L., Sarmiento, J.L., 2018. Autonomous biogeochemical floats detect significant carbon dioxide outgassing in the high-latitude Southern Ocean. Geophysical Research Letters 45, 9049–9057. doi:10.1029/2018GL078013.

Gregg, W.W., 2001. Tracking the SeaWiFS record with a coupled physical/biogeochemical/radiative model of the global oceans. Deep Sea Research Part II: Topical Studies in Oceanography 49, 81–105. doi:10.1016/S0967-0645(01)00095-9.

Gregg, W.W., 2008. Assimilation of SeaWiFS ocean chlorophyll data into a threedimensional global ocean model. Journal of Marine Systems 69, 205–225. doi:10.1016/j.jmarsys.2006.02.015.

Gregg, W.W., Rousseaux, C.S., 2017. Simulating PACE global ocean radiances. Frontiers in Marine Science 4, 60. doi:10.3389/fmars.2017.00060.

Gregg, W.W., Rousseaux, C.S., 2019. Global ocean primary production trends in the modern ocean color satellite record (1998-2015). Environmental Research Letters 14, 124011. doi:10.1088/1748-9326/ab4667.

Gregg, W.W., Rousseaux, C.S., Franz, B.A., 2017. Global trends in ocean phytoplankton: a new assessment using revised ocean colour data. Remote Sensing Letters 8, 1102–1111. doi:10.1080/2150704X.2017.1354263.

Gregor, L., Gruber, N., 2021. OceanSODA-ETHZ: a global gridded data set of the surface ocean carbonate system for seasonal to decadal studies of ocean acidification. Earth System Science Data 13, 777–808. doi:10.5194/essd-13-777-2021.

Gruber, N., 2011. Warming up, turning sour, losing breath: ocean biogeochemistry under global change. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369, 1980–1996. doi:10.1098/rsta.2011.0003.

Gruber, N., Boyd, P.W., Frölicher, T.L., Vogt, M., 2021. Biogeochemical extremes and compound events in the ocean. Nature 600, 395–407. doi:10.1038/s41586-021-03981-7.

Gupta, M., Follows, M.J., Lauderdale, J.M., 2020. The effect of Antarctic sea ice on Southern Ocean carbon outgassing: Capping versus light attenuation. Global Biogeochemical Cycles 34, e2019GB006489. doi:10.1029/2019GB006489.

Ha, N.T., Manley-Harris, M., Pham, T.D., Hawes, I., 2021. Detecting multi-decadal changes in seagrass cover in Tauranga harbour, New Zealand, using Landsat imagery and boosting ensemble classification techniques. ISPRS International Journal of Geo-Information 10, 371. doi:10.3390/ijgi10060371.

Hansell, D.A., 2013. Recalcitrant dissolved organic carbon fractions. Annual Review of Marine Science 5, 421–445. URL: https://doi.org/10.1146/annurev-marine-120710-100757, doi:10.1146/annurev-marine-120710-10075.

Hansell, D.A., Carlson, C.A., Repeta, D.J., Schlitzer, R., 2009. Dissolved organic matter in the ocean: A controversy stimulates new insights. Oceanography 22, 52–61. doi:10.5670/oceanog.2009.109.

Harringmeyer, J.P., Kaiser, K., Thompson, D.R., Gierach, M.M., Cash, C.L., Fichot, C.G., 2021. Detection and sourcing of CDOM in urban coastal waters with UV-visible imaging spectroscopy. Frontiers in Environmental Science 9, 647966. doi:10.3389/fenvs.2021.647966.

Harris, S., Lucas, C., 2019. Understanding the variability of australian fire weather between 1973 and 2017. PloS One 14, e0222328. doi:10.1371/journal.pone.0222328.

Hatton, I.A., Heneghan, R.F., Bar-On, Y.M., Galbraith, E.D., 2021. The global ocean size spectrum from bacteria to whales. Science Advances 7, eabh3732. doi:10.1126/sciadv.abh3732.

Hauck, J., Völker, C., 2015. Rising atmospheric co_2 leads to large impact of biology on southern ocean co_2 uptake via changes of the revelle factor. Geophysical Research Letters 42, 1459–1464. doi:10.1002/2015GL063070.

Hauck, J., Zeising, M., Le Quéré, C., Gruber, N., Bakker, D.C.E., Bopp, L., Chau, T. T. T., G.O., Ilyina, T., Landschützer, P., Lenton, A., Resplandy, L., Rödenbeck, C., Schwinger, J., Séférian, R., 2020. Consistency and challenges in the ocean carbon sink estimate for the global carbon budget. Frontiers in Marine Science 7, 571720. doi:10.3389/fmars.2020.571720.

Hayashida, H., Matear, R.J., Strutton, P.G., 2020. Background nutrient concentration determines phytoplankton bloom response to marine heatwaves. Global Change Biology 26, 4800–4811. doi:10.1111/gcb.15255.

Hedges, J.I., 1992. Global biogeochemical cycles: progress and problems. Marine Chemistry , 67–93.

Helms, J.R., Stubbins, A., Ritchie, J.D., Minor, E.C., Kieber, D.J., Mopper, K., 2008. Absorption spectral slopes and slope ratios as indicatorsof molecular weight, source, and photobleaching of chromophoric dissolved organic matter. Limnology and Oceanography 53, 955–969. doi:10.4319/lo.2008.53.3.0955.

Henson, S.A., Laufkötter, C., Leung, S., Giering, S.L.C., Palevsky, H.I., Cavan, E.L., 2022. Uncertain response of ocean biological carbon export in a changing world. Nature Geoscience 15, 248–254. doi:10.1038/s41561-022-00927-0.

Henson, S.A., Sarmiento, J.L., Dunne, J.P., Bopp, L., Lima, I., Doney, S.C., John, J., Beaulieu, C., 2010. Detection of anthropogenic climate change in satellite records of ocean chlorophyll and productivity. Biogeosciences 7, 621–640. doi:10.5194/bg-7-621-2010.

Hieronymi, M., Macke, A., 2012. On the influence of wind and waves on underwater irradiance fluctuations. Ocean Sciences 8, 455–471. doi:10.5194/os-8-455-2012.

Hobday, A.J., Alexander, L.V., Perkins, S.E., Smale, D.A., Straub, S.C., Oliver, E.C., Benthuysen, J.A., Burrows, M.T., Donat, M.G., Feng, M., 2016. A hierarchical approach to defining marine heatwaves. Progress in Oceanography 141, 227–238. doi:10.1016/j.pocean.2015.12.014.

Hoge, F.E., Vodacek, A., Blough, N.V., 1993. Inherent optical properties of the ocean: Retrieval of the absorption coefficient of chromophoric dissolved organic matter from fluorescence measurements. Limnology and Oceanography 38, 1394–1402. doi:10.4319/LO.1993.38.7.1394.

Holbrook, N.J., Scannell, H.A., Sen Gupta, A., Benthuysen, J.A., Feng, M., Oliver, E.C., Alexander, L.V., Burrows, M.T., Donat, M.G., Hobday, A.J., 2019. A global assessment of marine heatwaves and their drivers. Nature Communications 10, 1–13. doi:10.1038/s41467-019-10206-z.

Holligan, P.M., Viollier, M., Harbour, D.S., Camus, P., Champagne-Philippe, M., 1983. Satellite and ship studies of coccolithophore production along a continental shelf edge. Nature 304, 339–342. URL: https://doi.org/10.1038/304339a0, doi:10.1038/304339a0.

Hopkins, J., Henson, S.A., Poulton, A.J., Balch, W.M., 2019. Regional characteristics of the temporal variability in the global particulate inorganic carbon inventory. Global Biogeochemical Cycles 33, 1328–1338. URL: https://doi.org/10.1029/2019GB006300, doi:10.1029/2019GB006300.

Hossain, M., Bujang, J., Zakaria, M., Hashim, M., 2015. The application of remote sensing to seagrass ecosystems: An overview and future research prospects. International Journal of Remote Sensing 36, 61–114. doi:10.1080/01431161.2014.990649.

Hu, C., 2009. A novel ocean color index to detect floating algae in the global oceans. Remote Sensing of Environment 113, 2118–2129. doi:10.1016/j.rse.2009.05.012.

Hu, C., Wang, M., Lapointe, B.E., Brewton, R.A., Hernandez, F.J., 2021. On the atlantic pelagic *sargassum*'s role in carbon fixation and sequestration. Science of The Total Environment 781, 146801. doi:10.1016/j.scitotenv.2021.146801.

Hu, L., Hu, C., He, M.X., 2017. Remote estimation of biomass of *ulva prolifera* macroalgae in the Yellow Sea. Remote Sensing of Environment 192, 217–227. doi:10.1016/j.rse.2017.01.037.

Huang, C., Yunmei, L., Liu, G., Guo, Y., Yang, H., Zhu, A., Song, T., Huang, T., Zhang, M., Shi, K., 2017. Tracing high time-resolution fluctuations in dissolved organic carbon using satellite and buoy observations: Case study in Lake Taihu, China. International Journal of Applied Earth Observation and Geoinformation 62, 174–182. URL: https://www.sciencedirect.com/science/article/pii/S0303243417301356, doi:https://doi.org/10.1016/j.jag.2017.06.009.

Huang, Y., Nicholson, D., Huang, B., Cassar, N., 2021. Global estimates of marine gross primary production based on machine learning upscaling of field observations. Global Biogeochemical Cycles 35, e2020GB006718. doi:10.1029/2020GB006718.

Huang, Y., Wu, S., Kaplan, J.O., 2015. Sensitivity of global wildfire occurrences to various factors in the context of global change. Atmospheric Environment 121, 86–92. doi:10.1016/j.atmosenv.2015.06.002.

Huber, S., Hansen, L.B., Nielsen, L.T., Rasmussen, M.L., Sølvsteen, J., Berglund, J., von Friesen, C.P., Danbolt, M., Envall, M., Infantes, E., Moksnes, P., 2021. Novel approach to large-scale monitoring of submerged aquatic vegetation: A nationwide example from Sweden. Integrated Environmental Assessment and

Management doi:10.1002/ieam.4493.

Hughes, T.P., Anderson, K.D., Connolly, S.R., Heron, S.F., Kerry, J.T., Lough, J.M., Baird, A.H., Baum =, J.K., Berumen, M.L., Bridge, T.C., Claar, D.C., Eakin, C.M., Gilmour, J.P., Graham, N.A.J., Harrison, H., Hobbs, J.P.A., Hoey, A.S., Hoogenboom, M., Lowe, R.J., McCulloch, M.T., Pandolfi, J.M., Pratchett, M., Schoepf, V., Torda, G., Wilson, S.K., 2018. Spatial and temporal patterns of mass bleaching of corals in the Anthropocene. Science 359, 80–83. doi:10.1126/science.aan8048.

Humphreys, M.P., Lewis, E.R., Sharp, J.D., Pierrot, D., 2022. PyCO2SYS v1.8: marine carbonate system calculations in Python. Geoscientific Model Development 15, 15–43. doi:10.5194/gmd-15-15-2022.

Hung, C.C., Gong, G.C., Chou, W.C., Chung, C.C., Lee, M.A., Chang, Y., Chen, H.Y., Huang, S.J., Yang, Y., Yang, W.R., 2010. The effect of typhoon on particulate organic carbon flux in the southern East China Sea. Biogeosciences 7, 3007–3018. doi:10.5194/bg-7-3007-2010.

Ibrahim, A., Franz, B., Ahmad, Z., Healy, R., Knobelspiesse, K., Gao, B.C., Proctor, C., Zhai, P.W., 2018. Atmospheric correction for hyperspectral ocean color retrieval with application to the Hyperspectral Imager for the Coastal Ocean (HICO). Remote Sensing of Environment 204, 60–75. doi:10.1016/j.rse.2017.10.041.

IOCCG, 2019. Uncertainties in Ocean Colour Remote Sensing. Technical Report. Mélin, F. (e.d.), Reports of the International Ocean-Colour Coordinating Group, No. 18, IOCCG, Dartmouth, Canada. URL: http://dx.doi.org/10.25607/OBP-696.

IOCCG, 2020. Synergy between Ocean Colour and Biogeochemical/Ecosystem Models. Technical Report. Dutkiewicz, S. (ed.), IOCCG Report Series, No. 19, International Ocean Colour Coordinating Group, Dartmouth, Canada. URL: http://dx.doi.org/10.25607/OBP-711.

IOCCG, 2021. Observation of Harmful Algal Blooms with Ocean Colour Radiometry. Technical Report. Bernard, S., Kudela, R., Robertson Lain, L. and Pitcher, G.C. (ed.), IOCCG Report Series, No. 20, International Ocean Colour

Coordinating Group, Dartmouth, Canada.

IOCCG Protocol Series, 2021a. Aquatic Primary Productivity Field Protocols for Satellite Validation and Model Synthesis. IOCCG Ocean Optics and Biogeochemistry Protocols for Satellite Ocean Colour Sensor Validation, Volume 7.0, edited by R.A. Vandermeulen, J. E. Chaves, IOCCG, Dartmouth, NS, Canada.

IOCCG Protocol Series, 2021b. Particulate Organic Matter Sampling and Measurement Protocols: Consensus Towards Future Ocean Color Missions. IOCCG Ocean Optics and Biogeochemistry Protocols for Satellite Ocean Colour Sensor Validation, Volume 6.0, IOCCG, Dartmouth, NS, Canada.

IPCC, 2019. IPCC Special report on the ocean and cryosphere in a changing climate.

Jackson, G.A., 1995. Comparing observed changes in particle size spectra with those predicted using coagulation theory. Deep Sea Research Part II: Topical Studies in Oceanography 42, 159–184. doi:10.1016/0967-0645(95)00010-N.

Jackson, G.A., Maffione, R., Costello, D.K., Alldredge, A.L., Logan, B.E., Dam, H.G., 1997. Particle size spectra between 1 μm and 1 cm at Monterey Bay determined using multiple instruments. Deep-Sea Research Part I 44, 1739–1767. doi:10.1016/S0967-0637(97)00029-0.

Jackson, T., Sathyendranath, S., Platt, T., 2017. An exact solution for modeling photoacclimation of the carbon-to-chlorophyll ratio in phytoplankton. Frontiers in Marine Science 4, 283. URL: https://www.frontiersin.org/article/10.3389/fmars.2017.00283, doi:10.3389/fmars.2017.00283.

Jamet, C., Ibrahim, A., Ahmad, Z., Angelini, F., Babin, M., Behrenfeld, M.J., Boss, E., Cairns, B., Churnside, J., Chowdhary, J., Davis, A.B., Dionisi, D., Duforêt-Gaurier, L., Franz, B., Frouin, R., Gao, M., Gray, D., Hasekamp, O., He, X., Hostetler, C., Kalashnikova, O.V., Knobelspiesse, K., Lacour, L., Loisel, H., Martins, V., Rehm, E., Remer, L., Sanhaj, I., Stamnes, K., Stamnes, S., Victori, S., Werdell, J., Zhai, P.W., 2019. Going beyond standard ocean color observations: Lidar and polarimetry. Frontiers in Marine Science 6, 251. URL: https://www.frontiersin.org/article/10.3389/fmars.2019.00251, doi:10.3389/fmars.2019.00251.

Jemai, A., Wollschläger, J., Voß, D., Zielinski, O., 2021. Radiometry on Argo floats: from the multispectral state-of-the-art on the step to hyperspectral technology. Frontiers in Marine Science 8, 676537. doi:10.3389/fmars.2021.676537.

Jickells, T.D., An, Z.S., Andersen, K.K., Baker, A.R., Bergametti, G., Brooks, N., Cao, J.J., Boyd, P.W., Duce, R.A., Hunter, K.A., Kawahata, H., Kubilay, N., laRoche, J., Liss, P.S., Mahowald, N., Prospero, J.M., Ridgwell, A.J., Tegen, I., Torres, R., 2005. Global iron connections between desert dust, ocean biogeochemistry, and climate. Science 308, 67–71. doi:10.1126/science.1105959.

Johnson, K.S., Berelson, W.M., Boss, E.S., Chase, Z., Claustre, H., Emerson, S.R., Gruber, N., Körtzinger, A., Perry, M.J., Riser, S.C., 2009. Observing biogeochemical cycles at global scales with profiling floats and gliders: prospects for a global array. Oceanography 22, 216–225.

Johnson, K.S., Bif, M.B., 2021. Constraint on net primary productivity of the global ocean by argo oxygen measurements. Nature Geoscience 14, 749–774. doi:10.1038/s41561-021-00807-z.

Johnson, K.S., Plant, J.N., Coletti, L.J., Jannasch, H.W., Sakamoto, C.M., Riser, S.C., Swift, D.D., Williams, N.L., Boss, E., Haëntjens, N., Talley, L.D., Sarmiento, J.L., 2017. Biogeochemical sensor performance in the SOCCOM profiling float array. Journal of Geophysical Research: Oceans 122, 6416–6436. doi:10.1002/2017jc012838.

Jonasz, M., 1983. Particle-size distributions in the Baltic. Tellus B: Chemical and Physical Meteorology 35, 346–358. doi:10.3402/tellusb.v35i5.14624.

Jonasz, M., Fournier, G.R., 2007. Light scattering by particles in water: Theoretical and experimental foundations. Academic Press, San Diego.

