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Review

Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions

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A B S T R A C T

Aquatic color radiometry remote sensing of coastal and inland water bodies is of great interest to a wide variety of research, management, and commercial entities as well as the general public. However, most current satellite radiometers were primarily designed for observing the global ocean and not necessarily for observing coastal and inland waters. Therefore, deriving coastal and inland aquatic applications from existing sensors is challenging. We describe the current and desired state of the science and highlight unresolved issues in four fundamental elements of aquatic satellite remote sensing namely, mission capability, in situ observations, algorithm development, and operational capacity. We discuss solutions, future plans, and recommendations that directly affect the science and societal impact of future missions with capability for observing coastal and inland aquatic systems.

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1. Introduction and background

Coastal and inland water bodies have a direct interface with society, providing value for recreation, food supply, commerce, transportation, and human health. Coastal waters are defined here as those within close enough proximity to land for terrestrial processes to impact water constituents. Inland waters refer to fresh or brackish water bodies of sufficient size to have several observable pixels from current and future spaceborne sensors. Due to the close proximity of human population to these waters, they are under pressure from direct human activities as well as climate change (Allan et al., 2013; Halpern et al., 2008). Understanding the issues of water quality and the impact of environmental change on the ecological and biogeochemical function of these water bodies is of interest to a broad range of communities. Remote sensing offers one of the most spatially and temporally comprehensive tools for observing these waters (NRC (National Research Council), 2011), yet for a variety of reasons, researchers and managers today still face many similar challenges as four decades ago (Bukata, 2013; Palmer, Kutser, & Hunter, 2015b). Drawing from discussions at a recent workshop on remote sensing of coastal and inland waters (Mouw & Greb, 2012), we provide here a comprehensive review of the current status of and challenges in remote sensing of coastal and inland waters, with recommendations for future satellite missions. The review is focused on aquatic color radiometry covering the spectral range

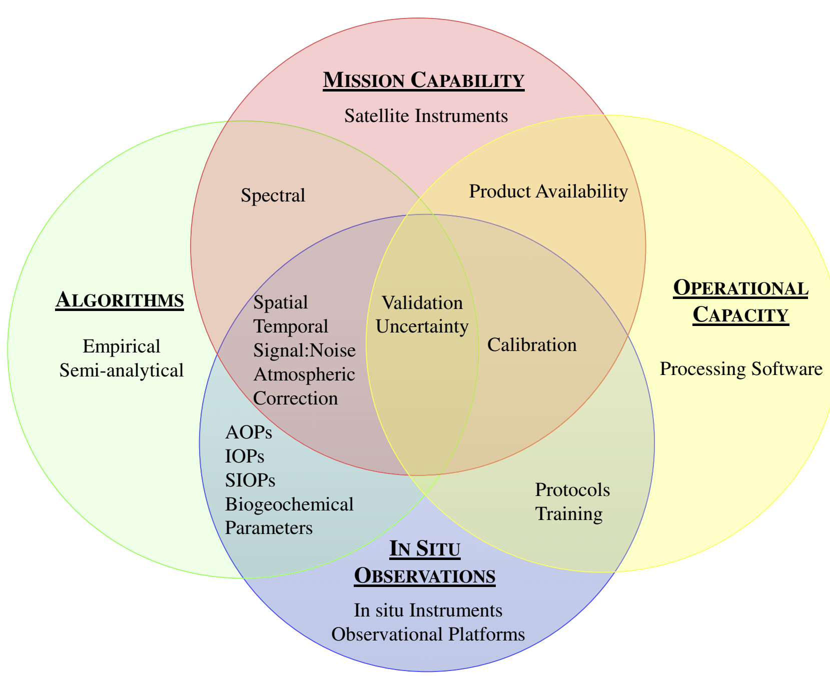

Fig. 1. Integration schematic of the fundamental elements of aquatic color satellite remote sensing.

from the ultraviolet (UV) to the shortwave infrared (SWIR) as several key biogeochemical and water quality parameters can be derived from spectral reflectance in this range.

We define the four functional elements of satellite remote sensing systems as: (1) mission capability, (2) algorithms, (3) in situ observations, and (4) operational capacity (Fig. 1). *Mission capability* refers to the actual hardware configuration of the sensor and orbital platform that correspond to specific spectral, spatial, radiometric, and temporal characteristics. *Algorithms* are the tools that connect satellite observations to optical, biogeochemical, and water quality parameters (near-surface is implied with all subsequent mention of these parameters). *In situ observations* are used to calibrate and validate algorithms. *Operational capacity* refers to the capacity of the mission to routinely provide high quality measurements that support an array of uses and applications. This paper is subdivided into these four functional elements. Within each subdivision, the current and desired state of the science, unresolved issues, solutions, future plans, and recommendations are addressed. The concluding section provides an overview of the challenges, solutions and recommendations for the future.

2. Mission capability

2.1. Current and desired state of the science

A number of sensors have been launched since the Coastal Zone Color Scanner (CZCS) in 1978 (http://www.ioccg.org/sensors_ioccg.html), including the Sea-viewing Wide Field-of-view Sensor (SeaWiFS), the MODerate resolution Imaging Spectroradiometer (MODIS), the MEdium Resolution Imaging Spectrometer (MERIS), and most recently the Visible Infrared Imaging Radiometer Suite (VIIRS). These instruments are equipped with sensors optimized for measuring water-leaving radiance or reflectance over most of the world's oceans, but not over many inland or coastal waters (Table 1). Other sensors with finer spatial, spectral, or temporal coverage include the Korean Geostationary Ocean Color Imager (GOCI, 130° E) and the Hyperspectral Imager for the Coastal Ocean (HICO, 5.73 nm spectral resolution between 400 and 900 nm, 96 m spatial resolution, 42 km swath) aboard the International Space Station.

Significant progress has been made in studying coastal and inland waters using global sensors such as MODIS medium resolution data (250 and 500 m) and MERIS full resolution (FR) data (300 m) (e.g., Feng, Hu, Chen, Tian, & Chen, 2012a, Feng et al., 2012b; Hu et al., 2010; Matthews, Bernard, & Robertson, 2012; Miller & McKee, 2004; Moses, Gitelson, Berdnikov, & Povazhny, 2009; Palmer, Kutser, & Hunter, 2015b; Palmer et al., 2015a). However, progress from the measurements of basic parameters to quantitative understanding of various biophysical and biogeochemical processes in these waters has been hindered by the limited capabilities of these sensors. In coastal and inland waters optically active constituents (OACs) often vary independently requiring improved spectral and radiometric resolutions, while physical drivers such as tides and geographic boundaries set up different spatial and temporal scales compared to the open ocean, requiring improved resolution than what is currently provided by existing space-based assets (Table 1).

Due to the relatively coarse spatial resolution of the current ocean-centric sensors, many inland water investigations have utilized sensors designed primarily for observing terrestrial systems, such as Landsat. The advantages Landsat provides include the longevity of successive missions (1972–present) and a 30 meter pixel size. Landsat has been used to enumerate the abundance of lakes greater than 0.002 km^2

Table 1
Gap analysis outline of the existing, desired and needed resources for the primary elements needed for optical remote sensing of coastal and inland waters.

	Previous/existing	Desired	Needed
Mission capability	300 m–1 km, multispectral, polar orbiting.	100–500 m, polar orbiting and geostationary with greater spectral resolution and coverage, wide dynamic range and high signal to noise to allow for detection across broad parameter ranges.	Investment in geostationary and coastal/inland focused missions to optimize coverage, resolution and availability of new and improved measurements.
Algorithms	Multiple approaches optimized to different datasets for various regions.	A menu of algorithm choices with clear information about their respective strengths and limitations.	• Coordinated algorithm comparison to condense and clarify strengths and limitations and identify fit for purpose options. • Research into biogeochemical property variability and relationships with optical properties.
In situ observation	• Non-coordinated, multi-agency efforts with data going to many different data repositories, if any and often with limited public data access. • Some coincident observations but not all minimum required observations.	• Limited number of centralized publically-available data repositories ensuring access to consistent high quality data. • Protocols that cover a dynamic range of variability. • At minimum, collect coincident observations of the standard suite of parameters (Table 4); if possible collect a broader suite of data products.	• Invest in technology development to address instrumentation gaps; such as sensors designed for high turbidity waters, and hyperspectral b_b. • Clear, consistent and coordinated data sharing policies across agencies. • Update protocols. • Investment in sustaining and increasing observation networks.
Operational capacity	• Global–open ocean mission/product heritage. • Tailored products available for some regions and applications. • Support and training often geared more to expert users. • Limited access to some satellite color data streams, especially in NRT mode.	• Routine and sustained delivery of high-quality operational color data in NRT and delayed modes for coastal and inland waters. • Development of merged/blended remote sensing and integrated remote sensing-in situ (information) products. • Development of robust color-derived proxies and indicators. • Optimal algorithms identified for most/all coastal and inland regions with limitations and uncertainties clearly indicated.	• Ongoing coordinated field observations for each coastal/inland region[1] to ensure continual validation. • Identification of best performing practices and approaches and continual evaluation as new approaches are developed. • Facilitate user data/product access and utilization, including development of application portals. • Expanded user outreach and training. • Free, open and timely access (NRT and delayed modes) to all satellite color data streams. • Implement user-driven community of practice for remote sensing of coastal and inland water to facilitate communication, best practices and harmonization efforts.

