Characterizing and Predicting Change in the Global Ocean Biosphere: A Four-Dimensional Observing Strategy for the 2028–2037 Decadal Survey

A response to the Request for Information for the Decadal Survey for Earth Science and Applications from Space 2028–2037 (ESAS 2028)

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Co-authors listed alphabetically.

Corresponding author: Susanne E. Craig, GESTAR II, University of Maryland Baltimore County, and Ocean Ecology Laboratory, NASA Goddard Space Flight Center — susanne.e.craig@nasa.gov

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It is one of a series of five ocean biology and biogeochemistry white papers led by this author team.

The authors welcome feedback and comment; please contact the corresponding author.

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Susanne E. Craig[1,2,*]

Daniella Asturias[2,3], Heather Benway[3,4], Leocadio Blanco Bercial[5,6], Joaquim Goes[7], Patrick Gray[8], Hannah Joy-Warren[9], Sasha Kramer[10], Morgaine McKibben[2,11], Catherine Mitchell[12], Frank Muller-Karger[13], Carina Poulin[2,11], Nirmal Ralia[14]

*Co-authors listed alphabetically. *Corresponding author: susanne.e.craig@nasa.gov*

[1]GESTAR II University of Maryland Baltimore County; [2]Ocean Ecology Laboratory, NASA Goddard Space Flight Center; [3]Woods Hole Oceanographic Institute; [4]Ocean Carbon and Biogeochemistry (OCB) Project Office; [5]Arizona State University; [6]Bermuda Institute of Ocean Science; [7]Department of Marine Biology and Paleoenvironment, Lamont Doherty Earth Observatory at Columbia University; [8]University of Maine; [9]Applied Physics Laboratory, University of Washington; [10]Boston University; [11]Science Systems and Applications Inc.; [12]Bigelow Laboratory for Ocean Sciences; [13]Institute for Remote Sensing, College of Marine Science, University of South Florida; [14]School of Geosciences, University of Louisiana Lafayette

Executive Summary

Ocean ecosystems constitute the largest habitable volume on Earth and regulate climate, support fisheries and a global Blue Economy valued at an estimated $1.5 trillion annually and provide services on which human wellbeing depends. Four decades of satellite ocean color observations have transformed understanding of phytoplankton distribution, biodiversity, and productivity, and NASA's PACE mission is now extending this record with unprecedented hyperspectral and polarimetric capabilities. Yet, passive ocean color remote sensing remains fundamentally two-dimensional – it detects only the optical signature of the uppermost, sunlit ocean; provides little or no coverage during polar night, persistent cloud cover, and low-sun conditions; and offers no independent means of validating its own retrievals. This white paper, submitted in response to the Biosphere sphere, presents the science case and a phased observing strategy for achieving a four-dimensional (three spatial dimensions plus time), pole-to-pole characterization of global ocean ecosystems. The vision presented here draws heavily on Earth's Living Ocean, the science vision report of NASA's Ocean Biology and Biogeochemistry Program [1]. We recommend 1) sustaining hyperspectral ocean color and polarimetric continuity, 2) adding a mature, ocean-optimized profiling lidar to resolve water column particle distributions and fill coverage gaps in polar and persistently cloudy regions, 3) expanding autonomous and suborbital in situ observing networks, and 4) investing in ecosystem models and data assimilation systems capable of ingesting these complementary data streams. Together, these elements would resolve a critical, decades-old gap in our ability to characterize, understand, and predict how global ocean ecosystems – from phytoplankton production to the fisheries and top predators they sustain – are responding to compounding natural and human-driven stressors, and whether those ecosystems are approaching thresholds beyond which their structure and function change abruptly and persistently.

1. Introduction: The Science Question and Societal Challenge

Marine ecosystems are diverse, complex, highly productive, and often fragile. The resources and services they provide, from fisheries to climate regulation to recreation, underpin the wellbeing of billions of people. The diversity of algal and animal communities and overall photosynthetic production are primary determinants of ocean ecosystem function, and these attributes are closely linked: highly productive systems tend to support shorter food webs, with fewer trophic links between phytoplankton and the apex consumers upon which coastal economies depend. In all cases, ecosystem structure, function, persistence, and resilience are intimately tied to the physical-chemical environment, yet establishing mechanistic links between environmental disturbances and ecosystem response remains a central, unresolved challenge in ocean science.

