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SATELLITE SENSOR REQUIREMENTS FOR MONITORING ESSENTIAL BIODIVERSITY VARIABLES OF COASTAL ECOSYSTEMS

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Abstract

The biodiversity and high productivity of coastal terrestrial and aquatic habitats is the foundation for important benefits to human societies around the world. Field surveys can cover only a small fraction of these globally-distributed habitats, which need to be sampled much more frequently and systematically. Sunlight reflected by these areas contains the absorption, scattering, and fluorescence signatures of the surface ocean (functional phytoplankton groups; colored dissolved and particulate matter), and biologically-structured habitats (floating and emergent vegetation; benthic habitats like coral, seagrass, algae). These can be used to evaluate sets of Essential Biodiversity Variables (EBVs), including the distribution and abundance of species populations, traits of organism assemblages, and fragmentation of different elements of a particular habitat using remote sensing methods. Satellite-based sensors can provide the synoptic, repeated, and frequent observations needed to characterize EBVs over scales spanning tens of meters to kilometers. These ecosystem elements can change rapidly with disturbances like extreme tides, extreme fresh or salt water availability, extreme temperatures, severe storms, and human use, pollution, or physical destruction over scales relevant to human activity. Yet, making the observations needed to evaluate EBVs and how they change requires a new generation of satellite sensors with high fidelity in four categories:

a. *Spatial resolution*, of order 30 m pixels or better, to observe coastal wetlands and submerged biologically structured habitats.

b. *Spectral resolution*, of order of 5 nm in the visible and 10 nm in the short-wave infrared spectrum (or at least two or more bands, at 1030, 1240, 1630, 2125, and/or 2260 nm) for atmospheric correction, aquatic, and vegetation assessments;

c. *Radiometric quality,* with signal to noise ratios (SNR) above 800, 14-bit digitization, absolute radiometric calibration < 2%, relative calibration 0.2%, polarization sensitivity <1%, high radiometric stability and linearity, and minimizing sunglint; and

d. *Temporal resolution* of hours to days.

We refer to these specifications as *H4* imaging. An agile satellite in a 3-day repeat low-Earth orbit could sample several hundred coastal habitats daily. Global coverage may be achieved with several *H4* satellites. Such information is required to sustain ecosystem services, including food provisioning and water security around the world.

Keywords

Coastal zone, wetland, aquatic, vegetation, ecology, remote sensing, hyperspectral, *H4* imaging, Essential Biodiversity Variables, EBV

Introduction

Water and life – no two features more completely define planet Earth and no two are more inextricably intertwined. This link is especially strong in the coastal zone, where life is diverse and productive at many levels of the food web. Yet monitoring changes in life and habitat in coastal habitats has been difficult. Field measurements on land or in adjacent shallow aquatic areas can be detailed and of high quality, but they are often limited by temporal frequency. Because they are expensive and hard to conduct, these studies and surveys typically cover only small areas. Thus, for the most part, the highly variable aquatic and emergent elements of coastal habitats, including wetlands, remain among the least sampled habitats on the Earth's surface. The physical and biological elements of coastal habitats can change rapidly with many types of disturbance, such as extreme tides, extreme temperatures, lack of or too much fresh water, severe storms, and human use, pollution, or physical destruction.

Characterizing coastal habitats in a manner that is relevant to scientific, conservation, and other socio-economic goals requires measurements that are sensitive to temporal changes, that are cost-effective, and that allow for an assessment across large spatial scales. These criteria are the basis for Essential Climate Variables (Bojinski et al., 2014) and for systematic ecological observations using Essential Biodiversity Variables (EBV; Pereira et al., 2013). In this manuscript, we outline specifications for satellite remote sensing of coastal measurements that offer the potential for rapid, frequently repeated, and consistent high-quality observations to characterize changes in EBVs across a wide range of terrestrial and aquatic ecosystems. We specifically address EBV relevant to community composition and trait diversity. We refer to this remote sensing strategy as *H4* imaging because it is based on requirements for high spatial, high temporal, high spectral, and high radiometric quality, as described below.

Many terrestrial ecosystems are just as diverse and difficult to monitor as coastal aquatic areas. They contain mosaics of different habitats with assorted substrates and living elements spread over scales spanning tens of meters to kilometers. They can change rapidly due to the overlap in phenologies of different populations of organisms, or because of a disturbance like a fire or a hurricane. To characterize the diversity, composition, and function of both terrestrial and coastal ecosystems, we need the type of synoptic observations described here.

The Relevance of the Coastal Zone

Humanity benefits directly from marine resources concentrated along the coast, including obtaining clean water, food, energy, pharmaceuticals, and using spaces for recreation (Hay and Fenical, 1996; Mimouni et al., 2012; Malve, 2016). Areas within 100 km of the coast provide benefits equivalent to over 60% of the world's total Gross National Product, or over US$26 trillion every year (MEA, 2005a). Coastal areas include wetlands, broadly defined as biologically structured habitats where water saturation is a dominant factor in determining the plant and animal communities that occupy these areas. Wetlands include rocky shores, coral reefs, and sea grasses to a depth of 6 m at low tide per the definition used by the Ramsar Convention (Scott and Jones, 1995; Finlayson, 2016). This definition is loosely based on the classification developed by Cowardin et al. (1979) for the U.S. government. Coastal wetlands alone provide over US$15 trillion in annual benefits, including significant protection to human life and property (MEA, 2005b; Barbier, 2016; Narayan et al., 2017). Yet, between 30 and 70% of wetlands were lost in the 20th century as a result of development, pollution, poor water management, and overfishing (Bromberg-Gedan et al. 2009; Bruland, 2008; Davidson, 2014; Hu et al., 2017). An additional

20-70% of coastal wetlands could be lost by 2080 because of sea level rise and continuing related human pressures (Nicholls, 2004; Gardner et al., 2015).