[1] Region delineation for the United States could begin by following those outlined by the North American Carbon Program, coastal carbon synthesis (East Coast, West Coast, Gulf of Mexico, Arctic and Great Lakes). Similar delineation for other regions of the world could to be identified by ongoing efforts and funding support priorities.

across non-glaciated land (Verpoorter, Kutser, Seekell, & Tranvik, 2014), in addition to serving as a useful tool to retrieve water clarity (Barnes et al., 2014; McCullough, Loftin, & Sader, 2013; Olmanson, Bauer, & Brezonik, 2008), total suspended solids, chlorophyll concentration, indicators of some dominant phytoplankton groups with limited success (Torbick et al., 2013), and crude estimates of colored dissolved organic matter (CDOM) under certain conditions (Kutser, 2012).

There are several future missions planned (IOCCG, 2012; http://www.ioccg.org/sensors/scheduled.html) which collectively address many of the current instrument shortcomings; for example the GEOstationary Coastal and Air Pollution Events (GEO-CAPE) mission (95°W, 375-m resolution, possibly hyperspectral) (Fishman et al., 2012) and the Hyperspectral Infrared Imager (HyspIRI) (60-m resolution, hyperspectral, 16-day revisit) (Devred et al., 2013). The Pre-Aerosol, Clouds and ocean Ecosystem (PACE) mission will extend the current polar-orbiting capability by substantially increasing spectral resolution. The European Space Agency (ESA) and EUMETSAT are coordinating on the upcoming Sentinel-3 platform with the Ocean and Land Colour Instrument (OLCI), which is envisioned to provide continuity of MERIS-class polar orbiting observations, in particular global 300 m resolution. Additionally, Sentinel-2 and Landsat-8 are anticipated to have capability useful for coastal and inland waters (Pahlevan & Schott, 2013) and when combined together, will have revisit frequency of 5 days. The design specifications of PACE and OLCI in combination with GEO-CAPE and HyspIRI are anticipated to provide greatly enhanced capability to effectively enable wider applications for coastal and inland waters (Fig. 2).

2.2. Unresolved issues

Radiometer design has four types of requirements: 1) spatial coverage and resolution, 2) temporal coverage and revisit frequency, 3) spectral coverage as well as number and position of spectral bands, and 4) radiometric quality (IOCCG, 2012). Relative to these requirements for the open ocean, coastal and inland waters require additional considerations for atmospheric correction and bio-optical algorithms as well as for correcting effects due to bottom reflectance and bright-target adjacency or stray light contamination.

2.2.1. Spatial resolution

For coastal and inland waters, processes such as nearshore tidal currents, resuspension events, and point-source delivery of nutrients, suspended sediments and CDOM, as well as highly dynamic surface algal bloom events can create variability on much smaller spatial scales than for most open-ocean waters (Fig. 2). For well mixed conditions, Bissett et al. (2004) showed optimal resolution of 100 m for nearshore waters (within 200 m of shore) and >1 km for offshore waters (10 km from shore). However, when phytoplankton that are able to regulate their buoyancy are present, such as some cyanobacteria, 30 m spatial resolution was found to significantly underestimate chlorophyll concentration due to the horizontal and vertical structure of the bloom (Kutser, 2004). In the case of river plume regions, Aurin, Mannino, and Franz (2013) demonstrated a resolution of ~500 m or better is required to resolve dispersion of OACs. Generally, for spatially non-uniform distribution of water properties, coarser spatial resolution can lead to underestimates in derived biogeochemical properties (Kutser, 2004; Lee, Hu, Arnone, & Liu, 2012), thus arguing for higher spatial resolution for spatially heterogeneous water bodies.

2.2.2. Temporal resolution

Given the fast temporal dynamics and frequent cloud cover in coastal and inland waters, polar-orbiting sensors provide little information on the short-term changes of water properties (hours to days) (Fig. 2). For example, high-frequency changes in OACs driven by tidal and subtidal currents require 3–4 h temporal-resolution (Chen, Hu, Muller-Karger, & Luther, 2010, Tzortziou, Neale, Megonigal, Lee Pow, & Butterworth, 2011). These rapid changes can only be characterized with high-frequency measurements from a geo-stationary platform (Table 1). Multiple images per day will also allow for quantification of biological and biogeochemical rate processes such as primary productivity, net community production, and photochemical oxidation. Lee et al. (2012) showed that eight GOCI measurements during a day were sufficient to resolve diurnal changes in phytoplankton biomass and primary productivity. In some cases, high-frequency observation can be more important than high spatial resolution for algal blooms. Some species have the ability to develop or exceptionally expand the size of their blooms within several hours (Hu & Feng, 2014).

2.2.3. Spectral resolution

OACs in coastal and inland waters may vary independently. Therefore, improved discrimination between OACs, particularly among phytoplankton, requires increased spectral resolution in coastal and inland waters. While CDOM and non-algal particles (NAPs) decrease exponentially with increasing wavelength imparting only a monotonous effect on reflectance, the spectral impacts by phytoplankton are highly variable depending on species composition, pigment packaging and physiological status (Kirk, 1994). Further, the ability to discriminate phytoplankton groups beyond single dominance by a nuisance species has emerged in oceanographic studies (IOCCG, 2014), and is highly desirable for coastal and inland waters due to the importance phytoplankton composition has on fisheries and whole ecosystem functioning.

With the exception of Hyperion (Pearlman et al., 2003) and HICO (Lucke et al., 2011), the past and current suite of satellite sensors are multispectral to optimize the detection of chlorophyll and other phytoplankton pigments (~440–560 nm and 670 nm), chlorophyll fluorescence (~685 nm), and CDOM and NAP absorption (412 nm) (Aurin & Dierssen, 2012; Gitelson, Schalles, & Hladik, 2007; Lee, Carder, Arnone, & He, 2007, Lee et al., 2007). With the exception of the MERIS 620 nm and MODIS 645 nm bands, a large spectral region between 555 and 670 nm is not routinely sampled. However, the pigment phycocyanin (PC), an indicator of cyanobacteria, absorbs light strongly around 620 nm (Bryant, 1981), allowing quantification of its concentration from remotely sensed data (Mishra, Mishra, Lee, & Tucker, 2013; Ruiz-Verdu, Simis, de Hoyos, Gons, & Pena-Martinez, 2008; Simis, Peters, & Gons, 2005, Simis et al., 2007; Qi, Hu, Duan, Cannizzaro, & Ma, 2014). Additionally, *Trichodesmium* have pigments with absorption peaks in the blue green wavelengths (Dupouy et al., 2008). Exploitation of specific bands associated with pigment absorption peaks enables the

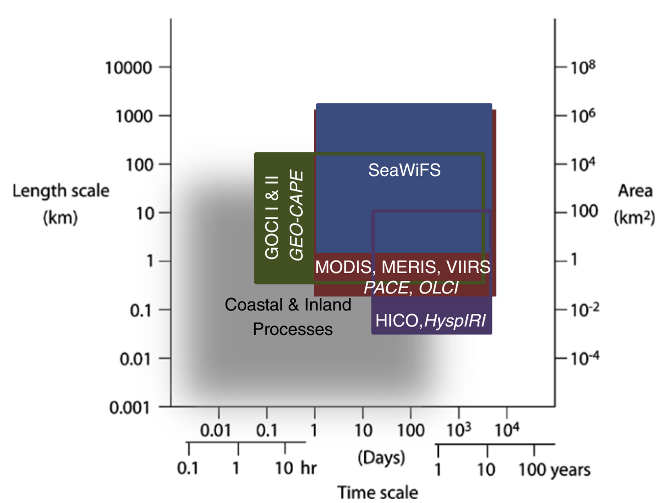

Fig. 2. Length- and timescales of coastal and inland processes in relation to heritage, current and planned aquatic color sensors (SeaWiFS, MODIS, MERIS, VIIRS, HICO, GOCI, OLCI) and missions (PACE/ACE, GEO-CAPE, HyspIRI). Planned sensors and missions are italicized.
Adapted from Robinson (2010).

ability to improve and expand retrieval of phytoplankton species or functional groups (e.g., Ryan, Davis, Tufillaro, Kudela, & Gao, 2014).

