

MONITORING COASTAL AND WETLAND BIODIVERSITY FROM SPACE

NAS DS RFI#2 Response / Earth System Science theme III: Marine and Terrestrial Ecosystems and Natural Resource Management

1. Description of the Science and Applications Target: **Addressing the increasing impact of humans on the environment and climate is one of the grand challenges of our time. This includes deriving actionable knowledge to conserve and guide the sustainable use of resources from wetlands, coastal and marine aquatic habitats, and ice-edge environments around the world. Developing such knowledge to promote well-planned, healthy, and resilient coastal communities around the globe requires advanced, space-based observation technologies.**

This grand challenge requires a focus on this science question:

How do the diversity and resilience of coastal ecosystems that span solid (terrestrial and ice) to aquatic habitats change under present and future environmental conditions, what is driving this change, and how do we use knowledge about how they operate to sustain the services they provide?

Water and life - no two features more completely define planet Earth, and no two are more inextricably intertwined. Biology thrives where water and a solid boundary, like land or ice, come together. The coastal zone includes marine environments, saline, brackish and freshwater marshes, peatlands, mangroves, seagrass beds, coral reefs, floodplains and shorelines of rivers, estuaries and lakes, as well as human-made habitats like wastewater treatment ponds, urban and industrial coastlines, and aquaculture facilities. Ice edges are critical habitats that sustain marine ecosystems of the Arctic and around Antarctica. Combined, these coastal zones encompass less than 10% of the Earth's surface (Fig. 1), yet over 70% of the human population lives near a coast, lake, estuary, or wetland. These ecosystems change over time scales of hours and days, and show differences over distances of tens of meters to kilometers. It is impossible to observe all coastal zones of the world at these scales all the time. Here we argue that we need to observe several hundred of these ecosystems around the world at relatively high spectral resolution (5-15 nm VIS and SWIR), temporal scales (days), and spatial resolution (30-60 m) to characterize the interactions between terrestrial, ice habitats, and adjacent aquatic habitats (Fig. 2), in order to monitor and understand their biodiversity, health, value, trends, and causes underlying changes. We state why this is important and outline the requirements for collecting such time-series of observations around the world.

Coastal zones host the most significant and diverse bacterial, algal, plant and animal populations on the planet. Indeed, the benefits that we derive from boundary ecosystems are intimately tied to the diversity of life and to the underlying diversity in habitats of these ecosystems. The economic, environmental and social benefits of coastal zones are estimated at \$US 56 trillion [MEA, 2005; Keddy 2010; Barbier et al. 2011; Costanza et al. 2014]. Yet biodiversity losses from the coastal zone are among the highest in the world [Dudgeon et al. 2006, Waycott et al. 2009, Vorosmarty et al. 2010]. Globally, since the start of the 20th century, freshwater species have declined by 76% [WWF 2014], and perhaps 71% of wetlands have been lost along with half of the world's coral reefs [Davidson, 2014; De'ath et al. 2012, WWF 2014]. By 2025, the world's

human population will have grown by one more billion, with coastal areas showing the highest rates. The risk is “high” that over 70% of humanity will lose more resources such as good water and fish from coastal zones and wetlands [World Economic Forum 2015].

In this sense, *an important “Quantified Earth Science Objective” (QESO; NRC 2015) is the change in the functional biodiversity of coastal and wetland ecosystems, from canopy to benthos*. Changes in biodiversity are intimately tied to changes in phenology and in biogeochemical cycles, reflecting underlying environmental influences. At this time we don’t have science-quality multidimensional remote sensing time series of observations of any of the globe’s coastal ecosystems. Quantifying biodiversity and the underlying processes that affect it at this scale is difficult because the geography, climatic conditions, and chemical and physical characteristics, including the substrate and the amount and flow of fresh or salt water in coastal zones, all show high temporal and spatial variability.

This variability defines resilience in coastal habitats [Vega-Rodriguez et al. 2015; Isbell et al. 2015]. Many species have evolved complex life cycles to take advantage of favorable conditions at different times of the year. Phenology, the timing of change in the physical expression and activity of life, is among the most sensitive biological indicators of environmental change and ecosystem function [Chen 2011; Thackeray et al. 2011]. Common phenology measures are the timing of vegetation leaf-out, flower blooming, butterfly emergence, and bird migration [Liu et al. 2015; Jeong et al. 2013; Parmesan, 2007]. In aquatic environments, phenology includes the timing and duration of changes in the abundance and community composition of phytoplankton and other microorganisms (including cyanobacteria and other harmful organisms), and in the diversity and abundance of aquatic plants [Edwards and Richardson 2004; Winder and Schindler 2004]. These are indicators of bad or good water quality that sustains fish and other animals.

Remote sensing provides the observations needed to understand the rapid changes observed in coastal wetland and aquatic communities, in water quality, and the impacts of flooding over different geographic areas. Eklundh et al. [2011] used field tower observations to show that the color of Nordic wetlands can change significantly over just a week. Tzortziou et al. [2011] highlighted the consistent impact of wetlands on estuarine optical properties during semi-diurnal tidal exchanges of humic organic matter. Kudela et al. [2015] used field hyperspectral observations to show that phytoplankton blooms can be displaced by toxic cyanobacteria in a few days in Pinto Lake, CA. Hestir et al. [2015] documented rapid changes in cyanobacteria in lakes in Italy (Fig. 3). Chen et al. [2010] observed phytoplankton blooms that evolve over 2-3 day periods in Tampa Bay. Dierssen et al. [2015] concluded that monthly measurements are insufficient to quantify episodic plankton blooms in Long Island Sound. Ouyang et al. [2013] detected an invasive wetland species measuring phenology of different organisms with spectroscopy.

The science that will generate the understanding of how these biological communities change in the coastal zone requires mapping of the changing physical expression (phenology) of different primary producers over large areas and across a range of specific habitats in different geographic domains. This requires spectroscopy (hyperspectral observations), at a spatial resolution sufficient to resolve the strongly inhomogeneous features that characterize boundary ecosystems and consistent with long-term Landsat observations, and at weekly or better time resolution [Zhang et al. 2003; Buermann et al. 2014; Becker et al. 2007]. Also

required is a new paradigm for transferring products to applications, including informing management of the status and impacts of uses of resources by humans.