Jones, E.M., Baird, M.E., Mongin, M., Parslow, J., Skerratt, J., Lovell, J., Margvelashvili, N., Matear, R.J., Wild-Allen, K., Robson, B., Rizwi, F., Oke, P., King, E., Schroeder, T., Steven, A., Taylor, J., 2016. Use of remote-sensing reflectance to constrain a data assimilating marine biogeochemical model of the Great Barrier Reef. Biogeosciences 13, 6441–6469. doi:10.5194/bg-13-6441-2016.

Juhls, B., Overduin, P.P., Hölemann, J., Hieronymi, M., Matsuoka, A., Heim, B., Fischer, J., 2019. Dissolved organic matter at the fluvial–marine transition in the Laptev Sea using in situ data and ocean colour remote sensing. Biogeosciences 16, 2693–2713. doi:10.5194/bg-16-2693-2019.

Karl, D., Winn, C., 1991. A Sea of Change: Monitoring the Oceans' Carbon Cycle. Environmental Science Technology 25, 1977–1981. doi:10.1021/es00024a600.

Katz, R.W., Brown, B.G., 1992. Extreme events in a changing climate: variability is more important than averages. Climatic change 21, 289–302. doi:10.1007/BF0013972.

Kerr, S.R., 1974. Theory of size distribution in ecological communities. Journal of the Fisheries Research Board of Canada 31, 1859–1862. doi:10.1139/f74-241.

Kiefer, D.A., Berwald, J., 1992. A random encounter model for the microbial planktonic community. Limnology and Oceanography 37, 457–467. doi:10.4319/lo.1992.37.3.0457.

Kintisch, E., 2013. A sea change for U.S. oceanography. Science 339, 1138–1143. doi:10.1126/science.339.6124.1138.

Koestner, D., Stramski, D., Reynolds, R.A., 2021. Characterization of suspended particulate matter in contrasting coastal marine environments with angle-resolved polarized light scattering measurements. Applied Optics 60, 11161–11179. doi:10.1364/AO.441226.

Kolber, Z., Falkowski, P.G., 1993. Use of active fluorescence to estimate phytoplankton photosynthesis in-situ. Limnology and Oceanography 38, 1646–1665. doi:10.4319/lo.1993.38.8.1646.

Kolber, Z.S., Prasil, O., Falkowski, P.G., 1998. Measurements of variable chlorophyll fluorescence using fast repetition rate techniques: defining methodology and experimental protocols. Biochimica Et Biophysica Acta-Bioenergetics 1367, 88–106. doi:10.1016/S0005-2728(98)00135-2.

Kostadinov, T.S., Milutinović, S., Marinov, I., Cabré, A., 2016. Carbon-based phytoplankton size classes retrieved via ocean color estimates of the particle size distribution. Ocean Sciences 12, 561–575. doi:10.5194/os-12-561-2016.

Kostadinov, T.S., Robertson-Lain, L., Kong, C.E., Zhang, X., Maritorena, S., Bernard, S., Loisel, H., Jorge, D.S.F., Kochetkova, E., Roy, S., Jönsson, B., Martinez-Vicente, V., Sathyendranath, S., 2022. Particle size distribution and size-partitioned phytoplankton carbon using a two-component coated-spheres bio-optical model: Monthly global 4 km imagery based on the OC-CCI v5.0 merged ocean color satellite data set. PANGAEA doi:10.1594/PANGAEA.939863.

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, C09015. doi:10.1029/2009jc005303.

Kostadinov, T.S., Siegel, D.A., Maritorena, S., 2010. Global variability of phytoplankton functional types from space: assessment via the particle size distribution. Biogeosciences 7, 3239–3257. doi:10.5194/bgd-7-4295-2010.

Kovač, Ž., Platt, T., Sathyendranath, S., Antunović, S., 2017. Models for estimating photosynthesis parameters from in situ production profiles. Progress in Oceanography 159, 255–266. doi:10.1016/j.pocean.2017.10.013.

Kovač, Ž., Platt, T., Sathyendranath, S., Morović, M., 2016. Analytical solution for the vertical profile of daily production in the ocean. Journal of Geophysical Research: Oceans 121, 3532–3548. doi:10.1002/2015JC011293.

Kowalczuk, P., Tilstone, G.H., Zabłocka, M., Röttgers, R., Thomas, R., 2013. Composition of dissolved organic matter along an atlantic meridional transect from fluorescence spectroscopy and parallel factor analysis. Marine Chemistry 157, 170–184. doi:10.1016/j.marchem.2013.10.004.

Kulk, G., Platt, T., Dingle, J., Jackson, T., Jönsson, B.F., Bouman, H.A., Babin, M., Brewin, R.J.W., Doblin, M., Estrada, M., Figueiras, F.G., Furuya, K., González-Benítez, N., Gudfinnsson, H.G., Gudmundsson, K., Huang, B., Isada, T., Kovač, Ž., Lutz, V.A., Marañón, E., Raman, M., Richardson, K., Rozema, P.D., Poll, W.H., Segura, V., Tilstone, G.H., Uitz, J., Dongen-Vogels, V., Yoshikawa, T., Sathyendranath, S., 2020. Primary production, an index of climate change in the ocean: Satellite-based estimates over two decades. Remote Sensing 12, 826. URL: https://doi.org/10.3390/rs12050826, doi:10.3390/rs12050826.

Kulk, G., Platt, T., Dingle, J., Jackson, T., Jönsson, B.F., Bouman, H.A., Babin, M., Brewin, R.J.W., Doblin, M., Estrada, M., Figueiras, F.G., Furuya, K., González-Benítez, N., Gudfinnsson, H.G., Gudmundsson, K., Huang, B., Isada, T., Kovač, Ž., Lutz, V.A., Marañón, E., Raman, M., Richardson, K., Rozema, P.D., Poll, W.H., Segura, V., Tilstone, G.H., Uitz, J., Dongen-Vogels, V., Yoshikawa, T., Sathyendranath, S., 2021. Correction: Kulk et al. primary production, an index of climate change in the ocean: Satellite-based estimates over two decades. remote sens. 2020, 12, 826. Remote Sensing 13, 3462. doi:10.3390/rs13173462.

Lagerloef, G., DeCharon, A., Lindstrom, E., 2013. Ocean salinity and the aquarius/SAC-D mission: a new frontier in ocean remote sensing. Marine Technology Society Jour 47, 26–30. doi:10.4031/MTSJ.47.5.1.

Lamb, B.T., Tzortziou, M.A., McDonald, K.C., 2021. A fused radar-optical approach for mapping wetlands and deepwaters of the Mid–Atlantic and gulf coast regions of the United States. Remote Sensing 13, 2495. doi:10.3390/rs13132495.

Land, P.E., Findlay, H.S., Shutler, J.D., Ashton, I.G., Holding, T., Grouazel, A., Girard-Ardhuin, F., Reul, N., Piolle, J.F., Chapron, B., Quilfen, Y., Bellerby, R.G.J., Bhadury, P., Sailsbury, J., Vandemark, D., Sabia, R., 2019. Optimum satellite remote sensing of the marine carbonate system using empirical algorithms in the global ocean, the Greater Caribbean, the Amazon Plume and the Bay of Bengal. Remote Sensing of Environment 235, 111469. doi:10.1016/j.rse.2019.111469.

Land, P.E., Shutler, J.D., Findlay, H.S., Girard-Ardhuin, F., Sabia, R., Reul, N., Piolle, J.F., Chapron, B., Quilfen, Y., Salisbury, J., Vandemark, D., Bellerby, R., Bhadury, P., 2015. Salinity from space unlocks satellite-based assessment of ocean acidification. Environmental Science & Technology 49, 1987–1994. doi:10.1021/es504849s.

Lander, M., Holland, G.J., 1993. On the interaction of tropical-cyclone-scale vortices. I: Observations. Quarterly Journal of the Royal Meteorological Society 119, 1347–1361. doi:10.1002/qj.49711951406.

Landschützer, P., Gruber, N., Bakker, D.C.E., Stemmler, I., Six, K.S., 2018. Strengthening seasonal marine co_2 variations due to increasing atmospheric co_2. Nature Climate Change 8, 146–150. doi:10.1038/s41558-017-0057-x.

Landschützer, P., Laruelle, G.G., Roobaert, A., Regnier, P., 2020. A uniform pco_2 climatology combining open and coastal oceans. Earth System Science Data 12, 2537–2553.

Laney, S.R., Krishfield, R.A., Toole, J.M., Hammar, T.R., Ashjian, C.J., Timmermans, M.L., 2014. Assessing algal biomass and bio-optical distributions in perennially ice-covered polar ocean ecosystems. Polar Science 8, 73–85. doi:10.1016/j.polar.2013.12.003.

Lauderdale, J.M., Dutkiewicz, S., Williams, R.G., Follows, M.J., 2016. Quantifying the drivers of ocean-atmosphere CO_2 fluxes. Global Biogeochemical Cycles 30, 983–999. doi:10.1002/2016GB005400.

Laurenceau-Cornec, E.C., Le Moigne, F.A., Gallinari, M., Moriceau, B., Toullec, J., Iversen, M. H. anbd Engel, A., De La Rocha, C.L., 2020. New guidelines for the application of Stokes' models to the sinking velocity of marine aggregates. Limnology and Oceanography 65, 1264–1285. doi:10.1002/lno.11388.

Le Grix, N., Zscheischler, J., Laufkötter, C., Rousseaux, C.S., Frölicher, T.L., 2021. Compound high-temperature and low-chlorophyll extremes in the ocean over the satellite period. Biogeosciences 18, 2119–2137. doi:10.5194/bg-18-2119-202.

Le Menn, M., Poli, P., David, A., Sagot, J., Lucas, M., O'Carroll, A., Belbeoch, M., Herklotz, K., 2019. Development of surface drifting buoys for fiducial reference measurements of sea-surface temperature. Frontiers in Marine Science 6, 578. URL: https://doi.org/10.3389/fmars.2019.00578, doi:10.3389/fmars.2019.00578.

Le Quéré, C., Harrison, S.P., Prentice, C.I., Buitenhuis, E.T., Aumont, O., Bopp, L., Claustre, H., Cotrim Da Cunha, L., Geider, R., Giraud, X., Klaas, C., Kohfeld, K.E., Legendre, L., Manizza, M., Platt, T., Rivkin, R., Sathyendranath, S., Uitz, J., Watson, A.J., Wolf-Gladrow, D., 2005. Ecosystem dynamics based on plankton functional types for global ocean biogeochemistry models. Global Change Biology 11, 2016–2040. doi:10.1111/j.1365-2486.2005.01004.x.

Lee, K., Tong, L.T., Millero, F.J., Sabine, C.L., Dickson, A.G., Goyet, C., Park, G.H., Wanninkhof, R., Feely, R.A., Key, R.M., 2006. Global relationships of total alkalinity with salinity and temperature in surface waters of the world's oceans. Geophyscial Research Letters 33, L19605. URL: https://doi.org/10.1029/2006GL027207, doi:10.1029/2006GL027207.

Lee, S., Kang, Y.C., Fuhrman, J.A., 1995. Imperfect retention of natural bacterioplankton cells by glass fiber filters. Marine Ecology Progress Series 119, 285–290. doi:10.3354/meps119285.

Lee, Y.J., Matrai, P.A., Friedrichs, M.A.M., Saba, V.S., Antoine, D., Ardyna, M., Asanuma, I., Babin, M., Bélanger, S., Benoît-Gagné, M., Devred, E., Fernández-Méndez, M., Gentili, B., Hirawake, T., Kang, S.H., Kameda, T., Katlein, C., Lee, S.H., Lee, Z., Mélin, F., Scardi, M., Smyth, T.J., Tang, S., Turpie, K., Waters, K.J., Westberry, T.K., 2015. An assessment of phytoplankton primary productivity in the Arctic Ocean from satellite ocean color/in situ chlorophyll-a based models. Journal of Geophysical Research: Oceans 120, 6508–6541. doi:10.1002/2015JC011018.

Lee, Z.P., Hu, C., Shang, S., Du, K., Lewis, M.R., Arnone, R., Brewin, R.J.W., 2013. Penetration of UV-visible solar radiation in the global oceans: Insights from ocean color remote sensing. Journal of Geophysical Research 118, 4241–4255. doi:10.1002/jgrc.20308.

Lefévre, N., Diverrés, D., Gallois, F., 2010. Origin of co_2 undersaturation in the western tropical Atlantic. Tellus B: Chemical and Physical Meteorology 62, 595–607. doi:10.1111/j.1600-0889.2010.00475.x.

Legendre, L., Rivkin, R.B., Weinbauer, M.G., Guidi, L., Uitz, J., 2015. The microbial carbon pump concept: Potential biogeochemical significance in the globally changing ocean. Progress in Oceanography 134, 432–450. doi:10.

1016/j.pocean.2015.01.008.

Li, G., Wu, Y., Gao, K., 2009. Effects of typhoon Kaemi on coastal phytoplankton assemblages in the South China Sea, with special reference to the effects of solar UV radiation. Journal of Geophysical Research: Biogeosciences 114, G04029. doi:10.1029/2008JG000896.

Li, M., Shen, F., Sun, X., 2021. 2019–2020 australian bushfire air particulate pollution and impact on the south pacific ocean. Scientific Reports 11, 1–13. doi:10.1038/s41598-021-91547-y.

Lin, I.I., Hu, C., Li, Y.H., Ho, T.Y., Fischer, T.P., Wong, G.T., Wu, J., Huang, C.W., Chu, D.A., Ko, D.S., 2011. Fertilization potential of volcanic dust in the low-nutrient low-chlorophyll western North Pacific subtropical gyre: Satellite evidence and laboratory study. Global Biogeochemical Cycles 25, GB1006. doi:10.1029/2009GB003758.

Lindenthal, A., Langmann, B., Pätsch, J., Lorkowski, I., Hort, M., 2013. The ocean response to volcanic iron fertilisation after the eruption of Kasatochi volcano: a regional-scale biogeochemical ocean model study. Biogeosciences 10, 3715–3729. doi:10.5194/bg-10-3715-2013.

Liss, P.S., Slater, P.G., 1974. Flux of gases across the air-sea interface. Nature 247, 181–184. doi:10.1038/247181a0.

Liu, Y., Boss, E., Chase, A., Xi, H., Zhang, X., Röttgers, R., Pan, Y., Bracher, A., 2019. Retrieval of phytoplankton pigments from underway spectrophotometry in the Fram Strait. Remote Sensing 11, 318. doi:10.3390/rs11030318.

Liu, Z., Stewart, G., Cochran, K., Lee, C., Armstrong, R.A., Hirschberg, D.J., Gasser, B., Miquel, J.C., 2005. Why do POC concentrations measured using niskin bottle collections sometimes differ from those using in-situ pumps? Deep Sea Research Part I: Oceanographic Research Papers 52, 1324–1344. doi:10.1016/j.dsr.2005.02.005.

Lohrenz, S.E., Arone, R.A., Wiesenburg, D.A., DePalma, I.P., 1988. Satellite detection of transient enhanced primary production in the western Mediterranean Sea. Nature 335, 245–247.

Lohrenz, S.E., Cai, W.J., Chakraborty, S., Huang, W.J., Guo, X., He, R., Xueg, X., Fennel, K., Howden, S., Tian, H., 2018. Satellite estimation of coastal pco$_2$ and air-sea flux of carbon dioxide in the northern Gulf of Mexico. Remote Sensing of Environment 207, 71–83. doi:10.1016/j.rse.2017.12.039.

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 imager. Geophysical Research Letters 28, 4203–4206. doi:10.1029/2001GL013863.

Loisel, H., Mériaux, X., Berthon, J.F., Poteau, A., 2007. Investigation of the optical backscattering to scattering ratio of marine particles in relation to their biogeochemical composition in the eastern English Channel and southern North Sea. Limnology and Oceanography 52, 739–752. doi:10.4319/lo.2007.52.2.0739.

Lomas, M.W., Baer, S.E., Acton, S., Krause, J.W., 2019. Pumped up by the cold: Elemental quotas and stoichiometry of cold-water diatoms. Frontiers in Marine Science 6, 286. doi:10.3389/fmars.2019.00286.

Lomas, M.W., Bates, N.R., Johnson, R.J., Steinberg, D.K., Tanioka, T., 2022. Adaptive carbon export response to warming in the Sargasso Sea. Nature Communications 13, 1211. doi:10.1038/s41467-022-28842-3.

Long, J., Fassbender, A., Estapa, M., 2021. Depth-resolved net primary production in the northeast pacific ocean: a comparison of satellite and profiling float estimates in the context of two marine heatwaves. Geophysical Research Letters 48, e2021GL093462. doi:10.1029/2021GL093462.

Longhurst, A., Sathyendranath, S., Platt, T., Caverhill, C., 1995. An estimate of global primary production in the ocean from satellite radiometer data. Journal of Plankton Research 17, 1245–1271.

Losa, S.N., Soppa, M.A., Dinter, T., Wolanin, A., Brewin, R.J.W., Bricaud, A., Oelker, J., Peeken, I., Gentili, B., Rozanov, V., Bracher, A., 2017. Synergistic exploitation of hyper- and multi-spectral precursor sentinel measurements to determine phytoplankton functional types (SynSenPFT). Frontiers in Marine Science 4, 203. doi:10.3389/fmars.2017.00203.