The presence of a reference band between ~600 and 650 nm is highly beneficial for the removal of the bottom-reflectance "contamination" to the satellite signal (Barnes et al., 2013; Lee, Carder, & Arnone, 2002). Furthermore, the backscattering by suspended particulate material is less impeded by particulate absorption in this region of the spectrum, making it optimal for TSM detection in moderately turbid waters. Future missions such as PACE, GEO-CAPE and HyspIRI are considering broader spectral coverage and resolution, thus providing abundant spectral information for algorithm improvement and expansion. At the time of writing, the planned PACE, GEO-CAPE, and HyspIRI spectral range and full width half maximum (FWHM) were 340–1100 nm and 10 nm (Pahlevan et al. 2014), 410–2130 nm and 10–40 nm depending on band (Del Castillo, 2012), and 380–2500 nm and 10 nm (Devred et al., 2013), respectively.

2.2.4. Radiometric sensitivity

The trade between instrument sensitivity and dynamic range for existing sensors impacts atmospheric correction in coastal and inland waters. For example, the near infrared (NIR) channels (MODIS 748 and 869 nm) are designed to have high sensitivity (signal-to-noise ratio (SNR) > 800:1, Hu et al., 2012b) to improve atmospheric correction, yet these bands tend to saturate over highly turbid waters (suspended sediment concentration > ~35 mg L^{-1}, Aurin et al., 2013) or thick aerosols, causing the standard atmospheric correction to fail. Furthermore, the SWIR–NIR atmospheric correction approach (see Section 3.1.2), as implemented in the National Aeronautics and Space Administration's (NASA) SeaWiFS Data Analysis System (SeaDAS, http://seadas.gsfc.nasa.gov/), at the time of writing, requires the use of a turbidity index dependent on these NIR bands (Wang & Shi, 2007), thus also failing over these waters. It has been recommended that planned instruments have sufficient sensitivity while keeping below saturation for nearly all bright targets, including clouds (Hu, Feng, et al., 2012b; Wang, 2007). Specifically, SNRs are recommended to be >100–200 for the SWIR bands, >600 for the NIR bands, and >1000 for the UV–Vis bands. Additionally, the theoretical detection limits for bio-optical properties have been investigated for polar (Del Castillo, 2012) and geostationary orbits (Pahlevan, Lee, Hu, & Schott, 2014).

2.2.5. Bottom reflectance

Due to bottom properties (bottom substrate and depth) often varying independently from water column properties, algorithms developed for optically deep waters are not applicable for such environments. Numerous studies have elucidated how a shallow bottom affects remote-sensing reflectance (Lee, Carder, Mobley, Steward, & Patch, 1998, Lee et al., 1994; Maritorena, Morel, & Gentili, 1994), and preliminary algorithms (e.g. Dekker et al., 2011; Lee, Carder, Mobley, Steward, & Patch, 1999; Mobley et al., 2005) have been developed for the derivation of water-column and bottom properties from hyperspectral measurements. These algorithms have not been included into routine processing platforms, thus no systematic evaluation of algorithm performance is available. Bottom properties are generally patchy, requiring much finer spatial resolution than currently available.

2.3. Solutions, future plans and recommendations

With missions in the planning phase, those on a geostationary platform will provide capacity for studying short-term dynamics found in coastal and inland environments. The GOCI mission has demonstrated significant improvement in observing diurnal variability with a similar band suite as many of the heritage sensors (Wang et al., 2013). The GEO-CAPE mission is focused on coastal temporal and spatial scales with improvement in the number of spectral bands addressing many of the unresolved mission capability issues. However, satellite platforms cannot fully capture all scales of temporal and spatial variability (Fig. 2) and geostationary platforms are not able to observe high latitudes. Even so, much will be learned from sensors on geostationary platforms for low- and mid-latitudes lakes, which are significantly impacted by direct human activities and have significant interest from a variety of user communities. Aircraft sensors and continual in situ observational platforms are needed to fully capture all environments and the range of variability encountered.

Due to its 19-day repeat cycle, HyspIRI should focus on low-changing properties such as benthic type and bottom depth. Even with low revisit frequency, the planned hyperspectral capacity is valuable in several aspects. For example, once HyspIRI has fingerprinted a feature of interest, more frequent observations by polar and geostationary orbiters can be used to trace the feature to study changes, thus utilizing these data as part of a nested satellite constellation.

3. Algorithms

3.1. Current and desired state of the science

3.1.1. In water algorithms

The critical step of deriving quantitative in-water, optical, biogeochemical and water quality information from satellite-derived spectral remote sensing reflectance ($R_{rs}(\lambda)$, sr^{-1}) requires the use of bio-optical algorithms, and a wide suite of which have been developed, tested, and implemented (Gordon & Morel, 1983; IOCCG, 2000, 2006). These algorithms can be broadly categorized into two groups: empirical and semi-analytical (SA). Algorithm development in the ocean community began primarily focused on the retrieval of chlorophyll concentration in waters where phytoplankton dominate the optical properties or co-vary with other OACs. Conversely, the inland-water community recognized the optical complexity of lakes and the need for multi-component retrieval algorithms, well before many SA algorithms were being utilized in ocean applications (Bukata, 2013). Recently, Matthews (2011) provided a thorough review of empirical algorithms, while Odermatt, Gitelson, Brando, and Schaepman (2012) compiled a list of recently-published (2006–2011) retrieval algorithms and documented their relevant domains of biogeochemical and water-quality parameters in optically complex waters. Both empirical and semi-analytical algorithms can be used for effective generation of biogeochemical and water quality products from $R_{rs}(\lambda)$. The distinction between the two approaches can be unclear, as some empirical algorithms have been developed from methods based on the radiative transfer equation (e.g., Doxaran, Froidefond, Lavender, & Castaing, 2002), and most SA algorithms contain empirical relationships (e.g., Garver & Siegel, 1997; Lee et al., 2002).

Empirical algorithms contain explicit or implicit empirical expressions. For instance, empirical algorithms based on band ratios (Gordon et al., 1983; O'Reilly et al., 1998), band differences (Hu, Lee, & Franz, 2012a), and Principal Component Analysis (Craig et al., 2012; Sathyendranath, Hoge, Platt, & Swift, 1994) of $R_{rs}(\lambda)$ contain explicit empirical expressions, whereas empirical algorithms based on Artificial Neural Networks (Jamet, Loisel, & Dessailly, 2012; Schiller & Doerffer, 1999) usually hide the empirical expressions (and associated coefficients). The coefficients of empirical algorithms are fundamentally data-driven, although these relationships can be validated through derivations of the radiative transfer model.

SA algorithms, on the other hand, are developed based on relationships derived from the basic radiative transfer equation (Gordon, Brown, & Jacobs, 1975, Gordon et al., 1988; Morel, 1980; Morel & Gentili, 1993). The common and simplified relationship is:

$$R_{rs}(\lambda) = G(\lambda)\frac{b_b(\lambda)}{a(\lambda) = b_b(\lambda)} \tag{1}$$

where $G(\lambda)$ (sr^{-1}) is a modeling coefficient that accounts for the air-water interface effect, the angular variation of $R_{rs}(\lambda)$, and the effect of multiple scattering; a and b_b (both expressed in units of m^{-1}) are the bulk absorption and backscattering coefficients, respectively, and are expressed as the sum of the contributions from each OAC as follows (Kirk, 1994; Mobley, 1994),

$$a(\lambda) = a_w(\lambda) + a_{ph}(\lambda) + a_{dg}(\lambda) \tag{2a}$$

$$b_b(\lambda) = b_{bw}(\lambda) + b_{bp}(\lambda) \tag{2b}$$

Here a_w, a_{ph}, and a_{dg} are the absorption coefficients of water, phytoplankton pigments, and the combination of detritus (often termed a_{NAP}) and gelbstoff (or CDOM), respectively; b_{bw} and b_{bp} are the backscattering coefficients of water and particulate matter, respectively (see Table 2 for a summary of notation). The absorption and backscattering coefficients are inherent optical properties (IOPs) and are linked to the biogeochemical constituents through their mass-specific IOPs (MSIOPs) such as the chlorophyll-a specific absorption and mineral or detrital-specific (back)scattering coefficients.

Replacing a and b_b in Eq. 1 with Eq. 2a and 2b,

$$R_{rs}(\lambda) = G(\lambda)\frac{b_{bw}(\lambda) + b_{bp}(\lambda)}{a_w(\lambda) + a_{ph}(\lambda) + a_{dg}(\lambda) + b_{bw}(\lambda) + b_{bp}(\lambda)} \tag{3}$$

where, b_{bw} and a_w can be generally considered constant (in fact, they vary slightly with the temperature and salinity of water (Pegau, Gray, & Zaneveld, 1997; Sullivan et al., 2006)). Eq. 3 indicates that, at each wavelength $R_{rs}(\lambda)$ is a function of at least three different variables (a_{ph}, a_{dg}, and b_{bp}; or four variables when a_{dg} is split into a_{NAP} and a_{CDOM}). Additionally, if the water is optically shallow, at least two more variables must be considered: the type of substrate and bottom depth (Lee et al., 1998). Thus, the analytical inversion of $R_{rs}(\lambda)$ is fundamentally an ill-posed mathematical problem (see also Defoin-Platel & Chami, 2007). An inverse solution of Eq. 3 requires multiple spectral bands and accurate models for, or a priori information on, the primary optical relationships (e.g., MSIOPS).