2. Geophysical Measurements for the Coastal Zone: Changes in the composition and quantity of living and non-living material in the water column and shallow communities (benthos) are directly observable, and can be studied by:

- Measuring the concentration and quality of optically-active constituents in the water column (phytoplankton, suspended and colored dissolved materials);
- Differentiating between diverse phytoplankton functional groups, detritus, and colored dissolved organic matter (CDOM);
- Separating constituents in mixed patches of land and water;
- Characterizing the composition of shallow habitats, including corals and seagrasses;
- Characterizing inundation of wetlands;
- Characterizing the impact of episodic events such as storms on aquatic habitats;
- Differentiating between events and disturbance occurring over weeks to months.

The relationship between the health of different coastal communities, changes in land cover phenology, and water quality can be studied using remote sensing by characterizing:

- Relationships, including optical and ecological interdependencies, between wetland phenology, water quality, and nutrient and carbon fluxes;
- Spatial distribution and composition of wetland vegetation;
- Pathways of connectivity including lateral transport between habitats;
- Biodiversity by discriminating among phenology traits of organisms.
- The effect of inundation on canopy health and community zonation;
- Natural and human disturbance factors, including invasive or introduced species.

The concentration and type of atmospheric constituents (aerosols and trace gases such as Ozone, NO₂, SO₂, etc.) to which land and water environments are exposed to also have important impacts on organisms [Boucher, 2015]. These need to be addressed by:

- Comparing aerosol type and composition across marine and land environments;
- Characterizing temporal variations in aerosol type and vertical distribution;
- Characterizing spatiotemporal dynamics in atmospheric trace gases;
- Defining the causes of these changes;
- Testing linkages between these parameters and vegetation health and water quality.

This basic science doesn't require continuous global coverage (Fig. 3). Global mapping requirements invariably lead to satellite missions with temporal, spectral, and spatial resolution combinations unsuited to quantify phenology in coastal habitats. The Landsat satellites, for example, have provided nearly four decades of land observations at 30 m resolution, revolutionizing our understanding of global environmental change. Yet, the few and broad Landsat multispectral bands, low signal-to-noise ratio for various aquatic signals, and 16-day repeat cycle are not enough to observe biodiversity changes in coastal zones. Other land-observing missions have similar temporal or worse radiometric limitations. The European Space Agency's Sentinel 2 land imaging missions will provide 5 day repeat coverage, yet these broad-band multispectral data cannot resolve the diversity of biological signatures in the land and water. Ocean sensors such as the MEdium Resolution

Imaging Spectrometer (MERIS), the Ocean and Land Colour Instrument (OLCI), and the planned PACE mission are designed to make frequent observations with high quality spectral measurements but cannot effectively resolve spatially complex coastal zones because of their large pixel size (>300 m at nadir). None of the past, current, or planned sensors have the combination of capabilities required to monitor many key characteristics of coastal wetland, estuarine, and inland aquatic ecosystems.

To capture the primary relationships between adjacent habitats, several hundred different land-water and ice-water ecosystems around the world, including coastal urban environments, should be sampled over areas >25x25 km² with the following requirements.

3. Data Characteristics and Quality Requirements:

Temporal resolution: Detecting changes in phenology and water quality in terrestrial and aquatic coastal habitats requires 1-2 observations per week or more (Figs. 2 and 4; Table 1). Assimilating such products into hydrodynamic/water quality models improves skill to enhance nowcasting and forecasting activities for informed decision-making and mitigation activities (Pahlevan et al. 2012).

Spectral resolution: The spectral signatures of constituents like phytoplankton, other particulate matter, dissolved colored materials, bottom reflectance, and land cover, are all confounded in multispectral and in coarse spatial resolution data [Ampe et al., 2014; 2015; IOCCG 2000; Dekker et al. 2011; Hestir et al. 2008; Goodman et al. 2013]. For the coastal zone, spectral measurements are needed that will permit identification of and separation between living and non-living elements. For example, different phytoplankton pigments have key spectral absorption features. Chlorophyll-a absorbs strongly between 435–438 nm, and at 660 nm. Cyanobacteria show absorption features between 490–625 nm. Floating algae have spectral features in the 550–900 nm range. CDOM absorbs strongly in the UV and blue with an exponential decrease in absorption at higher wavelengths. Phytoplankton chlorophyll-a shows a fluorescence peak at 685 nm, but the apparent peak in reflectance shifts between 666–707 nm with the concentration of phytoplankton, suspended sediments, reflectance of a shallow bottom, and the absorption of light by oxygen (absorption band B) in the atmosphere. Similarly, *Mesodinium rubrum* contains the pigment phycoerythrin, which fluoresces in the yellow (peak at 565–570 nm) [Dierssen et al. 2015]. The fluorescence features allow detection of different organisms even in the presence of CDOM [Hu et al. 2005]. These quantities allow evaluation of other processes, such as production and calcification in coral reefs [Hochberg and Atkinson 2008]. Such measurements need to be made across the visible and near infrared regions of the spectrum, from at least 350–885 nm, with a high spectral resolution (~2–5nm). Additional information is required from the SWIR (e.g., SWIR: 1240 ± 12.5 nm and 2125 ± 25 nm) and UV-blue for atmospheric correction [Wang et al. 2012; Tzortziou et al. 2014; IOCCG 2010]. Thermal information should be available at similar spatial and temporal resolution as temperature is a first order determinant of plankton population (e.g. Sunagawa et al., 2015).

Full spectral information is needed to implement advanced algorithmic approaches that provide better, more detailed information about coastal biodiversity, including spectral matching and optimization algorithms. These also provide more flexible and accurate estimates of the concentration of chlorophyll-*a* and other pigments, biomass, physiological state of algae or vegetation, other inherent or apparent optical properties, and functional

group detection [Kudela et al. 2015; Gitelson et al. 2011; Odermatt et al. 2012; Dekker et al. 2011; Goodman and Ustin 2007; Mobley et al. 2005; Kutser et al. 2006; Lee et al. 1998, 1999; Uitz et al. 2010; Mouw et al. 2012; Brotas et al. 2013; Hu et al. 2003; Hu et al. 2005; Dierssen et al. 2015; Behrenfeld et al. 2009].

Wetland and aquatic vegetation characteristics can be measured using spectral reflectance [Santos et al., 2012; Turpie 2012; Tiner et al. 2015; Hestir et al. 2012; Hestir et al. 2015]. Observations of these spectra in time allows for quantification of vegetation type and health [Ouyang et al. 2012]. Several approaches help to interpret the mixed spectral signatures generated by different surfaces occupying a fraction of each pixel [Keshava and Mustard 2002; Plaza et al. 2010; Kruse et al. 1993; Roberts et al. 1998; Fernández-Manso et al. 2012; Bell et al. 2015]. Spectral data also provide estimates of the concentration of nitrogen and other vegetation biochemical constituents, including lignin and cellulose [Smith et al. 2003; Anderson et al. 2011]. The mission would help build spectral libraries for coastal terrestrial and aquatic environments [see Zomer et al. 2008; Santos et al. 2012].

