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Higher-level biogeochemical products and gaps in current Copernicus water quality portfolio. Water-ForCE

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List of Acronyms

AFAI	Alternative Floating Algae Index
CASI	Compact Airborne Spectrographic Imager
CCI	Climate Change Initiative
CDM	Coloured Dissolved Matter
CDOM	Coloured Dissolved Organic Matter
CEOS	Committee on Earth Observation Satellites
CHIME	Copernicus Hyperspectral Imaging Mission for the Environment
CMEMS	Copernicus Marine Environment Monitoring Service
CyaBI	Cyanobacterial Index
CO_2	Carbon Dioxide
CSA	Cyanobacterial Surface Accumulations
DOC	Dissolved Organic Carbon
EnMAP	German hyperspectral satellite mission (The Environmental Mapping and Analysis Program)
EO	Earth Observation
ESA	European Space Agency
EU	European Union
fAPAR	Fraction of PAR Absorbed by the Vegetation
GPP	Gross Primary Productivity
GRD	Green-Red-Difference
HELCOM	Helsinki Commission
K_d	Diffuse Attenuation Coefficient
L1	Level 1 processing of satellite data
L2	Level 2 processing of satellite data
LAI	Leaf Area Index
LC-SPACE	Horizon 2020 Space call

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LUE	Light utilised by vegetation
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate-Resolution Imaging Spectroradiometer
MSI	Multispectral Imager
NDAVI	Normalised Difference Aquatic Vegetation Index
NIR	Near-Infrared
OC-CCI	Ocean Colour Climate Change Initiative
OLCI	Ocean and Land Colour Instrument
pCO2	Partial Pressure of Carbon Dioxide
PHA-RI	Red tide detection method based on pseudo hue angle
PAR	Photosynthetically Available Radiation
PP	Primary Production
PRISM	Portable Remote Imaging Spectrometer
PRISMA	PRecursore IperSpettrale della Missione Applicativa
SAV	Submerged Aquatic Vegetation
SAR	Synthetic Aperture Radar
SDG	Sustainable Development Goal
SeaWiFS	Sea-viewing Wide Field-of-view Sensor
SPM	Suspended Particulate Matter
SWIR	Short-Wavelength Infrared
TOC	Total Organic Carbon
TP	Total Phosphorus
TSM	Total Suspended Matter
UAS	Unmanned Aerial Systems
UNEP	United Nations Environment Programme
VIIRS	Visible Infrared Imaging Radiometer Suite
WFD	Water Framework Directive
WP	Working Package

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Executive Summary

This report analyses the feasibility of remotely sensed higher-level products proposed in Deliverable 4.5. However, the scope of this work is widened based on the outcomes of other tasks within the Water-ForCE, notably from WP1 where gaps in the current Copernicus water quality products portfolio were revealed based on an analysis of users and stakeholders needs. Further, Deliverable 2.2 identified several missing groups of products among the Copernicus products. In this Report we analyse which of the requested, but currently missing, products are feasible in the foreseeable future. Moreover, we discuss which of the products could be included in the Copernicus core services and which should be delivered by the private sector.

We show that there are multiple higher level biogeochemical products (primary production, total phosphorus, total nitrogen), different carbon fractions (dissolved organic carbon, pCO_2, coloured dissolved organic matter), shallow water products (bathymetry, benthic habitat, carbon fixed by benthic habitat, etc.) as well as floating matter (plastic and other litter, floating cyanobacteria, macroalgal (Sargassum, Ulva) mats, etc.) products that are requested by users are feasible to deliver within the Copernicus portfolio. The level of maturity of the products is variable. Several of them require validation over wider range of waterbodies before they can be used in global service. Some product need assessment whether they should be delivered freely within the Copernicus core services or by industry as downstream services.

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1. Introduction

1.1 Water-ForCE

The Horizon-2020 project Water-ForCE (Water scenarios For Copernicus Exploitation) will develop a Roadmap for Copernicus Inland Water Services. The Roadmap will contain:

- Analysis of the landscape of user communities
- Analysis on how Copernicus water services can support policy development and monitoring of their implementation
- Gap analysis of the Copernicus water-related service portfolio
- Identification of future higher-level biogeochemical products
- Technical requirements for future Copernicus sensors to improve the water-related service portfolio
- Proposal for organising *in situ* measurement networks to validate Copernicus remote sensing and modelling products and to provide complementary data not collected by remote sensing
- Proposal on how to define relationships between Core Services and Downstream services
- Scenarios of the most optimal delivery of water services to different user communities.

The Water-ForCE project is coordinated by the University of Tartu (Estonia) with 20 participating organisations from all over Europe. It connects experts in water

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quality and quantity, Earth observation, policy, research, engineering and service sectors.

This report is part of Work Package 2 (WP2) "Water quality continuum" which focuses on the water quality related products from inland to coastal waters.

1.2 Purpose of the document

The Space call LC-SPACE-24-EO-2020 identified a specific element that should be addressed in the frame of the project – "development of high-level biogeochemical products, beyond basic variables for water quality and food web modelling or analysis". The report is our response to this part of the call.

1.3 Content of the Report

The preliminary title of the Report was "Higher-level biogeochemical products". It was planned that Task 2.4 will be based on the analysis carried out within Task 4.5 which analysed the user needs and currently available technical capabilities of different *in situ* sampling sensors and proposed higher-level biogeochemical products that can potentially be estimated by combining different *in situ* sensors. Task 2.4 should have then taken these products and assess whether some of them can be produced by combining different remote sensing products into remotely sensed higher-level biogeochemical products. This originally planned part of the work is shown in the Chapter 2 of this report.

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On the other hand, Water-ForCE WP1 and Task 2.2 identified broad groups of remote sensing products which are highly desired by users but currently not provided in the frame of the Copernicus program. The Deliverable 2.2 identified broad gaps in the water quality part of the current Copernicus product portfolio. These gaps need more detailed analysis before proposing the way forward in the Copernicus Roadmap which will be the main output of the Water-ForCE project. Therefore, this report analyses the gaps and proposes the ways forward to be included in the Roadmap. This analysis is provided in Chapter 3 of this report.

2. Definition of higher-level biogeochemical products

It is important to define what the 'higher-level products" refers to as no definition was provided in the Space call. One of the possible interpretations is that the higher-level products are those that combine more than one basic remote sensing product and involve algorithms or models that combine several input variables into a new product. Such *in situ* products were analysed in Deliverable 4.5 and are their respective remote sensing analogues are presented here in Chapter 2.1.

The second definition of a higher-level product is one that is calculated from a variable that can be directly mapped using an algorithm, or a parameter modelled from remote sensing. For example, satellites register the impact of Coloured Dissolved Organic Matter (CDOM) on water colour (the remotely sensed signal).

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Thus, CDOM can be considered as a basic product. A product many users need is dissolved organic carbon, DOC. However, a large fraction of DOC is not coloured. If we apply an assumed relationship between CDOM and DOC then we can map DOC concentration using CDOM as a proxy. In that case the DOC is a higher-level biogeochemical product.

Another possible definition of higher level products is generating products that are aggregated products in space or time (typically referred to as Level-3 processing) or add new layers of interpretation (typically referred to as Level-4 processing). Examples of achieving “higher-level” products from aggregation of remote sensing products include deriving indicators. In the Water Framework Directive (WFD), eutrophication is often estimated as the summer mean chlorophyll-a concentration for a given waterbody. In that case, daily chlorophyll-a observations are the basic product and the mean or median for all observations (pixels) of this waterbody over the summer period is the higher-level product contributing to WFD reporting. Such products are discussed in Chapter 2.2.

2.1 Combining remotely sensed variables as optical proxies for biogeochemical processes

Task 4.5 identified the following higher-level biogeochemical products, which can be obtained by means of combining data from multiple *in situ* sensors or using optical *in situ* proxies, and which have potential to be mapped using remote sensing products as input:

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- primary production (PP)
- total phosphorus (TP)
- dissolved organic carbon (DOC)
- partial pressure of carbon dioxide (pCO_2).

The carbon related products (DOC and pCO_2) were identified as a gap by many users as identified in the analysis carried out by the WP1 team. Therefore, carbon related products are discussed in more detail in Chapter 3 “Gaps in water quality products identified by the Water-ForCE deliverables”.

Primary production (PP)

Phytoplankton primary production (PP) represents the synthesis of organic matter produced in aquatic systems, an essential part of the food web forming the basis of the ecological pyramid. Measuring primary production in terms of carbon fixation is time-consuming and (using radioisotopes) increasingly regulated. These conventional methods require *in situ* incubations of typically several hours or longer and subsequent laboratory analysis. Consequently, it is difficult to carry out more than a few measurements per day and the results obtained are strictly point measurements (including depth profiles as appropriate). Alternative methods (see D4.5) to estimate primary production are based on intermediary processes (electron transport or oxygen evolution) and can be more efficient to carry out *in situ*. However, they are not widely established and mostly absent in regular monitoring practices.

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Bio-optical model simulations provide an alternative way to estimate primary production. For example, Kiefer and Mitchell (1983) and Behrenfeld and Falkowski (1997) developed primary production models for marine environment. A simple bio-optical model for lakes was developed by Arst et al. (2008), where the PP (in mg C m^{-3} h^{-1}) is a function of photosynthetically absorbed radiation and quantum yield of carbon fixation. The *in situ* version of the model uses three input variables: downwelling irradiance for PAR region, chlorophyll-a, and the diffuse attenuation coefficient of water (Kd). All these tree variables are available as satellite remote sensing products. It has been demonstrated that the model by Arst et al. (2008) can replicate vertical and temporal variation of the PP in lakes (Kauer et al., 2009, 2013, 2015; Soomets et al., 2019, 2020). Thus, it is possible to map lake PP using remote sensing. The model has been validated in several large eutrophic lakes, the oligotrophic Lake Geneva, and some coastal regions of the Baltic Sea. A wider validation in different lake types and coastal waters is therefore necessary. A wider research project on the topic is recommended before the PP product can be considered as an extension of the Copernicus water portfolio.