Various SA algorithms have been developed to invert Eq. 3 to derive the three primary OACs: chlorophyll-a concentration ([Chl]), CDOM absorption, and total suspended matter concentration (TSM). These algorithms can be broadly divided into two categories: bottom-up strategy (BUS) and top-down strategy (TDS). Examples of BUS include linear matrix inversion (Binding, Greenberg, & Bukata, 2012; Hoge & Lyon, 1996; Wang, Boss, & Roesler, 2005), spectral optimization (e.g., Bukata, Jerome, Kondratyev, & Pozdnyakov, 1995; Doerffer & Fisher, 1994; Lee et al., 1999; Maritorena, Siegel, & Peterson, 2002; Roesler & Perry, 1995) and look-up-tables (LUT) (Carder et al., 1991; Mobley et al., 2005); examples of TDS include the Quasi-Analytical Algorithm (QAA) (Lee et al., 2002), the Plymouth Marine Laboratory (PML) algorithm (Smyth, Moore, Hirata, & Aiken, 2006), and Loisel and Stramski's (2000) algorithm based on the diffuse attenuation coefficient. Both BUS and TDS exploit the dependence of bulk IOPs (and accordingly $R_{rs}(\lambda)$) on the spectral effects of the three primary components, either in the visible domain (IOCCG, 2006; O'Reilly et al., 1998) or extending into the red-infrared region (e.g., Binding et al., 2012; Dall'Olmo, Gitelson, & Rundquist, 2003; Gitelson, 1992; Moses et al., 2009). A fundamental difference is that while a BUS algorithm requires bio-optical models for each component during the retrieval process and derives each individual component and the bulk property simultaneously, a TDS algorithm does not necessarily require bio-optical models for each component during the inversion process, but rather retrieves the bulk property first before decomposing it into separate individual components. As a result, a BUS algorithm does not independently retrieve the spectrum of any component (i.e., the spectral dependence or relationships are provided as input to the inversion process), while a TDS algorithm can independently retrieve the spectrum of some components (e.g., a_{ph}), which can be later used to determine various water parameters (e.g., Craig et al., 2006).

Table 2
Notation.

AOPs — apparent optical properties
IOPs — inherent optical properties
[Chl] — chlorophyll concentration (mg m^{-3})
TSM — total suspended matter (mg L^{-1})
POM — particulate organic matter (mg L^{-1})
PIM — particulate inorganic matter (mg L^{-1})
DOM — dissolved organic matter (mg L^{-1})
DIM — dissolved inorganic matter (mg L^{-1})
$a(\lambda)$ — spectral total absorption (m^{-1})
$a_{CDOM}(\lambda)$ — spectral colored dissolved organic matter absorption (m^{-1})
$a_{NAP}(\lambda)$ — spectral non-algal particle absorption (m^{-1})
$a_{ph}(\lambda)$ — spectral phytoplankton absorption (m^{-1})
$b_{bp}(\lambda)$ — spectral particulate backscatter (m^{-1})
$b_{bp,NAP}(\lambda)$ — spectral particulate backscatter due to non-algal particles (m^{-1})
$b_{bp,ph}(\lambda)$ — spectral particulate backscatter due to phytoplankton (m^{-1})
$R_{rs}(\lambda)$ — spectral remotely sensed reflectance (sr^{-1})
$K_d(\lambda)$ — attenuation coefficient (m^{-1})
Z_{eu} (or $Z_{1\%}$) — euphotic zone depth (m)

$R_{rs}(\lambda)$ is fundamentally a multivariate function, and the MSIOPs of each component are not constant spatially nor temporally. Thus, the individual IOPs cannot be precisely retrieved from $R_{rs}(\lambda)$. A recent report (IOCCG, 2006) summarized the status of, and difficulties surrounding, the retrieval of IOPs from $R_{rs}(\lambda)$, and concluded that the most reliable parameters that can be retrieved are the total absorption and backscattering coefficients. The absorption spectra of the individual components often overlap each other and their shapes are not constant, thereby making the retrieved individual absorption coefficients less accurate (Lee, Arnone, Hu, Werdell, & Lubac, 2010a; Smyth et al., 2006), which will in turn affect the derivation of the water parameters. Thus, algorithms developed for coastal and inland waters need to take into account the regional differences in MSIOPs.

3.1.2. Atmospheric correction algorithms

Under most circumstances, over 90% of the light reaching a satellite over an aquatic target derives from the atmosphere (IOCCG, 2010). Therefore, the largest potential source of error and uncertainty in measuring $R_{rs}(\lambda)$ from space is the residual error from atmospheric correction. The Level-2 ocean color products distributed by the NASA Ocean Biology Processing Group (http://oceancolor.gsfc.nasa.gov/), have been atmospherically corrected using a variation of the "black-pixel" assumption. The premise of this assumption is that R_{rs}(NIR) is negligible because the absorption coefficient for water increases dramatically in the NIR (Gordon & Wang, 1994), so the sensor-measured NIR reflectance comes only from the atmosphere. After subtracting the well-known molecular (Rayleigh) scattering, this reflectance can be attributed to the aerosols, extrapolated to and subtracted from, the visible bands. However, in waters with abundant scattering materials (e.g., suspended sediments or intense algal blooms), R_{rs}(NIR) is no longer negligible, causing atmospheric correction failures. The standard algorithm has therefore been updated to include a bio-optical iteration scheme (Bailey, Franz, & Werdell, 2010), wherein the black-pixel assumption is used to make a first estimate of water's backscattering properties, from which R_{rs}(NIR) is estimated and then used in the process iteratively until solutions converge.

Even with bio-optical iterations, several problems emerge in highly turbid waters. For example, standard masking for bright pixels is a problem (Aurin et al., 2013); the NIR sensors often saturate, mistaking turbid waters for clouds (Wang & Shi, 2009), and non-convergence (or arrival at a false local minimum) often occurs in the iterative atmospheric correction. To address these issues, the atmospheric correction bands have been extended from the NIR to the SWIR (Wang, 2007; Wang, Son, & Shi, 2009; Zhang, Ma, Li, Zhang, & Duan, 2014) because of the significantly higher absorption coefficient for water in the SWIR than in the NIR (Shi & Wang, 2009). Aurin et al. (2013) present a strategy for applying the SWIR–NIR and NIR approaches in SeaDAS and the NOAA

CoastWatch Program (http://coastwatch.noaa.gov/) distributes operational MODIS coastal ocean color products that utilize the SWIR approach.

3.1.3. Desired state of algorithms

It is desirable to have a menu of algorithm choices with clear, consolidated information about their respective strengths and limitations. For the most part, the software to implement existing algorithms is freely available and can be run on established processing platforms (more detail is provided in Section 5). Users also have the ability to alter coefficients that are held constant within a given algorithm. One such example is provided in Werdell et al. (2013); however, few users know what coefficients should be altered for their region of interest, emphasizing the importance of providing information regarding the applicability of the algorithm and the associated limitations (Table 1).

3.2. Unresolved issues

In addition to widely varying ranges of OACs in coastal and inland waters, there are also significant variations in the contributions from inelastic scattering processes, type of algal species, particle (living or non-living) size distribution, mineral composition, and chemical composition of CDOM, thereby resulting in large seasonal and regional variations in the MSIOPs. Due to such inherent variability, various degrees of uncertainty will inevitably be present in retrieved water quality products. Here we discuss four of the most commonly retrieved parameters:

3.2.1. Water clarity

Water clarity is a basic water quality parameter that can be readily measured/represented by either the Secchi disk depth (Z_{sd}) or the photic depth ($Z_{\%}$). $Z_{\%}$ represents a depth where some percentage of light from the surface remains. Z_{sd} depends on the beam attenuation coefficient (Gordon, 1978; Preisendorfer, 1986; Tyler, 1968), which is dominated by forward scattering for which $R_{rs}(\lambda)$ contains almost no information (Gordon, 1993; Zaneveld, 1995). In order to achieve accurate estimation of Z_{sd} from $R_{rs}(\lambda)$, dedicated efforts are needed to quantify the variations of the particle backscattering ratio in different coastal and inland waters (Chen, Muller-Kargera, & Hu, 2007). Alternatively, $Z_{\%}$ depends not on the beam (direct) attenuation coefficient but on the diffuse attenuation coefficient, and is determined primarily by the bulk absorption and backscattering properties of the water column (Lee, Carder, Arnone, & He, 2007; Lee, Weidemann, et al., 2007). Limited evaluations of $Z_{\%}$ algorithms have been reported for oceanic, coastal and inland waters (Kloiber, Brezonik, & Bauer, 2002; Lee, Carder, Arnone, & He, 2007, Lee, Weidemann, et al., 2007; Salama & Verhoef, 2015; Shang, Lee, & Wei, 2010).

