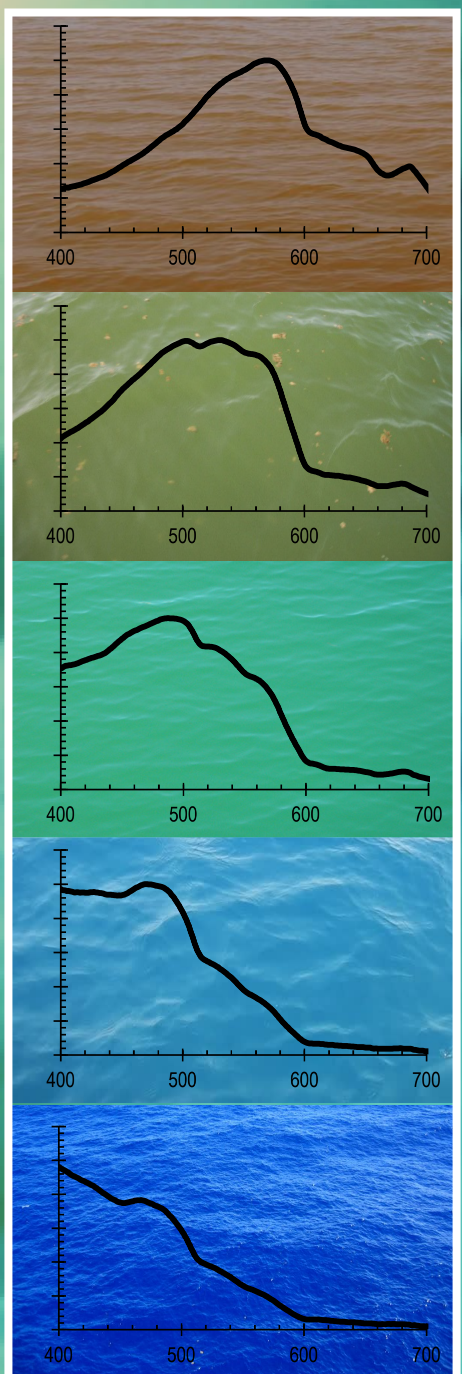
NOAA Technical Memorandum NMFS-F/SPO-255



Plankton, Aerosol, Cloud and ocean Ecosystem (PACE) Satellite Data for Aquaculture and Fisheries Management

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May 2025

U.S. DEPARTMENT OF COMMERCE

National Oceanic and Atmospheric Administration
National Marine Fisheries Service
Office of Science and Technology

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Section 1:

Getting Started with Ocean Color and Hyperspectral Data

Introduction to ocean color and hyperspectral data

Nearly every lifeform on this planet depends on just a tiny portion of the sun's electromagnetic spectrum ("visible light" from 400–700 nm) by which terrestrial and aquatic plants photosynthesize, create food, sequester carbon, and give us the oxygen that we breathe. When this visible light hits the surface of our planet and encounters our oceans, different materials within the water (e.g., phytoplankton, dissolved organic material, dying or dead organisms, floating seaweed, pollutants, suspended sediments from land, among other things) absorb and scatter different amounts and types (wavelengths) of light. The resulting optical fingerprint that these materials impart on the water can be unique, enabling sensitive ocean color sensors on satellites to surmise and map the composition of the ocean from space. How well we unravel the ocean's composition from this signal largely depends on how well we can see these colors.

Our heritage ocean color satellites detect anywhere from 5–10 wavelengths, which has limited our ability to distinguish some of the aforementioned ocean properties from one another. The launch of the **P**lankton, **A**erosol, **C**loud, and ocean **E**cosystem (PACE)[1] mission on February 8, 2024 introduced the satellite community to global "Hyper"-spectral measurements, meaning a spectrally continuous sampling of light. This has afforded the opportunity to sense the ocean through an entirely new lens by being able to resolve previously undetectable, subtle features unique to, for example, a particular phytoplankton class, or other ocean constituents.

NOAA plans to codify these hyperspectral ocean color capabilities well into the 2050s with the launch of the **Geo**stationary E**X**tended **O**rbit (GeoXO)[2] mission, preceded by NASA's **G**eostationary **L**ittoral **I**maging and **M**onitoring **R**adiometer (GLIMR)[3], which will offer perspectives from a geostationary orbit, where we can revisit the same area several times per day at higher resolutions than PACE. This document is intended to familiarize readers with the capabilities and nuances of available and emergent ocean color data products to help guide implementation plans for use in aquaculture and fisheries management at NOAA Fisheries.

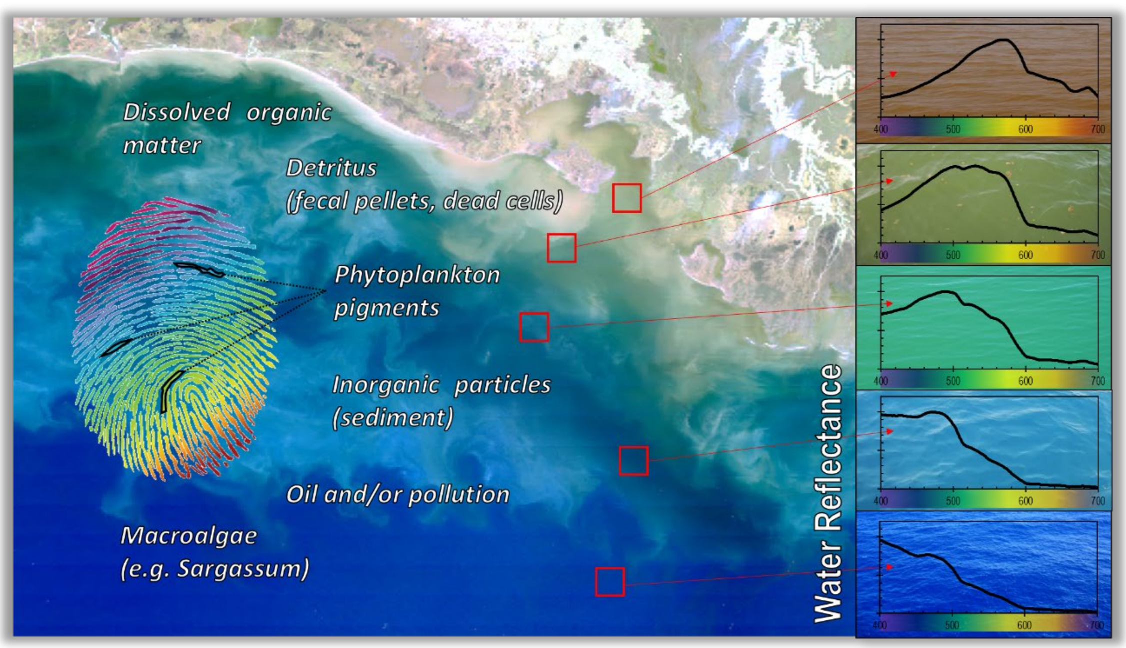


Figure 1. The 5 panels (right) display the spectrum of light corresponding to the ocean color shown. The shape of the color intensity changes across the spectrum, providing a unique fingerprint imparted by the materials in the water.

How is ocean color data currently used for fisheries management?

Ocean color data have an extensive history of usage in fisheries management, and the utility of this data stream for NOAA Fisheries continues to grow, especially as more applications for aquaculture[4] are explored. The following are only a few examples of how ocean color is utilized at NOAA Fisheries.

- Ocean color and other satellite-derived variables are included in ecosystem status reports[5], ecosystem socioeconomic profiles[6], and end-to-end ecosystem models[7], and these products are presented to U.S. Regional Fisheries Management Councils. This information gets reviewed annually during harvest recommendations for various species and is qualitatively considered in the risk tables or buffer setting processes that evaluate whether a reduction from max catch limits is warranted.

- Ocean color data are considered in the stock assessment process for several species. For instance, at the Southeast Fisheries Science Center, red[8] and gag[9] grouper assessments have used ocean color data to inform modeled mortality due to red tides, reducing overfishing risk[10]. At present, several research track stock assessments and fishery forecasts are using ocean color data (e.g., golden tilefish[11], Pacific swordfish[12], bigeye tuna[13], and more).

- NOAA's predictive spatial monitoring of highly migratory species[14] combines observer data and environmental data, including ocean color, to predict where and when fishery interactions may occur. This can help determine where vessels should fish or collect data, assess spatial management areas and closures, determine essential fish habitat, assist in ecosystem-based fisheries management, and understand the impacts of climate change on fisheries.

- NOAA's Climate, Ecosystems, and Fisheries Initiative (CEFI)[15] is reliant on the skill and performance of regionally tuned Modular Ocean Models (MOM-6)[16]. Ocean color satellite data provide a critical source of validation for the model's coupled Carbon, Ocean Biogeochemistry and Lower Trophics (COBALT)[17] component, and a high quality ocean color data record is necessary to tune the historical runs[18].

- Ocean color data are used to inform Harmful Algal Blooms (HAB) models being run around the country by the National HAB Forecast Branch of NCOOS[19] and its partners. Other tools include the Pacific Northwest HAB Bulletin[20] as well as the California-Harmful Algae Risk Mapping (C-HARM)[21] tool, which assesses toxin risk of Pacific coastal shellfish. These data are distributed to shellfish managers who use this information to make decisions to support safe seafood[22].

- Ocean color data are used or assimilated into a diverse portfolio of species distribution models developed and used in NOAA Fisheries. These models help managers identify areas of spatial and temporal overlap between managed species and commercial fisheries, which can be used to reduce bycatch[23], mitigate ship-strikes[24], or inform impact assessments, for example, offshore wind energy development[25].

In the context of ecosystem-based fisheries management, it is imperative to integrate the low end of the trophic continuum, as phytoplankton acutely respond to environmental variability, and their abundance, phenology, and overall composition determine the transfer efficiency and ultimate fate of energy in marine ecosystems. Currently, phytoplankton biomass can be directly inferred from satellites; inferences about phytoplankton community composition and physiology are additionally being made possible with recent advances toward hyperspectral radiometry. More broadly than trophic significance, the ocean's color and ambient underwater light field can also be considered, which directly impacts vision-driven behaviors[26] and potential mortality[27].

What is special about hyperspectral data?