Total phosphorus (TP)

Total phosphorus was identified by Task 4.5 as a higher-level biogeochemical product that can be estimated by *in situ* and remote sensing sensors. TP does not have a distinct optical signature and therefore cannot be estimated directly by remote sensing sensors. Nevertheless, TP has been shown to correlate with water clarity. In more turbid waters there are more particles and phosphorous is often

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particle bound. TP relationship with water clarity is affected by particle size distribution and spatial variation as well as by the fraction of phosphorous associated with particles (Lannergård et al., 2019). Several *in situ* studies of surface waters have dealt with water turbidity and TP relationship (Al-Ruzouq et al., 2020; Grayson et al., 1996; Kämäri et al., 2020; Kusari, 2022; Lannergård et al., 2019, etc.). Moreover, Kutser et al. (1995) showed that lake TP can be mapped (in a single lake) using Secchi depth as a proxy.

It is possible to develop empirical remote sensing algorithms based on statistical relationships between remotely sensed signal properties and water quality variables even if the variables do not have a direct impact on the remote sensing signal, like in the case of TP. Several remote sensing studies (Ding et al., 2020; Du et al., 2018; Fengyang et al., 2020; Gao et al., 2015; Hossen et al., 2022; Liu et al., 2015; S. Lu et al., 2020; Qiao et al., 2021; Shang et al., 2021; Song et al., 2012; Sun et al., 2014, 2022; Trevisan and Forsberg, 2007; Wu et al., 2010; Xiong et al., 2022, 2019; Yu et al., 2017; Zeng et al., 2022; Zhang et al., 2022) have developed empirical algorithms for mapping TP.

Both conventional empirical methods and machine learning algorithm development methods have been used to estimate TP from remote sensing data (Xiong et al., 2022). The most direct empirical derivation method applies the statistical relationship between reflectance and measured TP concentration to derive the TP remote sensing algorithm (Isenstein and Park, 2014; Xiong et al., 2019). Indirect derivation methods include the initial derivation of TP concentration from optically active substance concentrations, followed by selection of algorithms or

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wavebands to determine those individual concentrations, based on literature (Wu et al., 2010; Xiong et al., 2022). The direct empirical method is more broadly applied because it is simple and often delivers good results, whereas the indirect derivation method is complex and disposed to precision loss because of the two-step method (Xiong et al., 2022, 2019), whilst possibly having better global transferability. The relationships between TP and optically active substances in optically complex waters are complicated and may not be well expressed by regression models (Xiong et al., 2022). Unsurprisingly, machine learning has been successfully introduced into TP estimation too (Chang et al., 2013; Sun et al., 2014; Xiong et al., 2022). In general, machine learning algorithms outperform conventional algorithms used for water quality estimation (Chen et al., 2014; Concha and Schott, 2016; Sun et al., 2011; Xiong et al., 2022).

The optical variability of inland and coastal waters is very high. The abovementioned remote sensing studies have been carried out in a limited number of waterbodies. Therefore, further studies on the relationships between TP and observable optical water quality variables (turbidity, Secchi depth, Chl-a, K_d, etc.) have to be studied in as wide selection of waterbodies as possible before robust (applicable across a range of ecological and optical diversity) TP algorithms and measure of algorithmic uncertainty can be proposed to be used in the Copernicus portfolio.

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2.2 Spatiotemporal aggregation for higher-level indicators

It is possible to derive meaningful indicators from existing products in the Copernicus services. For example, monitoring agencies tend to report eutrophication indicators as the seasonal mean. Mean summer chlorophyll-a is calculated from the available (usually very limited) *in situ* sample analyses. Remote sensing extends the observational dataset by orders of magnitude based on daily (large waterbodies) or weekly (small waterbodies) satellite overpasses. Thus, deriving the distribution of remotely sensed chlorophyll-a values provides additional insight into how a waterbody behaves with respect to the reporting thresholds for high, good, moderate, poor or bad ecological status. In terms of data aggregation, both the "summer mean" across all observations of a water body and the data distributions may be considered higher-level biogeochemical products, to assist management of water bodies under the WFD.

Another example of a higher-level product is the cyanobacterial index developed by HELCOM. It consists of two parameters 1) cyanobacterial surface accumulations (CSA) combining information of volume, length of bloom and severity of surface accumulations and 2) cyanobacterial biomass (CyaBI) (https://www.helcom.fi/wp-content/uploads/2019/08/Cyanobacterial-bloom-index-HELCOM-pre-core-indicator-2018.pdf). In principle, both can be estimated from remote sensing data provided suitable sensors such as Sentinel-3 OLCI are used. Thus, the CSA and CyaBI can be considered as higher-level biogeochemical products.

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One question is whether such products should be provided as Copernicus core service for the whole Europe. The advantage of providing then through the core service is consistency in pan-European products for indicators in EU directives. However, some countries use already locally tuned algorithms that are then aggregated into higher level products. Thus, it has to be discussed among the EU member states whether they prefer to have unified pan-European higher-level products on top of country and region-specific results.

3. Gaps in higher-level biogeochemical water quality products identified from user and policy requirements analysis

WP1 “Policy, stakeholder and service analysis” assessed Copernicus user needs and requirements by performing analysis of legislation, interviewing different users and user groups as well as SDGs and ECVs. There are number of SDGs that are directly related to water quality, like zero hunger, clean water and sanitation, responsible consumption and production, climate action, life below water, and life in land. Many ECVs are directly or indirectly related to water quality as well. For example, ocean colour = water reflectance detected by many remote sensing instruments, is an ECV itself and marine habitats, plankton and other parameters derived from ocean colour are ECVs as well. Gap analysis of water quality products was performed also within Deliverable 2.2 “Recommendations on Copernicus water

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quality products". The water quality products required by a variety of users, but currently missing in the Copernicus portfolio, can be divided (from remote sensing perspective) into three groups:

1) carbon related products (e.g., dissolved organic carbon, DOC, total organic carbon, TOC, CO_2)
2) shallow water products (e.g., bathymetry, benthic cover, benthic habitat type, benthic disturbance)
3) surface material products (e.g., plastic and other litter, floating cyanobacteria, water hyacinth, macroalgae (e.g., Sargassum or Ulva), pollen).

The first group of products are described based on literature since they are well-researched. For the latter two groups, Water-ForCE organised a specialist workshop in Milan on September 20-21, 2022. Observations are presented in the sections to follow.

3.1 Carbon related products

Detecting organic carbon in inland and coastal waters is important from several perspectives ranging from biogeochemical modelling in climate studies to ecological health monitoring and water treatment for consumption.

Lakes play an important role in biogeochemical cycles (despite their relatively small total area). More than 90% of the total organic carbon in lakes and reservoirs is in the form of dissolved organic carbon (Wetzel 2001), but lakes can act both as carbon sinks and sources. Therefore, it is critical to know the DOC stock and trends in inland waters, to further the global stocktake of carbon pools, ultimately

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promote lake carbon to an Essential Climate Variable and include it in Earth system modelling.

In ecological context, a lake browning effect related to increased CDOM concentrations has been reported. It is also important to map CDOM in lakes as the CDOM increase, called lake browning, is happening both in small (Monteith et al. 2007; Kritzberg 2017; Kritzberg et al. 2020; Nydahl et al. 2019; Meyer-Jacob et al. 2019; Blanchet et al. 2022) and large lakes (Kutser and Ligi, in preparation) lakes. CDOM Browning protects aquatic biota from damaging UV radiation and increases resources for heterotrophic microorganisms, but it decreases primary production (lower light availability) and has negative impacts on higher trophic levels (Karlsson et al. 2015; Tranvik et al. 2018). Browning also increases lake surface water temperature (Kutser 2010) and has impact on lake mixing regimes (Woolway et al. 2019).

Carbon dioxide (CO_2) is a key substance involved in a number of biogeochemical processes in natural waters (Atamanchuk et al. 2014). The most common parameter, which describes the amount of dissolved CO_2 gas in water, is the partial pressure or pCO_2 (Atamanchuk et al. 2014). Inland waters are broadly considered as substantial sources of CO_2 to the atmosphere (Duarte et al. 2008; Kortelainen et al. 2006; Lazzarino et al. 2009; Sobek et al. 2005; Tranvik et al. 2009; Wen et al. 2021; Yan et al. 2021). Previous studies have shown that the temporal and spatial distributions of partial pressure of carbon dioxide (pCO_2) in inland waters often exhibited high heterogeneity, which caused great uncertainty in lake CO_2 flux calculations (Wen et al. 2021). Rivers and streams comprise higher pCO_2 than lakes

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and reservoirs in the same climatic zone, and tropical waters characteristically show higher pCO_2 than temperate, boreal, and arctic waters (Wen et al. 2021). In terms of drinking water provision, detection of dissolved organic matter was one of the most highly ranked needs in the user interviews carried out in WP1. This is not surprising, because inland waters are a major source of drinking water. DOC is a complex mixture of compounds that can affect aquatic microbial community structure and levels and can consequently cause problems with fouling of drinking water (taste, odour and hygiene problems). Removing DOC is one of the hardest parts of water treatment requiring chemical treatment. This adds to the cost of drinking water production. For the correct dosage, accurate information on water DOC content is required. Furthermore, the disinfection of water by chlorination (a crucial step in water treatment) creates carcinogenic organic compounds which affect human (McDonald and Komulainen, 2005; Koivusalo et al. 1997; Magnus et al. 1999). Therefore, the organic carbon has to be removed as much as possible. All this stresses the need for frequent information about inland water DOC over large areas for these waterbodies that are used as drinking water source.

Processes like droughts, wildfires, land use changes, eutrophication, permafrost thaw, etc. change both the amount and composition of DOC in inland and coastal waters (Xenopoulos et al. 2021). Nevertheless, Minor and Oyler (2021) showed that the DOC and its coloured component CDOM are the least studied components of the carbon cycle despite their relevance.

Remote sensing can detect only optically active water constituents, which in the case of proxies for dissolved carbon we focus on CDOM. Therefore, mapping of DOC,

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required by many users, is possible if there is a reasonable correlation between the coloured component - CDOM and the DOC. Many studies have shown that this is the case at specific scales (per lake as well as global relationships), at least in inland waters (Tranvik, 1990; Kallio, 1999; Molot and Dillon, 1997; Erlandsson et al. 2012; Kutser et al., 2015a). Exceptions are also reported (Hestir et al. 2015). Moreover, iron associated to organic matter acts as a colouring agent with similar optical properties increasing the uncertainty in lake CDOM estimation (Kutser et al., 2015a). On the other hand, Kutser et al. 2015a and Brezonik et al. 2019 have shown that the influence of iron on mapping of lake CDOM with remote sensing is small.