3.2.2. Chlorophyll-a concentration ([Chl])

[Chl] is a ubiquitous indicator of phytoplankton and is relatively easy to measure in the laboratory. In band-ratio approaches traditionally implemented for ocean waters, a change in the $R_{rs}(\lambda)$ blue–green ratio primarily represents a change in the total absorption coefficient in the blue spectral region (Lee et al., 2010b; Sathyendranath et al., 1994) that co-varies with changes in [Chl], at least to a first order (Gordon et al., 1988; Morel & Maritorena, 2001). The same principle has been applied to the development of a band-difference algorithm (Hu, Lee, & Franz, 2012a), which has the advantage of tolerance to spectrally related $R_{rs}(\lambda)$ errors over band-ratio algorithms. In coastal and inland waters, however, variations in the total absorption coefficient in the blue spectral region (and accordingly variations in the blue-green $R_{rs}(\lambda)$ ratios) may not necessarily be representative of actual changes in [Chl] (Bukata et al., 1995; Carder, Steward, Harvey, & Ortner, 1989; Sathyendranath, Prieur, & Morel, 1989). Thus, suitable SA algorithms are needed for the retrieval of [Chl] to minimize the effects of CDOM and other OACs (Bricaud, Claustre, Ras, & Oubelkheir, 2004; Carder, Chen, Cannizzaro, Campbell, & Mitchell, 2004; Darecki & Stramski, 2004). However, for waters with moderate-to-high [Chl] (>~10 mg/m^3), R_{rs} in the red and NIR bands are preferred for the retrieval of [Chl] (Gitelson, 1992; Gitelson et al., 2007, 2008; Gons, 1999) or dense floating algae (Hu et al., 2010; Matthews & Odermatt, 2015; Matthews et al., 2012). In such cases, the requirement for accurate modeling of a_{dg} can be relaxed as it is almost negligible. Likewise, focusing on the red and NIR bands will avoid the aforementioned atmospheric correction problems in the blue bands (Section 3.2.5). The fluorescence line height (FLH) has been used in positive relation with [Chl] where the magnitude of fluorescence is indicative of trophic status (Gower, 1980; Gower, Doerffer, & Borstad, 1999; Hu et al., 2005; Neville & Gower, 1977) or negative relation, suggesting a physical basis related to chlorophyll-a absorption and/or phytoplankton backscattering rather than fluorescence (Palmer, Hunter, et al., 2015a). Although high FLH indicates intense phytoplankton concentration, the inverse is not true, as FLH depends on absorption of CDOM and particle scattering as well as [Chl] (Huot, Brown, & Cullen, 2005; McKee, Cunningham, Wright, & Hay, 2007). Similar in form to the FLH, but not limited by a fixed peak, the maximum peak height (MPH) searches for the position and magnitude of the maximum peak in the red region of the spectra and has been demonstrated to work across a broad range of trophic status (Matthews & Odermatt, 2015; Matthews et al., 2012).

3.2.3. Total suspended matter (TSM)

Particulate backscattering coefficient (b_{bp}) contains information on living and non-living particles. Although b_{bp} can be quite reliably retrieved from $R_{rs}(\lambda)$, the conversion from b_{bp} to TSM is neither constant nor stable. Reflectance ratios (D'Sa, Miller, & McKee, 2007) have previously been adopted to remove much of the uncertainty induced by variable b_{bp} MSIOPs (Doxaran et al., 2002). However, dedicated efforts are still needed to further characterize the spatial and temporal variations of the b_{bp}/TSM ratio and define the separate contributions from phytoplankton and non-algal particles (Binding, Bowers, & Mitchelson-Jacob, 2005, Binding et al., 2012). One such effort is to first derive turbidity from $R_{rs}(\lambda)$, and then use regional relationship between turbidity and TSM to estimate TSM (Dogliotti, Ruddick, Nechad, Doxaran, & Knaeps, 2015). Parsing TSM into the contributions of particulate organic (POM) and inorganic matter (PIM) (Stavn & Richter, 2008) is of interest to many applications but far less mature than TSM alone (Table 3).

3.2.4. Colored dissolved organic matter (CDOM)

The abundance and composition of CDOM in natural waters play an important role in ecological and photochemical processes by modulating the spectral light regime. Remote estimation of a_{CDOM} from $R_{rs}(\lambda)$ is challenging due to the spectral overlap between a_{ph} and a_{dg} and the spectral similarity between a_{NAP} and a_{CDOM} (Brezonik, Olmanson, Finlay, & Bauer, 2015; Carder et al., 1991; Roesler, Perry, & Carder, 1989). Many studies have utilized empirical relationships between band ratios and a_{CDOM} with great success (Brezonik et al., 2015; Kahru & Mitchell, 2001; Mannino, Russ, & Hooker, 2008; Tehrani, D'Sa, Osburn, Bianchi, & Schaeffer, 2013; Tiwari & Shanmugam, 2011). However, the desire to retrieve many OACs simultaneously, demands improved separation of a_{ph} and a_{dg} from the total absorption coefficient and the removal of a_{NAP} from a_{dg} (Dong, Shang, & Lee, 2013; Le & Hu, 2013; Zhu, Yu, Tian, Chen, & Gardner, 2011).

3.2.5. Atmospheric correction

The atmospheric correction procedure in the nearshore is complicated by the potential for absorbing aerosols such as smoke, dust, and anthropogenic emissions (e.g. NO_2 and CO_2). While gaseous absorption is currently estimated using climatological models, there is no practical means to correct absorbing-aerosol effects due to lack of information on aerosol vertical distribution (Gordon, 1997). Absorbing atmospheric NO_2 from anthropogenic NOx emissions has been shown to vary significantly during a given day necessitating near simultaneous measurements for atmospheric correction from geostationary platforms (Fishman et al., 2012; Herman et al., 2009; Tzortziou et al., 2013). Stray light contamination from nearby bright land or clouds can be another problem for atmospheric correction (Meister & McClain, 2010; Santer & Schmechtig, 2000). Pixels adjacent to land or clouds are therefore generally masked, further degrading ability to view coastal and inland waters. However approaches to minimize the adjacency effect have recently been developed (Kiselev, Bulgarelli, & Heege, 2015; Sterckx, Knaeps, Kratzer, & Ruddick, 2015).

3.3. Solutions, future plans and recommendations

Fundamental to the success of any retrieval algorithm is the accuracy of satellite-derived $R_{rs}(\lambda)$, which is to a large degree dependent on improved atmospheric correction (Hu, Feng, & Lee, 2013). Thus, investments in atmospheric correction improvements, in addition to continued efforts to fully characterize MSIOPs in optically complex waters, will go a long way to increase the potential for reliable, satellite-derived products. In particular, the extrapolation-based atmospheric correction leads to the highest uncertainties in the UV and blue bands that are critical in deriving CDOM and blue-absorbing phytoplankton pigments. It is well recognized that algorithm development is a continually evolving process and improvements are expected with advancements in instrumentation and measurement techniques. Comparison or intercomparison exercises are recommended to document algorithm and associated product fit for purpose, in addition to consolidation and simplification of the range of algorithm options. Further, the desired goal is for product continuity rather than algorithm continuity (Table 1). With this in mind, the development of blended approaches that utilize a variety of algorithms and choose those that produce the least uncertainty in various water types may be advantageous in waters that are optically diverse over a given scene (Moore, Campbell, & Feng, 2001, Moore, Dowell, Bradt, & Verdu, 2014; Palmer, Hunter, et al., 2015a). Algorithms should be designed to be sensor independent with the ability to utilize a variety of band placements.

4. In–situ observations and bio-geo-optical inter-relationships

4.1. Current and desired state of the science

In situ observations are required for development, refinement, and validation of remote sensing algorithms. In order to fully support these activities, the desired aim for in situ sampling is for datasets to be as comprehensive as possible; requiring data be collected in many varied locations, over a variety of time periods, under conditions that encompass large dynamic ranges in optical and biogeochemical properties. In addition, IOPs, apparent optical properties (AOPs) and biogeochemical parameters need to be observed coincidently and be synoptically sampled over spatial scales that adequately resolve their variability within the pixel size of a remote imager. Considering the small scale horizontal (m) and vertical (cm) variability observed in optical constituents of coastal and inland waters (Dickey, Lewis, & Chang, 2006; Powell et al., 1975; Seuront & Strutton, 2004), this is a significant challenge. Common protocols that address the dynamic range and unique sampling requirements of coastal and inland water bodies need to be developed and followed across all agencies supporting these types of observations. Many agencies fund these types of observations, but there is a high degree of variability between projects in terms of parameters measured, data storage and quality assurance/quality control methodologies, making it difficult to develop pan-system algorithm development and validation strategies (Table 1). Observation archiving needs to be in centralized, publically available data repositories used across agencies that support such observations (Table 1).