Until recently, satellite remote sensing of ocean color has involved the analysis of discrete "bands" of color information. Each individual band possesses a unique spectral response function, which represents the range of wavelengths that a particular band is capable of seeing. A satellite radiometer measures the total intensity of electromagnetic radiation within that specific wavelength range and provides a single value for the overall radiant energy. Typical multi-spectral ocean color bands measure at a bandwidth of 20 nm or more (Figure 2, left). A wide bandwidth can be handy because it allows a satellite to collect photons more efficiently and thus reduce noise in the data output (i.e., too little light equates to grainy imagery). The tradeoff is that any spectral details within that wavelength range are lost.

By contrast, a hyperspectral spectrometer, such as that aboard the PACE satellite, breaks down light into its individual wavelengths (Figure 2, right). Providing information about specific wavelengths and their intensities allows for a more detailed analysis of the spectral fingerprint that the water imparts. With a continuous (i.e., gapless) spectrum of light sampled, various mathematical techniques such as derivative analyses can be employed to help amplify underlying patterns and/or subtle features[28] that may be otherwise hidden.

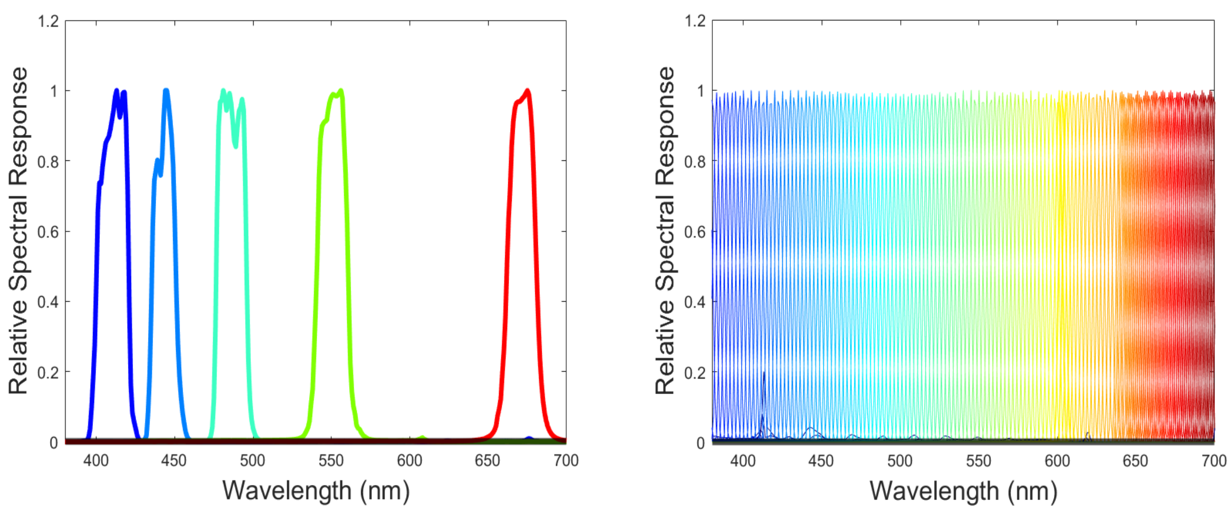


Figure 2. (Left) The relative spectral response of the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor compared to that of PACE (right). Narrower bandwidth and more bands are what constitute the "hyperspectral" nature of spectrometers.

One advantage of having hyperspectral information is that it can provide insights into phytoplankton community composition, among other applications. There are over 10,000 species and taxa of phytoplankton, spanning five orders of magnitude in size and containing unique assemblages of light-absorbing pigments. While all phytoplankton contain chlorophyll-a, additional pigments may be present, including other chlorophylls (b, c), various carotenoids, and phycobiliproteins. The presence or absence of certain pigments can be indicative of a particular phytoplankton class or species; thus, subtle spectral features can contain information that helps distinguish some phytoplankton from one another (e.g., differentiate dinoflagellates from diatoms), as well as help differentiate living from non-living materials. Sections 2 and 3 of this document go into more specific detail on the relative benefit that hyperspectral information imparts on individual ocean color products.

To what degree can I trust satellite ocean color data?

To answer this question, it is helpful to consider what we are physically observing when we look at the Earth's oceans from space. As mentioned in the Introduction, the color of the ocean is a direct function of how the materials in the water are absorbing and scattering light. However, before a satellite can detect this ocean-modified color signal, the sunlight must first journey into, and then out of, the Earth's atmosphere. Between this space, several other things are absorbing and scattering light, effectively changing the nature of the color that a satellite sees. Some of these things include aerosols, molecular (Rayleigh) scattering, gases in the atmosphere, dust, sun glint, and whitecaps on the ocean's surface, to name a few. Collectively, these elements account for the overwhelming majority (>90 percent) of the total light signal that a satellite sees. This atmospheric signal has to be accounted for and "removed" before we can infer anything about what lies beneath, and herein lies one source of uncertainty.

Our hyperspectral ocean color instruments, such as PACE, are engineered to estimate the ocean's individual color channels with less than a 5–10 percent margin of uncertainty, depending on what part of the color spectrum we are looking at. This level of uncertainty is achieved through a continuous process of sensor calibration updates, vicarious calibration from a traceable *in situ* reference sensor, and field validation campaigns to assess performance and correct for the inevitable degradation of the sensor in a harsh space environment.

The other source of uncertainty arises when using this color information to then empirically infer something about the contents of the ocean. The challenge is that we have to decipher what specific components of the ocean water are causing the color to change. For example, any combination of microscopic phytoplankton, dissolved organic matter, sediments, dead cells, suspended particles, floating seaweed, runoff, (some) pollution, or oil slicks will have their own unique "optical fingerprint" based on their presence, size, shape, abundance, and overall composition of these components. Sometimes, these signals overlap, for instance, while the photosynthetic pigment chlorophyll-a (contained within all phytoplankton) preferentially absorbs blue light, so also does dissolved organic matter (Figure 3). This is not a problem if the organic matter is created from phytoplankton, but when it comes from an outside source (e.g., river input), these competing signals do not co-vary, and they become more difficult to disentangle. Uncertainties for a product like chlorophyll-a are nominally ±35 percent, with better performance in offshore blue waters relative to nearshore, coastal waters. Modern advances in computing (e.g., machine learning) as well as sensor technology (hyperspectral + UV) offer pathways for enhanced distinction of these separate components and substantial uncertainty reduction for chlorophyll-a[29] in coastal waters.

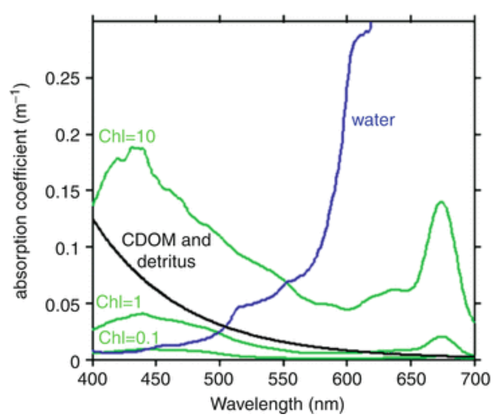


Figure 3. Spectral absorption of light from varying seawater constituents.

Even with the inherent uncertainties, the value of satellite ocean color observations should not be understated. It would take roughly 11 years for an average-speed ship (~10 mph) to measure what a satellite can detect in under 2 minutes, lending us a unique, synoptic view of biogeochemical processes over time and space scales that we just cannot resolve in the field. Even so, we will always need field measurements to help us connect what we see from satellites to what is really going on in the ocean, and it is worth noting that pairing field data with satellites ultimately maximizes the value of both data streams.

Which satellite(s) do I want to use?

The ocean is a relatively dark target as viewed from space, making up only 4–10 percent of the light signal seen from a satellite's perspective above the atmospheric layers. As such, ocean color satellite sensors need to be very sensitive in order to collect a usable signal, but not so sensitive that the radiance (light) signal saturates the optics. There are various trade-offs to consider when designing a satellite, and these impact the potential usability of data products. Different satellite missions may exhibit variations in the spatial resolution (size of the "pixel"), temporal resolution (how often a satellite passes the same area), and spectral resolution (how many discrete colors are sampled), making some satellites better suited for certain applications over others. A satellite with relatively high spatial resolution (e.g., Landsat - 30 meter pixels) would be useful to resolve very near-shore, estuarine, and freshwater environments, but as these satellites have to zoom in closer, it takes longer periods of time to revisit the same location (up to 16 days). Therefore, the applications may be best suited for characterization of temporally consistent environments. A satellite with a larger spatial footprint (e.g., MODIS, PACE - 1 km pixels) can cover the entire globe daily, so the applications are best suited for temporally dynamic features such as open ocean phytoplankton productivity. As an intermediate, a pair or constellation of sensors can be combined to help increase revisit time + increase spatial resolution (e.g., Sentinel-3A/3B OLCI – 300 meter pixels, 2–3 day revisit time).

In the future, NOAA (GeoXO – launching 2032) and NASA (GLIMR – launching ~2028) plan to launch geostationary satellites, which can "stare" at locations longer, and revisit a location multiple times per day, creating a sequence of images to mitigate cloud cover, as well as examine biological rates, fluxes, particle trajectories, and more. The tradeoff with a geostationary orbit is that it can only view a particular portion of the globe over a mission lifetime. Table 1 provides a quick user guide to several relevant ocean color platforms (past, present, and future), and their specifications. The Ocean Colour Climate Change Initiative[30] (OC-CCI) dataset merges multiple satellite data records and bias corrects sensor differences, making it ideal for analyzing long-term trends (1997 – present) in blue oceanic waters. The performance of this dataset in nearshore waters has not been adequately assessed, so use this product with caution and healthy skepticism in coastal and freshwater environments. This dataset is updated quarterly, and does not yet provide a near real-time product.

Table 1. Listing of satellite sensors with managing agency, and their nominal spatial resolution (pixel size), temporal resolution (revisit time), spectral resolution (number of bands in the visible range of wavelengths, 400 – 700 nm), and the time frame that the data are/will be available.