3.1.1 Current state of the art

The Copernicus inland water product portfolio does not contain specific products on organic carbon. The trophic state index is related to the production of organic matter but derived from chlorophyll-a estimates. There is no product which describes the concentration of CDOM. CDOM is, to a certain degree, provided for some seas in the CMEMS product portfolio as there is a product CDM443 (sometimes called ADG443), which has variable names in documentation, but is most often called “volume absorption coefficient of radiative flux in seawater due to dissolved organic matter and non algal particles”. However, validation of the product is not included in the CMEMS documentation for any of the sea areas for which CMEMS products are provided (Atlantic, Arctic, Baltic, Mediterranean, and Black Sea). EUMETSAT is providing a detritus and dissolved matter ADG443 product retrieved with a bio-optical model together with phytoplankton absorption and particle backscattering. However, unlike for most other products there is no information

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about the accuracy of the ADG443 product. ESA Ocean Colour Climate Change Initiative (OC-CCI) provides detrital and dissolved material absorption coefficient at 6 wavelengths retrieved with Lee al. (2002) QAA model. The a_{dg} product is available for the very largest lakes (Caspian Sea, Laurentian Great Lakes, Baikal, etc.) and seas/oceans. However, this is also a combined product of CDOM and particulate matter absorption.

Various approaches have been proposed for retrieving CDOM in inland and coastal waters. These range from simple empirical band ratio algorithms (Vertucci and Likens 1989; Kutser et al. 1996, 1998a,b, 2005a,b, 2015b; Hirtle and Rencz 2003; see also review papers by Odermatt et al. 2012 and Zhu et al. 2014) to semi-analytical and analytical methods that retrieve either concentrations of all optically active substances (Arst and Kutser 1994; Kutser et al. 2001; Pierson and Strömbeck 2001; Brando and Dekker 2003) or inherent optical properties (among them absorption by CDOM) simultaneously (Lee et al. 2002). These algorithms and models used to retrieve CDOM have been validated at relatively small scale (from a single lake to sometimes regional scale) (Brezonik et al. 2005, 2015; Kutser et al. 2001, 2005a,b, 2015a,b; Zhu et al. 2014; Koll-Egyed et al., 2021; Liu et al., 2021; Lyu et al., 2017; Mannino et al., 2014, 2008; Pahlevan et al., 2022).

One of the possible ways to deal with the shortcomings of empirical algorithms is using optical water type classifications. In that case lakes (or coastal waters) are first divided into different optical water types and then different algorithms are used for each water type to retrieve water quality parameters (Spyrakos et al. 2018).

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Remote sensing has been applied to estimate surface pCO_2 in oceans and coastal waters using often Moderate-Resolution Imaging Spectroradiometer (MODIS) imagery and MODIS-derived products (Else et al., 2008; Huang et al., 2013; Olsen et al., 2004; Robbins et al., 2018; Wen et al., 2021) together with statistical approaches and machine learning techniques (Bai et al., 2017, 2015; Chen et al., 2017; Fu et al., 2020; Olsen et al., 2004; Song et al., 2016; Wen et al., 2021). In general, the empirical algorithms and machine learning approaches can work reasonably well in many seas and coastal areas (Chen et al., 2017; Else et al., 2008; Fu et al., 2020; Wen et al., 2021). Unfortunately, remote sensing algorithms and models for pCO_2 in ocean and coastal waters cannot be used directly for inland waters since the pCO_2 in inland waters is driven by different factors and mechanisms. However, satellite observations of pCO_2 in inland waters could reach a relatively high frequency and continuous, large-scale, and long-term data coverage compared to field studies (Wen et al. 2021). pCO_2 in the water surface cannot be directly derived from optical remote sensing data. Recent studies have revealed the presence of four interrelated processes closely associated with water surface pCO_2, which include biological activity, physical mixing, thermodynamics, and air–water gas exchange (Wen et al. 2021). Environmental and biogeochemical variables that can be linked with these processes are water surface temperature, water salinity, phytoplankton concentration, CDOM, latitude and mixed layer depth (Jonsson et al., 2007; Morales-Pineda et al., 2014; Yang et al., 2019; Wen et al. 2021). Some of these variables can be derived from satellite data, e.g., lake surface temperature, chlorophyll-a concentration, CDOM, and solar radiation absorption, and used as indicators in the

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remote sensing models of water surface pCO_2 (Wen et al. 2021). Consequently, in principle, it should be possible to identify the spatiotemporal distribution of pCO_2 in inland waters using satellite-derived variables (Kutser et al. 2005a,b; Wen et al. 2021). Additionally, optical proxies, e.g., CDOM (Kutser et al. 2005a,b) and turbidity index (Saurav et al. 2021) that can be derived from satellite data have been used to estimate indirectly pCO_2 in some rivers and lakes. However, the accuracy and robustness of the prediction models need to be assessed for a variety of inland waters before remote sensing can be used for the large-scale estimation of pCO_2 (Wen et al. 2021). Additionally, the geochemical processes in inland waters can show strong spatiotemporal heterogeneity leading to the unstable, non-universal relationship between pCO_2 and its indicators (Kutser et al., 2015; Morales-Pineda et al., 2014; Ouyang et al., 2017; Qi et al., 2020; Valerio et al., 2021; Wen et al., 2021b; Yu et al., 2017). Therefore, the relationships in the prediction models vary among different inland waters and their regions, which is the current challenge of the pCO_2 remote sensing in inland waters (Bai et al. 2015; Matos Valerio et al. 2018; Morales-Pineda et al. 2014; Ouyang et al. 2017; Valerio et al. 2021; Wen et al. 2021; Yu et al. 2017). Consequently, the development of inverse models based on biogeochemical and environmental variables, machine learning algorithms, and numerous *in situ* data may lead to better applicability of the retrieval algorithms over longer periods and across larger spatial scales (Wen et al., 2021).

It must be noted that the retrieved pCO_2 values are the instantaneous value at the satellite transit time (Wen et al., 2021). To transform pCO_2 values from an instant value to hours/days, the relationship between instantaneous lake pCO_2 and

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the daily/weekly mean value has to be used (Wen et al., 2021). In addition, combined with the *in situ* measured values of the diurnal pCO_2 variation and seasonal pCO_2 variation in a lake, we could realise the conversion of the daily value to the seasonal mean value of lake pCO_2 through cross verification between different sensors with different time resolutions (Wen et al., 2021).

In future studies, reliable and generalized pCO_2 remote sensing models and algorithms need to be developed to evaluate pCO_2 in inland waters (Wen et al., 2021). Moreover, the conversion of the retrieved pCO_2 instantaneous values into days/months remains a major technical challenge, which is essential for the accurate estimation of global CO_2 flux from inland waters based on remote sensing technology (Wen et al., 2021).

3.1.2 Potential for carbon products to be included in the Copernicus portfolio

Several fractions of carbon can potentially be mapped in inland and coastal waters by the mean of remote sensing as was described above. However, most of research described above has relatively limited geographic scope. Thus, the first step would be to establish whether there is a meaningful part of the state of the art that could be applied globally. This requires further research.

There are potential local or regional users of carbon products (e.g. drinking water industry). Their needs can be satisfied by local services provided by industry. However, it is obvious that the carbon products that are feasible should be included in the Copernicus core services portfolio due to the importance of these products for carbon pools and climate studies.

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3.2 Shallow water products

There are multiple shallow water products requested by various user groups and there are shallow water characteristics which are indicators of different directives. For example, bathymetry, benthic cover, benthic cover type, physical disturbances of the sea/lake bottom are variables that are the most commonly requested. These variables can then be used to generate higher-level biogeochemical products. For example, the benthic coverage percentage and cover type will support estimates of carbon fixed in benthic vegetation. While the capacity of terrestrial ecosystems and aquatic phytoplankton in carbon fixation has predominantly been considered in carbon models, only scant attention has paid to the role of coastal (both inland and marine) vegetated ecosystems in global carbon budget (Laffoley and Grimsditch, 2009; Duarte 2017)

Benthic habitats (e.g. coral reefs, macroalgal beds) are often heterogenous even at less than one meter scale. Benthic disturbances (like scars created in benthic habitats by boat engines or other means) may also be limited in scale (narrow). Therefore, it is preferable to have as high spatial and spectral resolution of sensors that are used in collecting shallow water imagery. However, it has been demonstrated (Hedley et al. 2018) that 10 m resolution of Sentinel-2 is sufficient for developing of several shallow water products. Consequently, the launch of Sentinel-2 enables the development of Copernicus services in the shallow water domain, while the launch of CHIME and other hyperspectral missions (PRISMA, EnMAP, etc.) will further support developing high-resolution shallow water products. Additionally, several Copernicus contributing missions provide very high-resolution imagery at

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global scale, with daily revisit times. Thus, there are two questions: what can be done in the field of shallow water remote sensing using the satellite imagery available to Copernicus and should shallow water remote sensing become part of the free and open Copernicus (core) services, or rather provided as downstream services. The Water-ForCE project organised a workshop in Milan in September 20-21, 2022, to discuss these questions, with results presented in 3.2.2 below.

3.2.1 Current state of the art

Shallow water products are currently not offered through CLMS or CMEMS (D2.2 https://web-waterforce-files.vercel.app/wp2-d22-final-revised21012024.pdf).

Benthic variables that are retrievable by remote sensing include: habitat cover (bare vs. vegetated), habitat distribution maps, status or condition of benthic organisms (*e.g.* seagrass, corals), abundance of submerged aquatic vegetation (SAV) (*e.g.* percent cover, biomass, leaf area index), primary productivity of SAV, bathymetry, physical disturbances of marine bottom, etc. Many products are already provided for coral reef areas around the world by Allen Coral Atlas (allencoralatlas.org). For example, they deliver benthic maps, geomorphic maps, reef extent together with some background data like the NOAA Coral Reef Watch which estimates coral bleaching probability. There are companies that deliver satellite derived bathymetry and habitat maps at local to national scales, but these services are provided on commercial bases.