Many of the benefits that we derive from coastal ecosystems depend on the number of species, the abundance and biomass of organisms, the diverse interactions between organisms and the environment, and the number of different habitats in these areas (Malone et al., 2013). We have increasing evidence that biomass production increases with species richness in a wide range of marine and terrestrial ecosystems and not simply in response to abiotic effects (Duffy et al., 2017). Yet, changes in the community composition of lower trophic levels can have major impacts on higher trophic levels, determining the success or loss of animal populations such as fish, waterfowl, and marine mammals (Ji et al. 2010; Platt et al. 2003; Wood and Kellerman, 2015; Santora et al., 2017). Top-down pressures due to the harvesting of top predators and other higher trophic levels also often have impacts that can cascade down the food web.

Characterizing how community structure and the phenology of organisms that use coastal ecosystems shifts due to human activities, biotic interactions, and processes associated with a changing climate is a core focus of current scientific research. Indeed, among the highest priority research questions in coastal ecology are: How will the diversity of life in coastal zones change with climate and with increased human uses? How will these changes affect the ecology and biogeochemistry of coastal and other marine habitats? What are the relationships between species diversity and ecosystem function? Addressing these questions is key to tracking progress toward conservation, management, and sustainable development (e.g. Agenda 2030). Today it is difficult to address these questions because measurements of biodiversity are often limited in temporal frequency and they cover only small areas. Many coastal habitats are remote or difficult to access, further limiting sampling opportunities. For example, the Ocean Biogeographic

Information System (OBIS; Appeltans et al., 2012), the pre-eminent open-access database for international marine biodiversity assessments, shows large areas of the coast and the surface ocean with no data (Figure 1). Information latency is also low: there is a 5-10 year lag before research data are delivered to OBIS (Figure 1, inset). This seriously hampers the ability to monitor for change and any possible national or international response to an environmental issue.

Answering the fundamental ecology questions mentioned in the previous paragraph requires characterizing and detecting change in specific elements of coastal ecosystems, including factors that can be the environmental and human drivers of change. For example, monitoring the diversity of life and detecting change in the ecology and biogeochemistry of coastal zones requires monitoring the EBVs of species populations, species traits, and community composition (Figure 2). Understanding and explaining ecological change requires the context of long-term measurements of environmental parameters such as temperature, discharge, and indicators of water quality, and quantifying their anomalies. Further, monitoring ecosystem structure EBVs (Figure 2) also requires assessing changes in human activities, as these may be the factor leading to change in EBVs. EBVs have to be estimated consistently over large areas and all around the world, and this is only possible from the vantage point of Earth-observing satellites.

Characteristic Scales of Variation in Coastal Zones

Phytoplankton communities and their concentrations in coastal waters often change over scales of hours to days due to runoff, advection, mixing due to tides, currents, and winds, and to biotic interactions (Chen et al. 2010; Moreno Madriñán et al., 2012; Tzortziou et al., 2011). Several case studies have used spectrometers and other bio-optical devices deployed on platforms such as towers, boats, and aircraft to measure rapid changes in biodiversity and phenology (Adam et al., 2010; Pengra et al., 2007; Lantz, 2012). For example, Hestir et al.

(2015) documented changes in the concentration of cyanobacteria in lakes in Italy over scales of days with field spectroscopy data (Figure 3). Kudela et al. (2015) used field spectroscopy observations to show that phytoplankton blooms can be displaced by toxic cyanobacteria in only a few days in Pinto Lake, California. In order to detect long-term trends, such measurements of short-term variability are required over long periods of time. An excellent example of trends in an aquatic ecosystem was provided by Hunter-Cervera et al. (2016). They detected shifts in the timing of annual blooms of the phytoplankter *Synechococcus* with an automated submersible flow cytometer deployed at the Martha's Vineyard Coastal Observatory. Spring blooms occurred progressively earlier in the season as temperatures became warmer, and by 2012, the blooms began up to 20-days earlier than they had in 2003. At higher latitudes, shifts toward phytoplankton species more typical of warmer waters have also been documented (Hays et al., 2005; Dybas, 2006). Similarly, field studies of Nordic wetlands spectra show significant changes in vegetation colors in less than a week (Eklundh et al., 2011). Indeed, wetland species, including invasive species, can be identified by the change of spectral signatures over the growing cycle (Gilmore et al., 2008; Ouyang et al., 2013). The observations also demonstrate that phenology is a sensitive indicator of environmental change, but that observing such changes in phytoplankton or wetland vegetation requires sampling at frequencies of order of a week or faster to differentiate seasonal or longer-term changes relative to short-term variability.

The bio-optical methods used in the studies just described show that aspects of biodiversity and phenology are observable with remote sensing. Indeed, an extensive feasibility study conducted on behalf of the Committee on Earth Observing Satellites (CEOS; see Dekker and Pinnel, 2017) concluded that imaging spectrometers are the desired tool to conduct terrestrial and ocean remote sensing of freshwater, estuarine, and coastal environments to characterize water quality, bathymetry, and benthic habitats.

The spatial variability of coastal habitats is also high. Dominant spatial variability of physical, biological, geological, and biogeochemical properties of coastal waters changes with distance from the coast (Bissett et al., 2014). In terms of horizontal distribution, close to the coast, these properties tend to have peak variability at between 70 and 600 m. Farther offshore, out to about 5 km of the coast, features such as fronts and phytoplankton blooms show high variability around 100-200 m. Observing and monitoring these features and their variability requires sampling at between about 30 and 100 m (Moses et al., 2016). At distances larger than 10 km from the coast, features shows typical scales of 1 km or larger; these can be detected with coarser resolution sensors (Bissett et al., 2004). Wetland habitats show variability at smaller spatial scales. Turpie et al. (2015) studied the impact of varying spatial resolution on mapping of coastal tidal wetland habitats. They concluded that a spatial resolution of approximately 30-m pixels or better is ideal to map wetlands. Coarser spatial resolution sensors smear and confound spectral and spatial patterns.

