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# 1 **Remote sensing of inland waters: challenges, progress and** 2 **future directions**

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## 11 12 **1. Introduction**

13 In addition to providing water resources for various human uses (Postel, 2000), inland waters  
14 provide important and diverse habitat and ecosystem services, supporting of high levels of  
15 biodiversity (Brönmark and Hansson, 2002; Duker and Bore, 2001). They are important  
16 components of global carbon and nutrient cycles (Tranvik et al. 2009; Bastviken et al., 2011).  
17 However, like many other ecosystems, lakes and rivers are threatened by the synergistic effects  
18 of multiple, co-occurring environmental pressures, notably nutrient enrichment and other organic  
19 and inorganic pollution, climate change, acidification, the establishment and spread of invasive  
20 species, and the diversion or extraction of upstream source waters (Brönmark and Hansson,  
21 2002; Dudgeon et al., 2006). Their importance, as well as their sensitivity to and capacity to  
22 reflect climate, land use and other environmental change, has garnered inland waters increasing  
23 attention over recent years. The assessment and monitoring of lakes and rivers is crucial to our  
24 ability to understand and disentangle the effects of environmental change on freshwater  
25 ecosystems and to model future change. There is also an increasing regulatory need to increase

26 the coverage and frequency of freshwater monitoring, arising from legislation such as the  
27 European Union's Water Framework Directive for example. There are, however, upwards of 117  
28 million lakes on Earth (Verpoorter et al., 2014) and only a very small proportion of these are  
29 regularly and consistently monitored. Conventional, *in situ* monitoring is limited in terms of  
30 spatial coverage and representativeness, as well as in terms of frequency for many sites, and is  
31 simply non-existent in a great many others.

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

## 42 **1.1 Challenges: past and present**

43 The ocean colour sensors that have supported much of the research and service development in  
44 marine remote sensing have or had coarse spatial resolutions that makes them unsuitable for  
45 remote sensing applications over most rivers, lakes and reservoirs. This has meant that the  
46 inland water community has often had to make use of data from satellite sensors with higher  
47 spatial resolutions designed primarily for land applications, such as the National Aeronautics and  
48 Space Administration (NASA) Landsat series. However, while these sensors have adequate

49 spatial resolutions for many lakes, their spectral coverage and resolution, as well as their  
50 radiometric sensitivity, is not optimal for many applications over inland waters (e.g.,  
51 phytoplankton pigment or colored dissolved organic matter (CDOM) retrieval).

52 The optical complexity of inland waters, atmospheric correction issues, adjacency effects and  
53 some other unresolved problems add great additional challenges to inland water remote sensing  
54 in comparison with ocean colour remote sensing. The optical complexity of inland waters stems  
55 from the fact that these waters are typically characterised by high concentrations of  
56 phytoplankton biomass (typically on the order of between 1 and 100 mg m<sup>-3</sup> chlorophyll-a (chl-a),  
57 and up to 350 mg m<sup>-3</sup> (Gitelson et al., 1993) or higher, especially under “algal scum” conditions  
58 (Quibell, 1992)), mineral particles, detritus and CDOM that typically do not co-vary over space  
59 and time. Moreover, their optical properties are highly variable between and even within water  
60 bodies. These issues have complicated the development of algorithms for inland waters and  
61 typically limit their applicability between different sites. The continentality of the atmosphere  
62 over inland waters and their proximity to the land surface also introduces additional difficulties  
63 for atmospheric and adjacency correction procedures and this further impacts the performance of  
64 in-water algorithms.

65 Marine remote sensing research has benefitted from significant investment from space agencies  
66 and international funding organizations (e.g., the European Commission (EC)). This funding has  
67 supported large, multinational projects on the development and validation of satellite ocean  
68 colour products. In contrast, inland water remote sensing has historically been considered  
69 mainly a local, national or perhaps regional concern and as such has often fallen between the  
70 gaps between funding agencies. The inland water community is smaller in number, more  
71 fragmented and less well funded than the ocean colour community, particularly when one

72 considers the number and complexity of the challenges currently faced. Most inland water  
73 remote sensing groups are comprised of a small number of scientists and students and  
74 historically there has been a lack of coordination and collaboration among these groups at the  
75 national or international level. In marine remote sensing, organisations such as the International  
76 Ocean Colour Coordinating Group (IOCCG) fulfill a strategic role in establishing research  
77 agendas and coordinating community-wide activities, but until recently the inland water  
78 community has had limited representation within such organisations.