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3.2.1.1 Benthic habitats

The majority of the benthic habitat distribution maps are created using different image-based classification approaches, such as unsupervised (Bouvet et al. 2003), supervised (Fornes et al. 2006; Traganos and Reinartz 2018a) and object-based (Phinn et al. 2012; Zhang et al. 2013; Roelfsema et al. 2013) classification methods. Image-based methods require availability of ground truth data and/or detailed expert knowledge of the area (Campbell 2007). Lately, various machine learning methods have emerged (Traganos and Reinartz, 2018b; Wicaksono et al. 2019), which also require training data. An alternative approach in image classification is so called signal-based or physics-based classification, where measured and/or modelled spectral libraries are used to interpret imagery (Kutser et al. 2002, 2006; Mobley et al. 2005; Lesser and Mobley 2007; Vahtmäe et al. 2013). The signal-based classification does not require simultaneous field surveys as it is based on end-member spectral libraries. A spectral library for a specific site can be collected once or spectral libraries from other locations can be used as the spectral signatures of major benthic types are the same for inland and coastal waters, tropical or temperate climate (Kutser et al. 2020). Moreover, these methods retrieve benthic type and water depth (and sometimes also water properties) simultaneously while empirical methods require that either the depth or bottom type has to be known.

All analytical (physics based) approaches are more sensitive to the accuracy of reflectance data than empirical methods. More than 90% of signal measured above waterbodies by satellites originates from atmosphere. Consequently, a small

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error in atmospheric correction may be as large as the whole water leaving signal and can hamper using of analytical methods. Mapping of benthic habitats requires also removing water column effects. Both atmospheric correction and removing water column effects are inverse problems that do not have a single solution. One of the ways to reduce both the uncertainties is using forward modelling to propagate the benthic reflectance through the water column with variable depth and optical properties (using a radiative transfer or bio-optical model) and through atmosphere and use this top of atmosphere spectral library to interpret TOA reflectance image. For example, Kutser et al. (2002, 2006) showed that this approach gave more reliable results than the conventional approach with atmospheric correction as the first step and using of top of water surface spectral library.

Change in benthic habitats condition, such as coral bleaching and die-off (and replacement with algae), decrease in seagrass beds, replacement of perennial macroalage with fast growing filamentous species, etc. are important indicators of the health of benthic ecosystems. Such changes are detectable through colour changes in multi-temporal remote sensing images. Image differencing after radiometric normalisation offers possibility to detect such changes (Elvidge et al. 2004; Yamano et al. 2004).

A variety of approaches are available for the quantification of macrophytes abundance from remotely sensed images. First, there is an image classification approach, where classes with various abundance levels (such as low, medium, dense) are used instead of species/substrates classes (Pu and Bell, 2013; Koedsin et al. 2016; Kuhwald et al. 2022). Secondly, empirical methods can be used, where a

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relationship is established between image reflectance and *in situ* observed abundance metrics, such as percent cover (Lyons et al. 2012; Koedsin et al. 2016), biomass (Knudby and Nordlund 2011; Vahtmäe et al. 2022), or leaf area index (LAI) (Wicaksono and Hafitz 2013, Hill et al. 2014). The resultant empirical relationship is then applied to the entire image producing a continuous map of SAV abundance. Finally, more complex physics-based radiative transfer models have been used to for SAV quantification (Hedley et al. 2016; Ghirardi et al. 2019).

3.2.1.2 Benthic primary production

Well-established *in situ* methods, such as benthic chambers equipped with oxygen sensors have been developed for benthic primary production measurement (Rodgers et al. 2015, Miller et al. 2011, Olivé et al. 2016). Although these techniques yield very precise estimates of primary production and have extensively been used for carbon flux studies, the methods are inappropriate for large scale studies. This is because the patterns of primary production are highly variable both in time and space and it becomes unrealistic and inefficient to replicate the measurements at quantities sufficient to cover the inherent variability of photosynthetic production at all these scales (Vahtmäe et al. 2022). Therefore, it is necessary to develop remote sensing based methods for large-scale benthic production estimates. Quantitative estimates of SAV abundance (e.g. biomass or LAI) allows indirect assessment of primary productivity and carbon fixation in aquatic ecosystems (Hill et al. 2014). Current terrestrial production models use the method proposed by Monteith (1972), where GPP is a function of the PAR, the fraction of PAR absorbed by the vegetation

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(fAPAR), and the efficiency with which this absorbed light is utilised by vegetation (LUE) (Hilker et al. 2008; Rossini et al. 2012). Adaptations of Monteith models can be used in aquatic ecosystem for the benthic productivity assessment (Hochberg et al. 2006; Vahtmäe et al. 2022).

3.2.1.3 Bathymetry

Mapping of water depth in inland and coastal waters with sonar or LIDAR systems is time consuming and expensive. Satellite derived bathymetry is a cheaper alternative in waters where the water bottom is seen from space. Bathymetry retrieval is based on either empirical or analytical methods. Empirical methods rely on the collection of large number of hydrographic measurements (e.g. sonar, lidar) to establish relationship between image reflectance and *in situ* measured water depth. Varieties of empirical approaches are proposed including linear band model introduced by Lyzenga (1978) and band-ratio model introduced by Stumpf et al. (2003). Analytical model inversion approaches are more complex and require input of the spectral signatures of suspended and dissolved materials, as well as the bottom reflectance (Kutser et al. 2002, 2006; Hedley and Mumby 2003; Hedley et al. 2009, 2018; Giardino et al. 2012; Casal et al. 2020).

It is not surprising that the launch of Sentinel-2 has triggered interest in using this freely available and frequent source of information in bathymetry mapping (Hedley et al. 2018). Comparison with WorldView-2/3 has shown the combined advantage of WorldView's higher spatial resolution relative to Sentinel-2 (Wilson et al. 2022; Dattola et al. 2018). Vahtmäe et al. (2021) compared the performance of

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hyperspectral Compact Airborne Spectrographic Imager (CASI) and Sentinel-2 and concluded that hyperspectral CASI outperformed Sentinel-2 in benthic habitat mapping as well as in percent cover assessment. However, unlike airborne sensor data, Sentinel-2 data is free of charge and covers most of the Earth's shallow water areas (both inland and marine). In general, most of the published papers conclude that Sentinel-2 is suitable for bathymetry and shallow water benthic habitat mapping even if it cannot provide as much information as very high spatial or spectral resolution sensors (Hedley et al. 2018; Kovacs et a. 2018; Yunus et al. 2019. Kutser et al. 2020).

3.2.2 Potential of including shallow water products in the Copernicus portfolio

Based on the literature analysis above and on the presentations and discussions of the Water-ForCE Milan workshop there are several potential shallow water products that could be added to the Copernicus water portfolio.

Bathymetry maps of shallow coastal waters around the world may be of interest for many different purposes from spatial planning to navigation safety. National governments, monitoring agencies, and the tourism and aquaculture industry are interested in the bathymetry of lakes and coastal waters. Most potential users have regional to local scale needs and require the bathymetry map once. Consequently, creating a global bathymetry map would be a one-off exercise for most of the world, not a service needed with high frequency. On the other hand, there are regions in the world where shoreline and bathymetry change fast and where frequent (e.g. a few times per year) bathymetry mapping would be beneficial. However, water tends to be more turbid in such dynamic regions and the maximum

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depth that can be resolved with passive optical remote sensing is in the order of tens of centimetres. Thus, it is not feasible to use satellite derived bathymetry in such places.

Sentinel-2 imagery can be used for relatively large-scale bathymetry mapping and such service is provided by several companies (EOMAP, DHI, Numerical Optics, Argans and others). Whether the services already provided by different companies should be included in Copernicus core services needs debates.

European and/or global inland and coastal water habitat maps, created from Sentinel-2 imagery could be used in carbon sequestration studies (Duarte 2017). Moreover, benthic habitat maps provide important information for spatial planning, tourism, aquaculture, drinking water industry, etc. On the other hand, there are already global benthic and geomorphic maps available for tropical and subtropical regions. For example, the Allen Coral Atlas covers all regions of the world where corals can grow. It is based on Planet imagery with approximately 3 m spatial resolution. No equivalent product exists for European coastal and inland waters and creating consistent benthic products for the whole Europe may be a reasonable way forward.

Providing shallow water products and imagery with better spatial resolution (e.g. Sentinel-2 NG with 5 m resolution) and more spectral bands will enhance the potential of Copernicus to provide different shallow water products even further. The aim of the Copernicus Programme is not only to provide free core services, but also supporting the European space industry. Therefore, a balance has to be found between the public need in shallow water products that should be delivered free of

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charge by the Copernicus core services and between supporting European space industry.

3.3 Floating material products

Monitoring marine litter (including plastic), cyanobacterial blooms (either just below the water surface or floating on the water surface), infestations of invasive plants (like water hyacinth) in rivers and lakes, or floating macroalgae (e.g. *Sargassum, Ulva*) in coastal waters are just a few "surface" products highly demanded by different users. Theoretically, many of them can be produced from high spectral and spatial resolution remote sensing data (e.g. airborne hyperspectral imagery). There are now multispectral satellite sensors with high or very high spatial resolution. These are useful for detecting floating material on the water surface. However, their spectral resolution may not be sufficient to separate different types of floating material. Moreover, using high-resolution commercial satellites in routine monitoring over large areas is prohibitively expensive.

Copernicus satellites, like Sentinel-2, provide now an opportunity for mapping floating material as the data is available with reasonable spatial resolution and sufficient revisit times. Thus, now it is worth of analysing whether the floating material products should be included in the Copernicus portfolio. Water-ForCE organised a workshop in Milan in September 2022 in order to discuss what kind of floating material products can be produced with Copernicus. Water-ForCE Roadmap must provide also recommendations about what kind of products should be provided by Copernicus as a free service and what kind of products should be

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provided by different entities (companies, institutes) as commercial downstream services. These aspects of floating material products were also discussed in the Water-ForCE workshop.