Table 3
Recommended standard remotely sensed products.

	Standard products	Additional products
AOPs	$R_{rs}(\lambda)$, $K_d(\lambda)$, Z_{eu} (or $Z_{10\%}$)	
IOPs	$a(\lambda)$, $a_{CDOM}(\lambda)$, $a_{NAP}(\lambda)$, $a_{ph}(\lambda)$, $b_{bp}(\lambda)$	
Biogeochemical	[Chl], TSM, POM, PIM, DOM, DIM	Primary productivity, phytoplankton functional types

4.2. Unresolved issues

For the success of aquatic satellite remote sensing into the future, a data-oriented, long-term planning approach will need to replace a mission-oriented approach (NRC (National Research Council), 2011). Table 4 provides a list of minimum recommended observations that are required to develop remote sensing algorithms and also provide independent datasets for the validation of these parameters and products. Briefly, these include full characterization of AOPs ($R_{rs}(\lambda)$, $K_d(\lambda)$, $Z_{\%}$), IOPs ($a(\lambda)$, $a_{CDOM}(\lambda)$, $a_{NAP}(\lambda)$, $a_{ph}(\lambda)$, $b_{bp}(\lambda)$) and desired biogeochemical parameters ([Chl], TSM, POM, PIM, DOM, DIM). A discussion of protocols for consistent measurement of these parameters is presented in section 4.3. Technology considerations that need to be altered for coastal and inland systems include instrument sensitivity, dynamic range, and appropriate spatial, vertical, temporal and spectral resolution. Here we describe key aspects of data requirements particularly critical to the success of coastal and inland remote sensing.

4.2.1. Instrument capability

Measurements in extreme environments are problematic with off-the-shelf instrument configurations. A challenge in coastal and inland waters is high turbidity and strong absorption. As absorption increases, the effect of self-shading of upwelling radiance increases (Gordon & Ding, 1992; Leathers, Downes, & Mobley, 2004). For IOPs, commercially available scattering sensors have the capability to effectively resolve backscattering at very high levels ($>0.5\ m^{-1}$), but standard gain settings for these sensors are typically set to saturate at levels an order of magnitude lower (Sullivan, Twardowski, Zaneveld, & Moore, 2012) to maximize resolution in the dynamic ranges observed in the ocean.

The vertical depth resolution of satellite detection and variability within the first meter of the water column is a challenge with existing radiometric instrumentation, which are up to 1 m in height. In waters with diffuse attenuation coefficients (K_d) of 1 m^{-1}, 90% of water-leaving radiance emerges from the upper 1 m (see Zaneveld, Barnard, & Boss, 2005). Additionally, strong gradients in density and optical properties can persist in the upper 1 m where local freshwater input, including rain, or where surface algal scums accumulate. Emerging technology is allowing new radiometry systems to be developed that have slow descent rates (cm/s) or bottom-up profiling approaches improving depth resolution (Morrow et al., 2010; Sullivan, Donaghay, & Rines, 2010). Beyond just the first meter of the water column, depth profiles are important for providing information on how to weight a given optical property with respect to the optical signal observed by a satellite. In addition, innovative approaches (Lee, Pahlevan, Ahn, Greb, & O'Donnell, 2013; Tanaka, Sasaki, & Ishizaka, 2006) have also been developed to provide more precise measurements of water-leaving radiance in the field.

A variety of approaches have been developed to resolve optical and biogeochemical properties in the horizontal dimension over the areal coverage of a remotely imaged pixel. Towed undulating sensor packages can be deployed to sample a 1 kilometer pixel area with 250 m transect spacing in about 1 h (Voss et al., 2010). Airborne or shipboard range-gated lidar have the potential of rapidly depth-resolving both backscattering and absorption (Churnside, Tatarskii, & Wilson, 1998; Zimmerman, Sukenik, & Hill, 2012). Shipboard measurements of water-leaving radiance (see Mueller, Fargion, & McClain, 2003) can also be collected at the maximum cruising speed of a vessel.

Table 4
Recommended standard in situ observations for algorithm development, refinement and validation.

	Minimum parameters	Additional parameters
AOPs	$R_{rs}(\lambda)$, $K_d(\lambda)$, Z_{eu} (or $Z_{10\%}$)	
IOPs	$a(\lambda)$, $a_{CDOM}(\lambda)$, $a_{NAP}(\lambda)$, $a_{ph}(\lambda)$, $b_{bp}(\lambda)$	$b_{bp,NAP}(\lambda)$, $b_{bp,ph}(\lambda)$
Biogeochemical	[Chl], TSM, POM, PIM, DOM, DIM	HPLC pigments, primary productivity

*Spectral parameters should be observed at the highest spectral resolution allowed by the instrumentation or at 2–5 nm increments.

4.2.2. Technology gaps

There are also gaps in technology that currently straddle both inland, coastal, and open ocean regions. With planned missions moving toward greater spectral resolution and coverage, there is a need for comparable resolution for in situ measurements. Hyperspectral capability is currently commercially available for radiometry and absorption, but not for backscattering. Similarly, only a few custom systems exist for resolving the volume scattering function (angular distribution of scattered light), with available commercial systems providing volume scattering at up to three angles, each with very broad angular weighting over the backward hemisphere (Sullivan et al., 2012).

Open path designs for IOP measurements are preferred as shear from pumping water through a cavity can break up delicate aggregates, substantially altering bulk optical properties (Boss, Slade, & Hill, 2009). Scattering measurements are currently made in undisturbed volumes, but an unresolved need is open path measurements of absorption that are not sensitive to variable levels of ambient scattering. Absorption may be derived with ~1% accuracy by measuring the decay in vector irradiance from sunlight or from an isotropic point source using Gerhsun's Equation (Preisendorfer, 1961) or adaptations thereof (Maffione, Voss, & Honey, 1993; Tarashchanskiia, Kokhanenkob, Mirgazova, Ryabova, & Yagunova, 2011), although the long required pathlengths render the method impractical for routine sampling. Another possibility is photoacoustic methods, where an acoustic signal is generated by molecular and particulate absorption using a modulated light source (Trees & Voss, 1990).

The development of SA algorithms requires not only bulk absorption and backscattering, but also the contributions from all OACs. Automated in situ methods can only discriminate between bulk absorption by particulate and dissolved materials by using a prefilter on the intake of pumped absorption measurements (Twardowski, Sullivan, Donaghay, & Zaneveld, 1999). Filters with different pore sizes can be used to discriminate contributions of both absorption (pumped) and backscattering (shipboard flow-through) within different particle size ranges (Dall'Olmo, Westberry, Behrenfeld, Boss, & Slade, 2009; Lohrenz, Weidemann, & Tuel, 2005). One possibility for estimating phytoplankton absorption spectra in situ is the use of fluorescence excitation spectra, monitoring emission at 683 nm, which approximates photosynthetic absorption action spectra (Maske & Haardt, 1987). However, this approach is not applicable if cyanobacteria dominate, as most of their chlorophyll-*a* is located in non-fluorescing photosystem I (Seppälä et al., 2007). Scattering properties of individual particulate constituents can be obtained by modeling their optical contributions from fundamental data on particle fields. This requires: 1) characterizations of variables such as size, shape, refractive index, and orientation for many individual particles, in an undisturbed sample volume, and 2) sufficiently accurate forward models for computing scattering for particles with complex shape and composition. Both of these requirements are exceedingly challenging. One emerging technology that is able to resolve many of the particle parameters is digital holographic imaging (Davies, Nimmo-Smith, Agrawal, & Souza, 2011; Graham & Nimmo-Smith, 2010; Talapatra et al., 2012). Progress is also being made in modeling techniques (Bi, Yang, Kattawar, & Kahn, 2010; Gordon & Du, 2001; Mishchenko, Hovenier, & Travis, 2000).

The important point is that essentially all methodologies for determining biogeochemical parameters (TSM, POM, PIM, DOM, DIM) with analytical precision and accuracy suitable for remote sensing applications are laboratory-based at this time (Table 1). This gap in currently available instrumentation, is a hindrance to algorithm development and validation efforts (Twardowski, Lewis, Barnard, & Zaneveld, 2005). Nearly all of the biogeochemical properties derived from optical properties have been accomplished via empirical relationships, which are not robust in coastal and inland waters due to the wide variability in composition and relative concentrations. If models with sufficient accuracy are developed in the future to derive these biogeochemical properties from optical measurements, determinations of biogeochemical properties may then be made from optical sensors deployed on autonomous platforms, allowing collection of data over large dynamic ranges necessary to refine or develop new analytical-type remote sensing algorithms of these parameters (Table 1).