Sensor	Agency	Pixel Size	Revisit Time	# bands	Time Frame
CZCS	NASA	825 m	Not uniform	4	1978–1986
SeaWiFS	NASA	1 km	2 days	6	1998–2010
MODIS	NASA	1 km	1 day	10	2000–2024
VIIRS	NOAA	750 m	1 day	5	2012–present
Sentinel-3 OLCI	ESA	300 m	2–3 days*	11	2016–present
Landsat OLI	USGS	30 m	16 days	4	2013–present
Sentinel-2 MSI	ESA	10 – 60 m	5 days*	4	2015–present
GOCI	KIOST	250 – 500 m	1 hour (Korea)	6	2010–present
PACE OCI	NASA	1 km	1–2 days	Hyperspectral	2024–present
SBG	NASA	30 – 45 m	16 days	Hyperspectral	2028 (tbd) –
GLIMR	NASA	535 m	1.5–3 hours (US)	Hyperspectral	2028 (tbd) –
GeoXO OCX	NOAA	300 m	2 hours (US)	Hyperspectral	2030s (tbd) –
Landsat Next	USGS	10 – 20 m	6 days*	9	2030s (tbd) –

*Multiple sensors in constellation to meet this revisit time.

Accessing and interacting with data

There are some terms that may be useful to know when looking for satellite data. The processing level of data describes how much the original data has been manipulated. These levels generally range from L0–L4, with L3/L4 being the most processed:

Level 0: Raw digital counts. Note, you generally should not need to interact with L0–L1b files.

Level1a: Level 0 files with various ancillary information attached (e.g., geolocation).

Level1b: Level1a data with instrument calibrations applied.

Level2: Derived geophysical values (e.g., chlorophyll-a), at the native (highest) resolution of the sensor. These files will look warped because they are from the view of a satellite looking down at a round Earth. Since they retain the spatial resolution, these files would be used for data 'matchups'.

Level3: These data have been spatially and temporally aggregated and projected to a consistent, mapped grid. Here, the shape of, for example, the East Coast, will look as it looks on maps. These are the easiest to interact with; however, the resolution is generally coarser (4 km) because it takes in data from all satellite viewing angles. These are best for analyzing long-term trends, and are available at various time steps (1 day, 8 day average, monthly, annually, climatologically).

Level4: Model output or products from that combine multiple measurements. Alternatively, gap-filled data products with interpolation methods used to fill time or spatial gaps.

All the listed ocean color data in Table 1 are publicly available. Where do you find this data? NOAA provides a value-added service known as CoastWatch[31] that serves up satellite data[32], user tools[33], a Graphical User Interface data viewing portal[34], data analysis software[35], in addition to training modules[36], and a human-supported help desk. CoastWatch provides data at best effort, with support 8 hours a day, 5 days a week and has regional "Nodes" around the U.S. Some Nodes are housed in NOAA Fisheries science centers to help connect fisheries' needs with satellite data. You can also opt to use NOAA's ERDDAP[37] data server, which gives you a simple, consistent way to download subsets of scientific datasets (Level 3 and above) in common file formats and make graphs and maps on the spot. ERDDAP is useful for integrating with programming languages for automated downloads and more advanced analyses. The aforementioned OC-CCI dataset can also be found through NOAA's ERDDAP, but some individual missions (such as MODIS or SeaWiFS) are not included. For high assurance, near real-time operations, NOAA produces some ocean color data through NESDIS/Office of Satellite and Product Operations (OSPO)[38] and NOAA's formal archive of ocean color data is housed in NESDIS/NCEI/CLASS[39].

NASA's OBDAAC[40] archives most of the datasets listed in Table 1 and may be accessed through a browser tool[41]. Landsat 8/9 and Sentinel-2 data are the exception; for aquatic applications, some of these high resolution ocean color products[42] are available, but surface reflectance should be used with caution[43]. NASA also provides a Graphical User Interface data analysis tool called SeaDAS[44], which enables data processing from L0–L3, and data visualization/analysis. More heavy data processing can be performed and automated at the command line using the OCSSW[45] system. The active Earthdata forum[46] can help you with any issues you have, from installation to data processing. Sometimes, you may just want to browse through ocean color data products quickly, in which case, the most user friendly mechanism is through NOAA STAR's OCView[47]. Scroll through daily or averaged global files with a click of a button, and toggle a range of options (e.g., true color, ocean color, temporally averaged files, anomalies, Level-2 granule locations and name, and more). NASA's Giovanni[48] and WorldView[49], as well as Copernicus' MyOcean viewer[50], also offer different flavors of similar capabilities, each with strengths and weaknesses. Many other portals, tools, and operational and experimental products are available through agencies and universities around the world.

PACE filename conventions

PACE data have some nuances in the file naming convention. Because of the hyperspectral nature of PACE (i.e., large files), the Level-2 (individual satellite scene) netcdf files are provided in different product "bundles," which one can differentiate by the file naming convention. By contrast, Level-3 (globally mapped, gridded products) netcdf files are larger in geographic expanse, and thus are separated into individual product types. The next section describes these products in more detail. For the latest updates in PACE data product offerings and algorithm status, visit https://pace.oceansciences.org/data_table.htm.

The format of the Level 2 filename convention and corresponding product suite are shown below:

PACE_OCI.[YYYYMMDD]T[HHMMSS].L2.OC_**AOP**.V#_0.NRT.nc

Rrs - remote sensing reflectance at 184 wavelengths (339–719 nm)

avw - apparent visible wavelength

nflh – normalized fluorescence line height

PACE_OCI.[YYYYMMDD]T[HHMMSS].L2.OC_**BGC**.V#_0.NRT.nc

chlor_a - chlorophyll-a

carbon_phyto - phytoplankton carbon

poc - particulate organic carbon

PACE_OCI.[YYYYMMDD]T[HHMMSS].L2.OC_**IOP**.V#_0.NRT.nc

Kd - diffuse attenuation coefficients at 19 wavelengths (351–711 nm)

a - total absorption coefficients at 19 wavelengths (351–711 nm)

aph - phytoplankton absorption coefficients at 19 wavelengths (351–711 nm)

adg - detrital and gelbstoff absorption coefficient at 442 nm

adg_s - detrital and gelbstoff absorption spectral slope parameter

bb - total backscatter coefficients at 19 wavelengths (351–711 nm)

bbp - particle backscatter coefficient at 442 nm

bbp_s - particle backscatter spectral slope parameter

PACE_OCI.[YYYYMMDD]T[HHMMSS].L2.**PAR**.V#_0.NRT.nc

ipar_planar_below - instantaneous photosynthetically available radiation (below water surface)

ipar_planar_above - instantaneous photosynthetically available radiation (above water surface)

par_day_scalar_below - daily scalar photosynthetically available radiation (below water surface)

par_day_planar_above - daily planar photosynthetically available radiation (above water surface)

par_day_planar_below - daily planar photosynthetically available radiation (below water surface)

PACE_OCI.[YYYYMMDD]T[HHMMSS].L2.**SFREFL**.V#_0.NRT.nc

rhos – surface reflectance at 52 wavelengths (339–2258 nm), corrected for Rayleigh scattering

Section 2:

PACE Ocean Color Products for Aquaculture/Fisheries

Product 1: Chlorophyll-a (chlor_a)

What is it?

- Chlorophyll-a (Figure 4) is a pigment contained within all phytoplankton and cyanobacteria cells. It is an estimate of algal biomass that is used for mapping the distribution of phytoplankton over time and space.

How does it impact aquaculture/fisheries?

- Chlorophyll-a is a useful proxy of the biomass of phytoplankton in the water, the food source to filter feeding organisms and zooplankton. This parameter has been utilized for aquaculture siting[51], farm aquaculture resource management[52] models, HAB forecasts[21], species distribution models (fish[53], mammals[54], top predators[55], other highly migratory species[56]), ecosystem models[7], ecosystem status monitoring[57], as a predictor of unregulated fishing activity[58], and more.

What are the limitations/caveats?

- Currently, chlorophyll-a can be confused with other dissolved materials in the water, and it can be over-estimated in coastal regions, particularly in areas with river inputs or sediment resuspension. It is useful to note that the amount of chlorophyll-a in a phytoplankton cell can vary substantially based on physiological and environmental conditions, and thus, it is possible that increases in chlorophyll-a do not explicitly represent increases in biomass.

Does HYPERSPECTRAL directly improve/enable this product?

- Having more information about the other components of the water will help separate the living from non-living components, and should improve the performance of the chlorophyll-a product substantially. Many efforts at improving chlorophyll-a have been attempted using regional tuning[59] methods, generalized additive models[60], and dynamic optical water types[61], or applying machine learning[62] techniques and neural networks[42], but lack unified community consensus or adoption.

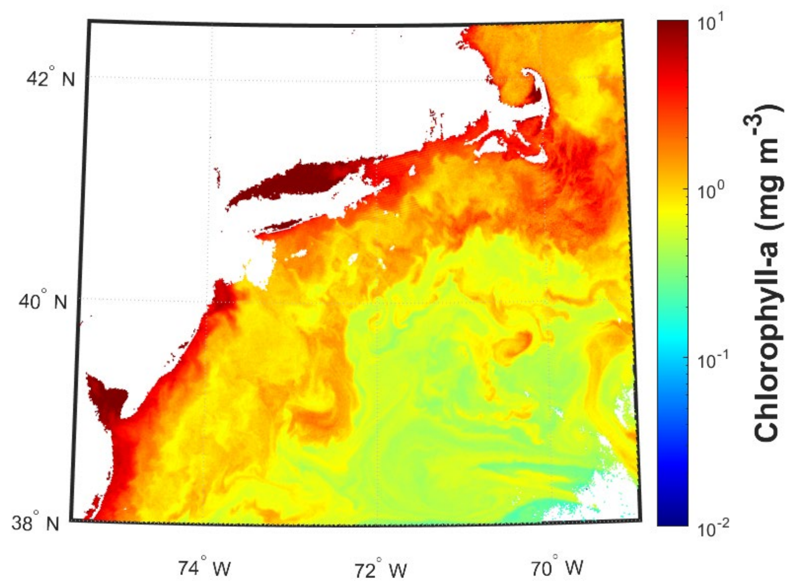


Figure 4. Projection of PACE-derived chlor_a in the Mid-Atlantic Ocean; May 13, 2024.

Product 2: Phytoplankton carbon (carbon_phyto)

What is it?