3.3.1 Current state of the art

Numerous types of floating material have been reported in surface waters through satellite ocean colour remote sensing (Qi et al. 2020). These include: marine litter and debris (e.g. Ciappa, 2022; Haarr et al. 2022; Knaeps et al. 2021; Martinez-Vicente et al. 2020; Salgado-Hernanz et al. 2021a,b; Themistocleous et al. 2020; Topouzelis et al. 2021, 2020a,b); macroalgae such as *Sargassum* (e.g. Dierssen et al. 2015; Fidai et al. 2020; Gower et al. 2013; Hu et al. 2015; Qi and Hu, 2021; Gower and King, 2011; Wang et al., 2018; Wang and Hu, 2021, 2016; Xiao et al. 2022) and green macroalgae Ulva (seaweed, e.g. Hu et al. 2010, 2017; Qi and Hu, 2021; Xiao et al. 2022); aquatic plants such as water hyacinth (*Pontederia crassipes,* e.g. Ade et al. 2022; Gerardo & de Lima, 2022; Janssens et al. 2022; Thamaga & Dube, 2019) and mats formed from the die-off floating seagrass (e.g. Dierssen et al. 2019, 2015; Suwandana et al. 2012; Veettil et al. 2020); various species of cyanobacteria (e.g. Trichodesmium, Nodularia, Aphanizomenon, Microcystis (Kutser 2004; Ahn and Shanmugam, 2006; Babin et al., 2005; Bertani et al., 2017; Blondeau-Patissier et al. 2014; Chaffin et al. 2021; Cullen et al. 1997; Duan et al. 2015; Gower et al. 2005; Hu et al. 2010a,b; Jia et al. 2019; Kislik et al. 2022; Kutser, 2009; Liu et al. 2021; Melendez-Pastor et al., 2019; Ogashawara, 2019; Qi et al. 2017; Rodríguez-Benito et al. 2020; Sayers et al. 2019; Xu et al. 2021; etc.); dinoflagellates such as floating Noctiluca (*Noctiluca scintillans*; e.g. Baliarsingh et al. 2017; Liu et al. 2022); Phaeocystis (forms floating foam when it

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degrades, Blauw et al., 2010; Lancelot, 1995; Peperzak et al., 1998) ; tree pollen (e.g. pollen of Scots pine); foams, whitecaps, bubbles (Dierssen 2019; Hu et al. 2023); oil slicks (Y. Lu et al. 2020); pumice rafts (Whiteside et al. 2021), etc.

Floating marine litter or debris frequently contains plastics (synthetic polymers), but also wood, metal, glass, rubber, clothing, paper, sea slicks, and any other disposed or abandoned non-biodegradable parts (Salgado-Hernanz et al. 2021; Topouzelis et al. 2021). Plastics makes up up to 95% of the global ocean marine litter and they can be divided into macroplastics (size >5 mm); microplastics (size <5 mm); and nanoplastics (size <100 nm, Salgado-Hernanz et al., 2021). Marine litter has consequences for wildlife, biodiversity, human health, the global economy, and the climate (UNEP, United Nations Environment Programme, 2021). Independent and objective monitoring, reporting, and review mechanisms are critical for the successful management and clean-up of marine litter. High-resolution multispectral data from satellite images can help to map, track, and remove marine litter from the environment since they can systematically monitor much larger areas in comparison to traditional *in situ* observations (Topouzelis et al., 2021). Various methodologies (sighting, photointerpretation, supervised and unsupervised classification, indices, etc.) and *in situ*, air- and space-borne remote sensing platforms (Sentinel-1, SAR; Sentinel-2, MSI; Sentinel 3, OLCI; Aqua, MODIS; Landsat 8, OLI, TIRS; Worldview-2 and -3; Prisma; PlanetScope; TanDEM-X; RADARSAT-2; TerraSAR-Xremote, etc.) have been used to detect and discriminate marine litter from other floating materials (Aoyama, 2016; Basu et al. 2021; Biermann et al. 2020a,b; Kikaki et al. 2020; Martinez-Vicente et al. 2020; Paula M. Salgado-Hernanz et al. 2021;

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Themistocleous et al. 2020; Topouzelis et al. 2020a, b). The spatial resolution of the sensors has been from 3 cm to 20 m, and a spectral range from microwaves to shortwave infrared (Aoyama, 2016; Basu et al. 2021; Biermann et al. 2020a,b; Kikaki et al. 2020; Martinez-Vicente et al. 2020; Paula M. Salgado-Hernanz et al. 2021; Themistocleous et al. 2020; Topouzelis et al. 2021). Currently, aircraft sensors with high spatial resolution (<3 m) and broad wavelength range (λ = 400 to 2500 nm) appear most suited to detect marine litter, whereas Synthetic Aperture Radar (SAR) sensors (λ = 3.1 to 5.6 cm) may detect sea-slicks (aggregated microplastics that are accumulated in the upper layer of the waterbody and by microbes and microorganisms, Salgado-Hernanz et al. 2021). Detection and monitoring are significantly impacted by different physical and technical limitations like atmospheric and sea-surface effects, clouds, radiometric, spatial, and temporal resolutions of satellite sensors, and availability of in situ data (Aoyama, 2016; Garaba et al., 2018; Garaba and Dierssen, 2018; Garcia-Garin et al. 2020; Moy et al. 2018; Topouzelis et al. 2021). Dedicated aerial surveys (crewed aircraft) present a significant advantage over satellites in terms of spatial resolution, they are still limited acquisition frequency, and are relatively costly. Their primary use is for proof-of-concept studies and to obtain reference data, rather than large-scale monitoring (Garcia-Garin et al., 2020; Moy et al. 2018; Topouzelis et al. 2021, 2020a,b). Uncrewed aerial systems (UAS) are much less costly, but relatively limited in terms of flight time and automation potential (Garcia-Garin et al. 2020; Moy et al, 2018; Topouzelis et al. 2021, 2020a,b). Technical advancements will allow for large-scale automated acquisition of remote sensing data using UAS, whilst satellites are the only platforms

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capable of continued global coverage and help to study remote, hard-to-reach areas (Basu et al. 2021; Biermann et al. 2020a,b; Topouzelis et al. 2021, 2020a,b, Martinez-Vicente, 2022).

Although varying in terms of application method, the processing steps are usually common in most detection algorithms: (1) pre-processing of the data and (2) classification of floating elements into marine debris (Aoyama, 2016; Basu et al., 2021; Garaba and Dierssen, 2018; Martínez-Vicente et al. 2019; Topouzelis et al. 2021). Pre-processing includes atmospheric correction, land masking, cloud detection, cloud edge, and shadow masking, white caps detection, glint removal, and correction (Topouzelis et al. 2021). Unfortunately, atmospheric correction models often fail or give incorrect results in the case of strong surface accumulations. The classification includes the processes needed for the identification of pixels containing concentrations of floating marine litter. (Aoyama, 2016; Basu et al. 2021; Topouzelis et al. 2021). A number of different methodologies including indices (e.g., the Floating Debris Index), and machine learning techniques have been proposed to detect floating marine litter and to discriminate between natural debris and marine litter (Biermann et al. 2020a,b; Garaba et al. 2018; Martinez-Vicente et al. 2020; Topouzelis et al. 2021). For a marine litter observation system to be operational at large scales, these methodologies and techniques need to be automated, cover large areas, and work with all available satellite datasets (Hu, 2022; Kremezi et al., 2022; Martin et al., 2021; Martínez-Vicente et al., 2019; Topouzelis et al., 2019, 2020, 2021; Zhou et al., 2022). Such developments require a significant amount of *in situ* validated cal/val data e.g., *in situ* observations of traditional cruises, calibration/validation targets,

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citizen scientist reports, etc. (ESA, 2021; Martínez-Vicente et al., 2019; Maximenko et al., 2019; Topouzelis et al., 2021).

Cyanobacterial blooms can cause various ecological and economic problems and the potential toxicity of some species can make them potentially hazardous to animal and human health. The effectiveness of airborne (Wrigley and Horne, 1974) and satellite (Öström, 1975) remote sensing in detecting phytoplankton blooms were demonstrated more than three decades ago (see references in Kutser, 2009). Developing robust remote sensing algorithms that perform well in stratified waters and in the case of cyanobacteria floating on the water surface requires large amount of match-up data. However, the water sampling techniques and strategies used in monitoring programs do not allow to use monitoring data as match-ups in the case when vertical stratification occurs or bloom is spatially very heterogenous. The data that can be used in match-up analysis should contain information about vertical profile of the biomass and very accurate coordinates as cyanobacterial biomass may vary in orders of magnitude with few tens of meters. Moreover, the 2 hour time window between in situ sampling and satellite overpass, requested by cal/val protocols, is too relaxed in heterogenous waters and the material floating on the water surface may travel far even in the matter of minutes.

Phytoplankton biomass can be described in terms of the concentration of chlorophyll-a and it is the main characteristic used in remote sensing of blooms. The chlorophyll-a retrieval algorithms based on blue to green band ratios work in clear (oligotrophic) waters whereas the green to NIR part of the spectrum has more potential in productive, turbid, and/or CDOM-rich coastal and inland waters because

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this spectral region is less affected by the overlap in the absorption of accessory pigments, detrital matter and CDOM (Arst and Kutser, 1994; Ekstrand, 1990; Holligan et al. 1983; Kutser et al. 1998a, 1998b, 1996; Kutser et al. 1995b, 1995a; Kutser and Arst, 1994; Lavender and Groom, 2001; Sathyendranath et al. 2001, 1997; Siegel et al. 1999; Stumpf and Tyler, 1988; Subramaniam and Carpenter, 1994; Tassan, 1995; Yacobi et al. 1995; Zimba and Gitelson, 2006, etc.). Additionally, many chlorophyll-a retrieval algorithms developed for turbid coastal and inland waters use the peak in reflectance spectra near 700 nm to quantify high phytoplankton abundance (Gitelson 1992; Cunningham et al. 2001; Dall'Olmo and Gitelson, 2006, 2005; Dekker, 1993; Gitelson et al., 1993; Gower and King, 2007; Gower et al., 1999; Hoogenboom et al. 1998; Jupp et al. 1994; Kallio et al., 2003, 2001; Kutser et al. 1997; Millie et al., 2002; Simis et al., 2007, 2005, etc.).

