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Remote sensing of inland waters: challenges, progress and future directions

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1. Introduction

In addition to providing water resources for various human uses (Postel, 2000), inland waters provide important and diverse habitat and ecosystem services, supporting of high levels of biodiversity (Brönmark and Hansson, 2002; Duker and Bore, 2001). They are important components of global carbon and nutrient cycles (Tranvik et al. 2009; Bastviken et al., 2011). However, like many other ecosystems, lakes and rivers are threatened by the synergistic effects of multiple, co-occurring environmental pressures, notably nutrient enrichment and other organic and inorganic pollution, climate change, acidification, the establishment and spread of invasive species, and the diversion or extraction of upstream source waters (Brönmark and Hansson, 2002; Dudgeon et al., 2006). Their importance, as well as their sensitivity to and capacity to reflect climate, land use and other environmental change, has garnered inland waters increasing attention over recent years. The assessment and monitoring of lakes and rivers is crucial to our ability to understand and disentangle the effects of environmental change on freshwater ecosystems and to model future change. There is also an increasing regulatory need to increase the coverage and frequency of freshwater monitoring, arising from legislation such as the European Union's Water Framework Directive for example. There are, however, upwards of 117 million lakes on Earth (Verpoorter et al., 2014) and only a very small proportion of these are regularly and consistently monitored. Conventional, *in situ* monitoring is limited in terms of spatial coverage and representativeness, as well as in terms of frequency for many sites, and is simply non-existent in a great many others.

Remote sensing has long been recognized as having the potential to complement conventional approaches to lake monitoring (Bukata, 2013 and references therein). Indeed, research on the remote sensing of inland waters has been undertaken for almost as many years as that in ocean colour science, but whereas satellite observations are used operationally to measure ocean colour, their use for monitoring inland waters has made less progress. Inland water remote sensing has faced, and continues to face, many challenges not only in terms of the science underpinning the retrieval of physical and biogeochemical properties over what are typically highly optically complex waters, but it has also suffered from the lack of funding, infrastructure and the mechanisms needed to coordinate research efforts across what has been historically a rather fragmented community.

1.1 Challenges: past and present

The ocean colour sensors that have supported much of the research and service development in marine remote sensing have or had coarse spatial resolutions that makes them unsuitable for remote sensing applications over most rivers, lakes and reservoirs. This has meant that the inland water community has often had to make use of data from satellite sensors with higher spatial resolutions designed primarily for land applications, such as the National Aeronautics and Space Administration (NASA) Landsat series. However, while these sensors have adequate spatial resolutions for many lakes, their spectral coverage and resolution, as well as their radiometric sensitivity, is not optimal for many applications over inland waters (e.g., phytoplankton pigment or colored dissolved organic matter (CDOM) retrieval).

The optical complexity of inland waters, atmospheric correction issues, adjacency effects and some other unresolved problems add great additional challenges to inland water remote sensing in comparison with ocean colour remote sensing. The optical complexity of inland waters stems from the fact that these waters are typically characterised by high concentrations of phytoplankton biomass (typically on the order of between1 and 100 mg m^{-3} chlorophyll-a (chl-a), and up to 350 mg m^{-3} (Gitelson et al., 1993) or higher, especially under “algal scum” conditions (Quibell, 1992)), mineral particles, detritus and CDOM that typically do not co-vary over space and time. Moreover, their optical properties are highly variable between and even within water bodies. These issues have complicated the development of algorithms for inland waters and typically limit their applicability between different sites. The continentality of the atmosphere over inland waters and their proximity to the land surface also introduces additional difficulties for atmospheric and adjacency correction procedures and this further impacts the performance of in-water algorithms.

Marine remote sensing research has benefitted from significant investment from space agencies and international funding organizations (e.g., the European Commission (EC)). This funding has supported large, multinational projects on the development and validation of satellite ocean colour products. In contrast, inland water remote sensing has historically been considered mainly a local, national or perhaps regional concern and as such has often fallen between the gaps between funding agencies. The inland water community is smaller in number, more fragmented and less well funded than the ocean colour community, particularly when one considers the number and complexity of the challenges currently faced. Most inland water remote sensing groups are comprised of a small number of scientists and students and historically there has been a lack of coordination and collaboration among these groups at the national or international level. In marine remote sensing, organisations such as the International Ocean Colour Coordinating Group (IOCCG) fulfill a strategic role in establishing research agendas and coordinating community-wide activities, but until recently the inland water community has had limited representation within such organisations.