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

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

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

## 116 **1.2 Progress to date**

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

123 In spite of their somewhat limited capabilities, satellite sensors have been used extensively in  
124 lake remote sensing for several decades now. Many studies have and continue to exploit the  
125 relatively high spatial resolution of sensors intended primarily for land applications. Verdin  
126 (1985), for example, used Landsat to retrieve chl-a and Secchi depth in US lakes. Dekker and  
127 Peters (1993) assessed Landsat TM capabilities in retrieving various Dutch lake water  
128 characteristics (seston dry weight, sum of chl-a and phaeopigments and Secchi depth), although  
129 accuracy of the results was found to be limited. Dekker et al. (2001, 2002) obtained reliable total  
130 suspended matter (TSM; dry seston weight) retrievals from Landsat and from the Satellite Pour  
131 l'Observation de la Terre (SPOT) sensor of the French Centre national d'études spatiales  
132 (CNES). Olmanson et al. (2008) used the Landsat archive for mapping lake water clarity over  
133 10,000 Minnesota lakes. Tebbs et al., (2013) mapped high-biomass cyanobacteria blooms in  
134 Lake Bogoria using Landsat-derived chl-a. Moreover, the long-term data archive from the  
135 Landsat satellite series provide an opportunity to study long-term changes taking place in lakes.  
136 Kutser (2012), for example, evaluated suitability of Landsat archive for mapping CDOM  
137 changes in Swedish lakes over the last thirty years. The later launch of sensors with improved  
138 radiometric and/or spectral capabilities led to improvements in our ability to retrieve information  
139 on in-water constituents. For example, the NASA Advanced Land Imager (ALI) onboard the

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

143 Similarly, many remote sensing investigations of lakes make use of sensors intended for ocean  
144 colour applications. Early examples include Bukata et al. (1981) who used NASA Coastal Zone  
145 Color Scanner (CZCS) imagery and model simulations to show that green-to-red rather than  
146 blue-to-green ratios were necessary for the retrieval of chl-a in optically complex waters,  
147 particularly those with high phytoplankton biomass. Mortimer (1988) used CZCS thermal data to  
148 identify bar fronts and upwelling zones. Binding et al. (2007) merge CZCS and NASA Sea-  
149 Viewing Wide Field-of-View Sensor (SeaWiFS) data to obtain long time series of water clarity  
150 (Secchi depth) for the lower Laurentian Great Lakes. SeaWiFS data have also been used chl-a  
151 retrieval for lakes (e.g., Witter et al., 2009; Heim et al., 2005), as well as chl-a, dissolved organic  
152 carbon (DOC) and suspended matter retrieval (e.g., Pozdnyakov et al. 2005; Korosov et al. 2007)  
153 for further use in spatiotemporal analysis (e.g., Pozdnyakov et al. 2013; Shuchman et al. 2006) in  
154 very large lakes (e.g., Balikal, Lagoda). NASA Moderate-Resolution Imaging Spectroradiometer  
155 (MODIS) has been used over a number of lakes, particularly for the retrieval of chl-a (e.g., Wang  
156 et al., 2011, 2008; Bergamino et al., 2010; Chavula et al., 2009; de Moraes Novo et al., 2006),  
157 TSM, turbidity and Secchi depth (e.g., Kaba et al., 2014; Knight and Voth, 2012; Zhang et al.,  
158 2010; Tarrant et al., 2010; Chang et al., 2009) and surface water temperature (e.g., Bresciani et  
159 al., 2011; Crossman and Horel, 2009; Reinart and Reinhold, 2008). These examples are by no  
160 means exhaustive, but do demonstrate the insight that has been possible to be gained through the  
161 use ocean colour data despite their relatively coarse spatial resolutions and their limited spectral  
162 coverage.