Macreadie, P.I., Anton, A., Raven, J.A., Beaumont, N., Connolly, R.M., Friess, D.A., Kelleway, J.J., Kennedy, H., Kuwae, T., Lavery, P.S., Lovelock, C.E., Smale, D.A., Apostolaki, E.T., Atwood, T.B., Baldock, J., Bianchi, T.S., Chmura, G.L., Eyre, B.D., Fourqurean, J.W., Hall-Spencer, J.M., Huxham, M., Hendriks, I.E., Krause-Jensen, D., Laffoley, D., Luisetti, T., Marbá, N., Masque, P., McGlathery, K.J., Megonigal, J.P., Murdiyarso, D., Russell, B.D., Santos, R., Serrano, O., Silliman, B.R., Watanabe, K., Duarte, C.M., 2019. The future of Blue Carbon science. Nature Communications 10, 3998. doi:10.1038/s41467-019-11693-w.

Mahowald, N., Ward, D.S., Kloster, S., Flanner, M.G., Heald, C.L., Heavens, N.G., Hess, P.G., Lamarque, J.F., Chuang, P.Y., 2011. Aerosol impacts on climate and biogeochemistry. Annual Review of Environment and Resources 36, 45–74. doi:10.1146/annurev-environ-042009-094507.

Mahowald, N.M., Baker, A.R., Bergametti, G., Brooks, N., Duce, R.A., Jickells, T.D., Kubilay, N., Prospero, J.M., Tegen, I., 2005. Atmospheric global dust cycle and iron inputs to the ocean. Global Biogeochemical Cycles 19, GB4025. doi:10.1029/2004gb002402.

Mannino, A., Russ, M.E., Hooker, S.B., 2008. Algorithm development for satellite-derived distributions of DOC and CDOM in the U.S. Middle Atlantic Bight. Journal of Geophysical Research: Oceans 113, C07051. doi:10.1029/2007JC004493.

Mannino, A., Signorini, S.R., Novak, M.G., Wilkin, J., Friedrichs, M.A.M., Najjar, R.G., 2016. Dissolved organic carbon fluxes in the Middle Atlantic Bight: An integrated approach based on satellite data and ocean model products. Journal of Geophysical Research: Biogeosciences 21, 312–336. doi:10.1002/2015JG003031.

Marañón, E., 2015. Cell size as a key determinant of phytoplankton metabolism and community structure. Annual Review of Marine Science 7, 241–264. doi:10.1146/annurev-marine-010814-015955.

Mariette, J., Blanchard, O., Berné, O., Ari, T.B., 2021. An open-source tool to assess the carbon footprint of research. Preprint doi:10.48550/arXiv.2101.10124.

Maritorena, S., Fanton d'Andon, O.H., Mangin, A., Siegel, D.A., 2010. Merged satellite ocean color data products using a bio-optical model: Characteristics, benefits and issues. Remote Sensing Environment 114, 1791–1804. doi:10.1016/j.rse.2010.04.002.

Martin, J.H., Knauer, G.A., Karl, D.M., Broenkow, W.W., 1987. VERTEX: carbon cycling in the northeast Pacific. Deep Sea Research Part A. Oceanographic Research Papers 34, 267–285. doi:10.1016/0198-0149(87)90086-0.

Martinez-Vicente, V., Bracher, A., Ramon, D., Sathyendranath, S., Kutser, T., 2020. Colour and Light in the Ocean. Frontiers Media SA, Lausanne. doi:10.3389/978-2-88963-421-7.

Martínez-Vicente, V., Dall'Olmo, G., Tarran, G., Boss, E., Sathyendranath, S., 2013. Optical backscattering is correlated with phytoplankton carbon across the Atlantic Ocean. Geophysical Research Letters 40, 1154–1158. doi:10.1002/grl.50252.

Martínez-Vicente, V., Evers-King, H., Roy, S., Kostadinov, T.S., Tarran, G.A., Graff, J.R., Brewin, R.J.W., Dall'Olmo, G., Jackson, T., Hickman, A.E., Röttgers, R., Krasemann, H., Marañón, E., Platt, T., Sathyendranath, S., 2017. Intercomparison of ocean color algorithms for picophytoplankton carbon in the ocean. Frontiers in Marine Science 4, 378. doi:10.3389/fmars.2017.00378.

Massicotte, P., Asmala, E., Stedmon, C., Markager, S., 2017. Global distribution of dissolved organic matter along the aquatic continuum: Across rivers, lakes and oceans. Science of The Total Environment 609, 180–191. doi:10.1016/j.scitotenv.2017.07.076.

Mattei, F., Scardi, M., 2021. Collection and analysis of a global marine phytoplankton primary-production dataset. Earth System Science Data 13, 4967–4985. doi:10.5194/essd-13-4967-2021.

McKinna, L.I.W., Cetinić, I., Chase, A.P., Werdell, P.J., 2019. Approach for propagating radiometric data uncertainties through NASA ocean color algorithms. Frontiers in Earth Science 7, 176. doi:10.3389/feart.2019.00176.

Mcleod, E., Chmura, G.L., Bouillon, S., Salm, R., Björk, M., Duarte, C.M., Lovelock, C.E., Schlesinger, W.H., Silliman, B.R., 2011. A blueprint for blue carbon: toward an improved understanding of the role of vegetated coastal habitats in sequestering CO_2. Frontiers in Ecology and the Environment 9, 552–560. doi:10.1890/110004.

Menden-Deuer, S., Lessard, E.J., 2000. Carbon to volume relationships for dinoflagellates, diatoms, and other protist plankton. Limnology and Oceanography 45, 569–579. doi:10.4319/lo.2000.45.3.0569.

Mertikas, S.P., Donlon, C., Cullen, R., Tripolitsiotis, A., 2020. Scientific and operational roadmap for fiducial reference measurements in satellite altimetry calibration & validation, in: Mertikas, S.P., Pail, R. (Eds.), Fiducial Reference Measurements for Altimetry, Springer International Publishing, Cham. pp. 105–109.

Miller, W.L., Moran, M.A., 1997. Interaction of photochemical and microbial processes in the degradation of refractory dissolved organicmatter from a coastal marine environment. Limnology and Oceanography 42, 1317–1324. doi:10.4319/lo.1997.42.6.1317.

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. doi:10.1002/2017JC013146.

Mopper, K., Schultz, C.A., 1993. Fluorescence as a possible tool for studying the nature and water column distribution of DOC components. Marine Chemistry 41, 229–238. doi:10.1016/0304-4203(93)90124-7.

de Mora, L., Butenschön, M., Allen, J.I., 2016. The assessment of a global marine ecosystem model on the basis of emergent properties and ecosystem function: a case study with ERSEM. Geoscience Model Development 9, 59–76. doi:10.5194/gmd-9-59-2016.

Moran, S.B., Charette, M.A., Pike, S.M., Wicklund, C.A., 1999. Differences in seawater particulate organic carbon concentration in samples collected using small- and large-volume methods: the importance of DOC adsorption to the filter blank. Marine Chemistry 67, 33–42. doi:10.1016/S0304-4203(99)00047-X.

Morel, A., Maritorena, S., 2001. Bio-optical properties of oceanic waters: A reappraisal. Journal of Geophysical Research 106, 7163–7180. doi:10.1029/2000JC000319.

Mouw, C.B., Hardman-Mountford, N.J., Alvain, S., Bracher, A., Brewin, R.J.W., Bricaud, A., Ciotti, A.M., Devred, E., Fujiwara, A., Hirata, T., Hirawake, T., Kostadinov, T.S., Roy, S., Uitz, J., 2017. A consumer's guide to satellite remote sensing of multiple phytoplankton groups in the global ocean. Frontiers in Marine Science 4, 1–19. doi:10.3389/fmars.2017.00041.

Nagata, T., 1986. Carbon and nitrogen content of natural planktonic bacteria. Applied and Environmental Microbiology 52, 28–32. doi:10.1128/aem.52.1.28-32.1986.

Naik, H., Naqvi, S., Suresh, T., Narvekar, P., 2008. Impact of a tropical cyclone on biogeochemistry of the central Arabian Sea. Global Biogeochemical Cycles 22. doi:10.1029/2007GB003028.

National Academies of Sciences, Engineering, and Medicine, 2022. A Research Strategy for Ocean-based Carbon Dioxide Removal and Sequestration. Technical Report. Washington, DC: The National Academies Press. doi:10.17226/26278.

Neeley, A., Beaulieu, S.E., Proctor, C., Cetinić, I., Futrelle, J., Soto Ramos, I., Sosik, H.M., Devred, E., Karp-Boss, L., Picheral, M., Poulton, N., Roesler, C.S., Shepherd, A., 2021. Standards and practices for reporting plankton and other particle observations from images. Technical Report. Woods Hole Oceanographic Institution. doi:10.1575/1912/27377.

Nelson, N.B., Siegel, D.A., 2013. The Global Distribution and Dynamics of Chromophoric Dissolved Organic Matter. Annual Review of Marine Science 5, 20.1–20.3. doi:10.1146/annurev-marine-120710-100751.

Novak, M.G., Cetinić, I., Chaves, J.E., Mannino, A., 2018. The adsorption of dissolved organic carbon onto glass fiber filters and its effect on the measurement of particulate organic carbon: A laboratory and modeling exercise. Limnology and Oceanography: Methods 16, 356–366. doi:10.1002/lom3.10248.

Nowicki, M., DeVries, T., Siegel, D., 2022. Quantifying the carbon export and sequestration pathways of the ocean's biological carbon pump. Global Biogeochemical Cycles 36, e2021GB007083. doi:10.1029/2021GB007083.

O'Dowd, C., Facchini, M., Cavalli, F., Ceburnis, D., Mircea, M., Decesari, S., Fuzzi, S., Yoon, Y.J., Putaud, J.P., 2004. Biogenically driven organic contribution to marine aerosol. Nature 431, 676–680. doi:10.1038/nature02959.

Oelker, J., Losa, S.N., Richter, A., Bracher, A., 2022. TROPOMI-retrieved underwater light attenuation in three spectral regions in the ultraviolet and blue. Frontiers in Marine Science 9, 787992. doi:10.3389/fmars.2022.787992.

Olita, A., Sorgente, R., Natale, S., Gaberšek, S., Ribotti, A., Bonanno, A., Patti, B., 2007. Effects of the 2003 European heatwave on the central Mediterranean Sea: surface fluxes and the dynamical response. Ocean Science 3, 273–289. doi:10.5194/os-3-273-2007.

Oliver, E.C., Donat, M.G., Burrows, M.T., Moore, P.J., Smale, D.A., Alexander, L.V., Benthuysen, J.A., Feng, M., Gupta, A.S., Hobday, A.J., Holbrook, N.J., Perkins-Kirkpatrick, S.E., Scannell, H.A., Straub, S.C., Wernberg, T., 2018. Longer and more frequent marine heatwaves over the past century. Nature Communications 9, 1–12. doi:10.1038/s41467-018-03732-9.

Oliver, E.C.J., Benthuysen, J.A., Bindoff, N.L., Hobday, A.J., Holbrook, N.J., Mundy, C.N., Perkins-Kirkpatrick, S.E., 2017. The unprecedented 2015/16 Tasman sea marine heatwave. Nature Communications 8, 16101. doi:10.1038/ncomms16101.

Olsen, A., Key, R.M., van Heuven, S., Lauvset, S.K., Velo, A., Lin, X., Schirnick, C., Kozyr, A., Tanhua, T., Hoppema, M., Jutterström, S., Steinfeldt, R., Jeansson, E., Ishii, M., Pérez, F.F., Suzuki, T., 2016. The Global Ocean Data Analysis Project version 2 (GLODAPv2) – an internally consistent data product for the world ocean. Earth System Science Data 8, 297–323. doi:10.5194/essd-8-297-2016.

Ono, T., Saino, T., Kurita, N., Sasaki, K., 2004. Basin-scale extrapolation of shipboard pCO_2 data by using satellite SST and Chla. International Journal of Remote Sensing 25, 3803–3815. doi:10.1080/01431160310001657515.

Organelli, E., Barbieux, M., Claustre, H., Schmechtig, C., Poteau, A., Bricaud, A., Boss, E., Briggs, N., Dall'Olmo, G., D'Ortenzio, F., Leymarie, E., Mangin, A., Obolensky, G., Penkerc'h, C., Prieur, L., Roesler, C., Serra, R., Uitz, J., Xing, X., 2017. Two databases derived from BGC-Argo float measurements for marine biogeochemical and bio-optical applications. Earth System Science Data 9, 861–880. doi:10.5194/essd-9-861-2017.

Organelli, E., Claustre, H., 2019. Small phytoplankton shapes colored dissolved organic matter dynamics in the North Atlantic subtropical gyre. Geophysical Research Letters 56, 12183–12191. doi:10.1029/2019GL084699.

Organelli, E., Dall'Olmo, G., Brewin, R.J.W., Nencioli, F., Tarran, G.A., 2020. Drivers of spectral optical scattering by particles in the upper 500 m of the Atlantic Ocean. Optics Express 28, 34147–34166. doi:10.1364/OE.408439.

Organelli, E., Dall'Olmo, G., Brewin, R.J.W., Tarran, G.A., Boss, E., Bricaud, A., 2018. The open-ocean missing backscattering is in the structural complexity of particles. Nature Communications 9, 1–11. URL: https://doi.org/10.1038/s41467-018-07814-6, doi:10.1038/s41467-018-07814-6.

Organelli, E., Leymarie, E., Zielinski, O., Uitz, J., D'Ortenzio, F., Claustre, H., 2021. Hyperspectral radiometry on Biogeochemical-Argo floats: A bright perspective for phytoplankton diversity. A Supplement to Oceanography 34(4). pp. 90–91. doi:10.5670/oceanog.2021.supplement.02-33.

Osburn, C.L., Rudolph, J.C., Paerl, H.W., Hounshell, A.G., Van Dam, B.R., 2019. Lingering carbon cycle effects of hurricane Matthew in North Carolina's coastal waters. Geophysical Research Letters 46, 2654–2661. doi:10.1029/2019GL082014.

Oziel, L., Massicotte, P., Babin, M., Devred, E., 2022. Decadal changes in Arctic Ocean chlorophyll a: Bridging ocean color observations from the 1980s to present time. Remote Sensing of Environment 275, 113020. doi:10.1016/j.rse.2022.113020.

Pabortsava, K., Lampitt, R.S., Benson, J., Crowe, C., McLachlan, R., Le Moigne, F.A.C., Moore, C.M., Pebody, C., Provost, P., Rees, A.P., Tilstone, G.H., Woodward, E.M.S., 2017. Carbon sequestration in the deep Atlantic enhanced by Saharan dust. Nature Geoscience 10, 189–194. doi:10.1038/ngeo2899.

Paraguay-Delgado, F., Carreño Gallardo, C., Estrada-Guel, I., Zabala-Arceo, A., Martinez-Rodriguez, H.A., Lardizábal-Gutierrez, D., 2020. Pelagic *sargassum* spp. capture CO_2 and produce calcite. Environmental Science and Pollution Research 27, 25794–25800. doi:10.1007/s11356-020-08969-w.

Passow, U., Carlson, C.A., 2012. The biological pump in a high CO_2 world. Marine Ecological Progress Series 470, 249–271. doi:10.3354/meps09985.

Pearce, A.F., Feng, M., 2013. The rise and fall of the "marine heat wave" off Western Australia during the summer of 2010/2011. Journal of Marine Systems 111-112, 139–156. doi:10.1016/j.jmarsys.2012.10.009.

Pereira, R., Ashton, I., Sabbaghzadeh, B., Shutler, J.D., Upstill-Goddard, R.C., 2018. Reduced air–sea co_2 exchange in the Atlantic Ocean due to biological surfactants. Nature Geoscience 11, 492–496. doi:10.1038/s41561-018-0136-2.

Pham, T.D., Xia, J., Ha, N.T., Bui, D.T., Le, N.N., Tekeuchi, W., 2019a. A review of remote sensing approaches for monitoring blue carbon ecosystems: Mangroves, seagrasses and salt marshes during 2010-2018. Sensors 19, 1933. doi:10.3390/s19081933.

Pham, T.D., Yokoya, N., Bui, D.T., Yoshino, K., Friess, D.A., 2019b. Remote sensing approaches for monitoring mangrove species, structure, and biomass: Opportunities and challenges. Remote Sensing 11, 230. doi:10.3390/rs11030230.

Pitarch, J., Bellacicco, M., Organelli, E., Volpe, G., Colella, S., Vellucci, V., Marullo, S., 2019. Retrieval of particulate backscattering using field and satellite radiometry: Assessment of the QAA algorithm. Remote Sensing 12, 77. doi:10.3390/rs12010077.

Platt, T., Gallegos, C.L., Harrison, W.G., 1980. Photoinhibition of photosynthesis in natural assemblages of marine phytoplankton. Journal of Marine Research 38, 687–701.