The fragmented nature of the inland waters remote sensing community and funding has consequently impeded the exchange of skills and expertise across the community and made it more challenging to facilitate shared use *in situ* data and other resources necessary to address some of the key challenges and push the science forwards. The development and validation of atmospheric and in-water models for optically-complex waters can only be properly advanced through rigorous testing and refinement of candidate algorithms across the full spectrum of optical water types. However, many groups currently only have access to *in situ* data from a limited range of optical water types, and thus validation studies are often biased towards certain water types. More comprehensive validation studies can only realistically be achieved through close collaboration and the open exchange of data between international research groups. This argument can be extended to include access to infrastructure, such as fixed moorings for *in situ* radiometers (e.g., the AERONET-ocean color (-OC) stations) to support the vicarious calibration and atmospheric correction of satellite data. Currently, there is only a single AERONET-OC station in an inland water body (Lake Vanern, Sweden), an obvious constraint for atmospheric correction studies more broadly.

Downing (2014) highlights the isolationism that has existed between limnologists and oceanographers. This extends to the Earth observation community (Bukata, 2013) where historically there has been a notable lack of collaboration between ocean colour and inland water remote sensing scientists. This is, at least in part, a consequence of the nature of research funding, but has limited the exchange of skills and expertise between the two communities. In the last decade or so, some ocean colour scientists have extended their interests from the oceans through the coastal zone to the more optically-complex waters found inland, and in doing so have discovered some methods relatively new to ocean remote sensing which were actually used in inland water remote sensing decades ago (detailed in Bukata, 2013). Unfortunately, a large amount of valuable inland water remote sensing research has also been rather overlooked because it was published in the pre-digital era, and many interesting studies were only published in the gray literature (conference proceedings, PhD theses, etc.) or in inaccessible journals.

More generally, the wider scientific community has been slow to fully recognise the importance of freshwater ecosystems to global-scale processes (e.g., biogeochemical cycling, climate change, maintenance of biodiversity) and the provision of ecosystem services upon which human society relies. Inland waters only comprise a tiny fraction of the Earth's surface water, but it is becoming increasingly clear that are of disproportionate importance to the global biosphere (Downing, 2014). However, our knowledge of the global status of lakes and their responses to environmental change remains poor and there is an urgent need to better constrain our understanding of the role of lakes in regional- and global-scale processes. The wider adoption of remote sensing observations alongside existing *in situ* approaches will be crucial to furthering our understanding of the global status and role of inland waters.

1.2 Progress to date

Several recent works have reviewed water constituent retrieval algorithms applied to inland waters using various sensors (Odermatt et al., 2012; Matthews, 2011; Kutser, 2009), an ongoing and major challenge in such optically-complex systems. In this introductory paper, our aim was not to provide an exhaustive review of issues and previous work, but to highlight just a few examples from the past to show the particular challenge that inland water remote sensing scientists face and how these challenges have been and are currently being tackled.

In spite of their somewhat limited capabilities, satellite sensors have been used extensively in lake remote sensing for several decades now. Many studies have and continue to exploit the relatively high spatial resolution of sensors intended primarily for land applications. Verdin (1985), for example, used Landsat to retrieve chl-a and Secchi depth in US lakes. Dekker and Peters (1993) assessed Landsat TM capabilities in retrieving various Dutch lake water characteristics (seston dry weight, sum of chl-a and phaeopigments and Secchi depth), although accuracy of the results was found to be limited. Dekker et al. (2001, 2002) obtained reliable total suspended matter (TSM; dry seston weight) retrievals from Landsat and from the Satellite Pour l'Observation de la Terre (SPOT) sensor of the French Centre national d'études spatiales (CNES). Olmanson et al. (2008) used the Landsat archive for mapping lake water clarity over 10,000 Minnesota lakes. Tebbs et al., (2013) mapped high-biomass cyanobacteria blooms in Lake Bogoria using Landsat-derived chl-a. Moreover, the long-term data archive from the Landsat satellite series provide an opportunity to study long-term changes taking place in lakes. Kutser (2012), for example, evaluated suitability of Landsat archive for mapping CDOM changes in Swedish lakes over the last thirty years. The later launch of sensors with improved radiometric and/or spectral capabilities led to improvements in our ability to retrieve information on in-water constituents. For example, the NASA Advanced Land Imager (ALI) onboard the

Earth Observing-1 Mission (EO-1) was used to estimate CDOM absorption in boreal lakes (Kutser et al., 2005), while the first civilian hyperspectral sensor in space, Hyperion, also onboard EO-1, was used to retrieve chl-a and tripton (Giardino et al., 2007a).