However, pigments other than chlorophyll-a can be used as a proxy for phytoplankton biomass too. For example, most cyanobacteria contain a phycobilin pigment called phycocyanin (Jeffrey et al. 2011). It has been shown (Dekker, 1993; Schalles and Yacobi, 2000; Simis et al. 2007, 2005) that quantitative mapping of phycocyanin by remote sensing is possible. Phycocyanin is detectable due to an absorption feature at 615 nm and, in some situations, fluorescence around 650 nm. These features are not detectable at low abundance of cyanobacteria (Kutser et al. 2006) or when other phytoplankton are abundant (Simis et al. 2007), which means that quantitative mapping of phycocyanin by means of remote sensing may be limited and detecting specific spectral features caused by accessory pigments requires high spectral resolution of the sensors (Kutser, 2004). Laboratory (Quibell,

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1992; Richardson, 1996), airborne (Jupp et al. 1994) and space-borne data (Kutser, 2004) indicate that hyperspectral sensors with a spectral resolution of at least 10 nm should be acceptable to detect pigments like phycocyanin. Machine learning techniques can overcome some of the limitations of individual semi-empirical, semi-analytical, and quasi-analytical phycocyanin retrieval algorithms by combining, and benefiting from, the information available from multiple optical features to estimate phycocyanin (O'Shea et al., 2021; Simis et al., 2007, 2005; Song et al., 2014, 2012; Sun et al., 2012). For example, Mixture Density Network (MDN, Bishop, 1994) that uses line heights and band ratios to accurately estimate phycocyanin, in the presence of ΔRrs has shown good results in retrieving phycocyanin concentration from remote sensing imagery (O'Shea et al., 2021). MDN is particularly suited for non-unique inverse problems where a low number of training data are available and it has proved to be notably better than multispectral algorithms at preventing overestimation on low (<10 mg m^{-3}) phycocyanin concentrations (O'Shea et al., 2021).

Some cyanobacteria species produce surface blooms and scums (IOCCG, 2021). This biomass may be with very variable density from dust-like to mats several centimetres thick. Unfortunately, when scums form, volumetric concentration estimates are not possible. However, more work is needed to determine the intensity (e.g. layer thickness) of scums to support appropriate management response.

Quantitative mapping of algal blooms is complicated also due to the high spatial heterogeneity of the blooms. Patchy blooms may occur below the pixel size of current satellite sensors, even the 10-m resolution offered by MSI (Gitelson, 1992;

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Kutser, 2004; McKinna, 2015). To reduce spatial and temporal 'smearing' effects is to always use full resolution, daily Level 2 ocean colour data when applying algorithms and avoid the use of binned Level 3 products (McKinna, 2015).

Additionally, De Santi et al. 2019 studied whether the use of synthetic aperture radar (SAR) images can compensate for the weaknesses of optical images for cyanobacteria bloom monitoring purposes in the occurrence of cloudy skies (de Santi et al. 2019). They proposed a method to detect cyanobacteria bloom based on the dependency between wind vector and radar backscatter. Qualitative comparison with optical imagery gathered from Sentinel-2 and Sentinel-3 satellites combined with meteorological data reveals that the method shows reasonable results for most of the analysed cases (79%) strongly supporting the use of Sentinel 1 Level 2 products to improve the spatiotemporal detection of algal bloom and complete the observations from optical sensors (de Santi et al. 2019).

Massive landings of brown macroalgae *Sargassum* are regularly registered since 2011 in large areas in Pacific and Tropical Atlantic bringing along large negative impacts on local populations, coastal marine ecosystems, and the economic sector (tourism and fisheries). Remote sensing can help to detect, map, and estimate the trajectories and potential landings on the coasts. There are lots of associated studies (e.g. (Dierssen et al., 2015; Gower et al., 2013, 2006; Gower and King, 2020, 2011; Hu et al., 2015a, 2015b; Marmorino et al., 2011; Qi and Hu, 2021; Sun et al., 2021; Wang et al., 2019, 2018; Wang and Hu, 2021, 2016), still there are gaps mainly related to locations, species identification, and the quantity and the amount landing on beaches. ESA project '*Sargassum* Monitoring Service' managed to

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address some of these gaps in the Caribbean area (Jimenez-Mariani, 2020). *Sargassum* has distinctive reflectance curvature around 630 nm due to its chlorophyll c pigment, which provides a distinctive spectral signature when combined with the reflectance ratio between brown (ca 650 nm) and green (ca 555 nm) wavelengths (Hu et al. 2015). Additionally, the *Sargassum* Index derived from reflectance ratios at 650 and 630 nm has been used to effectively discriminate *Sargassum* from *Syringodium* wrack (Dierssen et al. 2015). For a 10-nm resolution sensor, several indices established from 6 bands (centred at 555, 605, 625, 645, 685, 755 nm) are shown to be effective to differentiate *Sargassum* from all other floating materials (Hu et al. 2015). Although, spectral discrimination is degraded when a pixel is mixed between *Sargassum* and water and a minimum of 20–30% Sargassum coverage within a pixel is required (Hu et al. 2015). As a result, many of the small slicks observed in high resolution image (Worldview-2, spatial resolution 2 m) are not visible in the reduced-resolution image (HyspIRI, 60 m, Hu et al. 2015). Despite this, the spectral shapes of Sentinel-3 OLCI have shown typical red-edge reflectance of floating vegetation and the local reflectance maximum of around 620 nm indicating the presence of *Sargassum* (Qi et al. 2020).

However, the results of the spectral measurements have shown that the characteristic features in reflectance spectra of major groups, like brown macroalgae and brownish corals, are globally consistent (Kutser et al., 2020). Typical features of the brown type are a peak at 600–610 nm and two shoulders at around 575 nm and 650 nm (Hochberg et al. 2004; Holden and LeDrew, 1999; Holden and LeDrew, 1998; Holden et al. 1997; Kutser et al. 2006b; Kutser et al. 2006; Kutser and

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Jupp, 2006; Maritorena, 2007; Vahtmäe et al. 2006, Kutser et al. 2020) and it is nearly impossible to separate them based on their reflectance spectra (Kutser et al. 2020).

Green macroalgae *Ulva*, a common seaweed, may become harmful to both the environment and humans once accumulated in coastal waters and on beaches causing environmental, ecological, and economical problems (e.g., water clarity, oxygen consumption, beach pollution, insect attraction, bad smells, etc., Qi & Hu, 2021). Ulva also occupies a similar habitat to the more preferable seagrasses and can replace seagrass as a result of coastal eutrophication. Remote sensing can help to provide information about distributions, temporal changes, and abundance and trace the origins. Typical reflectance spectra of *Ulva* show a high red-edge reflectance and local reflectance maximum of around 560 nm (Qi & Hu, 2021). Even the OLCI spectra have shown the red-edge reflectance characteristics typical for *Ulva* (Qi et al. 2020). The use of band-combination indices such as the alternative floating algae index (AFAI) and green-red-difference (GRD) help to remove spectrally coherent noise (e.g., from residual errors of atmospheric correction, sun glint correction, and whitecap correction), and to quantify the red-edge reflectance (to differentiate vegetation from non-living matters) or to quantify the spectral difference between different algae types (Qi and Hu, 2021). Additionally, detection and discrimination limits depend on the relative coverage of algae compared to clear substrate or water in a given pixel. When the sub-pixel proportion of algae coverage is 5%, reflectance is dominated by water in subtidal zones (Qi and Hu, 2021). For Sentinel-3 OLCI, the detection limit is approximately 0.5% of a pixel, while the discrimination limit varies between 0.8% for clear water and 2% for turbid water

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(Qi and Hu, 2021). For Sentinel-2 MSI, the detection limit is about 2%, while the discrimination limit is about 6% for all water types (Qi and Hu, 2021). Below these two limits, detection and discrimination of macroalgae using the two sensors are subject to large uncertainties (Qi and Hu, 2021). Additionally, green algae, seagrasses, and other submerged aquatic plants are hardly separable from each other based on their optical signature, since their spectral reflectance is dominated by chlorophyll a, and accessory pigments take a minor role (Kutser et al. 2020). Typically, they have relatively smoothly curved reflectance spectra with a local maximum in the green part of the spectrum, while the common to all plants high near-infrared signal is masked by water absorption (Kutser et al. 2006; Vahtmäe et al. 2006; Kutser et al. 2020).

Die-off produced mats of floating seagrass. The high turnover of buoyant leaves from submerged seagrass meadows can produce large aggregations of floating vegetation called seagrass wracks (Dierssen et al. 2015). Vegetative mats have ecological and economic significance providing a breeding habitat, impacting negatively the terrestrial ecosystems and the growth of salt marshes, and preventing human access to beaches (Dierssen et al. 2015). Additionally, they are hotspots of organic carbon degradation (Dierssen et al. 2015). Remote sensing can help to measure the extent and movement of the mats. Airborne remote sensing with the Portable Remote Imaging Spectrometer (PRISM, spatial res. 0.9-2.7 m) sensor has been highly effective at assessing the fine-scale aggregations of seagrass wrack that could not be easily observed from satellites (Dierssen et al. 2015). Moreover, remote sensing can help forecast when coastal clean-up efforts

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may be required. In this case, the type of floating vegetation may not be as important as the frequency and extent of the floating biomass and the high spatial and temporal resolution of the imagery becomes more important than spectral resolution (Dierssen et al. 2015).