4.2.3. Observations for atmospheric correction

An aspect neglected in the recommended standard observations is the importance of the atmospheric correction. The AErosol RObotic NETwork-Ocean Color (AERONET-OC) is a network of standardized SeaWiFS Photometer Revision for Incident Surface Measurements (SeaPRISM) (Zibordi et al., 2009) instruments that link aquatic reflectance and atmospheric observations necessary for assessing and improving atmospheric correction. AERONET-OC consists of fifteen sites in coastal waters around the globe, although only one site has been established in an inland freshwater system (http://aeronet.gsfc.nasa.gov/). SeaPRISMs autonomously make multiple sky and sea radiance observations with identical measuring systems and protocols, calibrated using a single reference source and method, and processed using the same code. The SeaPRISM bands are currently limited to nine in the 412–1020 nm spectral range and do not have sufficient resolution in the red to NIR to resolve peaks in reflectance that many recent algorithms have exploited for the detection of phycocyanin (Kutser, Metsamaa, Strombeck, & Vatmae, 2006; Simis et al., 2005) and freshwater surface algae (Alikas, Kangro, & Reinart, 2010; Gower, King, & Goncalves, 2008, Hu, 2009; Hu et al., 2010; Matthews et al., 2012; Wynne, Stumpf, Tomlinson, & Dyble, 2010; Wynne et al., 2008). AERONET-OC is an important asset that must evolve to meet the needs of planned missions. Ideally, AERONET-OC would cover the full spectral range, resolution, and SNR of all current and planned sensors with autonomy allowing for minimal maintenance.

4.3. Solutions, future plans and recommendations

Developing an effective strategy for collection and utilization of in situ observations is essential to advance the use of remote sensing of aquatic color as a central tool for research and applications in coastal and inland regions. Observations are needed for algorithm development and product validation efforts, but also for validation of water leaving radiances after challenging land-adjacent atmospheric corrections are applied. Sensors capable of measuring biogeochemical properties, IOPs, and radiometric parameters are required that have sufficient accuracies (typically 5%, Bailey & Werdell, 2006) over the dynamic range. Those working in coastal and inland waters need standard protocols for the required measurements according to optimal current methods. This aspect is exceptionally important due to the variety of entities making observations. There is a current ocean-centric set of protocols supported and maintained by NASA (Mueller et al., 2003) that can be used as a reference point. These protocols should be compatible and contextually relevant with best existing practices, for example, the U.S. EPA Quality Assurance Project Plan (QAPP) documents that are used to standardize technical procedures, quality expectations, and data collection strategies for environmental data. Workshops and courses are also needed that train the research community in using best practices in data collection. Finally, all relevant and rigorously quality controlled data, regardless of funding agency, should be archived in open community database(s) after a suitable time period following acquisition. An excellent model is the SeaWiFS Bio-optical Archive and Storage System (SeaBASS) maintained by NASA (http://seabass.gsfc.nasa.gov/).

Many existing observing efforts and programs in coastal and inland waters could and should be leveraged for optical remote sensing work. Expanding observations and augmenting existing observing networks, time series, and monitoring efforts with the recommended optical measurements could greatly increase their impact. For space agencies, increasing their support for in situ data collection and validation efforts in coastal and inland waters expands the relevancy, utilization and impact of their sensors/missions. Given the broad user groups involved and their diverse and extensive needs, the investment required for infrastructure needs to be shared across agencies.

5. Operational capacity

5.1. Current and desired state of the science

Ensuring adequate and sustained operational capacity can be challenging in coastal and inland waters where the variety of end users spans a myriad of needs, interests, applications and services, while environmental conditions are complex and diverse. Existing remote sensing capacity in support of coastal and inland water management needs span the gamut from operational missions, products and systems and their providers (e.g., EUMETSAT and NOAA) to experimental data and results from research and development (R&D) missions, systems and activities (e.g., by ESA and NASA). Global polar orbiting missions have not provided standard products for use in coastal and inland waters with enough certainty to be adapted by many national, state, and local resource management agencies, nor have they provided the full-suite of application/region-specific products that are fit for purpose (Schaeffer et al., 2013). Near real-time water quality monitoring using satellite data and locally customized algorithms (e.g., Hu, Barnes, Murch, & Carlson, 2014) can provide timely information on current and historical water quality and are ideally suited for non-remote sensing specialists. Collaborative efforts (Nezlin et al., 2008; Reifel et al., 2009), involving researchers and users have demonstrated the utility of satellite remote sensing for water quality monitoring. These and other efforts are helping to build an increasingly mature body of work and understanding that will support continued development of experimental and operational products as well as decision-support systems that utilize remote sensing data for various applications. However, much more work is needed to develop and provide support for user-driven applications.

Often users do not have extensive experience or specialized expertise regarding the access, processing and handling of remote sensing data. They are frequently limited to using the standard suite of products that were developed and optimized for global R&D missions, often at spatial scales (4 to 9 km) most suited for global application (Table 1). There are also intermediate, expert scientific users, who utilize primary or derived satellite data and products, generated by different sources (e.g., government, academic, or commercial entities). These applications are typically localized, and tend to rely on staff with the necessary level of interest, knowledge and training. Unfortunately, without stable funding and staff continuity, usage of remote sensing data might diminish or cease. In these situations, the primary question continues to be how to build and sustain necessary capacity.

For users with the appropriate level of knowledge and experience that have the need for non-standard algorithms, products (including full-resolution), or processing specifications, several processing software packages are freely available and can run on common desktop computers. The most utilized of these are NASA's SeaDAS, and the Basic European Remote Sensing (ERS), Envisat Advanced Along Track Scanning Radiometer ((A)ATSR) and MERIS Toolbox (BEAM; http://www.brockmann-consult.de/cms/web/beam/). However, many users outside of the remote sensing community report difficulty utilizing the software quickly and efficiently, pointing to the need for continued development that can help users quickly make the progression from data to products to information to knowledge.

The desired end goal is to have processing platforms that are fit for purpose and able to work across a variety of missions. The processing platforms should be sufficiently complicated to allow for customization by well-trained users, flexible enough to be responsive to diverse spatial, temporal and spectral capabilities and applications, while simple enough for a variety of users to benefit. They should have an element of decision support that could allow non-expert users to input what is known about their environment or application and receive recommendations for potential algorithms, products, analysis options, and uncertainty estimates. Application portals would identify standard color products fit for purpose as well as provide "recipes" or protocols for generating tailored products for a particular application. These application portals could take advantage of off-site cloud processing, eliminating the need for many users to download raw satellite data sets, allowing generation of derived products of interest distilled for the specific information required. Software should also be available for mobile platforms (phones or other), which could facilitate broader global use. Data, imagery and derived products should be available in near-real time (NRT) to support environmental disasters and other operational decision-making needs (Table 1); expansion of the network of direct broadcast receiving stations would be helpful in this regard.

There are a number of international remote sensing networks and programs that are attempting to build remote sensing capacity and support user data and information needs. Table 5 provides a full list of these networks, programs and organizations along with their website. There is clearly a significant amount of infrastructure already in place to facilitate utilization of remotely sensed data in the monitoring and management of coastal and inland waters. Even so, capacity building efforts are still needed to better link data providers and users. In many of these areas there remain significant issues, gaps and challenges as discussed further below.

5.2. Unresolved issues

Perhaps the most significant challenge in developing and advancing operational capacity is the mismatch often observed between what remote sensing data providers supply and end user needs. The Integrated Global Observing Strategy IGOS (2006) previously articulated a number of knowledge, resolution, continuity and integration challenges relative to coastal water observations, most of which are still germane today. The report identified key user-driven issues such as the need to better understand and quantify relationships between various OACs and indicators of ecosystem states (~health). Such color-based products and associated indicators were identified in UNESCO (2012) as critical inputs for end-to-end observing systems that address phenomena such as eutrophication and hypoxia, waterborne pathogens, HABs, benthic habitat assessments, and fisheries management. Key operational challenges identified in this context include developing and implementing new and improved algorithms and products (direct measures or indirect proxies) tailored to specific user needs and requirements, ensuring routine, sustained and unrestricted (free) access to high-quality operational and R&D mission data, more effectively integrating satellite and in situ data and facilitating the assimilation of these data into forecast models. Products need to have specified uncertainties, especially to support modeling and ecological forecasting activities, development of consistent, merged multi-sensor data products, and generation of integrated, high-level products. Cross-disciplinary integration challenges also exist, including the need to effectively link data sets across the land-sea interface, as well as link environmental and socio-economic data.

Space-based ocean color radiometry measurements are now being transitioned into routine and sustained operations by agencies such as NOAA (i.e., VIIRS) and EUMETSAT (i.e., OLCI), building on the successful heritage established by R&D agencies. Broadening the definition of operational to include delayed mode as well as NRT applications is a necessary paradigm shift to ensure that all operational missions implement and maintain robust supporting infrastructure and scientific/technical activities (e.g., reprocessing, cal/val, orbital maneuvers). Coupled with this is the need to continue to quickly transition complementary new and improved measurements from R&D missions into operations. There is also the “downstream” need to further develop derived remote sensing products and integrated information systems that use both (multi-sensor) satellite and in situ data (and their assimilation into forecast models), as well as ensuring suitable distribution pathways exist.