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

175 It should also be noted that many advances in inland water remote sensing have been achieved  
176 through the use of hyperspectral data from airborne or hand held sensors. Vertucci and Likens  
177 (1989) proposed a lake classification scheme based on water reflectance spectra and also  
178 developed an algorithm for DOC retrieval. The peak near 700 nm, now recognized as vital to the  
179 relative success of MERIS chl-a retrievals compared with the preceding land and ocean color  
180 sensors described above, was utilised in hyperspectral chl-a retrieval more than three decades  
181 ago (Vasilkov & Kopelevich, 1982; Gitelson, 1992). The first attempts to retrieve accessory  
182 pigments (and consequently dominant phytoplankton groups) from airborne data were also  
183 undertaken in a lake environment (Richardson et al. 1994). This study used derivative analysis,  
184 which was a novel approach for inland water remote sensing. More recent studies have used  
185 hyperspectral data to focus on phycocyanin retrieval for the identification and quantification of

186 cyanobacteria blooms in lakes (e.g., Li et al., 2012; Hunter et al., 2008, 2010a; Mishra et al.,  
187 2009; Randolph et al., 2008; Yang and Pan, 2006; and Simis et al., 2005 among others).

188 Band ratio type algorithms for estimating various lake water characteristics ranging from chl-a,  
189 CDOM, and suspended matter to water turbidity/transparency have been developed by many  
190 authors (e.g., Bukata et al., 1981, Dekker et al., 1991, Gitelson et al., 1993, Kutser et al., 1995,  
191 Kallio et al., 2001, Kutser et al., 2005; Koponen et al., 2007 to name only a few; see also  
192 references in the reviews by Matthews, 2011 and Odermatt et al., 2012) using multispectral  
193 satellite as well as hyperspectral data. Remote sensing has been used in mapping shallow water  
194 benthic habitat in inland waters (Giardino, et al., 2007b; Hunter et al., 2010b; Shuchman et al.,  
195 2013a), and to estimate lake primary production using satellite observations (Bergamino et al.,  
196 2010; Shuchman et at., 2013b). However, while primary production models have been used  
197 relatively widely in ocean waters, and have more recently been adapted for some optically-  
198 complex coastal waters, very few studies have attempted to adapt and validate these models for  
199 lakes or other inland waters.

200 More sophisticated neural network and physics-based inversion methods have also been used to  
201 estimate in-water Inherent Optical Properties (IOPs) (Odermatt et al., 2012). For example  
202 Hoogenboom et al. (1998) used matrix inversion for retrieving chl-a and suspended matter. Arst  
203 and Kutser (1994) used a modelling approach (described further in Kutser et al. (2001)) where  
204 chl-a, CDOM and suspended matter concentrations were estimated based on modelled spectra.  
205 Full measured hyperspectral lake reflectance spectra were compared with reflectance spectra  
206 generated through bio-optical modelling and it was assumed that the concentrations used in the  
207 model simulation correspond to real concentrations if the modelled spectrum matched with the  
208 measured one. Later, this approach was developed into the spectral library or look-up-table

209 approach (Yang et al., 2011), as for large images it is computationally more efficient to model  
210 reflectance spectra in advance rather than run the model when interpreting remote sensing  
211 spectrum from each pixel. Giardino et al. (2012) developed a software package incorporating  
212 their Bio-Optical Model Based tool for Estimating water quality and bottom properties from  
213 Remote sensing images (BOMBER), originally intended to retrieve optical and benthic  
214 properties for lakes but also applicable in other optically-complex contexts (estuaries, coastal  
215 zones, etc.). Brando et al. (2012) present an adaptive implementation of the linear matrix  
216 inversion (LMI) method which accounts for variability in both IOPs and mass-specific IOPs  
217 (SIOPs) over space and time in wide-ranging optically-complex waters. Several neural network  
218 inversion approaches have also been designed specifically for lake settings (the Lakes processor  
219 (Doerffer and Schiller, 2008) within the Basic ERS & Envisat (A) ATSR and Meris Toolbox  
220 (BEAM) (Fomferra and Brockmann, 2005)) or have been demonstrated to be transferable to  
221 some lakes from coastal zone settings (the Case 2 Regional (C2R; Doerffer and Schiller, 2007)  
222 and FUB Water processor (Schroeder et al., 2007), also BEAM plug-ins). SIOP coefficient  
223 tuning or approximation is then required to relate retrieved IOPs to the concentrations of water  
224 constituents such as chl-a and TSM.