Platt, T., Herman, A.W., 1983. Remote sensing of phytoplankton in the sea: surface-layer chlorophyll as an estimate of water-column chlorophyll and primary production. International Journal of Remote Sensing 4, 343–351.

doi:10.1080/01431168308948552.
Platt, T., Sathyendranath, S., 1988. Oceanic primary production: Estimation by remote sensing at local and regional scales. Science 241, 1613–1620. doi:10.1126/science.241.4873.1613.
Platt, T., Sathyendranath, S., 1993. Estimators of primary production for interpretation of remotely sensed data on ocean color. Journal of Geophysical Research 98, 14,561–14,576.
Platt, T., Sathyendranath, S., Ravindran, P., 1990. Primary production by phytoplankton: Analytic solutions for daily rates per unit area of water surface. Proceedings of the Royal Society of London Series B: Biological Sciences 241, 101–111.
Platt, T., Sathyendranath, S., Ulloa, O., Harrison, W.G., Hoepffner, N., Goes, J., 1992. Nutrient control of phytoplankton photosynthesis in the Western North Atlantic. Nature 356, 229–231. URL: https://doi.org/10.1038/356229a0, doi:10.1038/356229a0.
Platt, T., Sathyendranath, S., White III, G.N., Jackson, T., Saux Picart, S., Bouman, H., 2017. Primary production: Sensitivity to surface irradiance and implications for archiving data. Frontiers in Marine Science 4, 387. doi:10.3389/fmars.2017.00387.
Qi, L., Hu, C., Wang, M., Shang, S., Wilson, C., 2017. Floating algae blooms in the East China Sea. Geophysical Research Letters 44, 11,501–11,509. doi:10.1002/2017GL075525.
Qi, L., Hu, C., Xing, Q., Shang, S., 2016. Long-term trend of *ulva prolifera* blooms in the western Yellow Sea. Harmful Algae 58, 35–44. doi:10.1016/j.hal.2016.07.004.
Raitsos, D.E., Pradhan, Y., Lavender, S.J., Hoteit, I., McQuatters-Gollop, A., Reid, P.C., Richardson, A.J., 2014. From silk to satellite: half a century of ocean colour anomalies in the Northeast Atlantic. Global Change Biology In Press. doi:10.1111/gcb.12457.
Rasse, R., Dall'Olmo, G., Graff, J., Westberry, T.K., van Dongen-Vogels, V., Behrenfeld, M.J., 2017. Evaluating optical proxies of particulate organic

carbon across the surface Atlantic ocean. Frontiers in Marine Science doi:10.3389/fmars.2017.00367.

Redalje, D.G., Laws, E.A., 1981. A new method for estimating phytoplankton growth rates and carbon biomass. Marine Biology 62, 73–79. doi:10.1007/BF00396953.

Regnier, P., Resplandy, L., Najjar, R.G., Ciais, P., 2021. The land-to-ocean loops of the global carbon cycle. Nature 603, 401–410. doi:10.1038/s41586-021-04339-9.

Remer, L.A., Davis, A.B., Mattoo, S., Levy, R.C., Kalashnikova, O.V., Coddington, O., Chowdhary, J., Knobelspiesse, K., Xu, X., Ahmad, Z., Boss, E., Cairns, B., Dierssen, H.M., Diner, D.J., Franz, B., Frouin, R., Gao, B.C., Ibrahim, A., Martins, J.V., Omar, A.H., Torres, O., Xu, F., Zhai, P.W., 2019a. Retrieving aerosol characteristics from the PACE mission, part 1: Ocean color instrument. Frontiers in Earth Science 7, 152. doi:10.3389/feart.2019.00152.

Remer, L.A., Knobelspiesse, K., Zhai, P.W., Xu, F., Kalashnikova, O.V., Chowdhary, J., Hasekamp, O., Dubovik, O., Wu, L., Ahmad, Z., Boss, E., Cairns, B., Coddington, O., Davis, A.B., Dierssen, H.M., Diner, D.J., Franz, B., Frouin, R., Gao, B.C., Ibrahim, A., Levy, R.C., Martins, J.V., Omar, A.H., Torres, O., 2019b. Retrieving aerosol characteristics from the pace mission, part 2: Multi-angle and polarimetry. Frontiers in Environmental Science 7. doi:10.3389/fenvs.2019.00094.

Reul, N., Tenerelli, J., Chapron, B., Vandemark, D., Quilfen, Y., Kerr, Y., 2012. SMOS satellite L-band radiometer: a new capability for ocean surface remote sensing in hurricanes. Journal of Geophysical Research – Oceans 117, C02006. doi:10.1029/2011JC007474.

Reynolds, R.A., Stramski, D., 2021. Variability in oceanic particle size distributions and estimation of size class contributions using a non-parametric approach. Journal of Geophysical Research: Oceans 126, e2021JC017946. doi:10.1029/2021JC017946.

Reynolds, R.A., Stramski, D., Neukermans, G., 2016. Optical backscattering of particles in arctic seawater and relationships to particle mass concentration, size distribution, and bulk composition. Limnology and Oceanography 61, 1869–1890. doi:10.1002/lno.10341.

Reynolds, R.A., Stramski, D., Wright, V.M., Woźniak, S.B., 2010. Measurements and characterization of particle size distributions in coastal waters. Journal of Geophysical Research: Oceans 115, C08024. doi:10.1029/2009JC005930.

Richardson, K., Bendtsen, J., Kragh, T., Mousing, E.A., 2016. Constraining the distribution of photosynthetic parameters in the Global Ocean. Frontiers in Marine Science 3, 269. doi:10.3389/fmars.2016.00269.

Rinaldo, A., Maritan, A., Cavender-Bares, K.K., Chisholm, S.W., 2002. Cross-scale ecological dynamics and microbial size spectra in marine ecosystems. Proceedings of the Royal Society of London B: Biological Sciences 269, 2051–2059. doi:10.1098/rspb.2002.2102.

Risović, D., 1993. Two-component model of sea particle size distribution. Deep Sea Research Part I, 40, 1459–1473. doi:10.1016/0967-0637(93)90123-K.

Rödenbeck, C., Keeling, R.F., Bakker, D.C.E., Metzl, N., Olsen, A., Sabine, C., Heimann, M., 2013. Global surface-ocean p^{CO_2} and sea–air co_2 flux variability from an observation-driven ocean mixed-layer scheme. Ocean Sciences 9, 193–216. doi:10.5194/os-9-193-2013.

Rodrigues, R.R., Taschetto, A.S., Gupta, A.S., Foltz, G.R., 2019. Common cause for severe droughts in south america and marine heatwaves in the South Atlantic. Nature Geoscience 12, 620–626. doi:10.1038/s41561-019-0393-8.

Roemmich, D., Alford, M.H., Claustre, H., Johnson, K., King, B., Moum, J., Oke, P., Owens, W.B., Pouliquen, S., Purkey, S., Scanderbeg, M., Suga, T., Wijffels, S., Zilberman, N., Bakker, D., Baringer, M., Belbeoch, M., Bittig, H.C., Boss, E., Calil, P., Carse, F., Carval, T., Chai, F., Conchubhair, D.., d'Ortenzio, F., Dall'Olmo, G., Desbruyeres, D., Fennel, K., Fer, I., Ferrari, R., Forget, G., Freeland, H., Fujiki, T., Gehlen, M., Greenan, B., Hallberg, R., Hibiya, T., Hosoda, S., Jayne, S., Jochum, M., Johnson, G.C., Kang, K., Kolodziejczyk, N., Körtzinger, A., Traon, P.Y., Lenn, Y.D., Maze, G., Mork, K.A., Morris, T., Nagai, T., Nash, J., Garabato, A.N., Olsen, A., Pattabhi, R.R., Prakash, S., Riser, S., Schmechtig, C., Schmid, C., Shroyer, E., Sterl, A., Sutton, P., Talley, L., Tanhua, T., Thierry, V., Thomalla, S., Toole, J., Troisi, A., Trull, T.W., Turton, J., Velez-Belchi, P.J., Walczowski, W., Wang, H., Wanninkhof, R., Waterhouse, A.F., Waterman, S., Watson, A., Wilson, C., Wong, A.P.S., Xu, J., Yasuda, I., 2019. On the future of argo: A global, full-depth, multi-disciplinary array. Frontiers in Marine Science 6. doi:10.3389/fmars.2019.00439.

Rosso, I., Mazloff, M.R., Verdy, A., Talley, L.D., 2017. Space and time variability of the Southern Ocean carbon budget. Journal of Geophysical Research: Oceans 122, 7407–7432. doi:10.1002/2016jc012646.

Rost, R., Riebesell, U., 2004. Coccolithophores and the biological pump: responses to environmental changes. in (pp. 99-125). springer, berlin, heidelberg., in: Thierstein, H.R., Young, J.R. (Eds.), Coccolithophores: from molecular processes to global impact, Springer. pp. 99–125.

Rousseaux, C.S., Gregg, W.W., 2015. Recent decadal trends in global phytoplankton composition. Global Biogeochemical Cycles 29, 1674–1688. doi:10.1002/2015GB005139.

Roy, S., Sathyendranath, S., Platt, T., 2017. Size-partitioned phytoplankton carbon and carbon-to-chlorophyll ratio from ocean colour by an absorption-based bio-optical algorithm. Remote Sensing of Environment 194, 177–189. URL: https://doi.org/10.1016/j.rse.2017.02.015, doi:10.1016/j.rse.2017.02.015.

Russell, J.L., Long, D.G., Chang, P., Cowell, M., Curchitser, E., Dinniman, M.S., Fellows, C., Goodman, P., Hofmann, E., Jelenak, Z., Klinck, J., Krasting, J.P., Lovenduski, N.S., Lofverstrom, M., Mazloff, M.R., Petroy, S., Polit, A., Rodriguez, E., Schofield, O., Stoffelen, A., Stouffer, R.J., Wanninkhof, R., Weimer, C., Zeng, X., 2021. Measuring winds from space to reduce the uncertainty in the Southern Ocean carbon fluxes: Science requirements and proposed mission. Earth and Space Science Open Archive doi:10.1002/essoar.10506276.1.

Saba, V.S., Friedrichs, M.A.M., Antoine, D., Armstrong, R.A., Asanuma, I., Behrenfeld, M.J., Ciotti, A.M., Dowell, M., Hoepffner, N., Hyde, K.J.W., Ishizaka, J., Kameda, T., Marra, J., Mélin, F., Morel, A., O'Reilly, J., Scardi, M., Smith Jr, W.O., Smyth, T.J., Tang, S., Uitz, J., Waters, K., Westberry, T.K., 2011. An evaluation of ocean color model estimates of marine primary productivity in coastal and pelagic regions across the globe. Biogeosciences 8, 489–503. doi:10.5194/bg-8-489-2011.

Saba, V.S., Friedrichs, M.A.M., Carr, M.E., Antoine, D., Armstrong, R.A., Asanuma, I., Aumont, O., Bates, N.R., Behrenfeld, M.J., Bennington, V., Bopp, L., Bruggeman, J., Buitenhuis, E.T., Church, M.J., Ciotti, A.M., Doney, S.C., Dowell, M., Dunne, J., Dutkiewicz, S., Gregg, W., Hoepffner, N., Hyde, K.J.W., Ishizaka, J., Kameda, T., Karl, D.M., Lima, I., Lomas, M.W., Marra, J., McKinley, G.A., Mélin, F., Moore, J.K., Morel, A., O'Reilly, J., Salihoglu, B., Scardi, M., Smyth, T.J., Tang, S., Tjiputra, J., Uitz, J., Vichi, M., Waters, K., Westberry, T.K., Yool, A., 2010. Challenges of modeling depth-integrated marine primary productivity over multiple decades: A case study at BATS and HOT. Global Biogeochemical Cycles 24. doi:10.1029/2009GB003655.

Sabine, C., Sutton, A., McCabe, K., Lawrence-Slavas, N., Alin, S., Feely, R., Jenkins, R., Maenner, S., Meinig, S., Thomas, J., van Ooijen, E., Passmore, A., Tilbrook, B., 2020. Evaluation of a new carbon dioxide system for autonomous surface vehicles. Journal of Atmospheric and Oceanic Technology 37, 1305–1317. doi:10.1175/JTECH-D-20-0010.1.

Salinger, M.J., Renwick, J., Behrens, E., Mullan, A.B., Diamond, H.J., Sirguey, P., Smith, R.O., Trought, M.C., Alexander, L., Cullen, N.J., 2019. The unprecedented coupled ocean-atmosphere summer heatwave in the New Zealand region 2017/18: drivers, mechanisms and impacts. Environmental Research Letters 14, 044023. doi:10.1088/1748-9326.

Salisbury, J.E., Jönsson, B.F., 2018. Rapid warming and salinity changes in the Gulf of Maine alter surface ocean carbonate parameters and hide ocean acidification. Biogeochemistry 141, 401–418. doi:10.1007/s10533-018-0505-3.

Sarmiento, J.L., Gruber, N., 2006. Ocean Biogeochemical Dynamics. Princeton University Press, Princeton, Woodstock.

Sasse, T.P., McNeil, B.I., Abramowitz, G., 2013. A novel method for diagnosing seasonal to inter-annual surface ocean carbon dynamics from bottle data using neural networks. Biogeosciences 10, 4319–4340. doi:10.5194/bg-10-4319-2013.

Sathyendranath, S., Bracher, A., Brockmann, C., Platt, T., Ramon, D., Regner, P., 2017a. Colour and Light in the Ocean (CLEO) 2016: A Scientific Roadmap from the Workshop Organised by ESA and PML. Held at ESRIN, Frascati, Italy on 6 - 8 September, 2016. Technical Report. Workshop Report of the Colour and Light in the Ocean (CLEO) 2016 Workshop, ESA-ESRIN, Frascati, Rome.

Sathyendranath, S., Brewin, R.J.W., Brockmann, C., Brotas, V., Calton, B., Chuprin, A., Cipollini, P., Couto, A.B., Dingle, J., Doerffer, R., Donlon, C., Dowell, M., Farman, A., Grant, M., Groom, S., Horseman, A., Jackson, T., Krasemann, H., Lavender, S., Martinez-Vicente, V., Mazeran, C., Mélin, F., Moore, T.S., Müller, D., Regner, P., Roy, S., Steele, C.J., Steinmetz, F., Swinton, J., Taberner, M., Thompson, A., Valente, A., Zühlke, M., Brando, V.E., Feng, H., Feldman, G., Franz, B.A., Frouin, R., Gould, R.W., Hooker, S.B., Kahru, M., Kratzer, S., Mitchell, B.G., Muller-Karger, F.E., Sosik, H.M., Voss, K., Werdell, J., Platt, T., 2019a. An ocean-colour time series for use in climate studies: The experience of the Ocean-Colour Climate Change Initiative (OC-CCI). Sensors 19, 4285. doi:10.3390/s19194285.

Sathyendranath, S., Brewin, R.J.W., Jackson, T., Mélin, F., Platt, T., 2017b. Ocean-colour Products for Climate-Change Studies: What are their ideal characteristics? Remote Sensing of Environment 203, 125–138. doi:10.1016/j.rse.2017.04.017.

Sathyendranath, S., Platt, T., 1989. Computation of aquatic primary production: extended formalism to include effect of angular and spectral distribution of light. Limnology and Oceanography 34, 188–198.

Sathyendranath, S., Platt, T., 2007. Spectral effects in bio-optical control on the ocean system. Oceanologia 49, 5–39.

Sathyendranath, S., Platt, T., Brewin, R.J.W., Jackson, T., 2019b. Primary production distribution, in: Cochran, J.K., Bokuniewicz, J.H., Yager, L.P. (Eds.), Encyclopedia of Ocean Sciences, 3rd Edition. Elsevier. volume 1, pp. 635–640.

Sathyendranath, S., Platt, T., Kovač, Ž., Dingle, J., Jackson, T., Brewin, R.J.W., Franks, P., Marañón, E., Kulk, G., Bouman, H., 2020. Reconciling models of primary production and photoacclimation. Applied Optics 59, C100–C114. doi:10.1364/AO.386252.

Sathyendranath, S., Stuart, V., Nair, A., Oka, K., Nakane, T., Bouman, H., Forget, H.M., Maass, H., Platt, T., 2009. Carbon-to-chlorophyll ratio and growth rate of phytoplankton in the sea. Marine Ecological Progress Series 383, 73–84. doi:10.3354/meps07998.

Sauzède, R., Claustre, H., Uitz, J., Jamet, C., Dall'Olmo, G., D'Ortenzio, F., Gentili, B., Schmechtig, C., 2016. A neural network-based method for merging ocean color and Argo data to extend surface bio-optical properties to depth: Retrieval of the particulate backscattering coefficient. Journal of Geophysical Research - Oceans 121, 2552–2571.

Sauzéde, R., Johnson, J.E., Claustre, H., Camps-Valls, G., Ruescas, A.B., 2020. Estimation of oceanic particulate organic carbon with machine learning. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences 2, 949–956. doi:10.5194/isprs-annals-V-2-2020-949-2020.

Schiebel, R., 2002. Planktic foraminiferal sedimentation and the marine calcite budget. Global Biogeochemical Cycles 16, 1065. doi:10.1029/2001GB001459.

Schlosser, J.S., Braun, R.A., Bradley, T., Dadashazar, H., MacDonald, A.B., Aldhaif, A.A., Aghdam, M.A., Mardi, A.H., Xian, P., Sorooshian, A., 2017. Analysis of aerosol composition data for western United States wildfires between 2005 and 2015: Dust emissions, chloride depletion, and most enhanced aerosol constituents. Journal of Geophysical Research: Atmospheres 122, 8951–8966. doi:10.1002/2017JD026547.