- The phytoplankton carbon product (Figure 5) expresses the concentration of phytoplankton in terms of carbon concentration, instead of chlorophyll-a. Contrasting from the chlorophyll-a product, phytoplankton carbon is derived from an empirical relationship to the particle backscattering properties (see Product 7) of the water.

How does it impact aquaculture/fisheries?

- Some fisheries applications may prefer to work in units of carbon biomass instead of pigment-based (i.e., chlorophyll-a) biomass. A constant chlorophyll-a value can represent a wide array of cell concentrations, due to environmental conditions and individual cell physiology/stress[63]. For example, individual phytoplankton can produce more chlorophyll-a/cell in low-light conditions without changing the actual number of cells. The carbon product is not subject to these variations, and is a more direct indicator of phytoplankton biomass[64]. Modelers may also be interested in computing a carbon to chlorophyll ratio to tease out environmental or species variations, and this is obtained as carbon_phyto ÷ chlor_a. Use this ratio with caution, as it has not been independently validated.

What are the limitations/caveats?

- This product was empirically tuned with field data, but it is not currently representative of optically complex waters. The performance in coastal regions remains untested. This product relies on the "inherent optical property" (IOP)[65] suite of ocean color products, and thus can sometimes fail to arrive at a solution (i.e., no data) in waters with extreme scattering or chromophoric dissolved organic matter (CDOM) concentrations.

Does HYPERSPECTRAL directly improve/enable this product?

- Operational improvements to IOP backscatter products using hyperspectral data are anticipated, but still in development (at the time of this publication).

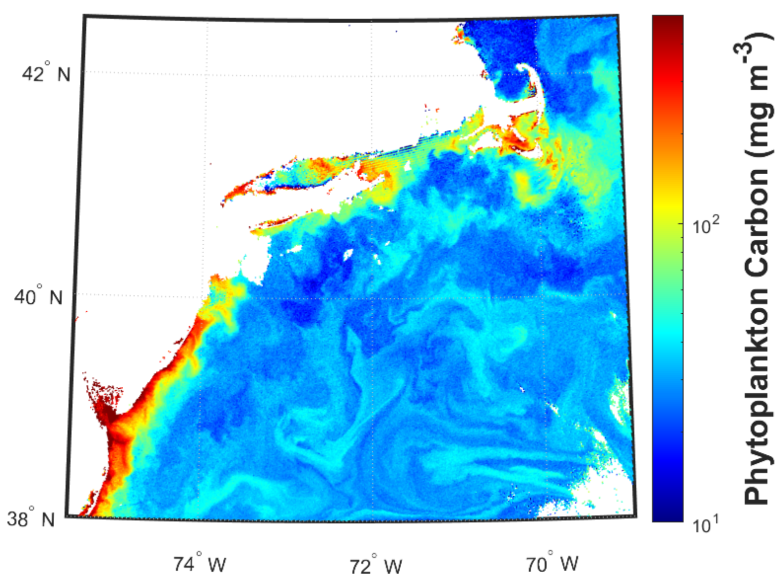


Figure 5. Projection of PACE-derived carbon_phyto in the Mid-Atlantic Ocean; May 13, 2024.

Product 3: Particulate Organic Carbon (POC)

What is it?

- Carbon-containing particles suspended in seawater can be categorized as organic (plankton, detritus, bacteria) or inorganic (sediments, calcified phytoplankton plates). Using carbon as a basis, ocean color can derive particulate organic carbon[66] (POC; Figure 6) and particulate inorganic carbon[67] (PIC, also PIC color index[68]). Currently, PACE only offers POC products; PIC products are available from multi-spectral sensors such as MODIS and VIIRS.

How does it impact aquaculture/fisheries?

- Studies directly using POC/PIC satellite products for fisheries applications are sparse; however, these products are very relevant in the context of carbon export processes. Suspended particulate matter (SPM), which represents all combined sources of suspended particles, is a parameter more likely recognized in the aquaculture community. It is a useful product for detecting high sediment loads, which compromise water quality and growth conditions[69] for many shellfish species and adversely impact shellfish burial rates[70]. Offshore fisheries can produce significant amounts of suspended particulate waste[71]. Suspended particles also can transport toxic heavy metals and organic compounds that accumulate in fish tissues[72].

What are the limitations/caveats?

- Depending on the absorption/scattering properties of the water mass, some regional tuning should be anticipated. The POC and PIC products are derived by independent methods and should not be considered additive properties.

Does HYPERSPECTRAL directly improve/enable this product?

- Proximally, PACE is anticipated to operationally offer a suspended particulate matter[73] product derived from *hyperspectral* measurements and machine learning techniques. A multi-spectral approach to deriving SPM, as well as POC in the presence of SPM[74] is being implemented by NOAA's CoastWatch (at the time of publication).

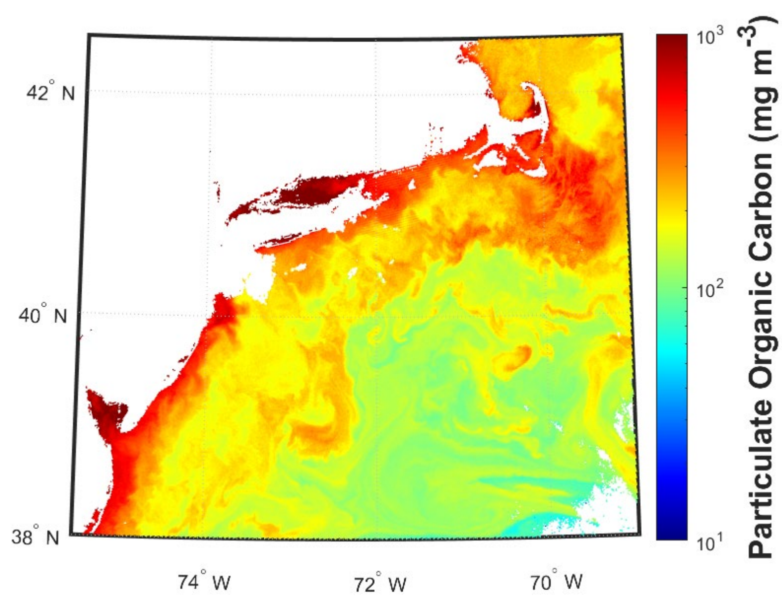


Figure 6. Projection of PACE-derived poc in the Mid-Atlantic Ocean; May 13, 2024.

Product 4: Diffuse attenuation coefficients (K_d)

What is it?

- As light enters the water column, it is attenuated exponentially with depth until it has been absorbed completely. The light attenuation coefficient (K_d; Figure 7) is a measure of the exponential slope of this light extinction, providing an indicator of how deep light can penetrate into the water. This enables the calculation of light intensity and quality at depth.

How does it impact aquaculture/fisheries?

- Light attenuation directly impacts water visibility, and vision is among the principal sensory modalities used by marine fauna, playing a critical role in fundamental day-to-day activities[75]. Fish rely on visual cues for the basic navigation of space[76], habitat selection[77], schooling[78] or shoaling[79], foraging[80] and prey capture[81], and for predator detection[82] and evasion[83]. Light availability in aquacultured teleosts has also been shown to influence all lifecycle stages including egg and larvae survival, smolt timing, and maturation during the on-growing phase and broodstock spawning[84].

What are the limitations/caveats?

- K_d algorithms are generally robust and reliable, though differences can be confusing. Semi-analytical approaches[85] reduce uncertainty in turbid, optically complex waters relative to more ubiquitous empirical approaches[86] that are highly correlated with chlorophyll-a.

Does HYPERSPECTRAL directly improve/enable this product?

- Hyperspectral capabilities offer a full suite of K_d coefficients across the visible spectrum. Historically, only the blue-green wavelength (490 nm) has been utilized for most applications. With the full spectrum, the characterization of the light field can be determined at any depth, and used to pinpoint the exact wavelength of light that penetrates the deepest into the water column, improving estimates of water visibility. Note, while computable, *water visibility* is not a standard product offering. In a pinch, a rough approximation of visibility distance (in meters) for a given wavelength can be made as $1 \div K_d(\lambda)$.

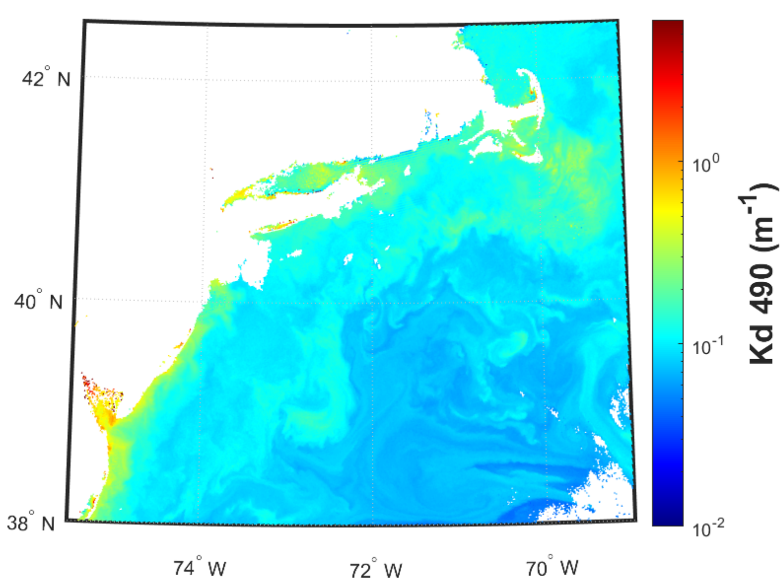


Figure 7. Projection of PACE-derived kd_490 in the Mid-Atlantic Ocean; May 13, 2024.

Product 5: Spectral phytoplankton absorption coefficients (a_{ph})

What is it?

- These absorption coefficients specifically define how light is absorbed by phytoplankton. This product partitions and isolates the phytoplankton component from the other absorbing materials in the water, like CDOM and other non-living components. Absorption near 440 nm (Figure 8) is often used as a reference, representing the peak of chlorophyll-a absorption.

How does it impact aquaculture/fisheries?

- The absorption of light by phytoplankton can vary by a factor of 4 or more at a constant chlorophyll-a value, so this parameter more accurately describes how much light has been utilized by living phytoplankton cells. This has implications for how much of this light energy will eventually be turned into biomass, and it is a central component of more advanced absorption-based primary productivity algorithms[87]. As a standalone product, it partially helps mitigate the obscuring impact of other absorbing materials in the water.