Resilience, the capacity to absorb disturbance without reorganizing into a persistently different state, is central to this challenge [2,3]. Marine systems exposed to sustained stress can cross thresholds and shift abruptly, as documented in the North Atlantic and North Pacific [4,5], and such transitions are often, though not always, preceded by measurable changes in variance, autocorrelation, and spatial patchiness of physical and chemical conditions that can potentially serve as early-warning indicators of approaching ecosystem change [6,7].

Ocean ecosystems are changing worldwide, and human activity is a major driver. Understanding and addressing these changes, while informing management, protection, and sustainable use of ocean resources, requires quantitative, global understanding of the linkages between ecosystem functioning and environmental forcing sufficient to reliably predict future change. The central science challenge motivating this submission is to:

> *Characterize how global ocean ecosystems will change in the future in response to compounding stressors from natural variability, climate change, and direct human impacts; identify the ecosystems most vulnerable to these stressors; and quantify how changes in ocean life and biogeochemistry affect our planet as a system of systems.*

This challenge is not new, but it has taken on renewed urgency. NASA's satellite ocean color record, beginning with the Coastal Zone Color Scanner in 1978 and continuing through SeaWiFS, MODIS, VIIRS, and now the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) mission, constitutes one of the great achievements of Earth observation, revolutionizing understanding of marine ecosystem composition, distribution, and phenology at scales unattainable by ship-based field campaigns. These observations have been foundational for detecting and attributing climate-driven change [8,9], for evaluating and developing global ecosystem and biogeochemical models [10–12], and for informing living marine resource management [13]. However, this same record has also revealed the limitations of a purely passive, surface-sensing approach and made clear that a paradigm shift is required to meet the coming decade's science and applications challenges. This submission addresses the Biosphere sphere as defined in the RFI, focusing specifically on the marine ecosystem component of the global biosphere, and is the first in a linked series of five white papers addressing the Grand Challenges of NASA's Ocean Biology and Biogeochemistry (OBB) Research Program [1]. Within the series, this paper focuses on characterization of ecosystem resilience and the thresholds themselves. The observing and analysis framework needed for detecting and forecasting abrupt events as they unfold is developed in a companion 'Transient Events' white paper submitted in response to this RFI [14].

2. State of the Science: Achievements and Limitations of the Ocean Color Record

The satellite ocean color era has profoundly advanced understanding of global ocean ecosystems and their susceptibility to climate variation, providing unprecedented documentation of surface phytoplankton distributions and biodiversity [15–17], seasonal-to-interannual variability [18], and phytoplankton physiological responses to changes in ocean physical processes, including long-term climate trends [19–24]. These observations have also enabled significant improvements in global ocean productivity assessment [25,26], provided improved insight on phytoplankton bloom dynamics and predator-prey relationships [27], established an observational foundation for quantifying biological carbon sequestration [28–31], and yielded observational constraints that have substantially improved numerical simulations of the global biosphere [10–12].

PACE, launched in 2024, is already extending this legacy, providing new global insight into phytoplankton biodiversity and productivity through combined hyperspectral and polarimetric measurements [32,33]. Continuity is essential, but length of record alone does not ensure detection of long-term change. The time needed to distinguish a forced trend from natural variability depends strongly on both the observable and the statistical approach used, with published estimates ranging from roughly 14-65 years across variables and assumed noise models. A mid-record discontinuity, for example, has been estimated to increase the time required to detect a global chlorophyll trend from ~27 to 43 years [8,34,35].