The free-floating water hyacinth has a rapid reproductive capacity. It outcompetes other aquatic plant species, forming dense, free-floating mats, which in many instances completely cover fresh-water surfaces (Ade et al. 2022; Gerardo & de Lima, 2022). Water hyacinth is spread to almost all continents (Ade et al. 2022; Gerardo & de Lima, 2022). It has negative impacts on wetland ecosystem processes like nutrient cycling, hydrology, and energy budgets and their introduction threatens ecosystem biodiversity and function, and often results in economic impact on fisheries, hydropower generation (e.g., waterways and pumping stations), and transportation services (Ade et al. 2022; Gerardo & de Lima, 2022). Remote sensing can be used for the spatio-temporal distribution of water hyacinth to monitor and control its blooming and invasion. Genus and species level discrimination between water hyacinth (*Eichornia crassipes*) and water primrose (*Ludwigia* spp.) using Sentinel-2 multispectral satellite data and machine-learning classifiers in summer and fall have been done by Ade et al. (2022). Their classifiers identified submerged and emergent aquatic vegetation at the community level (Ade et al. 2022). Random forest models using Sentinel-2 data achieved an average overall accuracy of 90%, and class accuracies of 79–91% and 85–95% for water hyacinth and water primrose, respectively (Ade et al. 2022). Sentinel-2 derived maps compared well to those derived from airborne imaging spectroscopy and they also identified

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misclassifications that can be attributed to the coarser Sentinel-2 spectral and spatial resolutions (Ade et al. 2022). Their results demonstrate that the intra-annual temporal gaps between airborne imaging spectroscopy observations can be supplemented with Sentinel-2 satellite data and thus, rapidly growing/expanding vegetation can be tracked in real-time (Ade et al. 2022).

Free floating duckweed, particularly *Lemna minor* is widely found in freshwaters all over the world. Duckweed provides multiple ecosystem functions and services, but its excessive spread can have negative environmental impacts (including ecological and socio-economic impacts), e.g., a reduction of flow velocity, an increase of sedimentation, decrease of light attenuation, and anoxia (Gerardo & de Lima, 2022). Remote sensing can be used to map and to estimate the density of duckweed. The NDAVI (Normalised Difference Aquatic Vegetation Index) has been identified as the vegetation index that depicts the presence of duckweeds in the surface of the watercourse (Gerardo and de Lima, 2022). NDAVI exploits the blue natural colour range and the NIR range (Gerardo & de Lima, 2022). Additionally, average spectral reflectance across wavelengths 350–2500 nm in response to *Lemna* areal coverages of 0–100% and three thickness levels (for 100% areal coverage only) indicate substantially greater NIR reflectance for dense areal coverages and thick-layered assemblages (Tian et al. 2010). Differences in reflectance in the short-wavelength infrared (SWIR) range (1450–1800 nm, and 1950–2350 nm) are effectively imperceptible for areas of <30% coverage (Tian et al. 2010). Overall reflectance in the 350–2500 nm region has been greater with increasing percent coverage and with increasing layer thickness, trending most

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sharply upward between 700 and 915 nm. At the same time, the depth of the water absorption features centred at wavelengths 977 and 1200 nm increase, creating distinctive features of the *Lemna* signature (Tian et al. 2010). However, the performance of remote sensing of submerged plants depends both on the depth of the top of the vegetation and on turbidity (Tian et al. 2010).

Each spring, **pine pollen** coats considerable expanses of surface waters such as the Baltic Sea (Pawlik and Ficek, 2022). There are areas where its concentrations in the surface layer are so high that they are the dominant constituent of the suspended particulate matter (Pawlik and Ficek, 2022). Large pollen concentrations are found not only in the immediate area of the shoreline but can also make up more than 40% of all the 1.25–250 μm SPM floating in offshore areas (Pawlik and Ficek, 2022). Since pollen contains a substantial amount of carbon and influences the optical properties of the water, we should learn more about its bio-optical and biogeochemical characteristics. Pine pollen has relatively unique reflectance spectral shapes (sharp increases from 400 nm to 500 nm) which are confirmed by laboratory experiments (Hu et al., 2023, Toming et al., unpublished). It may be hard to detect pollen in satellite-derived spectra, making it more difficult to differentiate pollen grains from marine debris using spectroscopy alone. Ancillary information, e.g., occurrence time, location, scale, and duration may be used to make an educated inference (Hu et al., 2023).

Conclusions

- Most floating materials have negative ecological and socio-economical effects.

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- Currently, satellites are the only platforms capable of contiguous global monitoring of floating material.
- With appropriate spectral resolution, spectral range, temporal resolution, sensitivity, geospatial resolution, and coverage, remote sensing sensors can be used to detect, map, and discriminate different types of floating material- very challenging at the current technological level.
- Appropriate pre-processing (atmospheric correction, cloud screening, sun glint removal, etc.) is extremely important to accurately detect and differentiate floating material.
- The success of the detection and discrimination are largely influenced by pixel coverage and the optical properties of the water, e.g., clear vs turbid. When the pixel coverage is small, the reflectance is dominated by water and the detection and discrimination of floating material contains high errors or is impossible.
- From an economical point of view, it is often important to know the frequency, movement and magnitude of the floating biomass and to know the type of floating vegetation is not so essential. Hence high spatial and temporal resolution of the sensor is more important than spectral resolution in that case.
- Hyperspectral information of different floating material (in different conditions, e.g., wet, dry, partially decayed, etc.), in situ validated calibration and validation data, as well as additional observational data (occurrence time,

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location duration, etc.) from in situ observations of traditional cruises, citizen scientist reports, social media, etc., are highly needed.

- For continued development of detection methods, specific efforts to collect in situ reference observations are required

3.3.2 Potential of including floating matter products in the Copernicus portfolio

Detecting material floating on the water surface is more straightforward than detecting water column properties. This can be achieved across a range of remote sensors including radar, optical and thermal sensors. However, recognising the type of floating material is a much larger challenge, which in some cases will even be impossible with hyperspectral sensors, such as when the occurrence is below the spatial resolution of the sensor (Kutser, 2004). It should also be expected that co-occurrence of materials from macroplastics to pieces of wood, seagrasses and macroalgae, mixed with foam, reduces estimation accuracy. Surface accumulations of cyanobacteria or rafts of macroalgae (*Sargassum*, *Ulva*) are relatively easier to diagnose, particularly in monospecific blooms.

The shape of the reflectance spectra of all brown algae is identical and the reflectance of all green algae and plants is similar (Kutser et al. 2020). Thus, it is relatively straightforward to recognise these two broad groups of floating material provided that the sensor has an appropriate selection of wavebands and spatial resolution that is compatible with the distribution of the surface accumulation. Reflectance spectra of bloom-forming cyanobacteria also present typical optical features that aid recognition and their detection in blooms.

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The Sentinel-2 MSI sensor can be used in detecting floating material in inland and coastal waters. Its usefulness has been described above. However, there are studies (Hu, 2022) that show that many of the spectral features attributed to floating material are artefacts caused by different spatial resolution of Sentinel-2 MSI pixels (10 m, 20 m and 60 m) at different wavebands. Moreover, spectral resolution of Sentinel-2 MSI reduces its ability to distinguish and discriminate among floating materials. In most cases the floating material is on the water surface in filaments that are narrower than the 10 m pixel and due to that the floating material reflectance can look like something else. Improved homogenous spatial resolution (for all the bands minimum 5m) would improve considerably the lower limits of detectability.

On the other hand, in many cases information about the floating material is usually needed at local scale and there is no need in recognising floating material from the spectral signature. Local knowledge tells with sufficient accuracy what the floating material is. For example, in areas infested with water hyacinth, it is important to map the areas where the hyacinth is at this particular moment of time. The issue that the spectral signature of the hyacinth is identical (when using multispectral sensors) to other green vegetation (seagrasses, *Ulva*) is not critical as these do not occur in the same problematic areas. Differentiating freely floating hyacinth from attached vegetation (e.g., reeds) is possible using multiple imageries and it does not matter if the spectral signatures are similar. In the same way, it can be deducted from the imagery that there are floating cyanobacteria if we have images with high reflectance from the offshore regions of the Baltic Sea in the middle of summer

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although recent studies (Hu, 2022; Hu et al. 2023) have shown pollen and cyanobacterial seasons may overlap and then we will have to analyse spectral features from the high reflectance areas in order to understand what material is floating on the water surface.

In a summary we may say that a generic “floating material” product available across inland and coastal waters is feasible and can be done with Copernicus sensors like Sentinel-2. Improved spectral and spatial characteristics of Sentinel-2NG and even Sentinel-3NG (both currently under discussion). Moreover, using sensor data at higher spatial, spectral and temporal resolution (from commercial satellites, airborne sensors, etc.) may be financially viable in specific regions. Therefore, it has to be assessed whether it will be reasonable to produce some of the floating material products as a free core service or should the services be provided at local or reginal scale and on commercial bases.

4. Recommendations for enhancement of Copernicus water services portfolio

Currently, there are no satellite sensor which specifically address all challenges related to coastal, and particularly, inland water remote sensing. Consequently, suboptimal (from spatial and spectral resolution and/or radiometric point of view) sensors are used for developing and delivering water quality related remote sensing products (Palmer et al. 2015). On the other hand, OLCI on Sentinel-3 is currently used to provide turbidity, Trophic State Index and reflectance for >4200 lakes. This is a

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small fraction of the total number of lakes on Earth (117 million according to (Verpoorter et al. 2014), but these 4200 lakes contain the majority of lake area and volume on Earth. Moreover, as described above, MSI on Sentinel-2 allows mapping of some water quality parameters in smaller lakes and rivers and supports detection of shallow water and floating matter products which are not currently in the Copernicus portfolio. Consequently, there are both user needs and existing technical capabilities to expand the Copernicus water quality services portfolio in these areas. Several of the above-mentioned products require further validation in a wide variety of lakes and coastal waters in order to offer robust products that can be delivered through the Copernicus services. There are also products that are already delivered by industry and/or academia using Copernicus or commercial data. Further stakeholder consultation may prove useful to determine whether the Copernicus core or downstream (including on-demand) services are more appropriate as a delivery mechanism.

5. References

Ade, C., Khanna, S., Lay, M., Ustin, S.L., Hestir, E.L., 2022. Genus-Level Mapping of Invasive Floating Aquatic Vegetation Using Sentinel-2 Satellite Remote Sensing. Remote Sens (Basel) 14, 3013. https://doi.org/10.3390/rs14133013

Ahn, Y.H., Shanmugam, P., 2006. Detecting the red tide algal blooms from satellite ocean color observations in optically complex Northeast-Asia Coastal waters. Remote Sens Environ 103, 419–437. https://doi.org/10.1016/J.RSE.2006.04.007

Al-Ruzouq, R., Gibril, M.B.A., Shanableh, A., Kais, A., Hamed, O., Al-Mansoori, S., Khalil, M.A., 2020. Sensors, features, and machine learning for oil spill detection and monitoring: A review. Remote Sens (Basel) 12, 1–42. https://doi.org/10.3390/RS12203338

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Aoyama, T., 2016. Extraction of marine debris in the Sea of Japan using high-spatial-resolution satellite images, in: Frouin, R.J., Shenoi, S.C., Rao, K.H. (Eds.), SPIE, p. 987817. https://doi.org/10.1117/12.2220370

Arst, H., Kutser, T., 1994. Data processing and interpretation of sea radiance factor measurements. Polar Res 13, 3–12. https://doi.org/10.1111/j.1751-8369.1994.tb00432.x

Arst, H., Nõges, T., Nõges, P., Paavel, B., 2008. In situ measurements and model calculations of primary production in turbid waters. Aquat. Biol. 2008, 3, 19–30. https://doi.org/10.3354/ab00059.