What are the limitations/caveats?

- While the magnitude of absorption is dynamic, the absolute shape of spectral absorption is currently based on a global average[88], and thus offers no real insights differentiating phytoplankton pigment absorption and should not be used for this purpose. Keep in mind that not all absorbed light is allocated to photosynthetic processes (i.e., some absorbed energy is lost to heat and fluorescence). The performance of this product can vary, and it may not perform well in highly scattering, or very high CDOM water-types.

Does HYPERSPECTRAL directly improve/enable this product?

- Operational improvements to IOP products using hyperspectral data are anticipated, but still in development (at the time of this publication). PACE Science and Applications Team members are actively working to improve this product using new approaches, including new hyperspectral inversion frameworks[29] for improved absorption products.

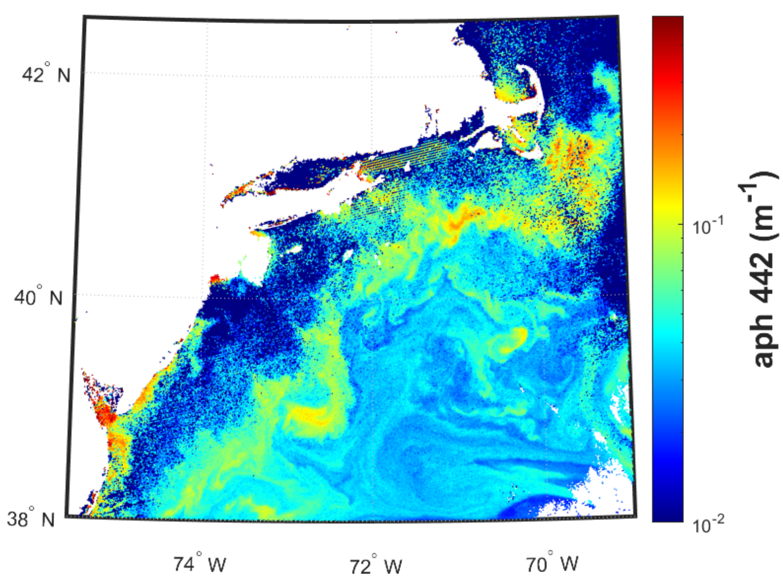


Figure 8. Projection of PACE-derived aph_442 in the Mid-Atlantic Ocean; May 13, 2024.

Product 6: Spectral non-algal particle plus dissolved organic matter absorption coefficient (a_{dg}) at 442 nm

What is it?

- This absorption coefficient specifically defines how light is absorbed by the combined effect of non-living particles (detrital) and CDOM (Figure 9).

How does it impact aquaculture/fisheries?

- The increased absorption of light by detritus + CDOM can indicate the presence of a declining phytoplankton bloom, or land-based detritus + CDOM from river input. In cases of known high river discharge events (e.g., after a storm event or heavy rainfall or ice melt), this product is a useful water mass tracer[89]. CDOM has been found to be useful in source tracking of aquaculture[90] as well as wastewater[91] pollution.

What are the limitations/caveats?

- While the algorithm is tunable, its standard configuration defines a constant "shape" of detrital/CDOM absorption, so there is no information that can be derived about the origin of the materials other than through a subjective spatial-temporal context. Note, this is a combined detrital matter + CDOM product, and not a standalone CDOM product. The slope parameter for adg (adg_s) is an exponential coefficient that enables the user to reconstruct the hyperspectral spectrum from a single wavelength.

Does HYPERSPECTRAL directly improve/enable this product?

- Operational improvements to IOP products using hyperspectral data are anticipated, including the separation of a_d (detritus) from a_g (CDOM, or "gelbstoff"), but still in development (at the time of this publication). PACE Science and Applications Team members are actively working to improve this product using new approaches, including new hyperspectral inversion frameworks[29] for improved absorption products.

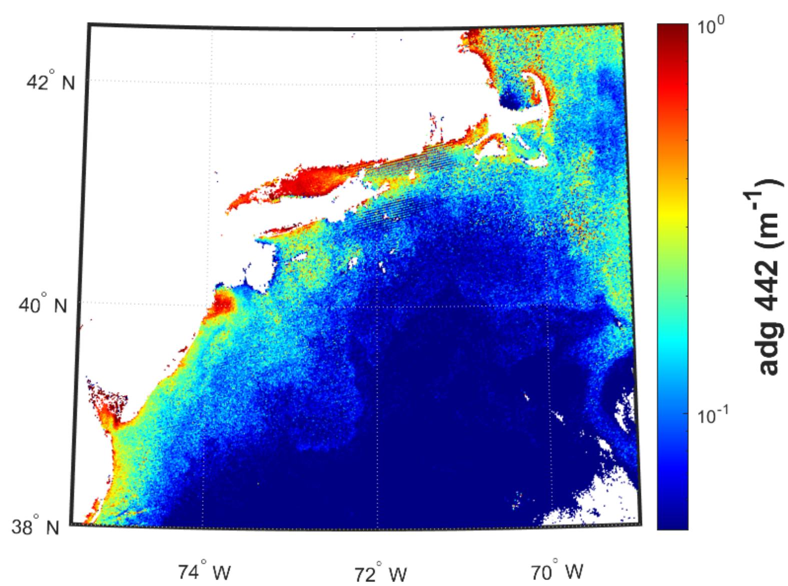


Figure 9. Projection of PACE-derived adg_442 in the Mid-Atlantic Ocean; May 13, 2024.

Product 7: Spectral particle backscattering coefficient (b_{bp}) at 442 nm

What is it?

- This backscatter coefficient (Figure 10) defines how light is scattered in the backwards direction by particles in the water. This product provides an indicator of the concentration of particles in the ocean and is a proxy indicator of particulate carbon concentrations.

How does it impact aquaculture/fisheries?

- Many phytoplankton exhibit unique backscattering characteristics[92], primarily as a function of cell size[93], and sometimes composition (e.g., Coccolithophore blooms[94]). Particle backscatter is a particularly useful tool to determine high sediment loads in nearshore environments, which tends to heavily scatter light. High sediment loads can cause gill saturation[69] in certain oyster species, and some fish species exhibit hypersensitivity to suspended sediment[95]. While not a direct measurement of SPM, it can be used to develop those products.

What are the limitations/caveats?

- The backscatter product is one of the most robust products offered in the "inherent optical property" (IOP) suite of ocean color products. The only caveat is that the IOP algorithms can sometimes fail to arrive at a solution (i.e., no data) in waters with extreme scattering or CDOM concentrations. The bbp product does not disentangle phytoplankton backscatter from other optical constituents (e.g., re-suspended sediment in coastal waters). The slope parameter for bbp (bbp_s) is a power law coefficient that enables the user to reconstruct the hyperspectral spectrum from a single wavelength.

Does HYPERSPECTRAL directly improve/enable this product?

- Operational improvements to IOP products using hyperspectral data are anticipated, but still in development (at the time of this publication). PACE Science and Applications Team members are actively working to improve this product using new approaches.

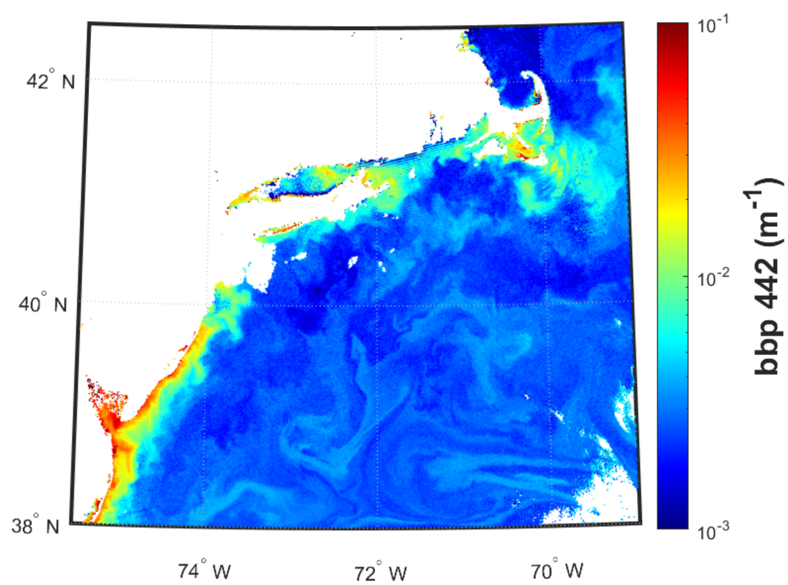


Figure 10. Projection of PACE-derived bbp_442 in the Mid-Atlantic Ocean; May 13, 2024.

Product 8: Normalized fluorescence line height (nFLH)

What is it?

- Normalized fluorescence line height is light leaving the ocean surface due to sun-induced chlorophyll fluorescence (Figure 11). This provides an indicator of phytoplankton physiology/nutrient stress, and is utilized input to some chlorophyll-a and HAB algorithms.

How does it impact aquaculture/fisheries?

- The nFLH product can help with preparing for HAB closures[96], assessing health status of a phytoplankton bloom[97], and identifying oceanic regions under nutrient stress[98]. This is also used as an input parameter for the dynamic pelagic Seascapes[99] product, a classification scheme which can help describe basin and gyre scale features and seasonal boundary shifts.

What are the limitations/caveats?

- Conditional uncertainties exist for this product, and caution should be exercised when interpreting results. Fluorescence line height has multiple dependencies on cellular pigment packaging and light saturation (non-photochemical fluorescence quenching), impacting phytoplankton fluorescence quantum yields (relative amount of light reradiated versus being absorbed). These uncertainties are exasperated in waters where phytoplankton are not the dominant source of optical variance, such as in the presence of suspended sediments or interference from bottom reflectance.

Does HYPERSPECTRAL directly improve/enable this product?

- The multispectral version of this product (nFLH[100]) uses a static set of wavelengths that are not explicitly optimized for the detection of fluorescence. Note, these particular wavelengths are not available on the VIIRS series (MODIS or OLCI are used instead). Hyperspectral data will improve the fluorescence line height approach by optimizing the choice of wavelengths, which is not possible with multispectral (e.g., MODIS, VIIRS) approaches. This will enhance the reliability and accuracy of the product.