This challenge arises because natural variability can be as important as the underlying trend itself: recurrent climate modes such as the El Niño-Southern Oscillation, the Pacific Decadal Oscillation, the North Atlantic Oscillation, and the Southern Annular Mode, can force much of the variance in the ocean color record, and thus, separating their signature from the forced anthropogenic trend is the central challenge for detecting and attributing change in ocean biology [4]. That problem is tractable sooner with the most informative observable: multivariate hyperspectral reflectance carries the climate signal earlier than derived chlorophyll, emerging across a substantial fraction of the ocean within two decades of consistent single-sensor observation, because the most informative wavebands are those with the least interannual variability [9,36]. Sustained, cross-calibrated hyperspectral observation, therefore, delivers not merely a longer record but a more detectable one. Moreover, the sensitivity of published trends to

processing and merging choices makes calibration homogeneity across missions a requirement rather than a refinement [23,37].

Despite these advances, passive ocean color alone cannot address the coming decade's Global Biosphere challenges. Three fundamental limitations stand out:

First, ocean color sensors detect only the optical signature of phytoplankton communities near the surface, whereas ocean ecosystems are three-dimensional and evolve continuously in time. Communities at each depth exchange materials with the layers above and below, and these exchanges shape ecosystem response to stressors. Yet, in situ measurements of depth-resolved phytoplankton distribution remain spatially and seasonally sparse [38]. As a result, empirical parameterizations and models have been the primary means for extrapolating surface properties into three dimensions [39,40]. Without global constraints on vertical ecosystem structure, substantial uncertainty remains in both contemporary ocean functioning and predictions of future change. Attributing an observed change is, likewise, a three-dimensional problem. Climate modes do not merely warm the surface; they reorganize stratification, mixed layer depth, and nutrient supply [21,41]. Thus, a given surface anomaly may reflect biomass rearranged vertically, or a physiological change in the chlorophyll-to-carbon ratio with no biomass change at all, rather than a real change in depth-integrated production [20,42]. Passive ocean color alone cannot readily distinguish amongst these possibilities because ~90% of the remotely sensed ocean color signal originates from the first optical depth [43]. Compounding this problem, diel vertical migration, the day to night redistribution of animals from zooplankton to fish, occurs throughout the global ocean [44,45] and actively transports on the order of 1 Pg C per year below the euphotic zone, roughly a tenth of gravitational export globally and a substantially larger fraction in some regions [29,46]. Yet diel vertical migration is largely invisible to passive ocean color, which is restricted to daylight observations of the near surface ocean, leaving this component of the biological carbon pump poorly constrained. Migrating populations can also intensify oxygen depletion at the upper margins of oxygen minimum zones [47]; as deoxygenation progresses [48] and hypoxic layers shoal, habitat compression redistributes animals, alters predator-prey interactions and fisheries, and changes the carbon fluxes these organisms mediate, all beyond the reach of surface-only observation [49,50].

Second, ocean color retrievals require sunlit, cloud free conditions with atmospheric aerosol assemblages that can be well modeled. The result is persistent data gaps over large ocean areas. Polar and other high latitude regions, as well as cloud-prone temperate boundary upwelling systems, are particularly affected [51–54], even though many of these regions are experiencing the most dramatic effects of climate warming [55]. Polar night and cloud can leave the Arctic and Southern Ocean without observations for months [51], and those dimly lit winter months set the stage for the blooms that follow [56].

Third, no independent, similarly scaled dataset has existed to validate ocean color retrievals globally. Instead, products have been validated using sparse, point-source field measurements, leaving open the potential for scale mismatches [57], spatial and seasonal sampling bias [53,57], and other undetected biases [58].

These limitations extend well beyond phytoplankton. The magnitude and vertical distribution of primary production determine where and when prey are available, and variability at the base of the food web propagates through zooplankton and forage fish to predators, fisheries, seabirds, and marine mammals. Many of the ecological and economic consequences of ecosystem change therefore emerge well above the trophic level directly observed by ocean color. Meeting the Global Biosphere science challenge for the coming decade requires moving beyond a single, passive remote sensing approach toward an integrated, multi-faceted observing system capable of characterizing ocean ecosystems in four dimensions.

3. Proposed Observing Strategy: A Four-Dimensional Global Biosphere Observing System

We propose an integrated observing and modeling strategy that reconstructs global ocean ecosystems in four dimensions – three spatial dimensions plus time – resting on six complementary elements (Sections 3.1-3.6).