Spatial resolution and spatial scope: A spatial resolution of the order of 30 m per pixel is required to assess land cover and coastal zone habitats over a range of geographic scales [Tiner et al. 2015; Hestir et al. 2015]. Coarser spatial resolution leads to significant spectral and spatial mixing and ambiguous and hard to interpret observations of coastal water and wetland types [Hestir et al. 2015; Turpie et al. 2015]. A spatial resolution of ~30 m has been recommended for oil spill detection and monitoring in coastal waters and understanding their impacts on coastal wetlands and biodiversity [Brekke and Solberg, 2005]. Such spatial resolution resolves the heterogeneity in ocean color and suspended materials in river plumes [Aurin et al 2013]. It would be sufficient for capturing ocean color variability in 90% of the surface area of the world's lakes [Verpoorter et al. 2014]. It also is required to capture the strong gradients (e.g., factors >5 change) in CDOM caused by tidal exchanges at the wetland-estuary interface [Tzortziou et al. 2011]. Furthermore, 30 m resolution data products allow for many more valid observations at the proximity of ice-edges in the climate sensitive Polar regions (Bélanger et al. 2007).

Additional requirements: The observations should be calibrated pre- and post-launch to enable ocean color-quality science [IOCCG, 2013], including using the moon [Stone and Kieffer, 2006]. The signal-to-noise (SNR) requirement should be equivalent to those set for PACE [PACE SDT, 2012] at PACE bandwidths but at 30-60 m resolution. A rigorous strategy for sun glint avoidance or to observe sunglint (e.g. detection of oil) is required.

4. Affordability of the required measurements in the decadal timeframe: The mission design described above should provide as a minimum ocean-color radiometric quality spectral data (VIS: 340-904 nm at <5 nm resolution; 1240 and 2125 nm at 12.5 nm and 25 nm width, respectively), at high temporal resolution (every 3 days or less), at medium (30 m) spatial resolution, observations for several hundred targets around the world, from the tropics to the poles, over areas of at least 25x25 km². **Such a mission can be assembled from present TRL 6, 7, and above elements to operate for a period of 5-6 y.**

These measurements would be responsive to NASA Earth science goals to detect changes in ecological and chemical cycles and biodiversity, enable better assessment of water quality and quantity, and would provide other societal benefits [NASA Science Plan 2014]. They would represent a revolution in coastal management applications.

This concept has been endorsed by:

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References

- Ampe EM, Hestir EL, Bresciani M, Salvatore E, Brando VE, Dekker A, Malthus TJ, Jansen M, Triest L, Batelaan O (2014) A Wavelet Approach for Estimating Chlorophyll-A From Inland Waters With Reflectance Spectroscopy. *Geoscience and Remote Sensing Letters*, IEEE 11:89-93
- Ampe EM, Raymaekers D, Hestir EL, Jansen M, Knaeps E, Batelaan O (2015) A Wavelet-Enhanced Inversion Method for Water Quality Retrieval From High Spectral Resolution Data for Complex Waters. *Geoscience and Remote Sensing*, IEEE Transactions on 53:869-882
- Anderson, J.E., Ducey, M.J., Fast, A., Martin, M.E., Lepine, L., Smith, M.-L., Lee, T.D., Dubayah, R.O., Hofton, M.A., Hyde, P., Peterson, B.E., and Blair, J.B. 2011. Use of wave-form lidar and hyperspectral sensors to assess selected spatial and structural patterns associat-ed with recent and repeat disturbance and the abundance of sugar maple (*Acer saccharum* Marsh.) in a temperate mixed hardwood and conifer forest. *J. Appl. Remote Sens.*, 5(1), art. no. 053504, doi:10.1117/1.3554639.
- Aurin, D., Mannino, A., and Franz, B. 2013. Spatially resolving ocean color and sediment disper-sion in river plumes, coastal systems, and continental shelf waters. *Remote Sens. Environ.*, 137, 212–225.
- Barbier, E.B., Hacker, S.D., Kennedy, C., Koch, E.W., Stier, A.C., and Silliman, B.R. 2011. The value of estuarine and coastal ecosystem services. *Ecol. Monogr.*, 81(2), 169–193.
- Becker, B.L., Luschb, D.P., and Qic, J. 2007. A classification-based assessment of the optimal spectral and spatial resolutions for Great Lakes coastal wetland imagery. *Remote Sens. Envi-ron.*, 108(1), 111–120, doi:10.1016/j.rse.2006.11.005.
- Behrenfeld, M.J., Westberry, T., O'Malley, R., Wiggert, J., Boss, E., Siegel, D., Franz, B., McClain, C., Feldman, G., Dall'Olmo, G., Milligan, A., Doney, S., Lima, I., and Mahowald, N. 2009. Satellite-detected fluorescence reveals global physiology of ocean phytoplankton. *Biogeosciences*, 6, 779–794.
- Bell, T., Cavanaugh, K.C., and Siegel, D.A. 2015. Remote monitoring of giant kelp biomass and physiological condition: An evaluation of the potential for the Hyperspectral Infrared Imager (HyspIRI) mission. *Remote Sens. Environ.*, 167, 215–218, doi:10.1016/j.rse.2015.05.003.
- Bélanger, S., Ehn, J.K., & Babin, M. (2007). Impact of sea ice on the retrieval of water-leaving reflectance, chlorophyll a concentration and inherent optical properties from satellite ocean color data. *Remote Sensing of Environment*, 111, 51-68.
- Boucher, O. (2015). Atmospheric Aerosols. In *Atmospheric Aerosols* (pp. 9-24). Springer Netherlands.
- Brekke A. and A. H. S. Solberg, 2005. Oil spill detection by satellite remote sensing. *Remote Sensing of Environment* 95, 1 –13
- Brotas, V., Brewin, R.J.W., Sá, C., Brito, A.C., Silva, A., Mendes, C.R., Diniz, T., Kaufmann, M., Tarran, G., Groom, S.B., Platt, T., and Sathyendranath, S. 2013. Deriving phytoplankton size classes from satellite data: Validation along a trophic gradient in the eastern Atlantic Ocean. *Remote Sens. Environ.*, 134, 66–77.
- Buermann, W., Parida, B., Jung, M., MacDonald, G.M., Tucker, C.J., and Reichstein, M. 2014. Recent shift in Eurasian boreal forest greening response may be associated with