Similarly, many remote sensing investigations of lakes make use of sensors intended for ocean colour applications. Early examples include Bukata et al. (1981) who used NASA Costal Zone Color Scanner (CZCS) imagery and model simulations to show that green-to-red rather than blue-to-green ratios were necessary for the retrieval of chl-a in optically complex waters, particularly those with high phytoplankton biomass. Mortimer (1988) used CZCS thermal data to identify bar fronts and upwelling zones. Binding et al. (2007) merge CZCS and NASA Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) data to obtain long time series of water clarity (Secchi depth) for the lower Laurentian Great Lakes. SeaWiFS data have also been used chl-a retrieval for lakes (e.g., Witter et al., 2009; Heim et al., 2005), as well as chl-a, dissolved organic carbon (DOC) and suspended matter retrieval (e.g., Pozdnyakov et al. 2005; Korosov et al. 2007) for further use in spatiotemporal analysis (e.g., Pozdnyakov et al. 2013; Shuchman et al. 2006) in very large lakes (e.g., Balikal, Lagoda). NASA Moderate-Resolution Imaging Spectroradiometer (MODIS) has been used over a number of lakes, particularly for the retrieval of chl-a (e.g., Wang et al., 2011, 2008; Bergamino et al., 2010; Chavula et al., 2009; de Moraes Novo et al., 2006), TSM, turbidity and Secchi depth (e.g., Kaba et al., 2014; Knight and Voth, 2012; Zhang et al., 2010; Tarrant et al., 2010; Chang et al., 2009) and surface water temperature (e.g., Bresciani et al., 2011; Crossman and Horel, 2009; Reinart and Reinhold, 2008). These examples are by no means exhaustive, but do demonstrate the insight that has been possible to be gained through the use ocean colour data despite their relatively coarse spatial resolutions and their limited spectral coverage.

The MEdium Resolution Imaging Spectrometer (MERIS) aboard the European Space Agency (ESA) Envisat platform was also primarily intended for oceanic observation, but presented improved spatial resolution compared with previous ocean colour sensors, as well as a few extra spectral bands at key wavelengths. Both of these new capabilities were useful in the retrieval of concentrations of optically active substances in lakes (Koponen et al., 2008), in identifying and the quantitative remote sensing of cyanobacterial blooms (Matthews et al., 2012) as well as in developing bloom monitoring systems (Wynne et al., 2013). Several studies presented in this special issue (Lunetta et al., this issue, Kallio et al., this issue, Kutser et al., this issue, Palmer et al., this issue, Sterckx et al., this issue) make use of MERIS imagery in lake research. Although no longer actively being acquired, MERIS data remain highly valuable in terms of its still under-exploited archive dataset and planned continuity through future missions (i.e., Sentinel-3 Ocean and Land Colour Imager (OLCI) of ESA).

It should also be noted that many advances in inland water remote sensing have been achieved through the use of hyperspectral data from airborne or hand held sensors. Vertucci and Likens (1989) proposed a lake classification scheme based on water reflectance spectra and also developed an algorithm for DOC retrieval. The peak near 700 nm, now recognized as vital to the relative success of MERIS chl-a retrievals compared with the preceding land and ocean color sensors described above, was utilised in hyperspectral chl-a retrieval more than three decades ago (Vasilkov & Kopelevich, 1982; Gitelson, 1992). The first attempts to retrieve accessory pigments (and consequently dominant phytoplankton groups) from airborne data were also undertaken in a lake environment (Richardson et al. 1994). This study used derivative analysis, which was a novel approach for inland water remote sensing. More recent studies have used hyperspectral data to focus on phycocyanin retrieval for the identification and quantification of cyanobacteria blooms in lakes (e.g., Li et al., 2012; Hunter et al., 2008, 2010a; Mishra et al., 2009; Randolph et al., 2008; Yang and Pan, 2006; and Simis et al., 2005 among others).