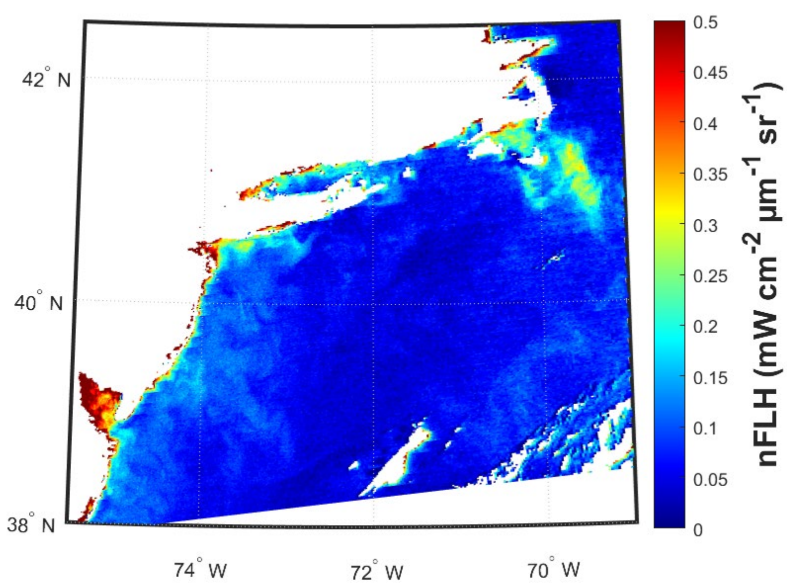


Figure 11. Projection of PACE-derived nflh in the Mid-Atlantic Ocean; May 13, 2024.

Product 9: Photosynthetically available radiation (PAR)

What is it?

- PAR is defined as the quantum energy flux from the Sun in the 400 - 700 nm range. There are several data products available in PACE data files. Scalar irradiance is derived by taking the sum of light from all angles onto a point on the ocean, that is, how much light is hitting the ocean. Planar irradiance scales the amount of light based on the cosine of the direction it comes from, and likely will not be used for fisheries/aquaculture applications. There are above water products (how much hits the surface) and below water products, which take into account the index of refraction as you cross the surface of the ocean's water (i.e., how much of that is actually getting to the contents of the water). In most cases, users would likely want to use the *par_day_scalar_below* product (Figure 12).

How does it impact aquaculture/fisheries?

- PAR directly impacts the quantum yield of photosynthesis, which is essentially a measure of how many photons of light are absorbed versus how much of that is actually fixed into carbon, that is, photosynthetic efficiency. Too much PAR can cause photo-inhibition of many cultured seaweeds[101]. While not the most significant factor, one study showed that PAR contributed to variability in Catch per Unit Effort[102] more than SST and fishing hour.

What are the limitations/caveats?

- PAR is a fairly robust product. Implementation of this algorithm is contingent on the availability of observed top-of-atmosphere radiances in the visible spectral regime that do not saturate over clouds, which is not a problem for most ocean color instruments.

Does HYPERSPECTRAL directly improve/enable this product?

- The scalar/planar above/below water products are newly provided products offered by the PACE mission. More spectral information yields better spectral characterization of the ambient light field.

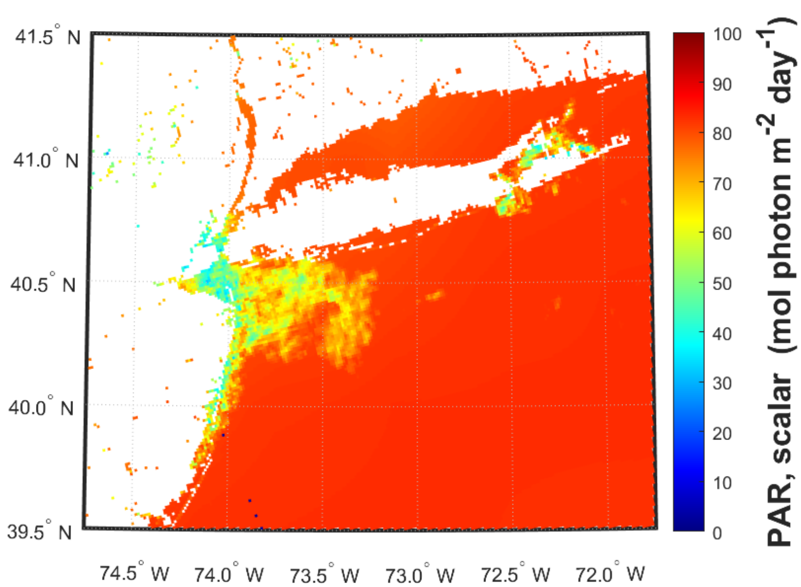


Figure 12. Projection of PACE-derived par in the Mid-Atlantic Ocean; May 13, 2024.

Product(s) 10: Remote sensing reflectance (Rrs)

What is it?

- The remote sensing reflectance is the base unit by which most ocean color algorithms are built on. It is a direct measure of the water-leaving reflectance, after the atmosphere and surface reflectance effects have been removed. Each wavelength of color has its own reflectance value 9Figure 13).

How does it impact aquaculture/fisheries?

- These products may be preferred for users who want to customize or build their own algorithms. This raw color information removes any the elements of uncertainty introduced by mechanistic assumptions made during "product" development. In one case of modeling the marine occurrence of Atlantic Sturgeon[103], the remote sensing reflectance products yielded the best predictive skill, as opposed to higher-order biogeochemical products, such as chlorophyll-a. Some published algorithms for HABs can be reconstructed using the reflectance channels (see Section 3).

What are the limitations/caveats?

- Remote sensing reflectance is subject to uncertainties introduced in the removal of the atmospheric signal. These products may underperform, or be expressed as negative values, especially in areas with complex aerosol loadings (near urban areas), or near the coast.

Does HYPERSPECTRAL directly improve/enable this product?

- For context, relative to MODIS (10 color bands) or VIIRS (5 color bands), PACE offers 120 visible color bands (plus additional UV bands) from which to develop algorithms. PACE Science and Applications Team members are actively working to improve the removal of the atmospheric signal, and thus improve the reflectance. The PACE mission was the first to use additional spectral information towards a multi-band atmospheric correction (MBAC)[104].

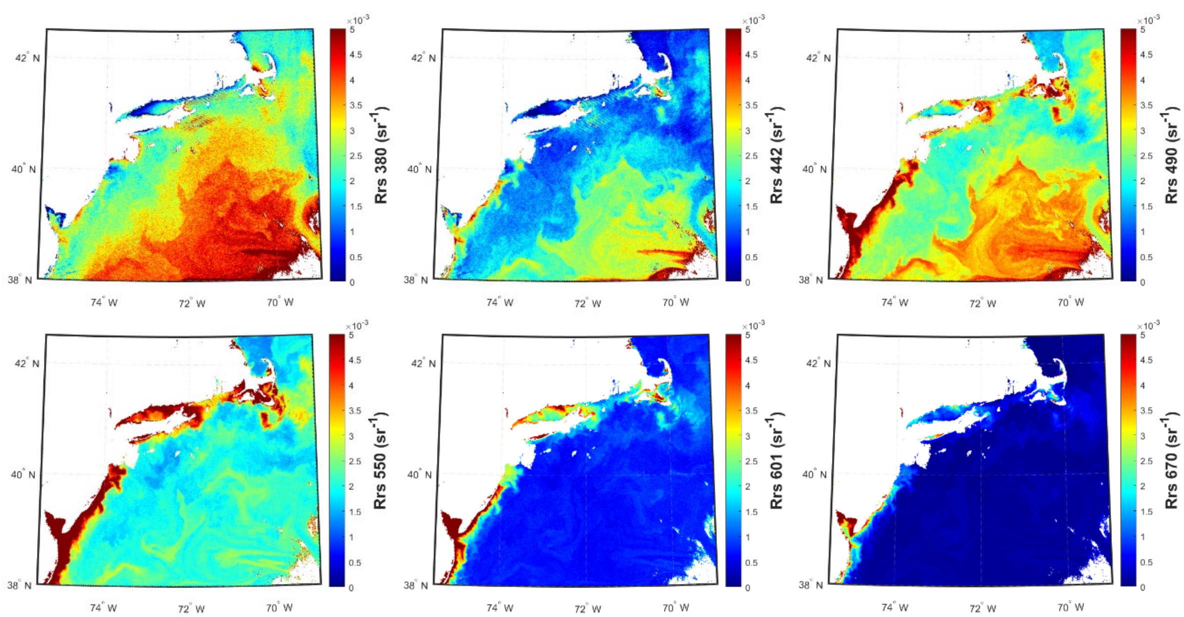


Figure 13. Projection of PACE-derived Rrs(λ) products in the Mid-Atlantic Ocean; May 13, 2024.

Product 11: Apparent visible wavelength (AVW)

What is it?

- In broad terms, visible light in underwater environments can be described by the total available amount light (i.e., intensity) in addition to the chromaticity (i.e., hue/color). The Apparent Visible Wavelength (AVW; Figure 14) is an optical water mass classification index that is sensitive to changes in water chromaticity. Since the entire visible-range spectrum is utilized in the calculation of AVW, this product ensures that any diagnostic signals present in the reflectance signal are considered, and thus affords the opportunity to describe and analyze subtle shifts in ocean color.

How does it impact aquaculture/fisheries?