- warmer and drier summers. *Geophys. Res. Lett.*, 41(6), 1995–2002, doi:10.1002/2014GL059450.
- Chen, Z., Hu, C., Muller-Karger, F.E., and Luther, M.E. 2010. Short-term variability of suspended sediment and phytoplankton in Tampa Bay, Florida: Observations from a coastal oceanographic tower and ocean color satellites. *Estuarine, Coastal Shelf Sci.*, 89(1), 62–72, doi:10.1016/j.ecss.2010.05.014.
- Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S.J., Kubiszewski, I., Farber, S., and Turner, R.K. 2014. Changes in the global value of ecosystem services. *Global Environ. Change*, 26, 152–158.
- Davidson, N.C. 2014. How much wetland has the world lost? Long-term and recent trends in global wetland area. *Mar. Freshwater Res.*, 65(10), 934–941, <http://dx.doi.org/10.1071/MF14173>.
- Dekker, A.G., Phinn, S.R., Anstee, J., Bissett, P., Brando, V.E., Casey, B., Fearn, P., Hedley, J., Klonowski, W., Lee, Z.P., Lynch, M., Lyons, M., Mobley, C., and Roelfsema, C. 2011. Inter-comparison of shallow water bathymetry, hydro-optics, and benthos mapping techniques in Australian and Caribbean coastal environments. *Limnol. Oceanogr.: Methods*, 9(9), 396–425.
- Dierssen, H.M. 2010. Perspectives on empirical approaches for ocean color remote sensing of chlorophyll in a changing climate. *Proceedings of the National Academy of Sciences* 107, no. 40 (2010): 17073–17078.
- Dierssen, H.M., McManus, G., Chlus, A., Qiu, D., Gao, B.-C., and Lin, S. 2015. Space station image captures a red tide ciliate bloom at high spectral and spatial resolution. *Proc. Natl. Acad. Sci. USA*, doi:10.1073/pnas.1512538112.
- Edwards, M., and Richardson, A.J. 2004. Impact of climate change on marine pelagic phenology and trophic mismatch. *Nature*, 430, 881–884.
- Eklundh, L., Jin, H., Schubert, P., Guzinski, R., and Heliasz, M. 2011. An optical sensor network for vegetation phenology monitoring and satellite data calibration. *Sensors*, 11(8), 7678–7709.
- Fernández-Manso, A., Quintano, C., and Roberts, D. 2012. Evaluation of potential of multiple endmember spectral mixture analysis (MESMA) for surface coal mining affected area mapping in different world forest ecosystems. *Remote Sens. Environ.*, 127, 181–193.
- Gitelson, A.A., Gao, B.-C., Li, R.-R., Berdnikov, S., and Saprygin, V. 2011. Estimation of chlorophyll-a concentration in productive turbid waters using a Hyperspectral Imager for the Coastal Ocean—The Azov Sea case study. *Environ. Res. Lett.*, 6(2), doi:10.1088/1748-9326/6/2/024023.
- Goodman, J., and Ustin, S.L. 2007. Classification of benthic composition in a coral reef environment using spectral unmixing. *J. Appl. Remote Sens.*, 1(1), 011501, doi:10.1117/1.2815907.
- Goodman, J.A., Purkis, S.J., and Phinn, S.R. (eds.). 2013. *Coral Reef Remote Sensing: A Guide for Mapping, Monitoring and Management*. Springer.
- Hestir, E.L., Khanna, S., Andrew, M.E., Santos, M.J., Viers, J.H., Greenberg, J.A., Rajapakse, S.S., and Ustin, S.L. 2008. Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. *Remote Sens. Environ.*, 112, 4034–4047.

- Hestir, E.L., Greenberg, J.A., and Ustin, S.L. 2012. Classification trees for aquatic vegetation community prediction from imaging spectroscopy. *IEEE Selected Topics Appl. Earth Obs. Remote Sens.*, 5(5), 1572–1584.
- Hestir, E.L., Brando, V.E., Bresciani, M., Giardino, C., Matta, E., Villa, P., and Dekker, A.G. 2015. Measuring freshwater aquatic ecosystems: The need for a hyperspectral global mapping satellite mission. *Remote Sens. Environ.*, 167, 181–195.
- Heumann, B.W. 2011. Satellite remote sensing of mangrove forests: Recent advances and future opportunities. *Prog. Phys. Geogr.*, 35(1), 87–108.
- Hochberg, E.J., and Atkinson, M.J. 2008. Coral reef benthic productivity based on optical absorption and light-use efficiency. *Coral Reefs*, 27(1), 49–59, doi:10.1007/s00338-007-0289-8.
- Hochberg, E.J., et al. 2011. HypsIRI Sun Glint Report. NASA JPL Publication 11-4.
- Hu, C., Hackett, K.E., Callahan, M.K., Andréfouët, S., Wheaton, J.L., Porter, J.W., and Muller-Karger, F.E. 2003. The 2002 ocean color anomaly in the Florida Bight: A cause of local coral reef decline? *Geophys. Res. Lett.*, 30(3), 1151, doi:10.1029/2002GL016479.
- Hu, C., Muller-Karger, F.E., Taylor, C., Carder, K.L., Kelble, C., Johns, E., and Heil, C. 2005. Red tide detection and tracing using MODIS fluorescence data: A regional example in SW Florida coastal waters. *Remote Sens. Environ.*, 97, 311–321.
- IOCCG. 2000. Remote Sensing of Ocean Colour in Coastal, and Other Optically-Complex, Waters. Sathyendranath, S. (ed.), Reports of the International Ocean-Colour Coordinating Group (IOCCG), No. 3, IOCCG, Dartmouth, Canada.
- IOCCG 2010. Atmospheric Correction for Remotely-Sensed Ocean-Colour Products. Reports of the International Ocean-Colour Coordinating Group (IOCCG), No. 10, IOCCG, Dartmouth, Canada.
- IOCCG. 2013. In-flight Calibration of Satellite Ocean-Colour Sensors. Frouin, R. (ed.), Reports of the International Ocean-Colour Coordinating Group (IOCCG), No. 14, IOCCG, Dartmouth, Canada.
- IOCCG. 2014. Phytoplankton Functional Types from Space. Sathyendranath, S. (ed.), No. 15, IOCCG, Dartmouth, Canada.
- Isbell, F., Craven, D., Connolly, J., et al. 2015. Biodiversity increases the resistance of ecosystem productivity to climate extremes. *Nature*, 526, 574–577, doi:10.1038/nature15374.
- Jeong, S.-J., Medvigy, D., Shevliakova, E., and Malyshev, S. 2013. Predicting changes in temperate forest budburst using continental-scale observations and models. *Geophys. Res. Lett.*, 40, 1–6.
- Keddy, P.A. 2010. *Wetland Ecology*. Cambridge Studies in Ecology. Cambridge Univ. Press, Cambridge, UK.
- Keshava, N., and Mustard, J.F. 2002. Spectral unmixing. *IEEE Signal Process. Mag.*, 19(1), 44–57.
- Kruse, F.A., Lefkoff, A.B., Boardman, J.W., Heidebrecht, K.B., Shapiro, A.T., Barloon, P.J., and Goetz, A.F.H. 1993. The spectral image processing system (SIPS)—Interactive visualization and analysis of imaging spectrometer data. *Remote Sens. Environ.*, 44, 145–163.
- Kudela, R.M., Palacios, S.L., Austerberry, D.C., Accorsi, E.K., Guild, L.S., and Torres-Perez, J. 2015. Application of hyperspectral remote sensing to cyanobacterial blooms