Band ratio type algorithms for estimating various lake water characteristics ranging from chl-a, CDOM, and suspended matter to water turbidity/transparency have been developed by many authors (e.g., Bukata et al., 1981, Dekker et al., 1991, Gitelson et al., 1993, Kutser et al., 1995, Kallio et al., 2001, Kutser et al., 2005; Koponen et al., 2007 to name only a few; see also references in the reviews by Matthews, 2011 and Odermatt et al., 2012) using multispectral satellite as well as hyperspectral data. Remote sensing has been used in mapping shallow water benthic habitat in inland waters (Giardino, et al., 2007b; Hunter et al., 2010b; Shuchman et al., 2013a), and to estimate lake primary production using satellite observations (Bergamino et al., 2010; Shuchman et at., 2013b). However, while primary production models have been used relatively widely in ocean waters, and have more recently been adapted for some optically-complex coastal waters, very few studies have attempted to adapt and validate these models for lakes or other inland waters.

More sophisticated neural network and physics-based inversion methods have also been used to estimate in-water Inherent Optical Properties (IOPs) (Odermatt et al., 2012). For example Hoogenboom et al. (1998) used matrix inversion for retrieving chl-a and suspended matter. Arst and Kutser (1994) used a modelling approach (described further in Kutser et al. (2001)) where chl-a, CDOM and suspended matter concentrations were estimated based on modelled spectra. Full measured hyperspectral lake reflectance spectra were compared with reflectance spectra generated through bio-optical modelling and it was assumed that the concentrations used in the model simulation correspond to real concentrations if the modelled spectrum matched with the measured one. Later, this approach was developed into the spectral library or look-up-table approach (Yang et al., 2011), as for large images it is computationally more efficient to model reflectance spectra in advance rather than run the model when interpreting remote sensing spectrum from each pixel. Giardino et al. (2012) developed a software package incorporating their Bio-Optical Model Based tool for Estimating water quality and bottom properties from Remote sensing images (BOMBER), originally intended to retrieve optical and benthic properties for lakes but also applicable in other optically-complex contexts (estuaries, coastal zones, etc.). Brando et al. (2012) present an adaptive implementation of the linear matrix inversion (LMI) method which accounts for variability in both IOPs and mass-specific IOPs (SIOPs) over space and time in wide-ranging optically-complex waters. Several neural network inversion approaches have also been designed specifically for lake settings (the Lakes processor (Doerffer and Schiller, 2008) within the Basic ERS & Envisat (A) ATSR and Meris Toolbox (BEAM) (Fomferra and Brockmann, 2005)) or have been demonstrated to be transferable to some lakes from coastal zone settings (the Case 2 Regional (C2R; Doerffer and Schiller, 2007) and FUB Water processor (Schroeder et al., 2007), also BEAM plug-ins). SIOP coefficient tuning or approximation is then required to relate retrieved IOPs to the concentrations of water constituents such as chl-a and TSM.

The application of remote sensing techniques to the quantification and monitoring of a range of parameters and processes, crucial to the quality and functioning of inland waters, continues to be at the centre of an active and growing community of practice. The occurrence of a large number of meetings, workshops and collaborative, international projects in recent years has inspired the current special issue, "Remote Sensing of Inland Waters", which intended to harness this momentum and highlight some of the current state-of-the-art and future priority directions of the community. This special issue updates and extends related, previous collections of works. Zilioli

(2001) and the numerous contributions of the *Science of the Total Environment* special issue entitled “Lake water monitoring in Europe” highlighted advancements linking remote sensing technologies and approaches with limnology in the European context at that time, and culminated in an invitation to the research and lake management communities to continue furthering such applications, including within other geographic settings. The previous *Remote Sensing of Environment* special issue on “Monitoring freshwater, estuarine and near-shore benthic ecosystems with multi-sensor remote sensing” (Goetz et al., 2008) included several contributions focused on inland freshwater systems (Gons et al., 2008; Olmanson et al., 2008; Ruiz-Verdú et al., 2008) in addition to applications to coastal, intertidal and estuarine zones. The recent “Remote Sensing” special issue of the *Journal of Great Lakes Research* (Shuchman and Leshkevich, 2013) highlighted research on the Great Lakes and large water bodies globally, including the use of both passive (optical) and active (radar, light detection and ranging (LiDAR) and acoustic) data, with applications ranging from coastal/shore zone characterization, in-water constituent retrieval and fundamental optics, ice classification, underwater gliders and aquatic vegetation.