These spatial scales are sampled adequately by current sensors such as the Operational Land Imager (OLI) on the Landsat-8 satellite, operated by the US Geological Survey, and the MultiSpectral Instrument (MSI) on Sentinel-2A/B, operated by the European Space Agency under the Copernicus program (Vanhellemont and Ruddick, 2014; Pahlevan et al., 2017a). The combination of Landsat-8/OLI and Sentinel-2A/B allows the development of applications that require relatively high temporal frequency, i.e. observations every 4 days or more frequent. However, this sensor class lacks the spectral definition in the visible and near-infrared light (i.e. spectral resolution of 5 nm or better between 380 nm and 900 nm, and about 10 to 20 nm between 900 and 2500 nm) needed to estimate the biodiversity of coastal organisms and habitats. Other satellite sensors meet the required 5- to 10-nm spectral resolution, but lack in spatial detail, such as the 1-km spatial resolution planned for the PACE ocean color sensor (PACE SDT, 2012).

The NASA Hyperspectral Infrared Imager (HyspIRI) mission concept, the JAXA HISUI instrument, and the DLR Environmental Mapping and Analysis Program (EnMAP; Guanter et al., 2015) will also have 30-m spatial resolution (Turpie et al., 2015). HyspIRI is being designed to sample nominally every 16 days, and EnMAP and HISUI are designed to acquire targets of interest intermittently. Thus, they will lack temporal detail needed to observe changes over scales of days.

Essential Biodiversity Variables in the Coastal Zone

Pereira et al. (2013; see also Geijzendorfer et al., 2015; Pettorelli et al., 2016; Kissling et al., 2017) proposed that EBVs can be grouped into six classes: genetic composition, species populations, species traits, community composition, ecosystem structure, and ecosystem function. Figure 2 highlights the classes of EBV that are well suited for remote sensing applications, like species populations, species traits, and ecosystem structure. The EBVs can be derived from surface spectral reflectance measurements in the visible and near-infrared light (i.e. from 380 nm to 2500 nm). The EBVs would be based on the signatures defined by the absorption, scattering, and fluorescence emissions that depend on specific traits of groups of species populations or elements in each habitat (Asner et al., 2017, Colgan et al., 2010). Kissling et al. (2017) emphasize that progress in defining these EBVs is stimulated by the coordinated collection and sharing of in situ biodiversity observations (e.g., Jetz et al. 2012) and open access to satellite datasets (e.g., Skidmore et al. 2015). Indeed, in situ data are fundamental to algorithm development efforts that link observable geophysical quantities and EBVs.

Satellite sensors cover large areas quickly and repeatedly. Estimates of wetland extent have been periodically generated from Landsat since the early 1970s (Tiner et al., 2015; Turpie et al., 2015; McCombs et al., 2016). In this timeframe, satellite instruments have also routinely measured ocean currents, surface winds, precipitation, and color and temperature of the ocean surface (Muller-Karger et al., 2013). These observations have resulted in an unprecedented understanding of physical changes in the environment and have advanced our knowledge of coastal and oceanic ecosystems. The state of the art remote sensing research focused on marine biodiversity includes open ocean detection of diatoms and their phenology (IOCCG, 2014; Racault et al., 2012; Soppa et al. 2016), tracking of harmful algal blooms (e.g., Soto et al., 2016), and phytoplankton size distribution and functional group detection (Uitz et al., 2010; Mouw et al., 2012; Brotas et al., 2013; Bracher et al., 2017). Remote sensing is critically important to map and monitor coral reef extent and health (Andréfouët et al., 2005), but there remain fundamental problems in the discrimination between coral and benthic algae (Hedley et al., 2016). Governments around the world, organized under the Group on Earth Observations (GEO) Biodiversity Observation System (GEO BON), are defining strategies to estimate EBVs from space. However, we cannot obtain key information to evaluate the EBVs of coastal aquatic and wetland habitats shown in Figure 2 from current or past satellite sensors. These sensors have shortcomings in their combined spectral, spatial, and temporal resolution (Hestir et al., 2015; Bracher et al., 2017; Dekker and Pinnel, 2017).

Figure 2 shows that there is great potential to derive EBVs around the world using satellites with higher spectral, temporal, and spatial resolution. Such satellite measurements would move these products to routine use and increase the value chain of Earth observations.

Remote sensing is an important tool to monitor anthropogenic activities (e.g., land use and cover change, oil spills) and their impact in coastal zones (Muller-Karger et al., 2014; Dekker and Pinnel, 2017). Remote sensing also offers significant potential to help in the design and management of marine protected areas (Kacherlriess et al., 2014). These applications require measurement of the condition of marine habitats, including water quality, sea surface temperature, currents, and eddies, and assessing the spatial extent of biologically structured habitats (reefs, seagrass meadows, mangrove forests, salt marshes, etc.). These factors can all affect species diversity and productivity of these systems. Since the launch of the Coastal Zone Color Scanner (CZCS; Gordon and Morel, 1983) and the first Landsat sensors (Tiner et al., 2015) in the 1970's, the coastal zone has been observed remotely with multispectral imaging missions designed for bright terrestrial targets or relatively dark targets such as the surface of the open ocean. Sensors launched since then lack either the spectral, temporal, or the spatial characteristics of coastal ecological processes, and therefore are not sufficient to identify assemblages of species populations, measure the fast changes of communities living in coastal areas, or evaluate the spatial structure and integrity of typical coastal aquatic and wetland habitats. No space-based mission has yet been designed to study and monitor the canopy to benthos continuum of global coastal habitats (Dekker and Pinnel, 2017).