Schroeder, S.B., Dupont, C., Boyer, L., Juanes, F., Costa, M., 2019. Passive remote sensing technology for mapping bull kelp (*nereocystis luetkeana*): A review of techniques and regional case study. Global Ecology and Conservation 19, e00683. doi:10.1016/j.gecco.2019.e00683.

Schuback, N., Tortell, P.D., Berman-Frank, I., Campbell, D.A., Ciotti, A., Courtecuisse, E., Erickson, Z.K., Fujiki, T., Halsey, K., Hickman, A.E., Huot, Y., Gorbunov, M.Y., Hughes, D.J., Kolber, Z.S., Moore, C.M., Oxborough, K., Prášil, O., Robinson, C.M., Ryan-Keogh, T.J., Silsbe, G., Simis, S., Suggett, D.J., Thomalla, S., Varkey, D.R., 2021. Single-turnover variable chlorophyll fluorescence as a tool for assessing phytoplankton photosynthesis and primary productivity: Opportunities, caveats and recommendations. Frontiers in Marine Science 8, 690607. doi:10.3389/fmars.2021.690607.

Schueler, C., Holmes, A., 2016. SeaHawk CubeSat system engineering, in: Ardanuy, P.E., Puschell, J.J. (Eds.), Remote Sensing System Engineering VI, International Society for Optics and Photonics. SPIE. pp. 38–43. doi:10.1117/12.2242298.

Shang, S., Li, L., Sun, F., Wu, J., Hu, C., Chen, D., Ning, X., Qiu, Y., Zhang, C., Shang, S., 2008. Changes of temperature and bio-optical properties in the South China Sea in response to Typhoon Lingling, 2001. Geophysical Research Letters 35, L10602. doi:10.1029/2008GL033502.

Sharp, J.H., 1973. Size classes of organic carbon in seawater. Limnology and Oceanography 18, 441–447. doi:10.4319/lo.1973.18.3.0441.

Sheldon, R.W., 1972. Size separation of marine seston by membrane and glass-fiber filters. Limnology and Oceanography 17, 494–498. doi:10.4319/lo.1972.17.3.0494.

Sheldon, R.W., Prakash, A., Sutcliffe Jr, W.H., 1972. The size distribution of particles in the ocean. Limnology and Oceanography 17, 327–340. doi:10.4319/lo.1972.17.3.0327.

Shutler, J.D., 2020. Offsetting is a dangerous smokescreen for inaction. Frontiers in Ecology and the Environment 18, 486–486. doi:10.1002/fee.2262.

Shutler, J.D., Grant, M.G., Miller, P.I., Rushton, E., Anderson, K., 2010. Coccolithophore bloom detection in the north east Atlantic using SeaWiFS: Algorithm description, application and sensitivity analysis. Remote Sensing of Environment 114, 1008–1016. doi:10.1016/j.rse.2009.12.024.

Shutler, J.D., Gruber, N., Findlay, H.S., Land, P.E., Holding, T., Sims, R., Green, H., Piolle, J.F., Chapron, B., Sathyendranath, S., Rousseaux, C., Donlon, C., Cooley, S., Turner, J., Valauri-Orton, A., Lowder, K., Widdicombe, S., Newton, J., Sabia, R., Rio, M.H., Gaultier, L., Submitted. The increasing importance of satellite observations to assess the ocean carbon sink and ocean acidification. Earth-Science Reviews .

Shutler, J.D., Land, P.E., Piolle, J.F., Woolf, D.K., Goddijn-Murphy, L., Paul, F., Girard-Ardhuin, F., Chapron, B., Donlon, C.J., 2016. FluxEngine: A flexible processing system for calculating atmosphere-ocean carbon dioxide gas fluxes and climatologies. Journal of Atmospheric and Oceanic Technology 33, 741–756. doi:10.1175/JTECH-D-14-00204.1.

Shutler, J.D., Wanninkhof, R., Nightingale, P.D., Woolf, D.K., Bakker, D.C.E., Watson, A., Ashton, I., Holding, T., Chapron, B., Quilfen, Y., Fairall, C., Schuster, U., Nakajima, M., Donlon, C.J., 2019. Satellites will address critical science priorities for quantifying ocean carbon. Frontiers in Ecology and the Environment 18, 27–35. doi:10.1002/fee.2129.

Skákala, J., Ford, D., Brewin, R.J.W., McEwan, R., Kay, S., Taylor, B., de Mora, L., Ciavatta, S., 2018. The assimilation of phytoplankton functional types for operational forecasting in the northwest European shelf. Journal of Geophysical Research: Oceans 123, 5230–5247.

Slade, W.H., Boss, E., Dall'Olmo, G., Langner, M.R., Loftin, J., Behrenfeld, M.J., Roesler, C., Westberry, T.K., 2010. Underway and moored methods for improving accuracy in measurement of spectral particulate absorption and attenuation. Journal of Atmospheric and Oceanic Technology 27, 1733–1746. doi:10.1175/2010JTECHO755.1.

Smale, D.A., Wernberg, T., Oliver, E.C., Thomsen, M., Harvey, B.P., Straub, S.C., Burrows, M.T., Alexander, L.V., Benthuysen, J.A., Donat, M.G., Feng, M., Hobday, A.J., Holbrook, N.J., Perkins-Kirkpatrick, S.E., Scannell, H.A., Gupta, A.S., Payne, B.L., Moore, P.J., 2019. Marine heatwaves threaten global biodiversity and the provision of ecosystem services. Nature Climate Change 9, 306–312. doi:10.1038/s41558-019-0412-1.

Smetacek, V., Zingone, A., 2013. Green and golden seaweed tides on the rise. Nature 504, 84–88. doi:10.1038/nature12860.

Smith, R.C., Eppley, R.W., Baker, K.S., 1982. Correlation of primary production as measured aboard ship in southern california coastal waters and as estimated from satellite chlorophyll images. Marine Biology 66, 281–288. doi:10.1007/BF00397033.

Smyth, T.J., Moore, G.F., Groom, S.B., Land, P.E., Tyrrell, T., 2002. Optical modeling and measurements of a coccolithophore bloom. Applied Optics 41, 7679–7688. doi:10.1364/AO.41.007679.

Song, H., Edwards, C.A., Moore, A.M., Fiechter, J., 2016. Data assimilation in a coupled physical-biogeochemical model of the California Current System using an incremental lognormal 4-dimensional variational approach: part 2–Joint physical and biological data assimilation twin experiments. Ocean Modelling, 106, 146–158.

Stedmon, C.A., Amon, R., Bauch, D., Bracher, A., Gonçalves-Araujo, R., Hoppmann, M., Krishfield, R., Laney, S., Rabe, B., Reader, H., Granskrog, M., 2021. Insights into water mass circulation and rigins in the central Arctic Ocean from in-situ dissolved organic matter fluorescence. Journal of Geophysical Research: Oceans 126, e2021JC017407. doi:10.1029/2021JC017407.

Stemmann, L., Boss, E., 2012. Plankton and particle size and packaging: From determining optical properties to driving the biological pump. Annual Review of Marine Science 4, 263–290. doi:10.1146/annurev-marine-120710-100853.

Stock, A., Subramaniam, A., Van Dijken, G.L., Wedding, L.M., Arrigo, K.R., Mills, M.M., Cameron, M.A., Micheli, F., 2020. Comparison of cloud-filling algorithms for marine satellite data. remote sensing. Remote Sensing 12, 3313. doi:10.3390/rs12203313.

Stramska, M., 2009. Particulate organic carbon in the global ocean derived from SeaWiFS ocean color. Deep Sea Research Part I: Oceanographic Research Papers 56, 1459–1470. doi:10.1016/j.dsr.2009.04.009.

Stramska, M., Cieszyńska, A., 2015. Ocean colour estimates of particulate organic carbon reservoirs in the global ocean – revisited. International Journal of Remote Sensing 36, 3675–3700. doi:10.1080/01431161.2015.1049380.

Stramski, D., 1990. Artifacts in measuring absorption spectra of phytoplankton collected on a filter. Limnology and Oceanography 35, 1804–1809. doi:10.4319/lo.1990.35.8.1804.

Stramski, D., Boss, E., Bogucki, D., Voss, K.J., 2004. The role of seawater constituents in light backscattering in the ocean. Progress in Oceanography 61, 27–56. URL: https://doi.org/10.1016/j.pocean.2004.07.001, doi:10.1016/j.pocean.2004.07.001.

Stramski, D., Joshi, I., Reynolds, R.A., 2022. Ocean color algorithms to estimate the concentration of particulate organic carbon in surface waters of the global ocean in support of a long-term data record from multiple satellite missions. Remote Sensing of Environment 269, 112776. doi:10.1016/j.rse.2021.112776.

Stramski, D., Reynolds, R.A., Babin, M., Kaczmarek, S., Lewis, M.R., Röttgers, R., Sciandra, A., Stramska, M., Twardowski, M.S., Franz, B.A., Claustre, H., 2008. Relationships between the surface concentration of particulate organic carbon and optical properties in the eastern South Pacific and eastern Atlantic Oceans. Biogeosciences 5, 171–201. doi:10.5194/bg-5-171-2008.

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, 239–242. doi:10.1126/science.285.5425.239.

Strömberg, K.H.P., Smyth, T.J., Allen, J.I., Pitois, S., O'Brien, T.D., 2009. Estimation of global zooplankton biomass from satellite ocean colour. Journal of Marine Systems 78, 18–27. doi:10.1016/j.jmarsys.2009.02.004.

Sun, C., Li, J., Liu, Y., Liu, Y., Liu, R., 2021. Plant species classification in salt marshes using phenological parameters derived from Sentinel-2 pixel-differential time-series. Remote Sensing of Environment 256, 112320. doi:10.1016/j.rse.2021.112320.

Sutton, A.J., Feely, R.A., Maenner-Jones, S., Musielwicz, S., Osborne, J., Dietrich, C., Monacci, N., Cross, J., Bott, R., Kozyr, A., Andersson, A.J., Bates, N.R., Cai, W.J., Cronin, M.F., De Carlo, E.H., Hales, B., Howden, S.D., Lee, C.M., Manzello, D.P., McPhaden, M.J., Meléndez, M., Mickett, J.B., Newton, J.A., Noakes, S.E., Noh, J.H., Olafsdottir, S.R., Salisbury, J.E., Send, U., Trull, T.W., Vandemark, D.C., Weller, R.A., 2019. Autonomous seawater pco$_2$ and ph time series from 40 surface buoys and the emergence of anthropogenic trends. Earth System Science Data 11, 421–439. doi:10.5194/essd-11-421-2019.

Sutton, A.J., Williams, N.L., Tilbrook, B., 2021. Constraining Southern Ocean CO_2 flux uncertainty using uncrewed surface vehicle observations. Geophysical Research Letters 48, e2020GL091748. doi:10.1029/2020GL091748.

Swan, C.M., Nelson, N.B., Siegel, D.A., Kostadinov, T.S., 2013. The effect of surface irradiance on the absorption spectrum of chromophoric dissolved organic matter in the global ocean. Deep Sea Research Part I: Oceanographic Research Papers 63, 52–64. doi:10.1016/J.DSR.2012.01.008.

Taboada, F.G., Stock, C.A., Griffies, S.M., Dunne, J., John, J.G., Small, R.J., Tsujino, H., 2019. Surface winds from atmospheric reanalysis lead to contrasting oceanic forcing and coastal upwelling patterns. Ocean Modelling 113, 79–111. doi:10.1016/j.ocemod.2018.11.003.

Taguchi, S., Laws, E.A., 1988. On the microparticles which pass through glass fiber filter type GF/F in coastal and open waters. Journal of Plankton Research 10, 999–1008. doi:10.1093/plankt/10.5.999.

Takahashi, T., Sutherland, S.C., Wanninkhof, R., Sweeney, C., Feely, R.A., Chipman, D.W., Hales, B., Friederich, G., Chavez, F., Sabine, C., Watson, A., Bakker, D.C.E., Schuster, U., Metzl, N., Yoshikawa-Inoue, H., Ishii, M., Midorikawa, T., Nojiri, Y., Körtzinger, A., Steinhoffm, T., Hoppema, M., Olafsson, J., Arnarson, T.S., Tilbrook, B., Johannessen, T., Olsen, A., Bellerby, R., Wong, C.S., Delille, B., Bates, N.R., de Baar, H.J.W., 2009. Climatological mean and decadal change in surface ocean pCO_2, and net sea–air CO_2 flux over the global oceans. Deep Sea Research Part II: Topical Studies in Oceanography 56, 554–577. doi:10.1016/j.dsr2.2008.12.009.

Tan, H., Cai, R., 2018. What caused the record-breaking warming in East China Seas during August 2016? Atmospheric Science Letters 19, e853. doi:10.1002/asl.853.

Tang, W., Fore, A., Yueh, S., Lee, T., Hayashi, A., Sanchez-Franks, A., Martinez, J., King, B., Baranowski, D., 2017. Validating SMAP SSS with in-situ measurements. Remote Sensing of Environment 200, 326–340. doi:10.1016/j.rse.2017.08.021.

Tang, W., Llort, J., Weis, J., Perron, M.M.G., Basart, S., Li, Z., Sathyendranath, S., Jackson, T., Sanz R., E., Proemse, B.C., Bowie, A.R., Schallenberg, C., Strutton, P.G., Matear, R., Cassar, N., 2021. Widespread phytoplankton blooms triggered by 2019–2020 Australian wildfires. Nature 597, 370–375. doi:10.1038/s41586-021-03805-8.

Tehrani, N.C., D'Sa, E.J., Osburn, C.L., Bianchi, T.S., Schaeffer, B.A., 2013. Chromophoric Dissolved Organic Matter and Dissolved Organic Carbon from Sea-Viewing Wide Field-of-view Sensor (SeaWiFS), Moderate Resolution Imaging Spectroradiometer (MODIS) and MERIS Sensors: Case study for the northern Gulf of Mexico. Remote Sensing 5, 1439–1464. doi:10.3390/rs5031439.

Terzić, E., Lazzari, P., Organelli, E., Solidoro, C., Salon, S., D'Ortenzio, F., Conan, P., 2019. Merging bio-optical data from Biogeochemical-Argo floats and models in marine biogeochemistry. Biogeosciences 16, 2527–2542. doi:10.5194/bg-16-2527-2019.

Terzić, E., Miró, A., Organelli, E., Kowalczuk, P., D'Ortenzio, F., Lazzari, P., 2021. Radiative transfer modeling with Biogeochemical-Argo float data in the Mediterranean Sea. Journal of Geophysical Reserach: Oceans 126, e2021JC017690. doi:10.1029/2021JC017690.

Tilstone, G.H., Taylor, B.H., Blondeau-Patissier, D., Powell, T., Groom, S.B., Rees, A.P., Lucas, M.I., 2015. Comparison of new and primary production models using SeaWiFS data in contrasting hydrographic zones of the northern North Atlantic. Remote Sensing of Environment 156, 473–489. doi:10.1016/j.rse.2014.10.013.

Traganos, D., Reinartz, P., 2018. Interannual change detection of mediterranean seagrasses using RapidEye image time series. Frontiers in Plant Science 9, 96. doi:10.3389/fpls.2018.00096.

Turnewitsch, R., Springer, B.M., Kiriakoulakis, K., Vilas, J.C., Arístegui, J., Wolff, G., Peine, F., Werk, S., Graf, G., Waniek, J.J., 2007. Determination of particulate organic carbon (POC) in seawater: The relative methodological importance of artificial gains and losses in two glass-fiber-filter-based techniques. Marine Chemistry 105, 208–228. doi:10.1016/j.marchem.2007.01.017.

Tzortziou, M., Osburn, C., Neale, P., 2007. Photobleaching of dissolved organic material from a tidal marsh-estuarine system of the Chesapeake Bay. Photochemistry and Photobiology 83, 782–792. doi:10.1111/j.1751-1097.2007.00142.x.

Tzortziou, M., Parker, O., Lamb, B., Herman, J.R., Lamsal, L., Stauffer, R., Abuhassan, N., 2018. Atmospheric trace gas (no_2 and o_3) variability in South Korean coastal waters, and implications for remote sensing of coastal ocean color dynamics. Remote Sensing 10, 1587. doi:10.3390/rs10101587.

Uematsu, M., Toratani, M., Kajino, M., Narita, Y., Senga, Y., Kimoto, T., 2004. Enhancement of primary productivity in the western North Pacific caused by the eruption of the Miyake-jima volcano. Geophysical Research Letters 31, L06106. doi:10.1029/2003GL01879.

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, GB3016. doi:10.1029/2009GB003680.

Uitz, J., Stramski, D., Gentili, B., D'Ortenzio, F., Claustre, H., 2012. Estimates of phytoplankton class-specific and total primary production in the Mediterranean Sea from satellite ocean color observations. Global Biogeochemical Cycles 26, GB2024. doi:1029/2011GB004055.

Vanhellemont, Q., 2019. Daily metre-scale mapping of water turbidity using CubeSat imagery. Optics Express 27, A1372–A1399. doi:10.1364/OE.27.0A1372.