This special issue focuses specifically on inland waters, considered here to include lakes, reservoirs and rivers. The papers cover a range of topics including: (1) validations of the retrieval of physical and biogeochemical parameters in inland waters; (2) the spatial and temporal analysis of these parameters; (3) methodological developments; and (4) applications of remote sensing of inland waters in management and scientific contexts. Contributions bridging multiple themes and their examination at local, regional or global scales and across diverse geographical settings were encouraged.

2. Contributions of the special issue

The contributions to this special issue cover a diverse range, in terms of geographic coverage, spanning inland waters from Africa, Europe, Asia, and North and South America, as well as optical characteristics, size, geomorphology and type, including predominantly lakes but also reservoirs (Curtarelli et al., this issue) and river systems (Brezonik et al., this issue; Lobo et al., this issue). Studies further ranged from local (e.g., Curtarelli et al., this issue; Giardino et al., this issue; Stratoulias et al., this issue) to regional (e.g., Brezonik et al., this issue; Brooks et al., this issue; Lunetta et al., this issue; Kallio et al., this issue) in scale, as well as the comparison of geographically disparate ecosystems (Oyama et al., this issue). Although radar, acoustic and LiDAR are known to be capable of providing information on inland waters (notably pertaining to ice cover (e.g., Leshkevich & Nghiem, 2013), bathymetry (e.g., Meadows, 2013) and water quantity, as well as fluorescence LiDAR water quality measurements (e.g., Palmer et al., 2013)), the contributions to this special issue made exclusive use of passive optical data of varying spectral resolutions, from both satellite and airborne sensors in combination with *in situ* measurements. Diverse biophysical and water quality parameters were targeted, as was the response of study sites to a number of environmental pressures.

Cyanobacteria detection and biomass quantification has been confirmed as a priority through several contributions on this topic, using both phycoyanin (Li et al., this issue) and cell counts (Lunetta et al., this issue), which are more consistently available from some conventional monitoring programs, as proxies. Oyama et al. (this issue) made use of a sequence of spectral indices applied to Landsat TM and ETM + data to distinguish dense cyanobacteria blooms from aquatic vegetation, which is often a challenge due to their similar signatures in the red and near-infrared (NIR) ranges. Li et al. (this issue) present a new approach to partition light absorption and thereby estimate phycocyanin. A substantial improvement over previous methods to retrieve low concentrations in particular was demonstrated, with implications for the sensitivity of bloom onset detection. The validation of an existing MERIS cyanobacteria product by Lunetta et al. (this issue) made use of an extensive (n > 2000) *in situ* dataset from across eight states of the US, and confirmed its potential to complement and inform operational monitoring activities.

Another recurring theme within the special issue is the mapping of shoreline and aquatic vegetation in addition to further benthic substrate classes. Giardino et al. (this issue) made use of airborne hyperspectral data to quantify and map suspended particulate matter, submerged aquatic vegetation (SAV) and benthic substrate in the shallow, turbid Lake Trasimeno, Italy. Mapping was further used to assess the role of SAV colonisation in maintaining the local transparency of the water, and vice versa. Brooks et al. (this issue) also consider SAV colonisation and spatial patterns, particularly the nuisance *Cladophora*, throughout the Laurentian Great Lakes. A forty-year Landsat image time-series was used for current and historic mapping, and revealed that both SAV coverage and water clarity are increasing and may be related to the presence of the invasive dreissenid (zebra and quagga) mussels. Stratoulias et al. (this issue) focus on the shoreline ecotone of Lake Balaton, Hungary, and the reed species, *Phragmites australis*. A phenomenon known as "reed die-back" has threatened *P. australis* populations throughout Europe, and *in situ* measurements coupled with airborne hyperspectral imagery are shown to identify biophysical signals that distinguish affected from unaffected stands.

Methodological advances with respect to the correction of the adjacency or environmental effect were proposed and validated (Kiselev et al., this issue; Sterck et al., this issue). Both approaches present a sensor-independent solution, acknowledging the growing number of archive, current and future sensors appropriate for the remote sensing of water bodies, and the importance of methodological transfer between images from different sensors. Kiselev et al. (this issue) combine an analytical solution to the point-spread function with radiative transfer modelling of a stratified atmosphere to estimate and remove the adjacency effect, whereas the Sterckx et al. (this issue) correction ("SIMilarity Environment Correction (SIMEC)") makes use of the correspondence with the near-infrared similarity spectrum.