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

232 (2001) and the numerous contributions of the *Science of the Total Environment* special issue  
233 entitled “Lake water monitoring in Europe” highlighted advancements linking remote sensing  
234 technologies and approaches with limnology in the European context at that time, and  
235 culminated in an invitation to the research and lake management communities to continue  
236 furthering such applications, including within other geographic settings. The previous *Remote*  
237 *Sensing of Environment* special issue on “Monitoring freshwater, estuarine and near-shore  
238 benthic ecosystems with multi-sensor remote sensing” (Goetz et al., 2008) included several  
239 contributions focused on inland freshwater systems (Gons et al., 2008; Olmanson et al., 2008;  
240 Ruiz-Verdú et al., 2008) in addition to applications to coastal, intertidal and estuarine zones. The  
241 recent “Remote Sensing” special issue of the *Journal of Great Lakes Research* (Shuchman and  
242 Leshkevich, 2013) highlighted research on the Great Lakes and large water bodies globally,  
243 including the use of both passive (optical) and active (radar, light detection and ranging (LiDAR)  
244 and acoustic) data, with applications ranging from coastal/shore zone characterization, in-water  
245 constituent retrieval and fundamental optics, ice classification, underwater gliders and aquatic  
246 vegetation.

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

254

## 255 **2. Contributions of the special issue**

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

271 Cyanobacteria detection and biomass quantification has been confirmed as a priority through  
272 several contributions on this topic, using both phycocyanin (Li et al., this issue) and cell counts  
273 (Lunetta et al., this issue), which are more consistently available from some conventional  
274 monitoring programs, as proxies. Oyama et al. (this issue) made use of a sequence of spectral  
275 indices applied to Landsat TM and ETM + data to distinguish dense cyanobacteria blooms from  
276 aquatic vegetation, which is often a challenge due to their similar signatures in the red and near-  
277 infrared (NIR) ranges. Li et al. (this issue) present a new approach to partition light absorption

278 and thereby estimate phycocyanin. A substantial improvement over previous methods to retrieve  
279 low concentrations in particular was demonstrated, with implications for the sensitivity of bloom  
280 onset detection. The validation of an existing MERIS cyanobacteria product by Lunetta et al.  
281 (this issue) made use of an extensive ( $n > 2000$ ) *in situ* dataset from across eight states of the US,  
282 and confirmed its potential to complement and inform operational monitoring activities.

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

297 Methodological advances with respect to the correction of the adjacency or environmental effect  
298 were proposed and validated (Kiselev et al., this issue; Sterck et al., this issue). Both approaches  
299 present a sensor-independent solution, acknowledging the growing number of archive, current  
300 and future sensors appropriate for the remote sensing of water bodies, and the importance of

301 methodological transfer between images from different sensors. Kiselev et al. (this issue)  
302 combine an analytical solution to the point-spread function with radiative transfer modelling of a  
303 stratified atmosphere to estimate and remove the adjacency effect, whereas the Sterckx et al. (this  
304 issue) correction (“SIMilarity Environment Correction (SIMEC)”) makes use of the  
305 correspondence with the near-infrared similarity spectrum.

306 Salama et al. (this issue) present a new, forward model analytical inversion solution  
307 (“2SeaColor”) for the retrieval of the depth profile of the downwelling diffuse attenuation  
308 coefficient. Important for inland waters, such as Lake Naivasha, Kenya to which its application  
309 is demonstrated, is the suitability of the model within highly turbid waters. Also challenging  
310 within highly turbid waters is the reliable *in situ* measurement of water column IOPs, such as  
311 attenuation, absorption and backscattering, for use in the development and validation of retrieval  
312 algorithms applied to satellite or airborne imagery. Sander de Carvalho et al. (this issue) assess  
313 different correction methods applied to such *in situ* IOP measurements from highly turbid  
314 Amazon floodplain lakes, their influence on remote sensing reflectance closure, and implications  
315 thereof.