Essential Biodiversity Variables in Open Ocean Habitats

We currently derive bulk phytoplankton pigment and carbon concentration in the pelagic global ocean from satellite ocean color measurements with a spatial resolution of about 1 km (Figure 2). Since 1996, these estimates have been made using observations collected from a series of sensors. Long term (i.e. decades) records of ocean color are crucial to assess the effects of natural and anthropogenic changes on oceans. The National Oceanic and Atmospheric Administration (NOAA) plans to continue the Visible Infrared Imaging Radiometer Suite (VIIRS) series on future Joint Polar Satellite System (JPSS) platforms, but this sensor does not measure radiance in the wavelengths of pigment fluorescence. This limits the ability to identify phytoplankton blooms in coastal waters affected by river discharge, where colored dissolved organic matter (CDOM) masks the spectral signature of chlorophyll. The US National Aeronautics and Space Administration (NASA) Plankton, Aerosol, Cloud, and ocean Ecosystem (PACE) mission will cover key gaps in the visible color spectrum (PACE SDT, 2012). PACE will have a nominal spatial resolution of 1 km and a spectral resolution of 5 nm from the ultraviolet to the near infrared. This could improve our ability to monitor biodiversity in pelagic ocean waters by quantifying phytoplankton functional types (IOCCG, 2014). This includes nitrogen-fixing organisms (e.g., *Trichodesmium*), calcifiers (coccolithophores), producers of dimethyl sulphide or DMS (e.g., *Phaeocystis*), silicifiers (e.g., diatoms), and harmful algal blooms.

PACE is expected to launch in the 2022-2023 timeframe and conduct observations over three to ten years. The European Space Agency has launched two multispectral Ocean and Land Colour Instruments (OLCI) as part of the Copernicus program to enable global ocean coverage every 1.5 days, not accounting for clouds. While the Sentinel-3 OLCI and PACE sensors offer improved capabilities to observe the global ocean, they are not designed to monitor coastal ecosystems. In coastal areas, the influence of the seafloor, land areas, and constituents that affect water quality are often confounded in the signals recorded by these coarse spatial resolution imaging devices. Thus, another class of sensors is required to adequately observe coastal zones.

Requirements for Observing Coastal Biodiversity and Ecosystem Change

Directly measuring EBVs (Figure 2) across the coastal zones of the world requires repeated observations of areas spanning hundreds to thousands of square kilometers, at a spatial resolution adequate to detect change across environmental gradients in aquatic and adjacent wetland settings. This requires high fidelity sampling in four different categories: *spatial resolution, spectral resolution, radiometric quality,* and *temporal resolution*. We refer to this demanding strategy as *H4* sensing. We examine each of these required dimensions below.

High spatial resolution: As mentioned above, Turpie et al. (2015) concluded that a spatial resolution higher than 30-m pixels is ideal to observe the emergent vegetation of coastal wetlands. This is an adequate resolution to map submerged biologically structured habitats like coral reefs and sea grass beds (Hedley et al., 2016; Wabnitz et al., 2010; Andréfouët et al., 2005), and to characterize coastal phytoplankton blooms and surface floating vegetation (Bissett et al., 2004; Moses et al., 2016).

High spectral resolution: NASA's Hyperion sensor operated on the Earth Observing 1 (EO-1) satellite as a technology demonstration between 2000 and 2017. It provided 30-m spatial resolution images with 220 bands from 400 to 2,500 nm, at 10 nm resolution and with signal-to-noise ratios intended for imaging bright land targets. Hyperion demonstrated the potential of high spectral resolution data to derive bathymetry, identify bottom types, and discriminate between wetland species in different coastal areas (Brando and Decker, 2003; Pengra et al., 2007). Pahlevan and Schott (2013) also demonstrated the higher-quality of Hyperion-derived chlorophyll-a concentrations compared to those derived from simulated Landsat sensors near the Niagara River discharge. In 2009, the US Office of Naval Research and NASA installed the Hyperspectral Imager for the Coastal Ocean (HICO) on the International Space Station (ISS; Davis and Tufillaro, 2013). HICO had a spectral resolution of 5.7 nm from 400 to 900 nm, a spatial resolution of 100 m, and a very infrequent revisit time for observing the same target on the ground. These limitations were in part due to the low-inclination orbit of the ISS, periodic maneuvers to raise and lower the space station, and limitations the operations schedule of the instrument. Although HICO ceased operations in 2014, it demonstrated the potential of high spectral resolution to derive bathymetry, bottom types, water optical properties, phytoplankton bloom types, suspended sediment type, and wetland vegetation maps (Ryan et al., 2014).

High spectral resolution has several other benefits. It enables algorithm development and the synthetic spectral reconstruction of different satellite sensor bands (e.g., Osterman et al., 2016). High spectral resolution is required to separate aquatic constituents by their light absorption, scattering, and fluorescence characteristics (PACE SDT, 2012). These include chlorophyll-*a* absorption at 435-438 nm and 660 nm, other pigment absorption features between 550 and 900 nm, and fluorescence by chlorophyll-*a* and other pigments (Hu et al. 2005; Dierssen et al. 2015). Other derived products include CDOM and sediment concentration. Additional EBV of interest that may be derived from high spatial and spectral resolution data are coral, macrophyte, and wetland extent (Figure 2).

Deriving EBVs for coastal habitats requires measurements at ~5 nm resolution in the visible (VIS: 340–900 nm spectral range) and at ~10 nm resolution in the short-wave infrared (SWIR: 900-2500 nm or at least bands at two or more wavelengths, including 1030, 1240, 1630, 2125, and 2260 nm). The SWIR measurements are required for differentiating wetland vegetation observations (Vaiphasa et al. 2005; Hestir et al., 2012), and are particularly critical for atmospheric correction algorithms over turbid waters (Jiang and Wang 2014; Frouin and Pelletier, 2015; Pahlevan et al., 2017b). Atmospheric correction approaches for a coastal mission can leverage the maturity of operational algorithms for ocean color missions (Ahmad et al. 2010), but need to be updated to address coastal and inland aerosol types (Pahlevan et al., 2017b), hyperspectral data, and higher spatial resolution. Atmospheric correction should incorporate procedures to evaluate and correct sun glint (e.g., Devred et al., 2013; Botha et al., 2016) and the radiance reflected from adjacent pixels (adjacency effect) (e.g. Duan et al., 2015).