Salama et al. (this issue) present a new, forward model analytical inversion solution ("2SeaColor") for the retrieval of the depth profile of the downwelling diffuse attenuation coefficient. Important for inland waters, such as Lake Naivasha, Kenya to which its application is demonstrated, is the suitability of the model within highly turbid waters. Also challenging within highly turbid waters is the reliable *in situ* measurement of water column IOPs, such as attenuation, absorption and backscattering, for use in the development and validation of retrieval algorithms applied to satellite or airborne imagery. Sander de Carvalho et al. (this issue) assess different correction methods applied to such *in situ* IOP measurements from highly turbid Amazon floodplain lakes, their influence on remote sensing reflectance closure, and implications thereof.

Several MERIS standard and "Case 2" suitable products were evaluated in special issue contributions. Kutser et al. (this issue) found that although the standard CDOM product was not suitable for accurate CDOM retrievals in his studied boreal-type lakes in Sweden, a number of other MERIS products were able to estimate and map different carbon fractions and should be further investigated. Notably, correlation was found between MERIS-retrieved absorption and CDOM, dissolved- and total- organic carbon. Kallio et al. (this issue) performed a validation of MERIS spectral inversion processor-retrieved water constituent and optical property retrievals for four Finnish lakes. Different processing levels of the Boreal Lake processor and local tuning of specific IOP coefficients relating retrieved absorption and backscattering to chl-a concentration, CDOM absorbance and total suspended matter concentration were further assessed. Palmer et al. (this issue) also present the performance of several MERIS spectral inversion and band difference processors, in retrieving Lake Balaton, Hungary chl-a concentrations. Extensive *in situ* data from conventional phytoplankton monitoring are used to separately calibrate and validate retrievals across a five year time series including all seasons. Highly variable results from the different algorithms and the robust time-series application of the fluorescence line height algorithm are demonstrated.

In addition to time-series analyses by Brooks et al. (this issue) and Palmer et al. (this issue) previously described, Lobo et al. (this issue) make use of a 40-year Landsat time series to assess the impacts of hydrological stage and gold mining activity on suspended particulate matter concentrations within the Tapajós River, Brazil and its tributaries. Challenges presented by time-series analysis, notably comparability between images of different sensors and atmospheric correction reliability were also explicitly addressed by Lobo et al. (this issue). The integration of hydrodynamic modelling with remotely sensed surface temperature, rainfall and phytoplankton biomass (chl-a concentration) products was carried out under distinct seasonal conditions by Curtarelli et al. (this issue). The possibility to evaluate three-dimensional processes and conditions, such as stratification and mixing, across the full lake area was demonstrated. Finally, Brezonik et al. (this issue) make use of several long term historic and current datasets from across the US to provide an in depth analysis of factors that influence the remote sensing of CDOM, which is highly variable and challenging to retrieve from inland waters, notably its spatial and temporal variability. Several CDOM retrieval algorithms are validated and compared in application to simulated Landsat 8 Operational Land Imager (OLI), Sentinel-2 MultiSpectral Imager (MSI) and Sentinel-3 OLCI spectral bands.

3. Outlook

The inland water remote sensing community has made significant progress since the first attempts were made to retrieve basic water quality information from the early Landsat satellites. In the decades since the launch of NASA's Earth Resources Technology Satellite (ERTS-1; later to become Landsat-1) our understanding of the radiative transfer process in optically-complex waters has developed immeasurably. In parallel, the models used to retrieve physical and biogeochemical parameters have increased in sophistication from simple empirical approaches to the more analytically-based inversion models now gaining in popularity. Similarly, there has been progress in the development of methods for the correction of atmospheric and adjacency effects over turbid waters. Collectively, these advancements have led to marked improvements in the accuracy, applicability and robustness of remote sensing products for inland waters.