- in inland waters. *Remote Sens. Environ.*, 167, 196–205, doi:10.1016/j.rse.2015.01.025.
- Kutser, T., Miller, I., and Jupp, D.L.B. 2006. Mapping coral reef benthic substrates using hyper-spectral space-borne images and spectral libraries. *Estuarine, Coastal Shelf Sci.*, 70, 449–460.
- Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G., and Patch, J.S. 1998. Hyperspectral remote sensing for shallow waters. I. A semianalytical model. *Appl. Opt.*, 37(27), 6329–6338.
- Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G., and Patch, J.S. 1999. Hyperspectral remote sensing for shallow waters. 2. Deriving bottom depths and water properties by optimization. *Appl. Opt.*, 38(18), 3831–3843.
- Liu, Y., S.-K. Lee, D. B. Enfield, B. A. Muhling, J. T. Lamkin, F. E. Muller-Karger, and M. A. Roffer, 2015: Potential impact of climate change on the Intra-Americas Seas: Part-1. A dy-namic downscaling of the CMIP5 model projections. *J. Marine Syst.*, 148, 56-69, doi:10.1016/j.jmarsys.2015.01.007.
- MEA (Millennium Ecosystem Assessment). 2005. *Ecosystems and Human Well-being: Synthesis. A Report of the Millennium Ecosystem Assessment*, Island Press, Washington, DC.
- Mobley, C.D., Sundman, L.K., Davis, C.O., Bowles, J.H., Downes, T.V., Leathers, R.A., Mon-tes, M.J., Bissett, W.P., Kohler, D.D.R., and Reid, R.P. 2005. Interpretation of hyperspectral remote-sensing imagery by spectrum matching and look-up tables. *Appl. Opt.*, 44(17), 3576–3592.
- Mouw, C.B., and Yoder, J.A., 2010. Optical determination of phytoplankton size composition from global SeaWiFS imagery. *J. Geophys. Res.*, 115, C12018.
- NASA Science Plan. 2014. Available at: http://science.nasa.gov/media/medialibrary/2015/06/29/2014_Science_Plan_PDF_Update_508_TAGGED.pdf.
- NRC, 2015. *Continuity of NASA Earth Observations from Space: A Value Framework* (2015). NRC report.
- Odermatt, D., Gitelson, A., Brando, V.E., and Schaepman, M. 2012. Review of constituent re-trieval in optically deep and complex waters from satellite imagery. *Remote Sens. Environ.*, 118, 116–126.
- Ouyang, Z.-T., et al. 2013. Spectral discrimination of the invasive plant *Spartina alterniflora* at multiple phenological stages in a saltmarsh wetland. *PLoS ONE*, 8(6), e67315, doi:10.1371/journal.pone.0067315.
- PACE SDT. 2012. *Pre-Aerosol, Clouds, and ocean Ecosystem (PACE) Mission Science Defini-tion Team Report*, http://decadal.gsfc.nasa.gov/PACE/PACE_SDT_Report_final.pdf.
- Pahlevan, N., J., G.A., Gerace, A.D., & Schott, J.R. (2012). Integrating Landsat 7 Imagery with Physics-based Models for Quantitative Mapping of Coastal Waters near River Discharges. *Photogrammetric Engineering and Remote Sensing (PE&RS)*, Vol. 78, 11.
- Parmesan, C. 2007. Influences of species, latitudes and methodologies on estimates of phenolog-ical response to global warming. *Global Change Biol.*, 13, 1860–1872.