3.1 Foundation: Sustained Hyperspectral Ocean Color

The first element of this strategy is the continuity of PACE-equivalent hyperspectral ocean color observations, providing an uninterrupted time series that overlaps and extends the heritage SeaWiFS, MODIS, and VIIRS satellite record, continuity that is essential for detecting and attributing the long-term ecosystem change described in Section 2. Continued algorithm development, especially machine learning approaches, is also needed to fully exploit PACE's hyperspectral and polarimetric measurements, providing quantitative characterization of phytoplankton community composition, including functional types such as calcifiers, silicifiers, and nitrogen fixers, across the global ocean. Differentiating phytoplankton groups from ocean color remains challenging. With PACE, however, the principal limitation is no longer the number of wavebands but the strong autocorrelation amongst them, which limits the independent information they carry. The continued sparsity of in situ validation data [16] also remains an important limitation, and sustained partnerships with long-term coastal and open ocean observing sites should be developed to increase the volume of new in situ validation data.

3.2 New Capability: An Ocean-Optimized Profiling Lidar

The second, and most transformative, new element is an advanced, ocean-optimized satellite lidar that builds on the proof-of-concept success of CALIOP [59], which although not designed for ocean applications, has yielded major scientific advances, including quantifying global phytoplankton stocks, detecting decadal polar ecosystem trends, and characterizing diel vertical migration [44,60,61]. Airborne demonstrations (e.g., SABOR [62], NAAMES [44]) have shown that space-qualified technology can resolve phytoplankton vertical structure at meter scale beyond 2.5 lidar optical depths with a standard 532 nm laser [43], a wavelength chosen for laser availability rather than optimal ocean penetration. At the spatial scales relevant to spaceborne observations, lidar and diffuse optical depths become comparable [63].

We envision a lidar delivering global, vertically resolved subsurface ‘curtains’ of phytoplankton distribution (Fig. 1) through the upper sunlit ocean to the 1% light level, which is ~4.5 diffuse optical depths for a blue-emitting laser (but see Section 4 for goal versus practicality). Blue wavelengths penetrate deepest in clear oligotrophic water, where the euphotic zone is deepest, but optimum laser penetration shifts towards green wavelengths as CDOM and phytoplankton absorption increases. Simple elastic-backscatter lidars such as CALIOP cannot separate in water molecular scattering from dissolved and particulate matter attenuation (i.e., measuring one quantity set by two unknowns). The High Spectral Resolution Lidar (HSRL) technique, however, can isolate the molecular and particulate returns, is a mature technology, and is, therefore, the highest priority recommendation for addition to the NASA ocean satellite Program of Record. The submission to this RFI by Collister and Hostetler [64] discusses the HSRL concept in depth and likewise recommends it as this survey’s highest priority. The HSRL is not the only potential application of lidar, and community assessments also suggest ultraviolet and fluorescence channels alongside 532 nm [63], China's Guanlan concept pairs multi-wavelength backscatter and fluorescence with altimetry [65], while the Brillouin design enables vertical profiling of temperature and salinity [66,67] but requires further development before being space ready. All trade swath width for depth and all require in-water validation. In summary, a profiling lidar would provide an independent global dataset for evaluating ocean color algorithms, quantifying their uncertainties, and linking surface optical signals to the three-dimensional structure of the ocean ecosystem.

3.3 Extending Coverage: Polar and Persistently Cloudy Regions

Because lidar measurements can be acquired through thin cirrus and gaps in scattered cloud and, unlike passive sensors, do not require sunlight, they dramatically extend coverage in the very regions where ocean color is poorest. CALIOP has already demonstrated lidar-derived phytoplankton biomass estimates right up to the ice edge during polar night and persistent cloud, when ocean color retrievals are entirely absent [61]; similar gains are expected in other cloudy regions such as temperate upwelling systems.