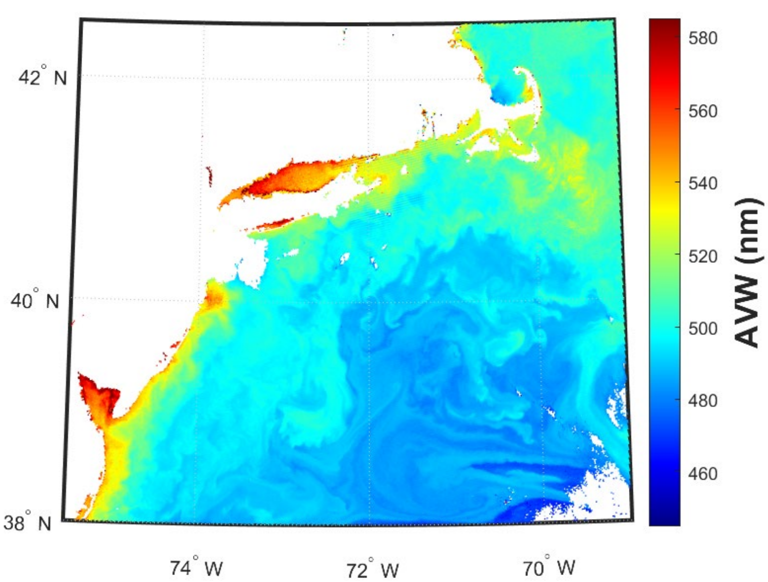
- Unlike other ocean color products, the AVW is not a derived geophysical variable, but instead an objective descriptor of the ocean's color. This makes it impervious to algorithm-induced biases and thus is useful and consistent across optically complex environments[105]. This is a useful monitoring tool to assess, not only changes to the color of the water but also information on what direction the color is shifting (i.e., more red or more blue). While the attribution/cause of shifts in water color are not elucidated with the product, it serves as an early indicator of changes in optical water properties or subsurface light quality.

What are the limitations/caveats?

- This product relies on the accuracy of remote sensing reflectance products, which are subject to uncertainties introduced in the removal of the atmospheric signal.

Does HYPERSPECTRAL directly improve/enable this product?

- This product was developed specifically for hyperspectral applications and is offered as part of the remote sensing product suite for PACE. AVW is also calibrated[106] for multi-spectral sensors to provide backwards compatibility.



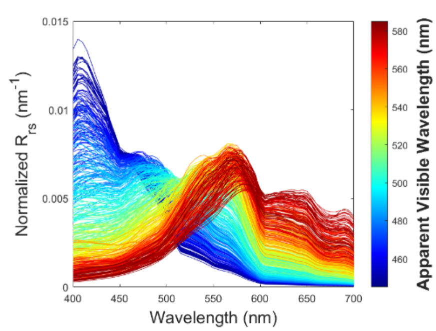


Figure 14. (Left) Projection of PACE-derived avw in the Mid-Atlantic Ocean; May 13, 2024. (Top) Corresponding reflectance spectra.

Product(s) 12: Multiple Ordination ANAlysis (MOANA)

What is it?

- This product returns near-surface concentrations (cells mL^{-1}) of three different picophytoplankton (i.e., phytoplankton <2 µm in size): *Prochlorococcus*, *Synechococcus*, and autotrophic picoeukaryotes (Figure 15). The algorithm uses empirical relationships between measured cell concentrations, *in situ* hyperspectral remote sensing reflectances, and sea surface temperatures. Details of this algorithm can be found in Lange et al. (2020)[107].

How does it impact aquaculture/fisheries?

- Picophytoplankton are composed of the cyanobacteria *Prochlorococcus* (~0.8 µm) and *Synechococcus* (~1 µm), as well as picoeukaryotes, which combined are responsible for 50 to 90% of all primary production in open ocean ecosystems[108] and contribute up to 30% of carbon export[109] in these regions. Geographically, *Prochlorococcus* tends to inhabit warmer and mostly oligotrophic waters surrounded by *Synechococcus* patches along frontal boundaries. These fronts often reside at boundaries where phytoplankton communities start to transition to higher concentrations of larger eukaryotic cells, such as picoeukaryotes and nanoeukaryotic flagellates. Thus, identification of *Prochlorococcus* and *Synechococcus* distributions may be useful in identifying trophic boundaries in oceanic ecosystems[110], in addition to providing insight into productivity, food web regimes, and carbon export.

What are the limitations/caveats?

- This algorithm will be classified as "provisional" until satellite data validation and science teams are able to validate this product. The practical utility of this product is intended for oceanic environments and should not be used to interpret phytoplankton community composition in complex coastal or estuarine ecosystems.

Does HYPERSPECTRAL directly improve/enable this product?

- This product is strictly contingent on input of hyperspectral remote sensing reflectance (see Product 10) from a wavelength range of 400 – 660 nm.

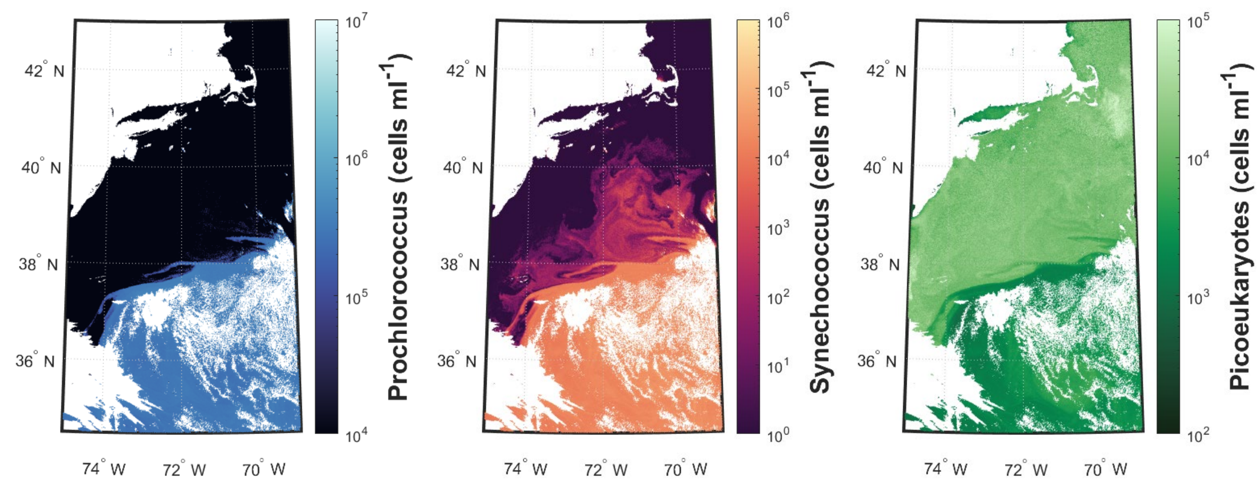


Figure 15. Projection of PACE-derived MOANA products in the Mid-Atlantic Ocean; May 13, 2024.

Product(s) 13: Surface reflectance (rhos)

What is it?

- "True color" images (Figure 16) are often generated with satellite imagery to visualize what an image would look like in real life, without algorithms applied. For oceans, these typically utilize red, green, and blue (RGB) bands from the satellite radiance data at the top of the atmosphere that have been corrected for the angular effects of Rayleigh scattering (also known as surface reflectance, or rhos). PACE now offers a full spectral suite of rhos products across the ultraviolet, visible, and near infrared spectra. Functionally, any three inputs can be supplied to make an "RGB" image (i.e., it does not have to be red, green, and blue), which can help create useful "false color" indices. You can try pressing the "f" key while browsing true color images on NOAA's OCView[47] to interactively toggle a false color enhancement.

How does it impact aquaculture/fisheries?

- The surface reflectance products can be very useful because they have minimal atmospheric correction applied, that is, no aerosol subtraction, which is a source of common data quality errors. Some algorithm developers prefer to use rhos in place of Rrs, especially for inland water bodies where atmospheric correction can be very challenging, as is the case for cyanobacteria monitoring[111]. Alternatively, using Rrs as input to RGB imaging can highlight subtle water features, and has recently been demonstrated to help determine copepod (*Calanus finmarchicus*) concentrations from satellite images[112].

What are the limitations/caveats?

- Typically, unless there is a very strong surface reflectance signal (e.g., algal slick), visual details of the ocean are not easily distinguished from RGB rhos products without some image enhancements (e.g., adjust contrast, gamma corrections; see right image below).

Does HYPERSPECTRAL directly improve/enable this product?

- The full range and resolution of spectral bands offered by the rhos suite are new to the ocean color community. This is an exciting prospect, enabling up to 22,100 possible unique false RGB combinations that can be derived from PACE for teasing out subtle signals of interest. Using hyperspectral data, Craig et al.[113] chose six custom rhos bands as input to a Bayesian model to derive robust biogeochemical parameters.

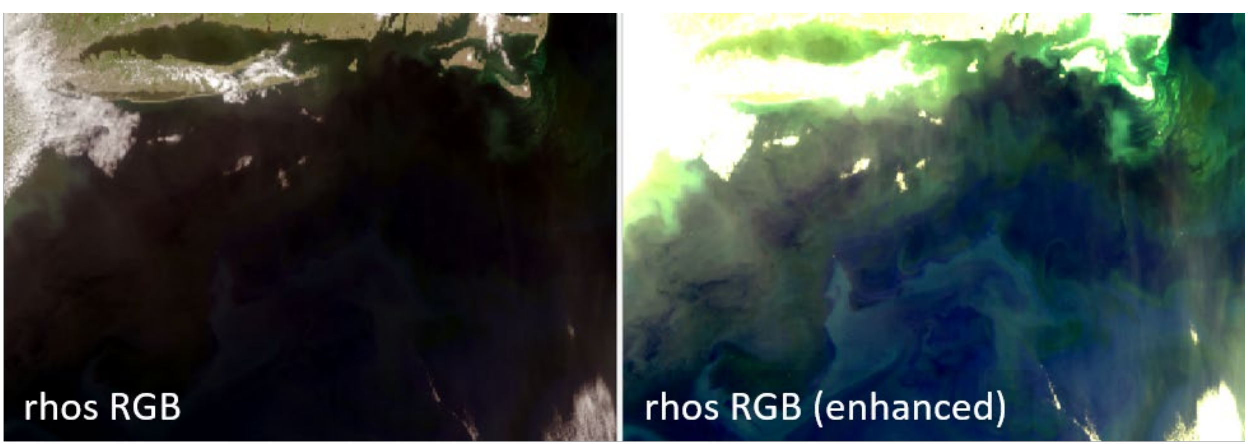


Figure 16. Projection of PACE-derived RGB products in the Mid-Atlantic Ocean; May 13, 2024.

Section 3:

Anticipated Enhancements to Ocean Color Products Enabled by PACE

Product(s) 1: Phytoplankton community composition (PCC)

What is it?