However, it is important that we recognise that some significant scientific challenges remain and that much work will be needed before Earth Observation (EO) products will be widely used in an operational context for monitoring inland waters. Improvements are still needed in the methods for the correction of atmosphere and land adjacency effects over inland waters, particularly in the presence of complex aerosols. The approaches presented in this issue (e.g., Kiselev et al., this issue; Sterckx et al., this issue) show considerable promise, but wider testing and validation of these approaches is needed. Similarly, numerous algorithms for the retrieval of biogeochemical parameters have been developed for inland waters but work is needed to establish the limits of their applicability and associated uncertainties for the full range of water optical types. These endeavours must also be supported by a more comprehensive understanding of the sources and magnitude of variability in the SIOPs of water constituents as our current knowledge of SIOPs variability in inland waters, and the errors associated with IOP measurements in highly turbid waters, is very limited. More widely, further work will also be needed to progress methods for data assimilation within ecological and hydrodynamic models. The integration and use of EO data within existing monitoring and regulatory frameworks also has yet to be tackled.

If the recent progress we have made towards the development of operational EO services for inland waters is to be sustained, the community will need better mechanisms to foster and coordinate research and collaboration across research groups, institutions and nations. The challenges outlined above cannot be tackled adequately by small research groups working in isolation; it requires strategic planning and coordination and a research environment where international facilities, resources, data and expertise can be more easily pooled and shared. Encouragingly, some progress is already being made here. The Group on Earth Observations (GEO) is coordinating efforts to the establishment of the Global Earth Observation System of Systems (GEOSS), which includes "Water" as one of the key societal benefits. The GEO have established a Water Quality Working Group (http://www.geo-water-quality.org) to help coordinate input to GEOSS from the inland water remote sensing community. The International Ocean Colour Group has also recently convened a working group on "Earth Observations in Support of Global Water Quality Monitoring" to provide strategic direction towards the implementation of a global water quality monitoring service. Further, the LIMNADES (Lake Bio-optical Measurements and Matchup Data for Remote Sensing; http://www.globolakes.ac.uk/limnades/) database has recently been established to help facilitate community-wide algorithm development and validation studies in a similar role to that fulfilled by the MERMAID and NOMAD databases in ocean colour remote sensing.

It is also immensely encouraging that in the last few years, several large projects on the remote sensing of inland waters have been funded (particularly within the European Union). These include (but are not limited to): the ESA Diversity II project (http://www.diversity2.info); EC FP7 Global Lake Sentinel Services (GLaSS) project (http://www.glass-project.eu); EC FP7 INFORM project (http://www.copernicus-inform.eu); EC FP7 eartH_2Observe project (http://www.earth2observe.eu), the Color of Water (CoW) project (http://www.met.uu.se/cow/) supported by the Swedish Reaserch Council for Environmental, Agricultural and Spatial planning and the UK Natural Environment Research Council GloboLakes project (http://globolakes.ac.uk). This level of investment in research and service development is long overdue, but hopefully reflects increasing recognition within national and international funding agencies that Earth observation can make a transformative contribution to global water resource management. It also suggests that the recent launch of Landsat-8 and, in particular, the forthcoming ESA Sentinel-2 and Sentinel-3 missions are providing a useful stimulus for EO-based research and service development for inland waters.

Indeed, importance of the forthcoming ESA Copernicus programme to the inland water community is highlighted in many of the contributions to this special issue (e.g. Brezonik et al., this issue; Giardino et al., this issue; Li et al., this issue; Lunetta et al., this issue; Kallio et al., this issue; Kutser et al., this issue; Palmer et al., this issue; Sterckx et al., this issue). This was also reflected by the strong representation of researchers from the community at the preparatory scientific meetings for both Sentinel-2 and Sentinel-3 missions. These new missions will not only fill a gap in data provision that has been present since ESA's Envisat mission ended, the move to free-to-access satellite data under the Sentinel programme will also result in a step-change in the use of satellite observations for monitoring inland water quality in the same way that opening access to the Landsat archive greatly increased the use of its data products for land monitoring (Wulder and Coops, 2014). It is equally important that the space agencies recognise the importance of these new missions to future inland water remote sensing research. To this end, the community needs to be actively engaged in the Cal/Val activities for the Sentinel and other future EO missions (e.g., NASA's PACE mission), certainly to a greater extent than it has been in the past.

The contributions to this special issue aptly document much of the progress that has been made by the inland water community over recent years. Many of the methods and applications showcased here show considerable promise and they will no doubt inspire and stimulate further excellent work in the field. Clearly, some substantial challenges remain and these will not be easily solved, but neither are they insurmountable. The prospect of operational, near-real time satellite monitoring of inland waters will become a reality if we can continue to build on the progress we have made in recent years.

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