316 Several MERIS standard and “Case 2” suitable products were evaluated in special issue  
317 contributions. Kutser et al. (this issue) found that although the standard CDOM product was not  
318 suitable for accurate CDOM retrievals in his studied boreal-type lakes in Sweden, a number of  
319 other MERIS products were able to estimate and map different carbon fractions and should be  
320 further investigated. Notably, correlation was found between MERIS-retrieved absorption and  
321 CDOM, dissolved- and total- organic carbon. Kallio et al. (this issue) performed a validation of  
322 MERIS spectral inversion processor-retrieved water constituent and optical property retrievals  
323 for four Finnish lakes. Different processing levels of the Boreal Lake processor and local tuning

324 of specific IOP coefficients relating retrieved absorption and backscattering to chl-a  
325 concentration, CDOM absorbance and total suspended matter concentration were further  
326 assessed. Palmer et al. (this issue) also present the performance of several MERIS spectral  
327 inversion and band difference processors, in retrieving Lake Balaton, Hungary chl-a  
328 concentrations. Extensive *in situ* data from conventional phytoplankton monitoring are used to  
329 separately calibrate and validate retrievals across a five year time series including all seasons.  
330 Highly variable results from the different algorithms and the robust time-series application of the  
331 fluorescence line height algorithm are demonstrated.

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



346 in application to simulated Landsat 8 Operational Land Imager (OLI), Sentinel-2 MultiSpectral  
347 Imager (MSI) and Sentinel-3 OLCI spectral bands.

348

### 349 **3. Outlook**

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

360 However, it is important that we recognise that some significant scientific challenges remain and  
361 that much work will be needed before Earth Observation (EO) products will be widely used in an  
362 operational context for monitoring inland waters. Improvements are still needed in the methods  
363 for the correction of atmosphere and land adjacency effects over inland waters, particularly in the  
364 presence of complex aerosols. The approaches presented in this issue (e.g., Kiselev et al., this  
365 issue; Sterckx et al., this issue) show considerable promise, but wider testing and validation of  
366 these approaches is needed. Similarly, numerous algorithms for the retrieval of biogeochemical  
367 parameters have been developed for inland waters but work is needed to establish the limits of

368 their applicability and associated uncertainties for the full range of water optical types. These  
369 endeavours must also be supported by a more comprehensive understanding of the sources and  
370 magnitude of variability in the SIOPs of water constituents as our current knowledge of SIOPs  
371 variability in inland waters, and the errors associated with IOP measurements in highly turbid  
372 waters, is very limited. More widely, further work will also be needed to progress methods for  
373 data assimilation within ecological and hydrodynamic models. The integration and use of EO  
374 data within existing monitoring and regulatory frameworks also has yet to be tackled.

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

391 community-wide algorithm development and validation studies in a similar role to that fulfilled  
392 by the MERMAID and NOMAD databases in ocean colour remote sensing.

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

407 Indeed, importance of the forthcoming ESA Copernicus programme to the inland water  
408 community is highlighted in many of the contributions to this special issue (e.g. Brezonik et al.,  
409 this issue; Giardino et al., this issue; Li et al., this issue; Lunetta et al., this issue; Kallio et al.,  
410 this issue; Kutser et al., this issue; Palmer et al., this issue; Sterckx et al., this issue). This was  
411 also reflected by the strong representation of researchers from the community at the preparatory  
412 scientific meetings for both Sentinel-2 and Sentinel-3 missions. These new missions will not  
413 only fill a gap in data provision that has been present since ESA's Envisat mission ended, the

414 move to free-to-access satellite data under the Sentinel programme will also result in a step-  
415 change in the use of satellite observations for monitoring inland water quality in the same way  
416 that opening access to the Landsat archive greatly increased the use of its data products for land  
417 monitoring (Wulder and Coops, 2014). It is equally important that the space agencies recognise  
418 the importance of these new missions to future inland water remote sensing research. To this  
419 end, the community needs to be actively engaged in the Cal/Val activities for the Sentinel and  
420 other future EO missions (e.g., NASA's PACE mission), certainly to a greater extent than it has  
421 been in the past.

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

429

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442

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