- Plaza, A., Martin, G., Plaza, J., Zortea, M., and Sanchez, S. 2010. Recent developments in spec-tral unmixing and endmember extraction. In: *Optical Remote Sensing—Advances in Signal Processing and Exploitation Techniques*, Springer, New York.
- Roberts, D.A., Gardner, M., Church, R., Ustin, S., Scheer, G., and Green, R.O. 1998. Mapping chaparral in the Santa Monica Mountains using multiple endmember spectral mixture models. *Remote Sens. Environ.*, 65, 267–279.
- Santo, A.G., Gold, R.E., McNutt, R.L., Jr., Solomon, S.C., Ercol, C.J., Farquhar, R.W., Hartka, T.J., Jenkins, J.E., McAdams, J.V., Mosher, L.E., Persons, D.F., Artis, D.A., Bokulic, R.S., Conde R.F., Dakermanji, G., Goss, M.E., Jr., Haley, D.R., Heeres, K.J., Maurer, R.H., Moore, R.C., Rodberg, E.H., Stern, T.G., Wiley, S.R., Williams, Bo.G., Yen, C.-W.L., and Peterson, M.R. 2001. The MESSENGER mission to Mercury: Spacecraft and mission design. *Planet. Space Sci.*, 49, 1481–1500.
- Santos, M.J., Hestir, E.L., Khanna, S., and Ustin, S.L. 2012. Image spectroscopy and stable isotopes elucidate functional dissimilarity between native and nonnative plant species in the aquatic environment. *New Phytol.*, 193, 683–695.
- Smith, M.-L., Martin, M.E., Plourde, L., and Ollinger, S.V. 2003. Analysis of hyperspectral data for estimation of temperate forest canopy nitrogen concentration: comparison between an air-borne (AVIRIS) and a spaceborne (Hyperion) sensor. *IEEE Trans. Geosci. Remote Sens.*, 41(6), 1332–1337.
- Stammes, P. (ed.). 2002. OMI Algorithm Theoretical Basis Document, Volume III, Clouds, Aer-osols, and Surface UV Irradiance, <http://eospsso.gsfc.nasa.gov/sites/default/files/atbd/ATBD-OMI-03.pdf>.
- Stone, T.C. and Kieffer, H.H. 2006. Use of the Moon to support on-orbit sensor calibration for climate change measurements, *Proc. SPIE* 6296, DOI: 10.1117/12.678605
- Sunagawa, S. et al., 2015. Structure and function of the global ocean microbiome. *Science*. Vol 348 (6237). DOI: 10.1126/science.1261359.
- Thackeray, S.J., Sparks, T.H., Frederiksen, M., Burthe, S., Bacon, P.J., Bell, J.R., Botham, M.S., Brereton, T.M., Bright, P.W., Carvalho, L., Clutton-Brock, T., Dawson, A., Edwards, M., El-liott, J.M., Harrington, R., Johns, D., Jones, I.D., Jones, J.T., Leech, D.I., Roy, D.B., Scott, W.A., Smith, M., Smithers, R.J., Winfield, I.J., and Wanless, S. 2011. Trophic level asyn-chrony in rates of phenological change for marine, freshwater and terrestrial environments. *Global Change Biol.*, 16, 3304–3313, doi:10.1111/j.1365-2486.2010.02165.x.
- Tiner, R.W., Lang, M.W., and Klemas, V.V. 2015. *Remote Sensing of Wetlands: Applications and Advances*, CRC Press, Boca Raton, FL, 574 pp.
- Turpie, K.R. 2012. Enhancement of a Canopy Reflectance Model for Understanding the Specu-lar and Spectral Effects of an Aquatic Background in an Inundated Tidal Marsh. Doctoral Dissertation, Graduate School of the University of Maryland, College Park, MD.
- Turpie, K.R. 2013. Explaining the spectral red-edge features of inundated marsh vegetation. *J. Coastal Res.*, 29(5), 1111–1117, doi:10.2112/JCOASTRES-D-12-00209.1.
- Turpie, K.R., Klemas, V.V., Byrd, K., Kelly, M., and Jo, Y.-H. 2015. Prospective HypsIRI glob-al observations of tidal wetlands. *Remote Sens. Environ.*, 167, 206–217.

- Tzortziou M., J. R Herman, Z. Ahmad, C.P. Loughner, N. Abuhassan, A. Cede, 2014. Atmospheric NO₂ Dynamics and Impact on Ocean Color Retrievals in Urban Nearshore Regions. *Journal of Geophysical Research-Oceans*. doi: 10.1002/2014JC009803.
- Tzortziou M., P. J. Neale, J. P. Megonigal, C. Lee Pow, and M. Butterworth, 2011. Spatial gradients in dissolved carbon due to tidal marsh outwelling into a Chesapeake Bay estuary. *Marine Ecology Progress Series*, 426, 41-56, doi: 10.3354/meps09017.
- Uitz, J., Claustre, H., Gentili, B., and Stramski, D. 2010. Phytoplankton class - specific primary production in the world's oceans: Seasonal and interannual variability from satellite observations. *Global Biogeochem. Cycles*, 24, GB3016, doi:10.1029/2009GB003680.
- Vega-Rodriguez M, Müller-Karger FE, Hallock P, Quiles-Perez GA, Eakin CM, et al. 2015. Influence of water-temperature variability on stony coral diversity in Florida Keys patch reefs. *Marine Ecology Progress Series*. 528:173-186. Doi: 10.3354/meps11268.
- Verpoorter, C., T. Kutser, D. A. Seekell, and L. J. Tranvik (2014), A global inventory of lakes based on high-resolution satellite imagery, *Geophys. Res. Lett.*, 41, 6396–6402, doi:10.1002/2014GL060641
- Vierling, L.A., Deering, D.W., and Eck, T.F. 1997. Differences in arctic tundra vegetation type and phenology as seen using bidirectional radiometry in the early growing season. *Remote Sens. Environ.*, 60(1), 71–82.
- Wang, L., Dronova, I., Gong, P., Yang, W., Li, Y., and Liu, Q. 2012. A new time series vegetation–water index of phenological–hydrological trait across species and functional types for Poyang Lake wetland ecosystem. *Remote Sens. Environ.*, 125, 49–63.
- Wang, M. Shi, W. and Jiang, L. 2012. Atmospheric correction using near-infrared bands for satellite ocean color data processing in the turbid western Pacific region, *Opt. Express* 20, 741-753.
- Winder, M., and Schindler, D.E. 2004. Climate change uncouples trophic interactions in an aquatic ecosystem. *Ecology*, 85, 2100–2106.
- Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., and Huete, A. 2003. Monitoring vegetation phenology using MODIS. *Remote Sens. Environ.*, 84, 471–475.
- Zomer, R.J., Trabucco, A., and Ustin, S.L. 2009. Building spectral libraries for wetlands land cover classification and hyperspectral remote sensing. *J. Environ. Manage.*, 90, 2170–2177, doi:10.1016/j.jenvman.2007.06.028.