In terms of developing new and improved products, the fundamental retrieval parameters with the greatest certainty are IOPs, while many environmental and management agencies are interested in derived biogeochemical or water quality parameters. Investments in characterizing variability in specific IOPs will help improve retrieval of the desired water quality products from $R_{rs}(\lambda)$, and benefit the derived operational products that directly support user needs. To help support these types of efforts, ongoing coordinated field observations are required. Management agencies and user communities working with the scientific/research community could provide collaborative opportunities for optical measurements to be made at the same time that water quality parameters are sampled.

5.3. Solutions, future plans and recommendations

Given the user (both research and applied) communities interested in coastal and inland remote sensing span a multitude of backgrounds and expertise, the establishment of a “Community of Practice” (CoP) in this area could fall under the umbrella of Group on Earth Observations (GEO) as part of the broader Global Earth Observation System of Systems (GEOSS) and complement existing CoPs such as the GEO Coastal Zone Community of Practice (http://www.czcp.org/), providing cohesion and a springboard for better coordination, integration and harmonization of national and international efforts. There are already a number of educational opportunities for training graduate students and professionals on in situ observational techniques and satellite approaches. However, there is a growing need to educate the broader user community who are interested in applying satellite products to their region or application but are not trained in optics and remote sensing. Previous and ongoing outreach efforts have been quite successful, but these efforts need to be significantly expanded in scope and coverage. One recommendation is that a panel of experts be formed who serve on a rotating basis in which users could pose questions and receive recommendations on the fit for purpose of particular satellite products, algorithms, data collection and/or analysis techniques. This could further be augmented with application portals and decision support tools and infrastructure developed for and in consultation with the user community. These new and improved capabilities would provide confidence to various user groups, reduce instances of poor fit for purpose, and improve decision-making as well as the quality of science resulting from the multitude of studies that require the integration of remotely sensed products.

There have been attempts to reduce the barrier that user groups report regarding file types, magnitude of data volumes and software commonly used by the scientific community, with the development of freely available software to query, visualize and perform simple calculations with data and imagery (e.g. NASA GIOVANNI and UNESCO-Bilko). However, end users still report a missing link in their ability to effectively utilize and integrate satellite data with other information, pointing to a need for continual training opportunities though workshops and online tutorials as well as provision of enhanced decision-support tools. The workshop training opportunities that exist often coincide with specialist meetings. It is recommended that these workshops be reformatted and offered in conjunction with broader community meetings as well as user group professional meetings to ensure maximum impact.

6. Conclusions

While global ocean remote sensing is relatively extensive in terms of number and type of observing assets, coastal and inland remote sensing has generally lagged behind. Most previous and current satellite assets were designed for global observing, thus coastal and inland users are left to utilize systems for which they were not necessarily the primary target or requirement. However, use of these data and systems for coastal and inland applications has greatly expanded the relevance and benefits to national, regional and local environmental and management agencies and other end users. In this context, significant advances have been made in supporting in situ observations, algorithm development and operational capacity and user engagement, but challenges still exist. Looking ahead, there are several missions in the planning stages whose focus is specifically on coastal and inland waters. Investments made now in in situ observations, algorithm development and user engagement as capacity building, will directly benefit the scientific and societal impact of these missions. Expanding the use of color remote sensing in coastal and inland waters as outlined here is critical to the future relevance of the science to national and regional environmental and management agencies.

In summary, the primary challenges, solutions and recommendations are listed below for the four fundamental elements.

- Mission capability — The current lack of on orbit missions focused on the scales of variability encountered in coastal and inland water bodies, necessitates the need for investment in geostationary and polar orbiting future missions with flexibility to handle appropriate sensitivity, spectral, spatial and temporal scales. Sensors need to move toward designs with greater spectral resolution and coverage that allow for resampling for a variety of applications.

Table 5
International networks, programs and organizations with coastal and/or inland water body remote sensing science, user, and management elements.

Organization	Website URL
International Ocean Colour Coordinating Group (IOCCG)	http://ioccg.org/
Ocean Color Radiometry-Virtual Constellation (OCR-VC)	http://www.ioccg.org/groups/OCR-VC.html
Committee on Earth Observation Satellites (CEOS)	http://www.ceos.org/
Group on Earth Observations (GEO)	http://www.earthobservations.org/
Global Earth Observation System of Systems (GEOSS)	https://www.earthobservations.org/geoss.shtml
Partnership for Observation of the Global Ocean (POGO)	http://www.ocean-partners.org/
Chlorophyll Globally Integrated Network (ChloroGIN)	http://www.chlorogin.org/
Societal Applications in Fisheries & Aquaculture using Remotely Sensed Imagery (SAFARI)	http://www.geosafari.org/index.html
Global Ocean Observing System (GOOS)	http://www.ioc-goos.org/
CoastColour	http://www.coastcolour.org/
Land–Ocean Interactions in the Coastal Zone (LOICZ)	http://www.loicz.org/
Global Observatory of Lake Responses to Environmental Change (GloboLakes)	http://www.globolakes.ac.uk/
Global Lakes Sentinel Services (GLaSS)	http://www.glass-project.eu/
Global Lake Ecological Observatory Network (GLEON)	http://www.gleon.org/

Table 6
Prioritized implementation of enabling activities for coastal and inland remote sensing.

Priority	Immediate	Near-term	Long-term
1	In situ observations: Establish limited number of centralized publically available data repositories. Operational capacity: Provide more training opportunities for non-specialists.	In situ observations: Invest in data collection in complex waters and the characterization of MSIOP variability. Operational capacity: Work to ensure free, open and timely (NRT or other) access to all satellite color data streams.	Mission capability: Ensure satellite mission capability with flexibility to handle appropriate sensitivity, spectral, spatial and temporal scales found in coastal and inland systems. Move toward sensor agnostic designs with greater spectral resolution and coverage that could be resampled for various applications.
2	In situ observations: Establish standard measurements for any in situ campaign supporting remote sensing. Update community (NASA et al.) protocols to include consideration of the dynamic range of properties encountered in these systems and extend to include biogeochemical properties.	Operational capacity: Identify best practices and approaches for use of color remote sensing data in applications. Develop decision support information and tools for algorithm and product selection. Develop application portals to facilitate access and fit for purpose use of color remote sensing data and derived products.	
3	Operational capacity: Establishment of a user-driven community of practice for remote sensing of coastal and inland waters to link freshwater and marine, satellite and in situ data, data providers and users, science and societal considerations, to work collaboratively with IOCCG, space agencies et al.	Algorithms: Perform an algorithm intercomparison for consolidation and/or simplification of algorithm choices. In situ observations: Create a 'NOMAD-like' dataset/s with coincident observations for the inland/coastal waters.	

- Algorithms — There is a need for intercomparison exercises leading to identification of strengths and limitations, consolidation and simplification of the range of options for in-water and atmospheric correction algorithms. Focus needs to move toward product continuity, rather than algorithm continuity, which could be done by blending algorithms in optically diverse regions. Algorithm design should allow for application to a variety of sensors with different band placements. Increased investment is required to fully understanding biogeochemical property variability and relationships with optical properties.
- In situ observations – Clear, consistent and coordinated data sharing policies between agencies with centralized publically available data repositories ensuring access to consistent high quality data, regardless of funding source, is needed. To help ensure in situ observational efforts are utilized to their fullest, a list of minimum recommended observations is identified. Expanding current efforts to include these observations could greatly increase their impact. Protocols need to be revisited and developed to accommodate the dynamic range of optical and biogeochemical variability in coastal and inland water. There exist technology gaps in instrumentation, such as the ability to sense in high turbidity water and to measure hyperspectral backscattering. All methodologies for determining biogeochemical parameters with an analytical precision and accuracy suitable for remote sensing are laboratory-based at this time, pointing to the need for continued technology investment. AERONET-OC needs to evolve to meet the spectral and SNR needs of planned missions.
- Operational capacity — The most significant challenge is the mismatch observed between information supplied by remote sensing data providers and information desired by end users and user's ability to work with software, data volumes and file types and identify products with the least uncertainty for given applications. These mismatches could be reduced through greater training opportunities at broad audience events and the establishment of a panel of rotating experts in which users could pose questions and receive recommendations about the fit for purpose. This could be further augmented with application portals populated with products that are fit for purpose, and accompanying decision support tools and infrastructure developed for and in consultation with the user community. Free, open and timely access to all data streams, provided in both near-real time as well as on a delayed basis depending upon application, and expanded investment and coordination of recommended standard observations remain crucial needs, that should be ensured. Development of a user-driven community of practice to address water quality needs in coastal and inland waters is strongly recommended.

The prioritized and recommended staggered implementation for primary actions needed to make progress for each of the functional elements are identified in Table 6.

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