- Phytoplankton absorb and scatter different colors, depending on their internal pigmentation and cellular composition/size. While all contain chlorophyll-a, several additional "accessory" pigments may be present, which is one means of helping distinguish different phytoplankton classes (e.g., diatoms, cyanobacteria, dinoflagellates, etc.). There are also unique backscattering properties of phytoplankton based on cell size, chemical composition, and taxonomy[114]. There are several PACE products that will address phytoplankton community composition, as well as some other approaches that are not dependent on hyperspectral data. The known algorithms in the queue for operational production at either NOAA or NASA are listed below. Only MOANA is provisionally available now (at the time of publication):

    - **MOANA** (Lange[115]): Resolves the concentration of smaller oceanic phytoplankton: *Synechococcus*, *Prochlorococcus*, and picoeukaryotes.
    - **Pigments** (Chase[116]): Phytoplankton pigments chlorophyll-a, -b, and -c along with photoprotective and photosynthetic carotenoids.
    - **Diatom carbon** (Chase[117]): Satellite-based diatom carbon estimates.
    - **Taxonomic groups** (Kramer[118]): Diatoms, dinoflagellates, nanoplankton, haptophytes, picoplankton, based on phytoplankton pigment estimates.
    - **Particle size class** (Kostadinov[119]): Size partitioning of oceanic particles, particle size distribution.
    - **Phytoplankton size class** (Turner[120]): Chlorophyll-a based partitioning of phytoplankton size classes (pico-, nano-, micro-plankton).
    - Note, there are many more approaches to derive phytoplankton community composition[121] described in the literature, but are not slated for operational production.

How does it impact aquaculture/fisheries?

- Not all phytoplankton are equally utilized in the food web. As one example for aquaculture applications, smaller phytoplankton are often not efficiently retained as food, and therefore, phytoplankton size can affect bivalve growth and condition[122]. For fisheries, NPZ[123] and ecosystem models[7] consider phytoplankton community composition as a variable to allocate trophic inputs and efficiency terms. These approaches may also aid in the detection and distinction of HABs, which are considered to enhance some stock assessments[124].

What are the limitations/caveats?

- These algorithms will be classified as "provisional" pending satellite data product validation. Each approach comes with its own set of unique uncertainties, and should be verified on a regional basis before operational use.

Does HYPERSPECTRAL directly improve/enable this product?

- Many PCC algorithms do exist with multi-spectral data, but hyperspectral is making a new class of algorithms possible by exploiting color bands not previously available. PACE is anticipated to be the first mission to operationally offer phytoplankton community composition products.

Product(s) 2: Harmful Algal Blooms (HABs)

What is it?

- HABs occur when colonies of phytoplankton produce toxic or harmful effects on people, fish, shellfish, marine mammals, and/or birds. Various spectral techniques have been used to remotely identify different HABs from ocean color[125] based on chlorophyll anomalies, spectral characteristics, or elevated fluorescence. By combining satellite "bloom detection" algorithms, paired with knowledge of local ecology, and additional *in situ* sampling to identify bloom type, satellites can be a useful tool for monitoring of HABs. Some example case studies of HAB detection are listed below:
    - ***Microcystis aeruginosa*** (CyAN[126]): Freshwater algae that can produce a toxin known as microcystin, which causes fish kills and contamination of drinking water.
    - ***Karenia brevis*** (Craig[127], Soto[128]): Ubiquitous red tide species occurring on the Florida coast, causing fish kills and respiratory issues in humans.
    - ***Pseudo-nitchzia*** (Anderson[129], Smith[130]): Diatom that produces domoic acid, which accumulates in shellfish, invertebrates, and sometimes fish, leading to mammal illness and death.
    - ***Alexandrium cantenella*** (Bucci[131]): Dinoflagellate that produces a saxitoxin and causes Paralytic Shellfish Poisoning (PSP).
    - ***Margalefidinium polykrikoides*** (Ahn[132], Kim[133]): Dinoflagellate causing "rust tides" that are toxic to finfish and shellfish.
    - ***Noctiluca scintillans*** (Qi[134]): Large dinoflagellate that can cause disruptions to trophic energy dynamics, potentially impacting fish yield[135].
    - **Floating algae index** (Hu[136], Sargassum Watch[137]): Used to detect surface slicks, including nuisance algae such as *Sargassum*.
    - **Red-band difference (RBD)** (Amin[138]): A generalized indicator frequently used to detect a variety of HABs based on high fluorescence.
    - **Maximum chlorophyll index (MCI)** (Gower[139]): A generalized indicator frequently used to detect high biomass blooms.
    - **Regional Forecast systems**: NCOOS and external partners supply operational forecast systems for various regions of the U.S., including Gulf Coast[140], Gulf of Maine[141], Lake Erie[142], Pacific Northwest[143], and California[144].

How does it impact aquaculture/fisheries?

- The impact of HABs can be economically and ecologically disruptive, owing to direct mortality of fish and marine mammals, seafood contamination and crop loss, fisheries and aquaculture closures, and trophic-food web disruptions.

What are the limitations/caveats?

- Some toxic species do not always produce toxins, and some species may become toxic at concentrations below detection limits. Tracking of HABs from satellites is most effective when paired with *in situ* ground verification and monitoring, and caution should be exercised when inferring HABs using satellite measurements as a sole source of information.

Does HYPERSPECTRAL directly improve/enable this product?

- Hyperspectral data enables the detection of subtle pigment signatures associated with specific phytoplankton, and can thus help determine the *likelihood* of toxicity.

Product 3: Absorption-based net primary production (NPP)

What is it?

- Net primary production (NPP) is the rate of conversion of dissolved carbon dioxide to organic carbon through photosynthesis minus the carbon used for respiration. NPP is an important part of the carbon cycle, and these products are used in local models (estimating food availability to fish populations) all the way up to global climate and Earth System models (to predict information about the oceans of today and tomorrow). Using newer absorption-based approaches to NPP holds several advantages over the traditional chlorophyll-a based approaches (e.g., the Vertically Generalized Production Model VGPM[145]):
    - Absorption is directly related to satellite measurements of radiance relative to chlorophyll-a, reducing input parameter uncertainty.
    - Absorption-based models encapsulate accessory pigment composition.
    - A spectral correction factor can account for changes in spectral quality with depth.
    - The framework can support the quantification of NPP below the mixed layer depth.
    - It can correct for iron stress using fluorescence quantum yield estimates.
    - Because of the "package effect," chlorophyll-specific phytoplankton absorption can vary over a factor of 4 or more for the same chlorophyll value. Light driven decreases in chlorophyll can be associated with constant or even increased photosynthesis.

How does it impact aquaculture/fisheries?

- For aquaculture, NPP can be used in siting as well as harvesting decision making[146], assessing the impact of marine cages[147] on the environment, and constructing dynamic energy budgets for shellfish growth models[148]. More broadly for fisheries, NPP is an important component to assess total trophic energy potential[149], recruitment[150] in relation to phytoplankton phenology, zooplankton productivity[151], ecosystem overfishing[152], species distribution[153] models, ecosystem status reports[154], and fisheries economic performance[155], among other applications.

What are the limitations/caveats?

- NPP is extremely challenging to validate[156], even under the best of circumstances. On long time scales, NPP is a very useful metric, but instantaneous/daily values derived from satellites may require some additional caution in interpretation. Most NOAA Fisheries applications currently use the chlorophyll-a based VGPM approach, with known reports of errors in NPP values and phenology in coastal and shelf waters. An absorption-based approach has shown promising results in mitigating these uncertainties.

Does HYPERSPECTRAL directly improve/enable this product?

- Hyperspectral data will offer an improved absorption-based approach to modeling net primary productivity[87]. This approach addresses several inefficiencies and uncertainties present in the more ubiquitous chlorophyll-a[157] and carbon based[158] approaches. While a multi-spectral version of this approach exists, several upgrades are being made using the hyperspectral nature of PACE, in addition to ongoing efforts at NOAA to parse out phytoplankton size class-based primary productivity (in active development at the time of publication).

Section 4:

Satellite Remote Sensing Products from Other Sources

Other satellite remote sensing products

What are they?

- **Anomalies**[159]: Anomaly products track the average conditions of a product (e.g., chlorophyll-a) for 60 days, and ratio that against the latest image. (+) Anomalies are depicted as red, while (–) anomalies are depicted as blue. This is particularly useful to demonstrate and detect early changes to environmental conditions. These can be generated for any satellite product and are highly recommended for monitoring applications.

- **Optical water mass classification**: Based on Wei et al.[160], NOAA produces a reflectance shape-based algorithm used to resolve the global water classes into one of 23 distinct water types.

- **QA scores**: The Quality Assurance (QA) score is a metric used to estimate and map the relative quality of ocean color data on a scale of 0 (not good) to 1 (excellent). Details are provided in Wei et al.[161]. The QWIP score uses a different approach, and is intended for use with hyperspectral data; see Dierssen et al.[162].

- **Turbidity**[163]: Spectral techniques have been demonstrated to estimate and map turbidity up to 1000FNU, with robust performance despite differences in sediment characteristics. Using either an iPhone or Android, the HydroColor[164] app allows users to estimate turbidity (and other parameters such as SPM, backscatter, and reflectance) directly from their phone, enabling on the ground monitoring that can complement satellite efforts.

- **Gap-filled products**[165]: Using a gap-filling procedure by combining multiple sensors with a Data Interpolating Empirical Orthogonal Functions (DINEOF), NOAA can provide daily gap-filled data products at 2-km resolution for models that cannot tolerate data gaps.

- **Seascape pelagic habitat classification**[166]: Seascapes identify spatially explicit water masses with particular biogeochemical features using a model and satellite-derived measurements. Dynamic seascapes are derived by combining satellite time series of sea surface temperature, salinity, sea surface height, sea ice, chlorophyll-a concentration, CDOM, and nFLH using a supervised thematic classification. The seascape products are generated as monthly and 8-day composites at 5 km spatial resolution.

- **Ocean phytoplankton phenology indices**[167]: Phytoplankton bloom phenology is an important indicator for the monitoring and management of marine resources and the assessment of climate change impacts on ocean ecosystems. This product provides the phenology output from three widely used bloom detection algorithms at three different spatial resolutions (4-km[168], 9-km[169], and 25-km[170]).

- **Other satellite data streams**: Including sea surface temperature[171], salinity[172], sea surface height (i.e., sea level)[173], ocean winds[174], synthetic aperture radar[175], sea ice[176], and true color imagery[177]. Many of these parameters are often used in conjunction with ocean color data for habitat classification and species distribution modeling.

Section 5:

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