Verdy, A., Mazloff, M.R., 2017. A data assimilating model for estimating Southern Ocean biogeochemistry. Journal of Geophysical Research – Oceans 122, 6968–6988. doi:10.1002/2016JC012650.

Verezemskaya, P., Tilinina, N., Gulev, S., Renfrew, I.A., Lazzara, M., 2017.

Southern Ocean mesocyclones and polar lows from manually tracked satellite mosaics. Geophysical Research Letters 44, 7985–7993. doi:10.1002/2017GL074053.

Vodacek, A., 1989. Synchronous fluorescence spectroscopy of dissolved organic matter in surface waters: Application to airborne remote sensing. Remote Sensing of Environment 30, 239–247. doi:10.1016/0034-4257(89)90065-5.

Vodacek, A., Blough, N.V., DeGrandpre, M.D., Peltzer, E.T., Nelson, R.K., 1997. Seasonal variations of CDOM and DOC in the Middle Atlantic Bight: Terrestrial inputs and photooxydation. Limnology and Oceanography 42, 674–686.

Vogt, L., Burger, F.A., Griffies, S.M., Frölicher, T.L., 2022. Local drivers of marine heatwaves: A global analysis with an Earth System Model. Frontiers in Climate 4. URL: https://www.frontiersin.org/article/10.3389/fclim.2022.847995, doi:10.3389/fclim.2022.847995.

Volk, T., Hoffert, M.I., 1985. Ocean carbon pumps: Analysis of relative strengths and efficiencies in ocean-driven atmospheric CO_2 changes, in: Sundquist, E.T., Broecker, W.S. (Eds.), Geophysical Monograph Series, American Geophysical Union, Washington, DC. pp. 99–110.

Von Appen, W.J., Waite, A., Bergmann, M., Bienhold, C., Boebel, O., Bracher, A., Cisewski, B., Hagemann, J., Hoppema, M., Iversen, M., Konrad, C., Krumpen, T., Lochthofen, N., Metfies, K., Niehoff, B., Nöthig, E.M., Purser, A., Salter, I., Schaber, M., Scholz, D., Soltwedel, T., Torres-Valdes, S., Wekerle, C., Wenzhöfer, F., Wietz, M., Boetius, A., 2021. Sea ice derived meltwater stratification delays export and favors pelagic secondary production: results from continuous observations. Nature Communications 12, 7309. doi:10.1038/s41467-021-26943-z.

Voss, K.J., Balch, W.M., Kilpatrick, K.A., 1998. Scattering and attenuation properties of *emiliania huxleyi* cells and their detached coccoliths. Limnology and Oceanography 43, 870–876. doi:10.4319/lo.1998.43.5.0870.

Wang, M., Hu, C., 2021. Satellite remote sensing of pelagic *sargassum macroal-*

gae: The power of high resolution and deep learning. Remote Sensing of Environment 264, 112631. doi:10.1016/j.rse.2021.112631.

Wang, M., Hu, C., Barnes, B.B., Mitchum, G., Lapointe, B., Montoya, J.P., 2019. The great Atlantic *sargassum* belt. Science 365, 83–87. doi:10.1126/science.aaw7912.

Wang, M., Hu, C., Cannizzaro, J., English, D., Han, X., Naar, D., Lapointe, B., Brewton, R., Hernandez, F., 2018. Remote sensing of *sargassum* biomass, nutrients, and pigments. Geophysical Research Letters 45, 12,359–12,367. doi:10.1029/2018GL078858.

Wang, Y., Chen, H.H., Tang, R., He, D., Lee, Z., Xue, H., Wells, M., Boss, E., Chai, F., 2022. Australian fire nourishes ocean phytoplankton bloom. Science of the Total Environment 807, 150775. doi:10.1016/j.scitotenv.2021.150775.

Wanninkhof, R., 2014. Relationship between wind speed and gas exchange over the ocean revisited. Limnology and Oceanography-Methods 12, 351–362. doi:10.4319/lom.2014.12.351.

Warwick-Champion, E., Davies, K.P., Barber, P., Hardy, N., Bruce, E., 2022. Characterising the aboveground carbon content of saltmarsh in Jervis Bay, NSW, using ArborCam and PlanetScope. Remote Sensing, 14, 1782. doi:10.3390/rs14081782.

Watson, A.J., Schuster, U., Shutler, J.D., Holding, T., Ashton, I.G.C., Landschützer, P., Woolf, D.K., Goddijn-Murphy, L., 2020. Revised estimates of ocean-atmosphere CO_2 flux are consistent with ocean carbon inventory. Nature Communications 11, 4422. doi:10.1038/s41467-020-18203-3.

Watts, J., Bell, T.G., Anderson, K., Butterworth, B.J., Miller, S., Else, B., Shutler, J., 2022. Impact of sea ice on air-sea co_2 exchange - a critical review of polar eddy covariance studies. Progress in Oceanography 201, 102741. doi:10.1016/j.pocean.2022.102741.

Weinbauer, M.G., Guinot, B., Migon, C., Malfatti, F., Mari, X., 2017. Skyfall–neglected roles of volcano ash and black carbon rich aerosols for microbial plankton in the ocean. Journal of Plankton Research 39, 187–198. doi:10.

1093/plankt/fbw100.

Werdell, P.J., Behrenfeld, M.J., Bontempi, P.S., Boss, E., Cairns, B., Davis, G.T., Franz, B.A., Gliese, U.B., Gorman, E.T., Hasekamp, O., Knobelspiesse1, K.D., Mannino, A., Martins, J.V., McClain, C.R., Meister, G., Remer, L.A., 2019. The Plankton, Aerosol, Cloud, ocean Ecosystem mission: status, science, advances. Bulletin of the American Meteorological Society 100, 1775–1794. doi:10.1175/BAMS-D-18-0056.1.

Wernberg, T., Bennett, S., Babcock, R.C., de Bettignies, T., Cure, K., Depczynski, M., Dufois, F., Fromont, J., Fulton, C.J., Hovey, R.K., Harvey, E.S., Holmes, T.H., Kendrick, G.A., Radford, B., Santana-Garcon, J., Saunders, B.J., Smale, D.A., Thomsen, M.S., Tuckett, C.A., Tuya, F., Vanderklift, M.A., Wilson, S., 2016. Climate-driven regime shift of a temperate marine ecosystem. Science 353, 169–172. doi:10.1126/science.aad8745.

Westberry, T.K., Boss, E., Lee, Z., 2013. Influence of Raman scattering on ocean color inversion models. Applied Optics 52, 5552–5561. doi:10.1364/AO.52.005552.

White, A.E., Letelier, R.M., Whitmire, A.L., Barone, B., Bidigare, R.R., Church, M.J., Karl, D.M., 2015. Phenology of particle size distributions and primary productivity in the North Pacific subtropical gyre (station ALOHA). Journal of Geophysical Research: Oceans 120, 7381–7399. doi:10.1002/2015JC010897.

Wicaksono, P., Lazuardi, W., 2018. Assessment of PlanetScope images for benthic habitat and seagrass species mapping in a complex optically shallow water environment. International Journal of Remote Sensing 39, 5739–5765. doi:10.1080/01431161.2018.1506951.

Wilhelmus, M.M., Nawroth, J., Rallabandi, B., Dabiri, J.O., 2019. Effect of swarm configuration onfluid transport during vertical collective motion. Bioinspiration and Biomimetics 15, 015002. doi:10.1088/1748-3190/ab435b.

Williams, N.L., Feely, R.A., Sabine, C.L., Dickson, A.G., Swift, J.H., Talley, L.D., Russell, J.L., 2015. Quantifying anthropogenic carbon inventory changes in the Pacific sector of the Southern Ocean. Marine Chemistry 174, 147–160. doi:10.1016/j.marchem.2015.06.015.

Williams, N.L., Juranek, L.W., Feely, R.A., Johnson, K.S., Sarmiento, J.L., Talley, L.D., Dickson, A.G., Gray, A.R., Wanninkhof, R., Russell, J.L., Riser, S.C., 2017. Calculating surface ocean pco_2 from biogeochemical Argo floats equipped with pH: An uncertainty analysis. Global Biogeochemical Cycles 31, 591–604. doi:10.1002/2016GB005541.

Wilson, S.T., Hawco, N.J., Armbrust, E.V., Barone, B., Björkman, K.M., Boysen, A.K., Burgos, M., Burrell, T.J., Casey, J.R., DeLong, E.F., Dugenne, M., Dutkiewicz, S., Dyhrman, S.T., Ferrón, S., Follows, M.J., Foreman, R.K., Funkey, C.P., Harke, M.J., Henke, B.A., Hill, C.N., Hynes, A.M., Ingalls, A.E., Jahn, O., Kelly, R.L., Knapp, A.N., Letelier, R.M., Ribalet, F., Shimabukuro, E.M., Tabata, R.K.S., A., T.K.K., White, A.E., Zehr, J.P., John, S., Karl, D.M., 2019. Kīlauea lava fuels phytoplankton bloom in the north pacific ocean. Science 365, 1040–1044. doi:10.1126/science.aax4767.

Witze, A., 2022. Why the Tongan eruption will go down in the history of volcanology. Nature 602, 376–378. doi:10.1038/d41586-022-00394-y.

Wolanin, A., Rozanov, V., Dinter, T., Bracher, A., 2015. Detecting CDOM fluorescence using high spectrally resolved satellite data: a model study. Springer Earth System Sciences, Springer, Heidelberg, Germany. pp. 109–121. doi:10.1007/978-3-319-13865-7_13.

Woolf, D.K., Land, P.E., Shutler, J.D., Goddijn-Murphy, L.M., Donlon, C.J., 2016. On the calculation of air-sea fluxes of co_2 in the presence of temperature and salinity gradients. Journal of Geophysical Research: Oceans 121, 1229–1248. doi:10.1002/2015JC011427.

Woolf, D.K., Shutler, J.D., Goddijn-Murphy, L., Watson, A.J., Chapron, B., Nightingale, P.D., Donlon, C.J., Piskozub, J., Yelland, M.J., Ashton, I., Holding, T., Schuster, U., Girard-Ardhuin, F., Grouazel, A., Piolle, J.F., Warren, M., Wrobel-Niedzwiecka, I., Land, P., Torres, R., Prytherch, J., Moat, B., Hanafin, J., Ardhuin, F., Paul, F., 2019. Key uncertainties in the recent air-sea flux of CO_2. Global Biogeochemical Cycles, 33, 1563–1548. doi:10.1029/2018GB006041.

Woźniak, S.B., Stramski, D., Stramska, M., Reynolds, R.A., Wright, V.M., Miksic, E.Y., Cichocka, M., Cieplak, A.M., 2010. Optical variability of seawater in relation to particle concentration, composition, and size distribution in the nearshore marine environment at Imperial Beach, California. Journal of Geophysical Research: Oceans 115, C08027. doi:10.1029/2009jc005554.

Wünsch, U.J., Murphy, K.R., Stedmon, C.A., 2015. Fluorescence quantum yields of natural organic matter and organic compounds: Implications for the fluorescence-based interpretation of organic matter composition. Frontier in Marine Science 2, 98. doi:10.3389/FMARS.2015.00098.

Xing, X., Boss, E., Zhang, J., Chai, F., 2020. Evaluation of ocean color remote sensing algorithms for diffuse attenuation coefficients and optical depths with data collected on BGC-argo floats. Remote Sensing 22, 2367. doi:10.3390/rs12152367.

Yang, B., Emerson, S.R., Peña, M.A., 2018. The effect of the 2013–2016 high temperature anomaly in the subarctic Northeast Pacific (the "Blob") on net community production. Biogeosciences 15, 6747–6759. doi:10.5194/bg-15-6747-2018.

Yang, C., Cagnazzo, C., Artale, V., Buongiorno Nardelli, B., Buontempo, C., Busatto, J., Caporaso, L., Cesarini, C., Cionni, I., Coll, J., Crezee, B., Cristofanelli, P., de Toma, V., Hesham Essa, Y., Eyring, V., Fierli, F., Grant, L., Hassler, B., Hirschi, M., Huybrechts, P., Le Merle, E., Elisa Leonelli, F., Lin, X., Madonna, F., Mason, E., Massonnet, F., Marcos, M., Marullo, S., Müller, B., Obregon, A., Organelli, E., Palacz, A., Pascual, A., Pisano, A., Putero, D., Rana, A., Sánchez-Román, A., Seneviratne, S.I., Serva, F., Storto, A., Thiery, W., Throne, P., Van Tricht, L., Verhaegen, Y., Volpe, G., Santoleri, R., 2022a. Independent quality assessment of essential climate variables: Lessons learnt from the Copernicus Climate Change Service. Bulletin of the American Meteorological Society doi:10.1175/BAMS-D-21-0109.1.

Yang, M., Bell, T.G., Bidlot, J.R., Blomquist, B.W., Butterworth, B.J., Dong, Y., Fairall, C.W., Landwehr, S., Marandino, C.A., Miller, S.D., Saltzman, E.S., Zavarsky, A., 2022b. Global synthesis of air-sea CO_2 transfer velocity estimates from ship-based eddy covariance measurements. Frontiers in Marine Science 9., 826421. doi:10.3389/fmars.2022.826421.

Yang, X., Zhu, Z., Qiu, S., Kroeger, K.D., Zhu, Z., Covington, S., 2022c. Detection and characterization of coastal tidal wetland change in the northeastern US using Landsat time series. Remote Sensing of Environment 276, 113047. doi:10.1016/j.rse.2022.113047.

Yoon, J.E., Kim, K., Macdonald, A.M., Park, K.T., Kim, H.C., Yoo, K.C., Yoon, H.I., Yang, E.J., Jung, J., Lim, J.H., Kim, J.H., Lee, J., Choi, T.J., Song, J.M., Kim, I.N., 2017. Spatial and temporal variabilities of spring asian dust events and their impacts on chlorophyll-a concentrations in the western North Pacific Ocean. Geophysical Research Letters 44, 1474–1482. doi:10.1002/2016gl072124.

Zang, Z., Xue, Z.G., Xu, K., Bentley, S.J., Chen, Q., D'Sa, E.J., Zhang, L., Ou, Y., 2020. The role of sediment-induced light attenuation on primary production during hurricane Gustav (2008) 17, 5043–5055. doi:10.5194/bg-17-5043-2020.

Zeebe, R.E., 2012. History of seawater carbonate chemistry, atmospheric CO_2, and ocean acidification. Annual Review of Earth and Planetary Sciences 40, 141–165. doi:10.1146/annurev-earth-042711-105521.

Zeebe, R.E., Wolf-Gladrow, D., 2001. CO_2 in seawater: equilibrium, kinetics, isotopes. 65, Gulf Professional Publishing.

Zhai, L., Platt, T., Tang, C., Sathyendranath, S., Fuentes-Yaco, C., Devred, E., Wu, Y., 2010. Seasonal and geographic variations in phytoplankton losses from the mixed layer on the Northwest Atlantic Shelf. Journal of Marine Systems 80, 36–46. doi:10.1016/j.jmarsys.2009.09.005.

Zhu, X., Miller, W.L., Fichot, C.G., 2020. Simple method to determine the apparent quantum yield matrix of CDOM photobleaching in natural waters. Environmental Science and Technology 54, 14096–14106. doi:10.1021/acs.est.0c03605.

Zscheischler, J., Westra, S., Van Den Hurk, B.J., Seneviratne, S.I., Ward, P.J., Pitman, A., AghaKouchak, A., Bresch, D.N., Leonard, M., Wahl, T., Zhang, X., 2018. Future climate risk from compound events. Nature Climate Change 8, 469–477. doi:10.1038/s41558-018-0156-3.

Table 1: Overview of the themes of the paper and guide to navigate the manuscript.

Theme	Acronym	Short description	Flux/Stock	Global Size/Rate	Section	Table
Primary Production	PP	Conversion of inorganic carbon (DIC) to organic carbon (POC) through the process of photosynthesis.	Flux	~50 Gt C yr^{-1}	3.1	2
Particulate Organic Carbon	POC	Organic carbon that is above >0.2 μm in diameter.	Stock	2.3↔4.0 Gt C	3.2	3
Phytoplankton Carbon	C-phyto	Organic carbon contained in phytoplankton	Stock	0.78↔1.0 Gt C	3.3	4
Dissolved Organic Carbon	DOC	Organic carbon that is < 0.2 μm in diameter.	Stock	~662 Gt C	3.4	5
Inorganic carbon and fluxes at the ocean interface	IC	Consisting of dissolved inorganic carbon (DIC, IC < 0.2 μm in diameter), particulate inorganic carbon (PIC, IC > 0.2 μm in diameter), and air-sea flux of IC between ocean and atmosphere.	Stock (DIC,PIC), Flux (air-sea IC exchange)	DIC (~38,000 Gt C), PIC (~0.03 Gt C), air-to-sea net flux of anthropogenic CO_2 (~3.0 Gt C y^{-1})	3.5	6
Blue Carbon	BC	Carbon contained in tidal marshes, mangroves, macroalgae and seagrass beds.	Stock	10↔24 Gt C	3.6	7
Extreme Events	EE	Events that occur in the upper or lower end of the range of historical measurements.	–	–	3.7	8
Carbon Budget Closure	CBC	How the stock of carbon in the ocean and elsewhere on the planet is partitioned.	–	~650,000,000 Gt C (on Earth)	3.8	9

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Table 2: Priorities, challenges, gaps and opportunities for satellite estimates of primary production.