3.4 Complementary Airborne, Autonomous, and Commercial Observations

Uncrewed aerial vehicles (UAVs) carrying ocean color sensors offer a complementary path to closing these data gaps, flying beneath persistent cloud decks to deliver the fine scale, repeat coastal and nearshore observations that satellites cannot. NASA's Earth Venture Suborbital FORTE mission [68] illustrates this approach, deploying UAV-based hyperspectral water reflectance sensors alongside crewed aircraft to characterize phytoplankton and biogeochemical dynamics across rapidly changing Arctic coastal and estuarine systems. This capability must be paired with sustained investment in autonomous platforms able to provide validation data in regions that are logistically difficult, e.g. around and beneath sea ice [56]. Commercial constellations acquired through NASA's Commercial Satellite Data Acquisition (CSDA) program are a further modular component, adding spatial resolution and revisit in coastal waters, though most were built for land imaging. Commercial providers should be strongly encouraged to work with NASA on the radiometric calibration that quantitative ocean color measurements require [69].

3.5 Suborbital and In Situ Integration

Satellite lidar and ocean color observations must be paired with a sustained, global array of autonomous platforms carrying optical and biogeochemical sensors: Biogeochemical-Argo (BGC-Argo) profiling floats and their goal for expansion under OneArgo [70,71], the OceanGliders network [72], Lagrangian floats, and uncrewed surface vehicles, coordinated with the Global Drifter Program and other Global Ocean Observing System (GOOS) networks [73,74]. These assets validate satellite retrievals and model predictions [75], bridge point measurements and satellite scales, and extend observation below the depths accessible from space [76]. Current field methods combine disparate measurements and instruments such as pigment analysis, flow cytometry, phytoplankton imaging systems, and particle counters. Together with ‘omics data (genomics, transcriptomics, proteomics, metabolomics, eDNA), these are essential for interpreting the three-dimensional plankton community structure resolved by ocean color and lidar, with ‘omics data, in particular, from programs such as BioGeoSCAPES [77] and Bio-GO-SHIP [78] providing information on the physiological state and metabolic function rather than distribution alone [79,80]. This directly addresses the ambiguity identified in Section 2, in which a surface anomaly may reflect a physiological change with no change in biomass. New approaches are urgently needed to merge these data automatically, with common metadata standards and machine readability.

3.6 Advanced Ecosystem Modeling and Data Assimilation

Reconstructing global ocean ecosystems in four dimensions depends on numerical models capable of synthesizing these diverse data streams. A central challenge is matching modeled state variables to directly observed quantities. Models incorporating ocean color, lidar, and in situ data should explicitly represent optical properties, both apparent (e.g., reflectance, diffuse attenuation) and inherent (e.g., absorption, scattering), and include radiative transfer modules [81,82]. Data assimilation of directly measured quantities, such as reflectance or particle backscattering, rather than derived products such as chlorophyll, improves state estimates of ecosystem structure, but remains far less mature than in physical oceanography models [83]. Ecosystem models must also be expanded to represent greater taxonomic and size diversity, vertical migration behavior, trophic and age structure, and species interactions. Most global ecosystem models currently represent only a few functional groups with minimal trophic complexity [11,84]. Trophic structure should extend beyond plankton to fish and upper-trophic consumers, as it is at these levels that ecosystem change becomes most apparent to society. Models and reanalyses of this kind are also the natural framework for quantifying resilience directly, by estimating recovery rates after perturbation [85] and testing whether candidate early warning indicators from satellite time series carry real predictive skill rather than sampling artifacts [86,87].

4. Key Measurement Requirements

The strategy above requires the following capabilities, in approximate order of priority. They are interdependent, and the observing elements depend, in turn, on models able to fuse them.

Ocean color continuity requires uninterrupted, PACE-equivalent hyperspectral and polarimetric observations, with sufficient overlap between missions to avoid discontinuities. This will enable records

long and homogeneous enough to separate mode-driven variability from the climate-forced trend. Resilience and early warning analysis rests on the same statistics, which gaps corrupt. Calibrated CSDA data can also contribute.