High radiometric quality: Retrieving estimates of constituent concentrations with better than 20% accuracy requires signal-to-noise ratios similar to those proposed for PACE (Hu et al. 2012). The sensitivity specifications, however, need to consider that different coastal waters exhibit low radiance values in different parts of the spectrum and that this changes with time due to the co-occurrence of different colored vegetation, phytoplankton, substances, and shallow bottoms. The NASA PACE Science Definition Team (PACE SDT, 2012) concluded that ocean observations require a sensor with signal to noise ratios (SNR) > 1000 for visible radiance bands, absolute radiometric calibration << 2%, and relative calibration 0.2%. The existing high-spatial resolution missions, including Landsat-8 and Sentinel-2A/B, have SNRs on the order 300-400 in the 443nm channel and lower in the longer wavelengths (Pahlevan et al. 2014; Pahlevan et al. 2017a and b). The wide range of radiances reflected by coastal habitats, from very dark to very bright, also requires 14-bit digitization, sensor radiometric stability and linearity, and strategies to monitor these characteristics. Aquatic observations require minimal polarization sensitivity (<1%). Stray light, spectral out-of-band, and crosstalk signals, including instrument response-versus-scan, spectral smile, and residual polarization should be minimal, and should be carefully monitored over time. On-orbit variation in instrument radiometric response with time should be monitored, and adjusted. Sustained calibration needs to include frequent observations of the moon (e.g., once per day over at least half of the lunar cycle), stable on-board reference standards, and vicarious calibration and product validation efforts. Observations must include an active sun glint avoidance and mitigation strategy, such as tilting > 20º from surface specular reflection. The platform should exhibit minimal platform jitter with high pointing accuracy, and accurate band-to-band registration. Furthermore, standard and reference in situ radiometric measurements such as those available from the Marine Optical BuoY (MOBY) (Clark et al. 2003) should be available for a mission-long vicarious calibration.

High temporal resolution: Observations at frequencies of hours to days are required to measure change in the distribution of planktonic organisms due to tidal or other circulation, phenology, or change in community structure. While the biodiversity of some structured communities like coral reefs, sea grass meadows, or mangrove forests may be expected to change more slowly, disturbance due to pollution events, severe storms, or cold or warm temperature extremes can lead to rapid changes in organism distribution, traits, or habitat structure. High temporal resolution also increases the chance of observing targets often obscured by clouds (Mercury et al., 2012). The proposed NASA GEOstationary Coastal and Air Pollution Events (GEO-CAPE) mission would acquire high quality hyperspectral measurements three to four times per day of targeted tropical and subtropical coastal areas in North America and opportunistically in other locations in the hemisphere of regard, but at 250-375 m spatial resolution (Salisbury et al., 2016). The geostationary mission would not cover high latitude areas, and more than one satellite would be required to observe other areas around the world.

Implementing *H4* Remote Sensing

Implementing an *H4* observation system is within reach. There may be several strategies to increase the signal-to-noise ratios at the desired spatial resolution of 30 m for observations of coastal aquatic habitats and of biologically structured habitats. One possibility is to relax the spatial resolution requirement for coastal aquatic observations to about 60 to 100 m to match the scales of variability in coastal aquatic properties. This would help match a higher SNR requirement by binning 30 m pixels to this coarser resolution. A separate strategy to obtain higher signal to noise ratios at high spatial resolution is to alter the platform or sensor motion to scan aquatic targets slower than land or wetland targets (e.g., Osterman et al., 2016).

To increase revisit time, aquatic measurements may be collected within a range of viewing angles (e.g., ±45°), following a strategy that mitigates sun glint. However, observations of above-water wetland vegetation require fixed viewing geometries to properly interpret the sequence of measurements in a time series of observations. Such off-nadir observations also help to minimize the contaminating effects of water reflections observed through wetland canopies and help improve biomass estimates (Turpie et al., 2015). A single, agile *H4* satellite in a 3-day repeat orbit could accommodate observations of several hundred coastal habitats distributed around the world every day, by consistently acquiring data with both along-track (for glint mitigation) and cross-track targeting (Osterman et al., 2016). Even one such device flown over a period of 3-5 years would enable the first comprehensive set of biodiversity proxies and estimates of their phenology in hundreds of coastal habitats around the world. Other possible solutions to achieve near-daily revisit times include one or several small, agile, satellite platforms that can point precisely with accurate knowledge of view geometry and location, flying in low-Earth orbit. This would help define a baseline to evaluate past observations collected with less capable sensors, and to assess long-term changes.

Global *H4* coverage with one single sensor is not feasible. Scaling *H4* to obtain weekly or better comprehensive global coverage requires flying a multi-satellite mission. This would provide both greater geographic coverage and observations at sub-tidal frequencies. Operational resource management efforts, and an obligation to evaluate changes occurring over decadal and longer timeframes, would require sustaining *H4* over longer periods, similar to those provided by Landsat and other operational satellite series.

The *H4* concept poses challenges with respect to data downlink, management, processing, and distribution. A global coastal *H4* mission will require increased informatics, with significantly more on-board processing and storage capacity than is typical for current science applications. Further, some monitoring applications will require near-real-time access to the *H4* data. Commercial companies are actively addressing such big-data challenges with super-high spatial resolution (<0.5 m pixels) multispectral (typically 8 bands) satellite constellations designed to observe land targets. We can learn important lessons from these initiatives.

Applications and Benefits

The need for biodiversity data is expressed in international treaties, including the Convention on Biological Diversity (CBD), the U.N. Sustainable Development Goals (including SDG 14), and the Ramsar Convention (MEA, 2005a and b; WOA, 2016). Similar treaties address the conservation of major fresh water bodies, such as the Laurentian Great Lakes. Of interest is using the concept of Essential Biodiversity Variables (EBVs) to monitor and assess long-term changes in coastal ecosystems including coastal water quality, coastal zone bloom, wetlands biodiversity and benthic communities.to evaluate changes in fishery potential.