Priority	**Challenges**	**Gaps**	**Opportunities**
(1) Parametrisation of satellite algorithms using *in-situ* data	• Accurate representation of the spatial and temporal variability of model parameters. • Continued financial support for *in-situ* observations. • Standard conversion factors and protocols, including those for ancillary measurements. • Satellite primary production is often estimated from an instant snapshot in time, meaning the diurnal variability in parameters and variables must be assumed (modelled).	• Lack of continuous measurements. • Better coordination at international level required.	• Use of novel *in-situ* platforms, use of active fluorescence-based methods and oxygen optode sensors. • Synergy across *in-situ* data sources (multiplatform sensors). • Use of artificial intelligence techniques for mapping model parameters. • Opportunities to exploit geostationary platforms to resolve diurnal variability in light and biomass. • Formulate priorities for funding (long-term time series, novel measurements).
(2) Uncertainty estimation and validation	• Validation of satellite-based primary production estimates is challenging (i.e., lack of independent *in-situ* data, differences in scale between *in-situ* and model data, differences in methods etc.)	• Uncertainty estimates satellite-based products are not readily provided. • Lack of *in-situ* data for validation. • Gaps in our understanding of uncertainty in key input variables and parameters to PP models. • Data gaps in satellite observations, e.g., cloudy pixels, coverage in polar regions.	• Benefit from enhanced computational capacity to run models for uncertainty estimation. • Use of emerging (hyperspectral, geostationary, lidar) sensors. • Continuous validation is crucial, opportunities with autonomous platforms.
(3) Linking surface satellite measurements to vertical distribution	• Resolve vertical structure of primary production, Chl-a, and PAR in satellite-based primary production models.	• High spatial and temporal *in-situ* data • Need for better physical products, such as mixed-layer depth, including uncertainties.	• Improve (basic) understanding of vertical structure. • Benefit from use of novel *in-situ* platforms. • Benefit from future satellite lidar systems.

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Table 2. Priorities, challenges, gaps and opportunities for satellite estimates of primary production. (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(4) Trends	• Difficulty in assessing direction of change in trends of primary production, estimates differ widely. • Deal with noise in non-linear systems (for example, to assess the impact of extreme events).	• Uncertainty estimates satellite-based products are not provided. • Length of satellite record not sufficient for climate change studies.	• Need for consistent and continuous satellite records for climate research. • Assimilation of satellite data into models.
(5) Understanding	• Better understand relationship between primary production, community structure and environment. • Understand feedbacks between physics and biology over a broad range of scales, and the implications for carbon cycling. • Understand the fate of primary production, i.e. secondary and export production. • Better understand the interactions between PP in different components of the Earth System. • Improved quantification of new production and net community production from space.	• Need for higher spatial and temporal resolution products to study diurnal variability. • Include inland and coastal waters. • Gaps in satellite information on data sets relevant to photochemical reactions.	• Unifying the integration of primary production across interfaces, i.e., bringing together primary production on land and in the ocean. • Regional models/algorithms with aim to merge/nest models for larger scale estimates • Meet challenges of the UN Ocean Decade. • Harness novel algorithms and satellites (hyperspectral, lidar and geostationary). • Harness satellite instruments covering the UV spectral range to give insight into photodegradation processes.

Table 3: Priorities, challenges, gaps and opportunities for satellite Particulate Organic Carbon (POC) estimates

Priority	Challenges	Gaps	Opportunities
(1) *In situ* measurement methodology	• Inclusion of particles of all sizes to determine total POC. • Quantifying contributions of differently-sized particles and different particle types. • Dealing with biases due to DOC in filters.	• Submicrometer particles missed and rare large particles potentially underrepresented in the standard filtration method. • No capability to measure contributions of differently-sized particles and different particle types. • A lack of a certified reference material for POC.	• Advance and standardise methods for improved measurement of total POC. • Develop measurement capabilities combining particle sizing, particle identification, and particle optical properties to address contributions of different particle sizes and types
(2) *In situ* data compilation	• Quality control and consistency across diverse datasets. • Limitations of satellite-*in-situ* data match-ups, e.g., spatio-temporal scale mismatch, availability of match-ups in various environments.	• Limitations in documentation of methods in historical datasets. • Best-practice guidelines for data quality control and synthesis efforts. • Undersampled environments.	• Improve and standardise best practices for documentation, quality control, sharing, and submission of data into permanent archives. • Collection of high-quality data along the continuum of diverse environments.
(3) Satellite algorithm retrievals	• Unified algorithms for reliable retrievals along the continuum of diverse aquatic environments ranging from open ocean to coastal and inland water bodies. • Global algorithms applied to environmental conditions outside the intended scope. • Satellite inter-mission consistency. • Atmospheric-correction tailored to a new generation of ocean colour sensors (e.g. geostationary and hyperspectral).	• Mechanistically-based flags associated with optical water types to ensure the application of algorithms (e.g., the current global algorithms) according to their intended use. • Advanced algorithms (e.g., adaptive algorithms based on mechanistic principles) to enable reliable retrievals across diverse environments including the optically-complex coastal water bodies.	• Recent development of a new suite of empirical satellite sensor-specific global POC algorithms provides the opportunity for routine production of refined global POC product. • Development of advanced algorithms that incorporate mechanistic principles for applications across the continuum of diverse aquatic environments. • Use of satellite geostationary and hyperspectral data in combination with *in-situ* data

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Table 3. Priorities, challenges, gaps and opportunities for satellite Particulate Organic Carbon (POC) estimates. (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(4) Partitioning into components	• Partitioning of POC into particle size fractions and biogeochemically important components. • Characterize the PSD of both total bulk particle assemblages and separately the various functional fractions. • Address coastal and other optically complex water bodies that may have both autochthonous and allochthonous contributions to POC, as opposed to dominance of autochthonous POC in the open ocean - assess the need to separate these two pools.	• Ability to reliably measure *in situ* various fractions is limited, e.g., separate living vs. non-living POC. • Insufficient global PSD measurements and lack of comprehensive global PSD data compilations. • A dearth of concurrent data on POC, PSD and carbon data on the components that make POC. • Insufficient knowledge of Inherent Optical properties (IOPs) (e.g., the volume scattering function (VSF)) for optics-based partitioning of POC.	• Support basic research on particle sizing, particle identification, and particle optical properties including polarization properties. • Development of light-scattering polarization sensors for deployment on autonomous *in-situ* platforms (in combination with other IOP sensors such as beam attenuation and backscattering). • Emerging techniques to separate living and non-living POC. • Support PSD measurements as part of a suite of basic required variables for ocean biogeochemistry studies and remote sensing. • Opportunities to harness satellite-based approaches to monitoring zooplankton, for quantifying their contribution to POC.

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Table 3. Priorities, challenges, gaps and opportunities for satellite Particulate Organic Carbon (POC) estimates. (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(5) Vertical profiles	• Reconstructing vertical profiles using data from space-borne, air-borne, and *in-situ* sensors. • Determining relationship(s) between remotely-sensed variables and characteristics of POC vertical profile, e.g., weighted average.	• Relationships between optical variables and POC (e.g., from sensors on autonomous *in-situ* platforms). • Uneven distribution of *in-situ* profiles of POC globally, with some areas severely undersampled.	• Development of POC algorithms for *in-situ* optical data (e.g., BGC-Argo) along with improvements of optical sensor technology (e.g., polarized scattering sensors for BGC-Argo). • Use multiple data (satellite, BGC-Argo) and model streams (including CMIP6 ocean bgc models) to reconstruct 3D and 4D POC in the ocean via statistical and data assimilation techniques. • Advance basic research to determine relationships between remote-sensing reflectance and other optical variables and vertical profiles of POC characteristics, including PSD and functional fractions. • Harness lidar-based remote sensing that can penetrate further into the water column than passive ocean colour remote sensing.
(6) Biogeochemical processes and the carbon pump	• Understand the fate of POC and its fractions globally, e.g., the role of POC in the biological pump.	• Interannual POC export variability in empirical and mechanistic models. • Fate of POC in shallow environments. • Role of horizontal advection.	• Widespread use of autonomous sensors and emerging observation techniques (e.g., "optical sediment traps" on BGC-Argo floats). • Data-driven estimates of vertical POC fluxes. • Constraining prognostic ocean BGC models using observations from remote and *in-situ* autonomous sensors.

Table 4: Priorities, challenges, gaps and opportunities for satellite phytoplankton carbon (C-phyto) estimates.

Priority	Challenges	Gaps	Opportunities
(1) *In-situ* data	• Extremely difficult to measure C-phyo *in situ*. • Very few observations from the field on photoacclimation parameters and their variability. • Challenges around standardization of phytoplankton carbon data submission using emerging *in-situ* techniques.	• Gaps in accurate *in situ* C-phyto data. • Gaps in consistent C-phyto surface time-series data sets. • Gaps in photo-acclimation parameters.	• The enlargement and exploration of data analysis of *in situ* supersites. • Accuracy of optical quantities used as input of C-phyto algorithms can be improved by empowering validation through autonomous mobile platforms such as BGC-Argo profiling floats and Lagrangian drifters.
(2) Satellite algorithm retrievals	• Separating the contributions of living and non-living particles to the particle backscattering coefficient. • Understanding the influence of phytoplankton composition and photoacclimation on the relationship between Chl-a, particle backscatter and C-phyto.	• A gap in our mechanistic understanding of how optical properties and particle types link to C-phyto. • Uncertainties infrequently reported with satellite C-phyto products.	• Harness long time-series satellite products. • Explore the combined use of satellite data with ecosystem modelling to improve C-phyto products. • Combining models of photoacclimation with size-based approaches and models of primary production, such that the carbon pools and fluxes are produced in a consistent manner.
(3) Vertical structure	• Challenging to collect, aggregate and produce an *in-situ* dataset that is representative of entire euphotic depth and at global scale.	• Biases towards *in-situ* C-phyto data collected at surface depths. • Lack of methods for extrapolating the surface satellite C-phyto products down through the entire euphotic zone.	• Use autonomous platforms such as BGC-Argo floats and moorings with satellite data and models to reconstruct the 4D views of C-phyto, from an Eulerian and Lagrangian perspective.

Table 5: Priorities, challenges, gaps and opportunities for satellite detection of Dissolved Organic Carbon (DOC).

Priority	**Challenges**	**Gaps**	**Opportunities**
(1) Spatial and temporal coverage of the coastal ocean	• Quantifying DOC stocks and fluxes in coastal waters require satellites with high temporal coverage. • Viewing high latitudes regions from space in winter months.	• Estimates of DOC stocks and fluxes in coastal environments are severely limited by the temporal coverage of existing ocean color satellites.	• With the advent of geostationary ocean-colour satellites, capable of imaging multiple times daily, there are exciting opportunities to address these challenges and gaps at regional scales.
(2) Understanding and constraining the relationship between CDOM and DOC	• Improved performance of satellite CDOM absorption retrievals is required. • The relationships between DOC and CDOM absorption tends to be variable seasonally and across coastal systems. • CDOM and DOC are largely decoupled in the open ocean. • High sensitivity to atmospheric correction (especially ambiguity with effects of Rayleigh scattering).	• Gaps in our understanding of the relationship between DOC and CDOM absorption. • There is a lack satellite UV and hyperspectral data for resolving DOC and its composition. • Reliable atmosphere-correction is needed for UV and shortwave visible wavelengths.	• Utilise the spectral slope of CDOM absorption, $S_{275-295}$, to constrain the variability between CDOM and DOC. • Develop mechanistic models of the processes regulating the relationship between CDOM and DOC, by integrating new insight on the effects of photobleaching. • Harness opportunities to acquire high-quality field measurements of DOC and CDOM absorption across different seasons and marine environments. • Emerging UV and hyperspectral satellites will open opportunities for CDOM and DOC retrievals. • Harness optical water type frameworks for algorithms selection and merging for better separation of NAP-CDOM effects.

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Table 5. Priorities, challenges, gaps and opportunities for satellite detection of Dissolved Organic Carbon (DOC). (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(3) Identification of sources and reactivity	• Challenging to identify specific pools of DOC of different sources and reactivity.	• Few studies assessing whether the DOM fluoresced signal can be detected from remote-sensing reflectance.	• Whether the fluorescence of DOC and CDOM can have a measurable influence on remote-sensing reflectance. • Opportunities with hyperspectral sensors that provide improved signal-to-noise ratio, atmospheric corrections, as well as enhanced spectral information in the UV-visible range • Opportunities with active remote-sensing approaches based on laser-induced fluorescence.
(4) Vertical measurements	• Remote sensing of CDOM and DOC is limited to surface measurements.	• Approaches that extrapolate surface DOC and CDOM to depth require extensive *in-situ* datasets (vertical profiles). Gaps exist for many regions and seasons	• Acquiring *in-situ* measurements from autonomous platforms like BGC-Argo equipped with DOM-fluorescence sensors and radiometry. • Opportunities with UV-lidar-based techniques to retrieve sub-surface information about CDOM in the ocean. • Opportunities to harness modelling approaches (physical and BGC modelling) to improve estimation of DOC dynamics at depth.

Table 6: Priorities, challenges, gaps and opportunities for satellite detection of inorganic carbon (IC) and fluxes at the ocean interface.

Priority	**Challenges**	**Gaps**	**Opportunities**
(1) *In-situ* data	• Strong reliance on *in-situ* data, considering many components of inorganic carbon are not directly observable from space. • *In-situ* data of a much coarser spatial and temporal resolution when compared with satellite data. • *In-situ* data products are heavily extrapolated. • Challenging to integrate *in-situ* datasets without community consensus on best practices and reference materials.	• Better spatial and temporal coverage of field observations required, not only at the surface but also the full water column. • Limited *in-situ* data time-series stations in key locations.	• Opportunities to improve the spatial and temporal resolution of *in-situ* data through autonomous platforms. • Opportunities to extend recent efforts to develop Fiducial Reference Measurements (FRM) to inorganic carbon.
(2) Satellite retrievals and mapping uncertainty	• Satellite inorganic carbon estimates in optically-complex water are challenging. • Challenging to retain the theoretical understanding of satellite algorithms, while harnessing new powerful statistical approaches (e.g. AI).	• Lack of pixel-by-pixel uncertainty estimates in the satellite inorganic products. • Lack of coincident *in-situ* observations of PIC, other highly scattering materials, and inherent optical properties, in optically-complex waters.	• New satellite sensors, with improved spatial, spectral and temporal resolution, may lead to improvements in IC satellite products. • Opportunities to harness and build on recent techniques used to map uncertainty in satellite organic carbon products.

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Table 6. Priorities, challenges, gaps and opportunities for satellite detection of inorganic carbon (IC) and fluxes at the ocean interface. (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(3) Models and data integration	• Bridging the differences (e.g., scales) in data products and models. • *In-situ*, data-driven products are sensitive to choice of extrapolation method.	• Closer collaboration between data generators and modellers is needed.	• Opportunities to harness improved computer processing power, and the development of new statistical tools. • Opportunities to improve model products by reconciling model carbon budgets with those from satellite and *in-situ* products. • Opportunities to harness an increasing range of data sources to improve data products, for example, through data assimilation reanalysis. • Opportunity for routine integration of *in-situ*, model, and satellite observations to enable routine assessment of the surface water $p\mathrm{CO_2}$, air-sea exchange and the net integrated air-sea flux (or ocean sink) of carbon.

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Table 6. Priorities, challenges, gaps and opportunities for satellite detection of inorganic carbon (IC) and fluxes at the ocean interface. (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(4) Mechanistic understanding of gas transfer	• Mechanistic understanding of gas transfer is challenged by our ability to measure and quantify key processes.	• Large uncertainties surrounding the influence of near surface temperature gradients on gas transfer. • Large uncertainty surrounding the importance of bubbles for air-sea CO_2 fluxes. • Carbon dynamics and air-sea CO_2 fluxes in mixed sea ice regions are poorly understood.	• Opportunity to establish FRM status and agree best practice for eddy covariance air-sea CO_2 fluxes. • Opportunities to exploit state-of-the-art techniques on novel platforms to improve understanding of air-sea CO_2 fluxes in different environments such as mixed sea ice regions. • Opportunity to quantify the magnitude of near surface temperature gradients on air-sea CO_2 fluxes. • Opportunity to develop/improve parameterisations that use sea surface roughness to estimate air-sea CO_2 transfer.

Table 7: Priorities, challenges, gaps and opportunities for satellite detection of Blue Carbon (BC).