The ocean-optimized profiling lidar should be a spaceborne HSRL-class, or equivalent, instrument with a laser emitting at ~532 nm, providing meter-scale vertical resolution retrievals of particulate backscattering and attenuation to at least ~3 diffuse optical depths, with a goal of ~4.5, corresponding to the base of the euphotic layer. The lidar should possess polarized and depolarized channels, provide global pole-to-pole coverage, and operate during both day and night.

The autonomous in situ network should be an expanded global array of BGC-Argo floats, gliders, and related platforms with optical and biogeochemical sensors, including systems able to operate in and around sea ice and other logistically challenging regions, providing depth, temperature, salinity, oxygen, nutrient, and bio-optical profiles at scales spanning minutes to years and meters to ocean basins.

Field and laboratory validation programs must be sustained and efficient, generating the in situ phytoplankton community composition and optical validation data required to develop and evaluate satellite algorithms, particularly for undersampled, rapidly changing regions such as the polar oceans. These programs should also generate coincident biomolecular and physiological measurements, taxonomically resolved community composition, and nutrient stress indicators collected under common protocols and metadata standards, since these constrain the physiological and functional terms in ecosystem models that optical retrievals alone cannot determine.

Modeling and data assimilation infrastructure requires ecosystem and biogeochemical models with explicit optical state variables and radiative transfer capability, coupled to data assimilation systems capable of ingesting reflectance-, lidar-, and autonomous platform-derived observations, along with sustained investment in Observing System Simulation Experiments (OSSEs).

5. Feasibility and Implementation within the Decadal Time Frame

The required technology is substantially mature. The core new capability, an ocean-optimized profiling lidar, builds on two decades of heritage: CALIOP has flown since 2006 and the HSRL technique is repeatedly validated from aircraft, placing it within reach of a zero-to-ten-year start.

Ocean color continuity likewise carries high technical readiness, building on PACE and its SeaWiFS, MODIS, and VIIRS heritage. The principal risk is programmatic rather than technical. The autonomous in situ network builds on the mature Argo and BGC-Argo programs, a proven model for cost-effective international and commercial partnership. The OneArgo plan would grow the array to 4,700 floats by 2030, including 1,000 biogeochemical floats, up from 556, and extend it into polar regions [71]. However, OneArgo is not yet funded and funding for current BGC-Argo will expire during 2026-27. U.S. leadership is achievable near-term only if these programs are sustained or renewed.

The principal challenges are therefore not sensor readiness but penetration depth, algorithm development, data synthesis, workforce capacity, and strategic and sustained funding. Current systems are signal to noise limited near three optical depths [63], so reaching the euphotic depth is a photon budget problem, not an unproven technique. Robust phytoplankton taxonomic discrimination requires sustained investment in field validation and interdisciplinary scientists, and biogeochemical data assimilation remains underdeveloped for ecosystem applications.

Interpreting vertical phytoplankton structure is not yet mature: it depends on mixing layer depth, seasonal mixed layer depth, and stratification strength, which set photoacclimation, bloom dynamics, predator-prey interactions, and ecotype distribution. Currently, some of these fields come from circulation models with sparse in situ constraint, cannot be validated from space, and are only partially recovered by the proposed lidar. Dedicated technology development is therefore warranted, for example in Brillouin lidar, which profiles temperature and salinity from the speed of sound in seawater [66,67].

6. Summary of Recommended Priorities

We recommend that the 2028 to 2037 decadal survey prioritize the following elements to address the Global Biosphere grand challenge:

1. Sustain and refine PACE-equivalent hyperspectral ocean color and polarimetric observations, including the algorithms and field and laboratory validation programs needed to quantify global phytoplankton composition, abundance, distribution, and phenology, and vigorously pursue commercial satellite partnerships (continued/near-term).
2. Add an ocean-optimized, HSRL-class or equivalent profiling lidar to NASA's ocean satellite Program of Record, providing vertically resolved retrievals through the sunlit surface layer (immediate/near-term).
3. Develop technologies to directly assess surface-ocean mixing properties and stratification from space (near-term/long-term).
4. Achieve a four-dimensional reconstruction of ocean ecosystems by integrating time-resolved ocean color and lidar retrievals with sustained autonomous profiling, airborne campaigns, and ship-based measurement, and couple the resulting fields to upper trophic level and fisheries models (near-term/long-term).
5. Develop and validate indicators of ecosystem resilience and proximity to ecological thresholds, including variance, autocorrelation, and spatial-pattern metrics derived from sustained four-dimensional records (near-term).
6. Invest in ecosystem and biogeochemical model development and data assimilation, including models with optical state variables linked directly to satellite measured quantities (continued).
7. Expand three-dimensional, global field characterization and modeling of phytoplankton community composition and functional roles (continued).
8. Support research to synthesize disparate observing streams – in situ imaging, ocean color, lidar, and autonomous platform data – and advance data assimilation modeling (continued).
9. Use models and Observing System Simulation Experiments to optimize and evaluate observing system design and deployment (near-term).
10. Expand international engagement and data sharing, building on the Argo program model, to achieve seamless use of satellite and in situ data across partners (continued).
11. Invest in cloud-based Big Data infrastructure and an interdisciplinary, climate- and biology-literate workforce capable of synthesizing these growing, multi-sensor data streams (continued).

7. Conclusion

NASA's satellite ocean color record has provided a phenomenal, but fundamentally two-dimensional, view of the global ocean biosphere. The stakes of understanding how ocean ecosystems will respond to compounding stressors, for climate regulation, food security, and the broader Blue Economy, demand a paradigm shift to a four-dimensional, integrated observing system. By investing in these six elements, the 2028-2037 Decadal Survey can resolve a limitation that has constrained ocean ecosystem science for the entire satellite era and deliver the sustained, actionable understanding of ecosystem change that policymakers, resource managers, and the public need.

Figures

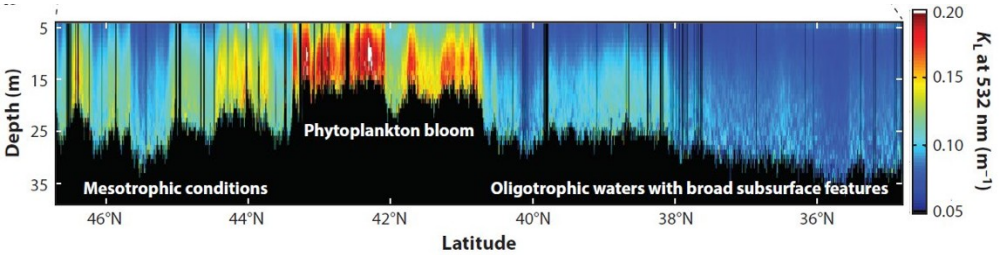

Figure 1. Example airborne high-spectral-resolution lidar "curtain" showing the vertical distribution of a phytoplankton bloom (red/yellow) transitioning to oligotrophic waters with broad subsurface features (blue), measured along the U.S. eastern seaboard. K_L = lidar attenuation coefficient at 532 nm. Reproduced from Hostetler et al. [43], as presented in the OBB Science Vision report [1].

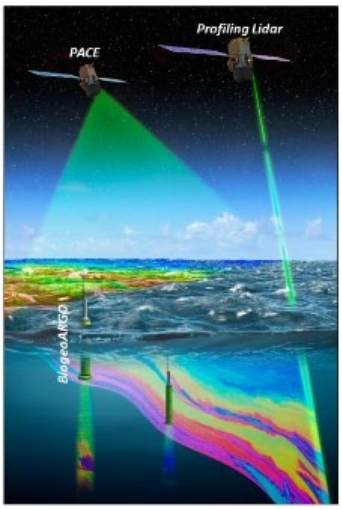

Figure 2. Conceptual rendering of the proposed four-dimensional Global Biosphere observing system, combining sustained hyperspectral ocean color imagery (e.g., PACE) with a new ocean-optimized profiling lidar and a global array of autonomous in situ platforms (e.g., BGC-Argo). Reproduced from Hostetler et al. [43], as presented in the OBB Science Vision report [1].

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