The need for global monitoring of marine biodiversity has been recognized by the Group on Earth Observations (GEO) and the Intergovernmental Oceanographic Commission (IOC; FOO, 2012). GEO and the IOC have agreed to implement a Marine Biodiversity Observing System (MBON; Duffy et al. 2013) as an integral part of the GEO BON. *H4* also addresses the needs of terrestrial and fresh water studies (Schimel et al., 2015; Jetz et al., 2016). Combining *H4* observations with those from ocean color missions, land-observing missions, and in situ monitoring would expand the scope of coastal science. Example *H4* applications include:

(1) *Coastal Water Quality and Coastal Zone Blooms. H4* addresses the fundamental requirements of coastal ecology and resource monitoring programs of evaluating EBVs that inform about the quality, diversity, and productivity of coastal aquatic habitats as a function of nutrient inputs, light, and other physical and biotic factors. Specifically, H4 will provide information on:

- Functional phytoplankton groups (red tide, coccolithophore, large and small phytoplankton cell concentration, etc.).
- Floating vegetation (*Sargassum*, other large algae, sea grasses)
- Seascapes (dynamic, multivariate biogeographic classification; e.g., Kavanaugh et al., 2016)

(2) Wetland Biodiversity. H4 provides observations of wetland areal extent, canopy characteristics, species populations assemblages, and phenology, including change in emergent vegetation and water quality due to disturbance.

(3) Benthic Communities. H4 monitors EBVs that track the areal extent, composition, and health of shallow subtidal foundation species (e.g., coral reef, seagrasses, kelp) and the integrity of benthic communities.

In summary, the combined open ocean, coastal, and wetland *H4* observation strategy will revolutionize applied ecological research and enable operational assessments and management applications that sustain coastal ecosystem services, including provisioning of food and clean water, around the world.

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FIGURES and FIGURE CAPTIONS

Figure 1. The Ocean Biogeographic Information System (OBIS) is the pre-eminent open-access database for international marine biodiversity assessments. This map shows the density of taxonomic records from the OBIS in 1x1° cells of the global ocean in near-surface pelagic and coastal waters (upper 20 m; n=10.8 million; Mollweide projection map of the number of records per km^2; color bar in $\log_{10}$ scale). Nearshore records represent benthic and water column data combined in waters from 0 m to 5 m bottom depth. Pelagic records are sampled from the surface ocean (upper 20 m) starting at a bottom depth of 5 m near the coast. The four inset maps show regions around the globe with dense OBIS records, yet these also demonstrate inconsistent spatial coverage. Right hand graphics: The shallow pelagic records (>5 m bottom depth) generally shows 2 to 3 orders of magnitude more observations than nearshore areas in most latitude bands. The sudden increase in nearshore records in the 2005-2010 timeframe is largely a contribution of observations collected in the Florida Keys region (USA). The overall decline in data after 2010 highlights typical delays in processing and reporting biological observations to OBIS. Systematic sampling by satellite remote sensing, combined with field observations, animal tracking, and modeling, promise to fill the widespread gaps in space and time and enable routine assessments of marine biodiversity in the world’s coastal and pelagic zones.

Figure 2. Current capabilities of remotely sensed data for measuring Essential Biodiversity Variables (EBVs; Pereira et al., 2013). The EBVs are a subset of the GOOS Essential Ocean Variables for biology and ecology (FOO, 2012). Legend: 'Unproven' indicates that methods have not yet been developed to collect these measurements from satellite/aerial data. 'Demonstrated in limited cases' are methods that have been demonstrated and which could be made operational with

the proposed H4 imaging approach. 'Routine use' indicates measurements that are produced regularly, and at present include distribution, abundance, and phenology of bulk phytoplankton only in the open ocean (i.e. derived chlorophyll-a concentration). 'Habitat model required' indicates EBVs that can be predicted on the basis of habitat correlations developed from remotely sensed data. 'NA' indicates that the observation is not applicable.

Figure 3. Illustration of rapid changes in concentration of nuisance cyanobacteria, quantified as a *phycocyanin pigment index*. In situ measurements conducted every 15 minutes on a daily basis with a hand-held spectrometer were used to identify the organism in Upper Mantua Lake (Italy). Gaps in the time series are due to night and cloudy days. The frequency of sampling of a Landsat sensor (16 days), shown as grey vertical bars, would alias changes in the concentration of phytoplankton, sediment load, and other water quality factors. Orange vertical bars illustrate a 3-day sample frequency – i.e., five times the Landsat frequency. Some species of cyanobacteria can outcompete other phytoplankton, form noxious or toxic blooms, and ultimately reduce water quality for the rest of the food web and human consumption. (After Hestir et al. 2015.)