Priority	**Challenges**	**Gaps**	**Opportunities**
(1) Satellite sensors	• Requirement for monitoring at high temporal (hourly) and spatial (tidal) scales.	• A lack of long-term satellite datasets for change detection in many BC ecosystems.	• New hyperspectral observations will lead to improved BC detection. • High spatial resolution (3-5 m) imagery becoming available from a constellation of commercial satellite sensors. • Geostationary satellite instruments will meet the requirements for high temporal (hourly) BC monitoring. • Scope to build on efforts to develop satellite climate records with a focus on BC.
(2) Algorithms, retrievals and model integration	• Many BC approaches are regional, difficult to go to global scales. • Uncertainty estimation for BC fluxes challenging. • Difficult to monitor the dynamics of sediment carbon remotely. • Dealing with sub-pixel variability of macroalgae when using courser resolution satellite data.	• Limited availability of *in-situ* data for development and validation of BC remote sensing approaches. • Lack of BC ecosystem models limits our ability to quantify full BC carbon budgets.	• Harness computation power and statistical analysis of big data (e.g., techniques like machine learning). • Fusion of hyper-spectral optical and SAR data provides a promising approach for characterization of tidal wetlands. • New *in-situ* monitoring techniques (e.g., drones) are becoming useful to bridge the scales between satellites and *in-situ* observations.
(3) Data access and accounting	• Existing products and approaches are not easily accessible to non-expert users. • Challenges to ensure cost-effective monitoring using commercial satellites.	• Lack of products suited to project development and carbon accounting. • Products needed at global scales, at higher spatial and temporal resolution.	• Increasing efforts to develop BC habitat mapping portals that are user friendly. • Opportunities to link OMICS with satellite data.

Table 8: Priorities, challenges, gaps and opportunities for satellite detection of Extreme Events (EE) and their impacts on the ocean carbon cycle.

Priority	**Challenges**	**Gaps**	**Opportunities**
(1) *In-situ* data	• Some EEs are extremely challenging and dangerous to monitor *in-situ* using ship-based techniques.	• Major gaps in availability of *in-situ* observations of EE events. • Gaps are greater in subsurface waters. • Long time-series *in-situ* observations needed for baselines.	• To harness the expanding network of autonomous *in-situ* platforms.
(2) Satellite sensing technology	• Some EEs require high temporal and spatial coverage, which challenges current remote sensing systems. • Dealing with cloud coverage during tropical cyclones. • Satellite retrievals in the presence of complex aerosols from volcanic eruptions.	• High temporal and spatial resolution data is required for monitoring some EE events. • Gaps in satellite data for some EE events (e.g., clouds). • Gaps in knowledge on the optical properties of aerosols for some events. • Long time-series remote sensing data is needed for baselines.	• Synergistic use of different long-term high-frequency and high-resolution remote sensing data. • Harness emerging sensors with increased spectral, spatial and temporal resolution. • Opportunities to derive satellite-based indicators of EE's for determining good environmental status.
(3) Model synergy and transdisciplinary research	• Need to utalise ESMs for understanding EEs and projecting future scenarios. • Need to bring communities from multiple fields together.	• Higher resolution ESMs with improved representation of marine ecosystems. • Investment in transdisciplinary research related to EEs.	• Harness enhancements in computation power and improvements in ESMs and data assimilation techniques. • Remove knowledge barriers by promoting and open data approach cross-disciplinary research and data access.

Table 9: Priorities, challenges, gaps and opportunities for using satellite data for Carbon Budget Closure (CBC).

Priority	**Challenges**	**Gaps**	**Opportunities**
(1) *In-situ* data	• Quality, quantity and spatial distribution of *in-situ* measurements varies depending on the pool or flux being studied, and depends on the measurement platform used.	• Very few datasets exist on concurrent and co-located *in-situ* measurements of all the key pools and fluxes needed to evaluate model budgets. • Remote regions that play a key role in global budgets (e.g., Southern Ocean) are severely under-sampled. • Gaps in key measurements in many regions (e.g., photosynthesis irradiance parameters, for organic carbon budgeting).	• New *in-situ* technologies being integrated into networks of autonomous platforms, for improved carbon measurements. • Methods being developed to quantity carbon pools and fluxes from routine optical autonomous observations. • Properties of carbon budgets can be interrogated using *in-situ* compilations to check and constrain satellite or model budgets.
(2) Satellite algorithms, budgets and uncertainties	• There need to be coherence in the input satellite data fields for different satellite carbon algorithms when computing budgets. • Some of the pools and fluxes of carbon require satellite data with higher spatial, temporal and spectral resolution. • There needs to be consistency in algorithms used to quantify budgets, and these algorithms must respect properties of the ecosystem we know from *in-situ* data. • Uncertainties in individual products are essential to analyse multiple products to compute the budgets. • Products must be evaluated in relation to other products, to see whether they hold together in a coherent fashion.	• Many satellite carbon products lack associated estimates of uncertainty. • More work is needed to improve estimates of uncertainties in model parameters. • More efforts needed towards dynamic, rather than static, assignment of parameters in carbon algorithms. • Increasing emphasis needs to be placed on harmonising satellite carbon products across different planetary domains (ocean, land, ice and air).	• Opportunities to harness climate data records. • Opportunities to harness emerging sensors with increased spectral, spatial and temporal resolution. • New approaches and statistical techniques offer potential to get at pools and fluxes of carbon from satellite that were previously not feasible.

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Table 9. Priorities, challenges, gaps and opportunities for using satellite data for Carbon Budget Closure (CBC). (continued from previous page).

Priority	Challenges	Gaps	Opportunities
(3) Model and satellite integration	• Challenges dealing with the contrasting spatial scales in models and satellite observations. • Quantifying carbon budgets also requires appreciation of the different temporal scales that the pools and fluxes operate on.	• Uncertainties in the satellite observations and model simulations needed. • Greater emphasise should be placed on promoting model diversity.	• Opportunities to harness new developments in data assimilation to help constrain carbon budgets, such as combined physical and biological data assimilation. • Scope to harness developments in machine learning to help combine data and models. • Future enhancements in computation power should lead to better representations of spatial scales in models.

Table 10: A selection of upcoming satellite sensors with applications in ocean carbon research and monitoring.

Sensor	Description	Reference
Plankton, Aerosol, Cloud, ocean Ecosystem (PACE)	PACE will have a hyperspectral Ocean Color Instrument (OCI), measuring in the ultraviolet (UV), visible, near infrared, and several shortwave infrared bands. It will also contain two multi-wavelength, multi-angle imaging polarimeters for improved quantification of atmospheric aerosols and ocean particles (Remer et al., 2019a,b). PACE is scheduled to launch in 2024.	https://pace.gsfc.nasa.gov
Geosynchronous Littoral Imaging and Monitoring Radiometer (GLIMR)	GLIMR is a geostationary and hyperspectral ocean colour satellite that will observe coastal oceans in the Gulf of Mexico, portions of the south-eastern US coastline, and the Amazon River plume. It will provide multiple observations (hourly), at around 300 m resolution across the UV-NIR range (340 -1040 nm). GLIMR is expected to be launched in 2027.	https://eospso.nasa.gov/missions/geosynchronous-littoral-imaging-and-monitoring-radiometer-evi-5
Environmental Mapping and Analysis Program (EnMAP)	EnMAP is a German hyperspectral satellite mission measuring at high spatial resolution (30 m) from 420-1000 nm in the visible and near-infrared, and from 900 nm to 2450 nm in the shortwave infrared. It aims to monitor and characterise Earth's environment on a global scale. It was launched in April 2022.	https://www.enmap.org
FLuorescence EXplorer (FLEX)	FLEX is a mission designed to accurately measure fluorescence, and provide global maps of vegetation fluorescence that reflect photosynthetic activity and plant health and stress, which is important for understanding of the global carbon cycle. FLEX is expected to be launched in 2025.	https://earth.esa.int/eogateway/missions/flex

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Table 10: A selection of upcoming satellite sensors with applications in ocean carbon research and monitoring.

Sensor	Description	Reference
Sentinel-4 (S-4)	S4 mission consists of an Ultraviolet-Visible-Near-Infrared (UVN) light imaging spectrometer instrument embarked to be onboard the Meteosat Third Generation Sounder (MTG-S) satellite. It will provide geostationary data over European waters and planned to be launched in 2023.	https://sentinel.esa.int/web/sentinel/missions/sentinel-4
Sentinel-5 (S-5)	S5 mission consists of a hyperspectral spectrometer system operating in the UV, visible and shortwave-infrared range. Though focused primarily on retrieving information on the composition of the atmosphere, it can retrieve information on ocean colour. Preliminary applications using the precursor mission (S-5p, launched in October 2017), has demonstrated retrieval of diffuse attenuation (K_d) in the blue and UV regions. Owing to the hyperspectral nature of the instrument, it also has applications in deriving information on the composition of the phytoplankton in the ocean (e.g., Bracher et al., 2017).	https://sentinel.esa.int/web/sentinel/missions/sentinel-5
Copernicus Hyperspectral Imaging Mission for the Environment (CHIME)	CHIME will provide routine hyperspectral observations from the visible to shortwave infrared. The mission will complement Copernicus Sentinel-2 satellite for high resolution optical mapping. Planned to be launched in the second half of this decade.	https://www.esa.int/ESA_Multimedia/Images/2020/11/CHIME

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Table 10: A selection of upcoming satellite sensors with applications in ocean carbon research and monitoring.

Sensor	Description	Reference
Earth Cloud, Aerosol and Radiation Explorer (EarthCARE)	EarthCARE will contain an atmospheric lidar, cloud profiling radar, a multi-spectral imager, and a broad-band radiometer, with the objective to allow scientists to study the relationship of clouds, aerosols, oceans and radiation. It is planned for launch in 2023	https://earth.esa.int/eogateway/missions/earthcare
Surface Water and Ocean Topography Mission (SWOT)	SWOT will contain a wide-swath altimeter that will collect data on ocean heights to study currents and eddies up to five times smaller than have been previously been detectable. It is planned for launch in November 2022	https://swot.jpl.nasa.gov/mission/overview/
Satélite de Aplicaciones Basadas en la Información Ambiental del Mar (SABIA-Mar)	SABIA-Mar was conceived to observe water color in the open ocean (global scenario, 800 m resolution) and coastal areas of South America (regional scenario, 200 m resolution) and provide information about primary productivity, carbon cycle, marine habitats and biodiversity, fisheries resources, water quality, coastal hazards, and land cover/land use. The satellite will carry two push-broom radiometers covering a 1496 km swath and measuring in 13 spectral bands from 412 to 1600 nm. SABIA-Mar is scheduled to be launched in 2024.	https://www.argentina.gob.ar/ciencia/conae/misiones-espaciales/sabia-mar

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Table 10: A selection of upcoming satellite sensors with applications in ocean carbon research and monitoring.

Sensor	Description	Reference
Surface Biology and Geology (SBG)	SGB is being designed to address, via visible to shortwave imaging spectroscopy, terrestrial and aquatic ecosystems and other elements of biodiversity, geology, volcanoes, the water cycle, and applied topics of social benefit. In the current architecture considered, the instrument payload will consist of a hyperspectral imager measuring at 30-45 m resolution in >200 spectral bands from 380 to 2250 nm and a thermal infrared imager measuring at 40-60 m resolution in >5 spectral bands from 3 to 5 and 8 to 12 microns, with revisit of 2-16 and 1-7 days, respectively. Launch is scheduled for 2026.	https://sbg.jpl.nasa.gov
MetOp-SG Multi-Viewing Multi-Channel Multi-Polarisation Imaging (3MI) instrument	3MI is a passive optical radiometer with large swath (2200 km) dedicated primarily to aerosol characterization for applications in climate monitoring, atmospheric chemistry, and numerical weather prediction, but with ocean color capability. It will provide multi-spectral (12 spectral bands from 410 to 2130 nm), multi-polarization (+60 deg., 0 deg., and -0 deg.), and multi-angular (14 directions) views of a Earth target at 4 km resolution. The first MetOp-SG A-series satellite carrying 3MI will be launched in 2024, the second in 2031, and the third in 2038.	https://earth.esa.int/web/eoportal/satellite-missions/m/metop-sg

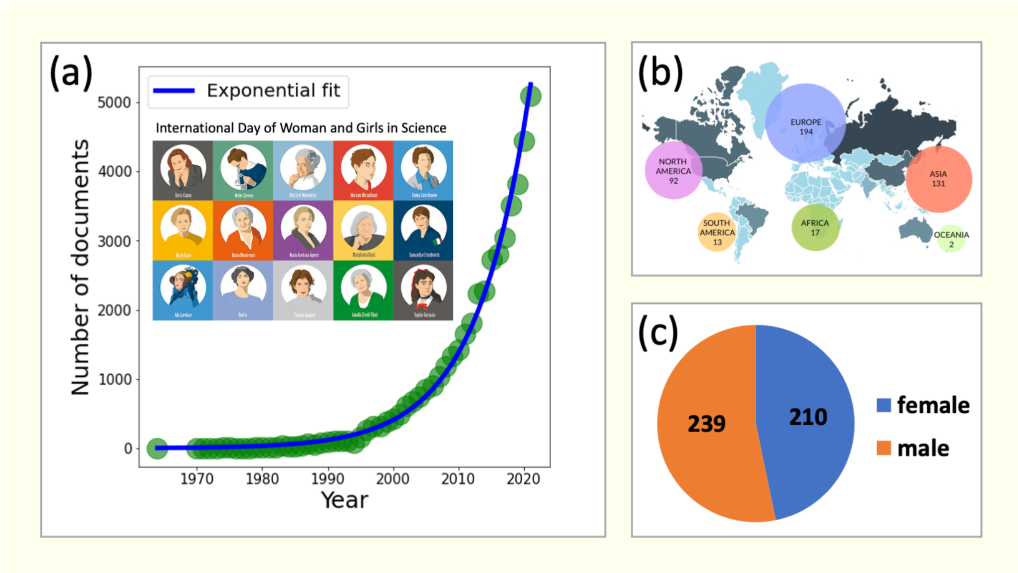

Figure 1: (a) Number of documents identified (green circles) in chronological order from a Scopus search (https://www.scopus.com/) using the terms "Ocean carbon satellite" (using All fields). Blue line represents an exponential fit to the increase in the number of documents over the past 50 years. Inset figure highlights that the timing of the meeting followed the International day of women and girls in science (11^{th} February 2022). (b) Geographical representation of the 449 scientists and stakeholders who participated in the "Ocean Carbon from Space" workshop in February 2022. (c) Gender split of the workshop participants.

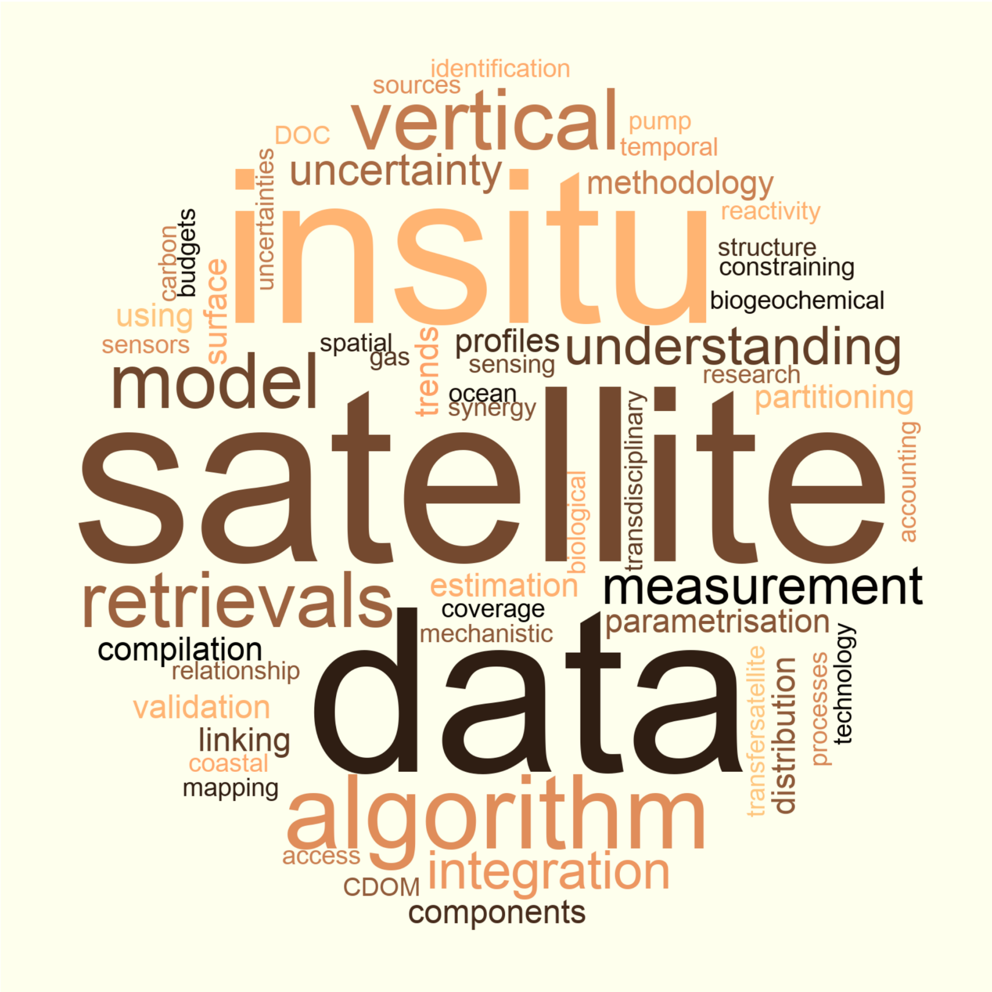

Figure 2: A word cloud designed to show the dominant themes and subthemes emerging from all priorities identified. Created using a word cloud generator in Python (https://github.com/amueller/word_cloud).