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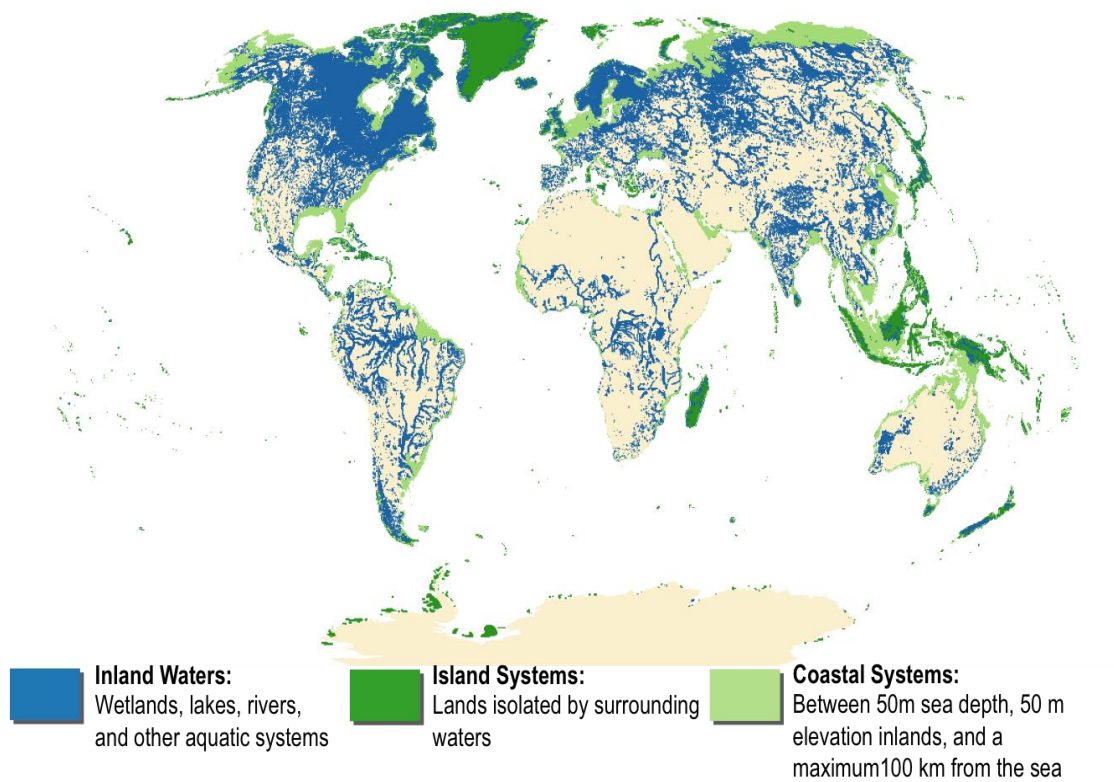


Figure 1: Global distribution of the world's boundary zones between land and water. *Data Sources: Millennium Ecosystem Assessment & FAO-UN.*

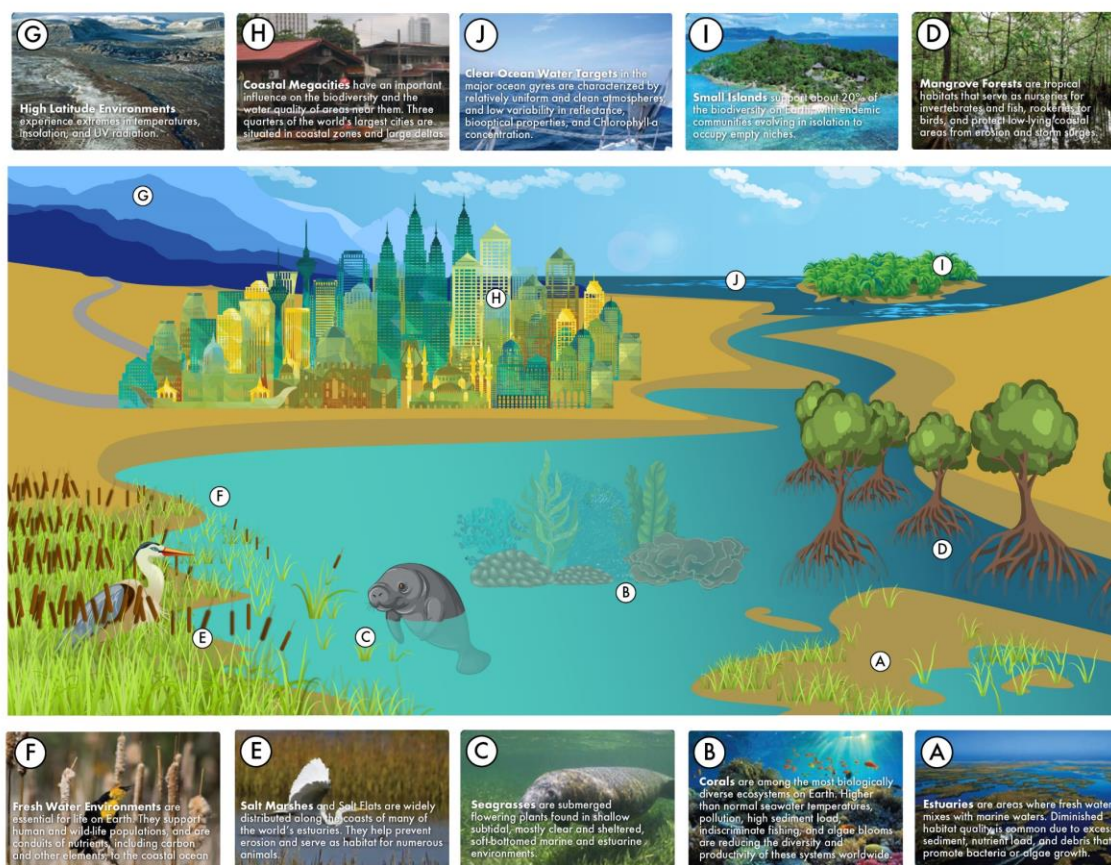


Figure 2. Types of coastal, wetland, and boundary habitats (including high latitude sea-ice environments) that host most of the enormous biodiversity on Earth and provide critical ecosystems services. The letters refer to the individual types of habitats listed in Table 1 and samples as in Figure 4 [Figure from Muller-Karger et al., in preparation, 2016 – not for reproduction].