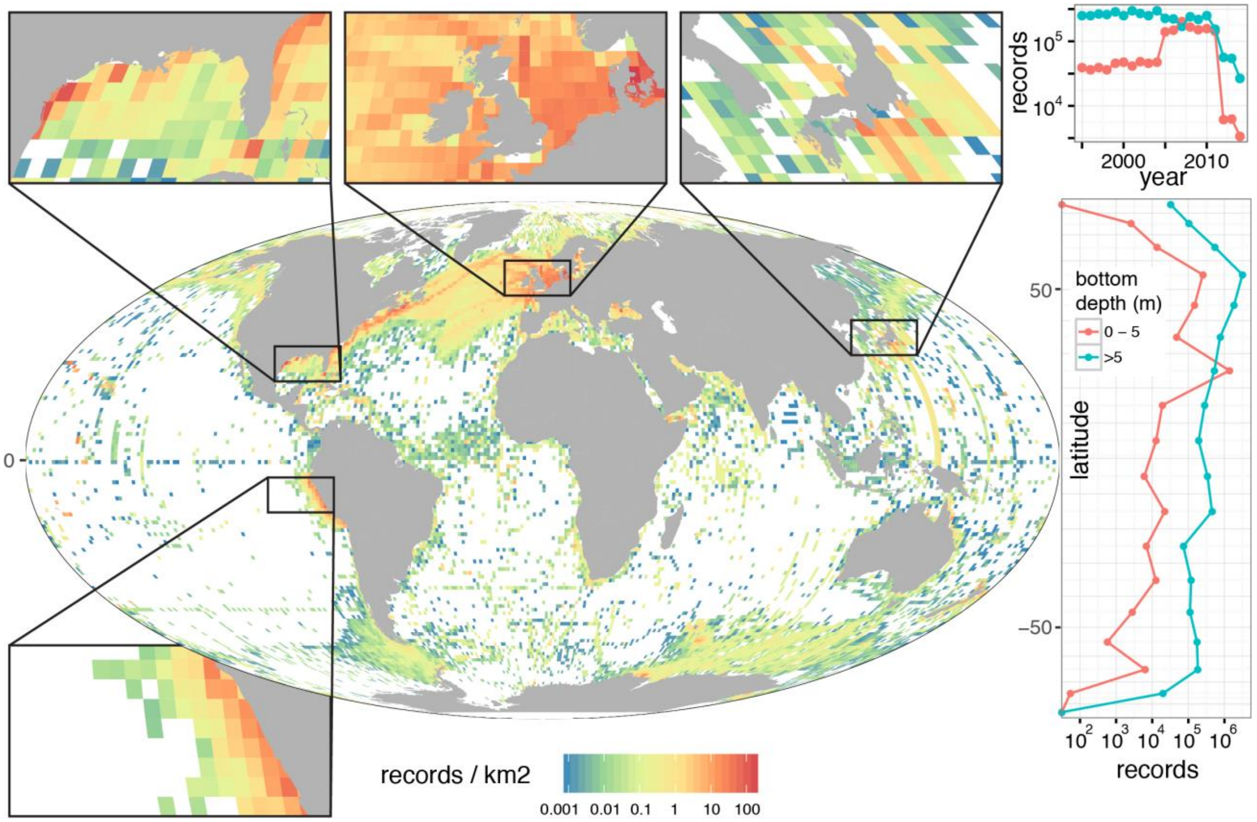
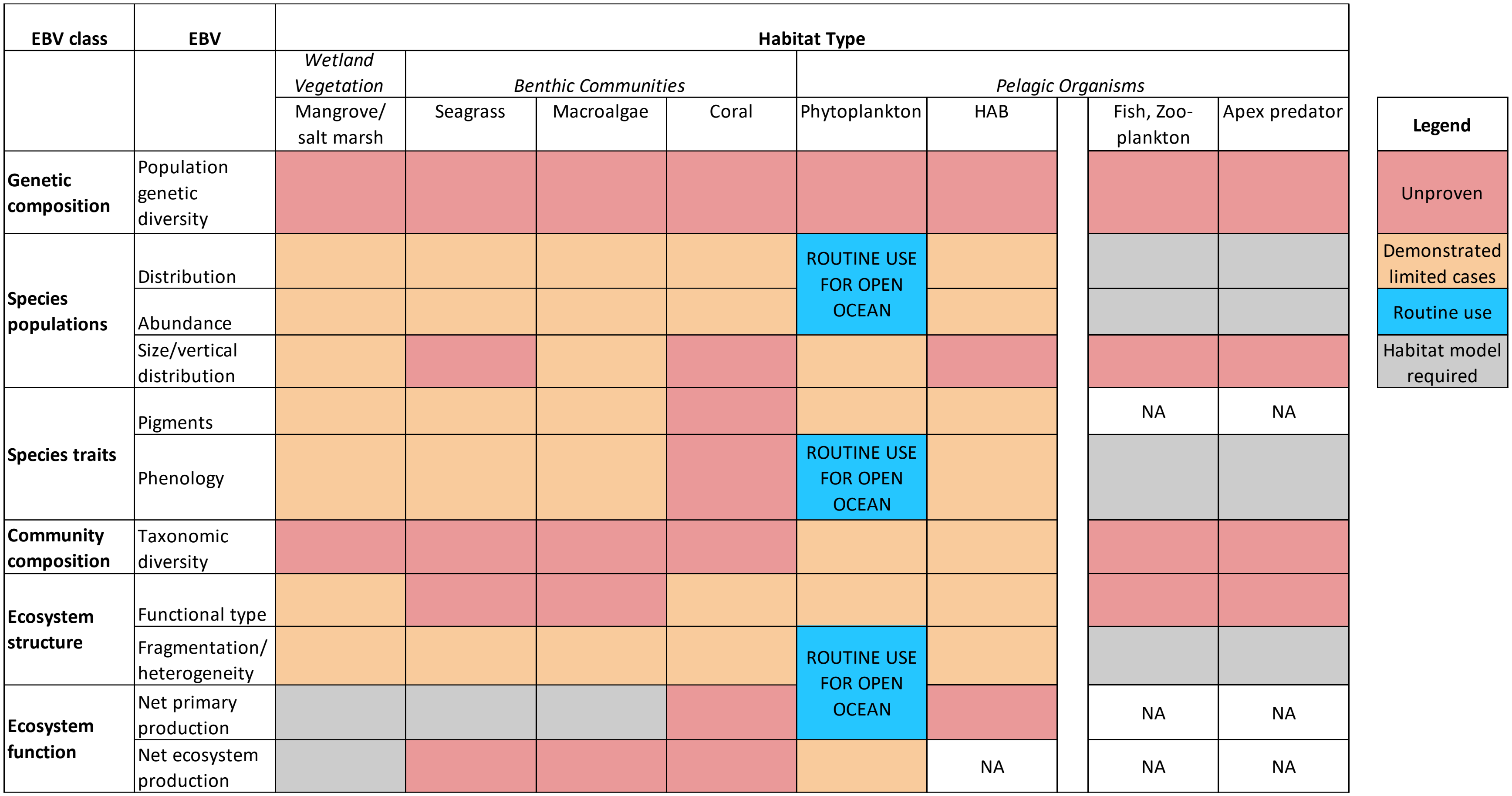

records
10^5
10^4
2000
2010
year
50
0
−50
latitude
bottom
depth (m)
0 – 5
>5
10^2 10^3 10^4 10^5 10^6
records
records / km2
0.001 0.01 0.1 1 10 100

Figure 1



EBV class	**EBV**	**Habitat Type**								
		Wetland Vegetation	*Benthic Communities*			*Pelagic Organisms*				
		Mangrove/ salt marsh	Seagrass	Macroalgae	Coral	Phytoplankton	HAB		Fish, Zoo-plankton	Apex predator
Genetic composition	Population genetic diversity	🟥	🟥	🟥	🟥	🟥	🟥		🟥	🟥
Species populations	Distribution	🟧	🟧	🟧	🟧	🟦 ROUTINE USE FOR OPEN OCEAN	🟧		▨	▨
	Abundance	🟧	🟧	🟧	🟧		🟧		▨	▨
	Size/vertical distribution	🟧	🟥	🟧	🟥	🟧	🟥		🟥	🟥
Species traits	Pigments	🟧	🟧	🟧	🟥	🟧	🟧		NA	NA
	Phenology	🟧	🟧	🟧	🟥	🟦 ROUTINE USE FOR OPEN OCEAN	🟧		▨	▨
Community composition	Taxonomic diversity	🟥	🟥	🟥	🟥	🟧	🟧		🟥	🟥
Ecosystem structure	Functional type	🟧	🟥	🟥	🟧	🟧	🟧		🟥	🟥
	Fragmentation/ heterogeneity	🟧	🟧	🟧	🟧	🟦 ROUTINE USE FOR OPEN OCEAN	🟧		▨	▨
Ecosystem function	Net primary production	▨	▨	▨	🟥		🟥		NA	NA
	Net ecosystem production	▨	🟥	🟥	🟥	🟧	NA		NA	NA

Legend
🟥 Unproven
🟧 Demonstrated limited cases
🟦 Routine use
▨ Habitat model required

Figure 2

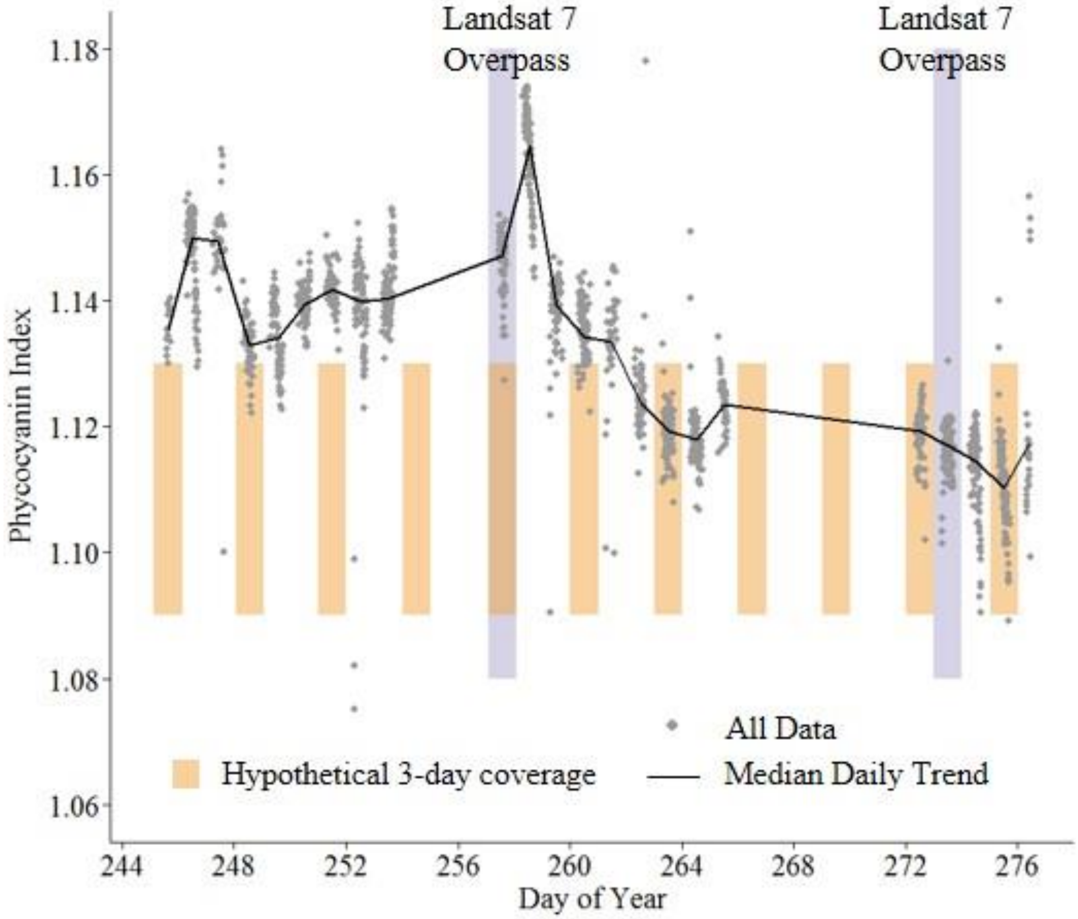

Landsat 7
Overpass
Landsat 7
Overpass
Phycocyanin Index
1.18
1.16
1.14
1.12
1.10
1.08
1.06
All Data
Hypothetical 3-day coverage
Median Daily Trend
244
248
252
256
260
264
268
272
276
Day of Year

Figure 3