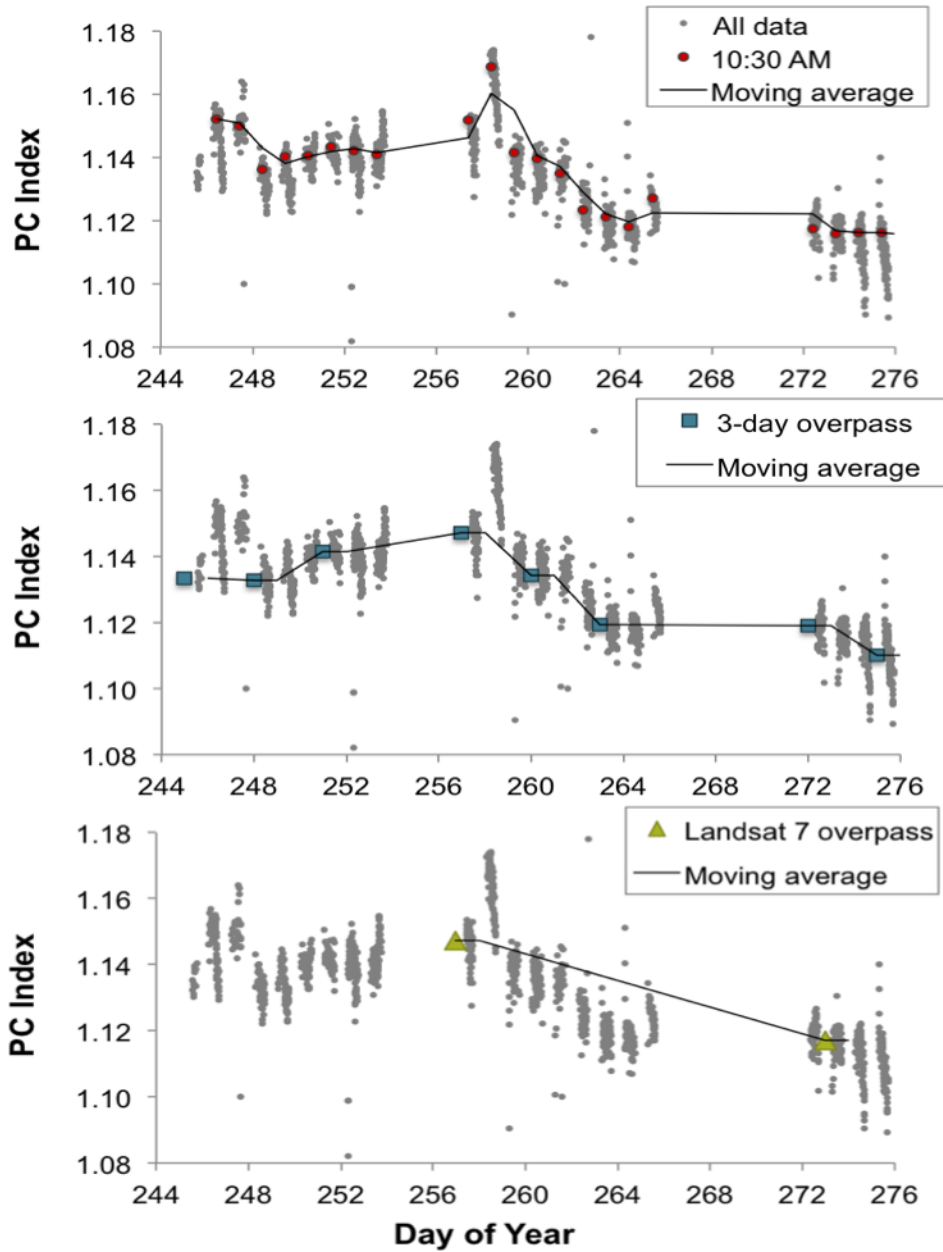


Figure 3. Cyanobacteria concentrations in Upper Mantua Lake (Italy) change rapidly over a few days. TOP: in situ measurements conducted near-daily with a hyperspectral hand-held sensor were used to identify the organism. MIDDLE: Blue symbols show the temporal variability that measurements collected every 3 days would detect at five times the Landsat frequency. BOTTOM: the frequency of sampling of a Landsat sensor (16 days) would alias changes in the concentration of phytoplankton, sediment load, and other water quality factors [after Hestir et al. 2015]. [Figure from Muller-Karger et al., in preparation, 2016 – not for reproduction]

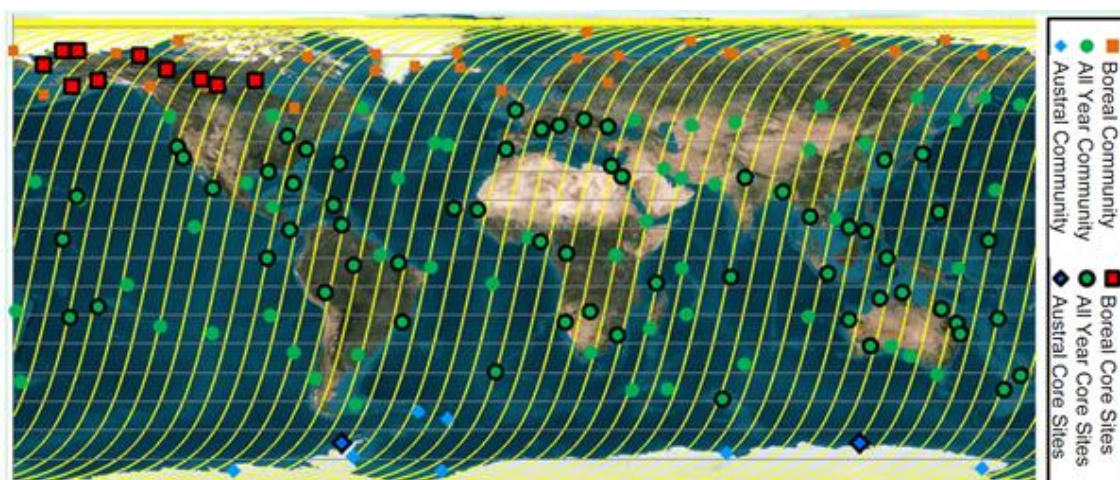


Figure 4. Sample (mock) target acquisition of approximately 160 coastal, wetland, and other boundary environments, accounting for acquisitions changing from northern to southern high latitudes due to illumination. The targets correspond to those shown in Figure 2 and Table 1. [Figure from Muller-Karger et al., in preparation, 2016 – not for reproduction]

Table 1. Sample monthly target acquisitions for locations shown in Figure 4. Letters associated with each target type correspond to the habitats shown in Figure 2. [Table from Muller-Karger et al., in preparation, 2016 – not for reproduction]

Sample monthly target acquisitions showing seasonal changes, accounting for regional cloud cover

Orbit	A. Estuaries	B. Corals	C. Seagrasses	D. Mangrove Forests	E. Salt Marshes and Salt Flats	F. Fresh Water Environments	G. High Latitude Environments	H. Coastal Megacities	I. Small Islands	J. Clear Ocean Water Targets
3-Day Total	16	37	11	18	29	26	44	5	25	8
Monthly Total	160	370	110	180	290	260	440	50	250	80
Cloud Losses	45%	37%	42%	40%	43%	46%	52%	46%	43%	37%
Downlink Losses	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
Est. Monthly Good	86	228	63	105	161	137	208	26	140	49
Req'd Target Types 5 obs/month	10	7	7	7	7	10	7	4	7	6
Req'd Monthly Total	50	35	35	35	35	50	35	20	35	30
Margin	72%	551%	80%	200%	360%	174%	494%	30%	300%	63%