Atamanchuk, D., Tengberg, A., Thomas, P.J., Hovdenes, J., Apostolidis, A., Huber, C., Hall, P.O.J., 2014. Performance of a lifetime-based optode for measuring partial pressure of carbon dioxide in natural waters. Limnol Oceanogr Methods 12, 63–73. https://doi.org/10.4319/lom.2014.12.63

Babin, M., Cullen, J.J., Roesler, C.S., Donaghay, P.L., Doucette, G.J., Kahru, M., Lewis, M.R., Scholin, C.A., Sieracki, M.E., Sosik, H.M., 2005. New approaches and technologies for observing harmful algal blooms. Oceanography 18, 210–227. https://doi.org/10.5670/OCEANOG.2005.55

Bai, Y., Cai, W.J., He, X., Zhai, W., Pan, D., Dai, M., Yu, P., 2015. A mechanistic semi-analytical method for remotely sensing sea surface pCO2 in river-dominated coastal oceans: A case study from the East China Sea. J Geophys Res Oceans 120, 2331–2349. https://doi.org/10.1002/2014JC010632

Bai, Y., Cai, W.J., He, X., Zhai, W., Pan, D., Dai, M., Yu, P., 2015. A mechanistic semi-analytical method for remotely sensing sea surface pCO2 in river-dominated coastal oceans: A case study from the East China Sea. J Geophys Res Oceans 120, 2331–2349. https://doi.org/10.1002/2014JC010632

Bai, Y., Zhu, Q., Wang, D., Lu, H., Chen, X., Gong, F., 2017. Satellite remote sensing of the aquatic pCO2 in the basin of the South China Sea 50. https://doi.org/10.1117/12.2278057

Bak, S.-H., Yoon, H.-J., 2016. Analysis on optical property in the South Sea of Korea by using Satellite Image : Study of Case on red tide occurrence in August 2013. The Journal of the Korea institute of electronic communication sciences 11, 723–728. https://doi.org/10.13067/JKIECS.2016.11.7.723

Baliarsingh, S.K., Dwivedi, R.M., Lotliker, A.A., Sahu, K.C., Kumar, T.S., Shenoi, S.S.C., 2017. An optical remote sensing approach for ecological monitoring of red and green Noctiluca scintillans. Environ Monit Assess 189. https://doi.org/10.1007/s10661-017-6037-9

Basu, B., Sannigrahi, S., Basu, A.S., Pilla, F., 2021. Development of novel classification algorithms for detection of floating plastic debris in coastal waterbodies using multispectral sentinel-2 remote sensing imagery. Remote Sens (Basel) 13. https://doi.org/10.3390/rs13081598

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Behrenfeld M.J., Falkowski P.G. 1997. A consumer's guide to phytoplankton primary productivity model. Limnology and Oceanography, 42, 1479-1491.

Bertani, I., Steger, C.E., Obenour, D.R., Fahnenstiel, G.L., Bridgeman, T.B., Johengen, T.H., Sayers, M.J., Shuchman, R.A., Scavia, D., 2017. Tracking cyanobacteria blooms: Do different monitoring approaches tell the same story? Science of The Total Environment 575, 294–308. https://doi.org/10.1016/J.SCITOTENV.2016.10.023

Biermann, L., Clewley, D., Martinez-Vicente, V., Topouzelis, K., 2020a. Finding Plastic Patches in Coastal Waters using Optical Satellite Data. Sci Rep 10. https://doi.org/10.1038/s41598-020-62298-z

Biermann, L., Clewley, D., Martinez-Vicente, V., Topouzelis, K., 2020b. finding plastic patches in coastal Waters using optical Satellite Data. Scientific RepoRtS | 10. https://doi.org/10.1038/s41598-020-62298-z

Bishop, C.M. 1994. Mixture Density Networks: NCRG/94/004 Aston University, Aston, UK (1994)

Blanchet, C. C., C. Arzel, A. Davranche, and others. 2022. Ecology and extent of freshwater browning - What we know and what should be studied next in the context of global change. Science of the Total Environment 812. doi:10.1016/j.scitotenv.2021.152420

Blauw, A.N., Los, F.J., Huisman, J., Peperzak, L., 2010. Nuisance foam events and Phaeocystis globosa blooms in Dutch coastal waters analyzed with fuzzy logic. Journal of Marine Systems 83, 115–126. https://doi.org/10.1016/j.jmarsys.2010.05.003

Blondeau-Patissier, D., Gower, J.F.R., Dekker, A.G., Phinn, S.R., Brando, V.E., 2014. A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans. Prog Oceanogr 123, 123–144. https://doi.org/10.1016/j.pocean.2013.12.008

Bouvet, G.; Ferraris, J.; Andrefouet, S. 2003. Evaluation of large-scale unsupervised classification of New Caledonia reef ecosystems using Landsat 7 ETM+ imagery. Oceanologica Acta 26, 281–290.

Brando, V.E., Dekker, A.G., 2003. Satellite hyperspectral remote sensing for estimating estuarine and coastal water quality IEEE Transactions on Geoscience and Remote Sensing 41, 1378-1387.

Brezonik, P. L., Menken, K., Bauer, M. E., 2005. Landsat-based remote sensing of lake water quality characteristics, including chlorophyll and colored dissolved organic matter (CDOM). Lake and Reservoir Management 21(4), 373–382.

Brezonik, P.L., J.C. Finlay, C.G. Griffin, W.A. Arnold, E.H. Boardman, N. Germolus, R.M. Hozalski and L.G. Olmanson, 2019. Iron influence on dissolved color in lakes of the Upper Great Lakes States. PLoS One **14**. doi:10.1371/journal.pone.0211979

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Brezonik, P.L., Olmanson, L.G. Finlay, J.C. Bauer, M.E., 2015. Factors affecting the measurements of CDOM by remote sensing of optically complex inland waters. Remote Sensing of Environment 157, 199-215.

Campbell, G. Phinn, S.R., Dekker, A.G., Brando, V.E., 2011. Remote sensing of water quality in an Australian tropical freshwater impoundment using matrix inversion and MERIS images. Remote Sensing of Environment 115, 2402–2414.

Campbell, J.B. Introduction to Remote Sensing, 4th ed.; The Guilford Press: New York, NY, USA, 2007.

Casal, G.; Hedley, J.D.; Monteys, X.; Harris, P.; Cahalane, C.; McCarthy, T. 2020. Satellite-derived bathymetry in optically complex waters using a model inversion approach and Sentinel-2 data. Estuarine, Coastal and Shelf Science, Volume 241, 2020, 106814.

CEOS, 2018. Feasibility Study for an Aquatic Ecosystem Earth Observing System 195.

Chaffin, J.D., Bratton, J.F., Verhamme, E.M., Bair, H.B., Beecher, A.A., Binding, C.E., Birbeck, J.A., Bridgeman, T.B., Chang, X., Crossman Jill and Currie, W.J.S., Davis, T.W., Dick, G.J., Drouillard, K.G., Errera, R.M., Frenken, T., MacIsaac, H.J., McClure, A., McKay, R.M., Reitz, L.A., Santo Domingo, J.W., Stanislawczyk, K., Stumpf, R.P., Swan, Z.D., Snyder, B.K., Westrick, J.A., Xue, P., Yancey, C.E., Zastepa, A., Zhou, X., 2021. The Lake Erie HABs Grab: A binational collaboration to characterize the western basin cyanobacterial harmful algal blooms at an unprecedented high-resolution spatial scale. Harmful Algae 108. https://doi.org/10.1016/j.hal.2021.102080

Chang, N. bin, Xuan, Z., Yang, Y.J., 2013. Exploring spatiotemporal patterns of phosphorus concentrations in a coastal bay with MODIS images and machine learning models. Remote Sens Environ 134, 100–110. https://doi.org/10.1016/j.rse.2013.03.002

Chen, J., Quan, W., Cui, T., Song, Q., Lin, C., 2014. Remote sensing of absorption and scattering coefficient using neural network model: Development, validation, and application. Remote Sens Environ 149, 213–226. https://doi.org/10.1016/j.rse.2014.04.013

Chen, S., Hu, C., Cai, W.J., Yang, B., 2017. Estimating surface pCO2 in the northern Gulf of Mexico: Which remote sensing model to use? Cont Shelf Res 151, 94–110. https://doi.org/10.1016/J.CSR.2017.10.013

Ciappa, A.C., 2022. Marine Litter Detection by Sentinel-2: A Case Study in North Adriatic (Summer 2020). Remote Sens (Basel) 14, 2409. https://doi.org/10.3390/rs14102409

Concha, J.A., Schott, J.R., 2016. Retrieval of color producing agents in Case 2 waters using Landsat 8. Remote Sens Environ 185, 95–107.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Cullen, J.J., Ciotti, Á.M., Davis, R.F., Lewis, M.R., 1997. Optical detection and assessment of algal blooms. Limnol Oceanogr 42, 1223–1239. https://doi.org/10.4319/LO.1997.42.5_PART_2.1223

Cunningham, A., Wood, P., Jones, K., 2001. Reflectance properties of hydrographically and optically stratified fjords (scottish sea lochs) during the spring diatom bloom. Int J Remote Sens 22, 2885–2897. https://doi.org/10.1080/01431160118022

Dall'Olmo, G., Gitelson, A.A., 2005. Effect of bio-optical parameter variability on the remote estimation of chlorophyll-a concentration in turbid productive waters: experimental results. Applied Optics, Vol. 44, Issue 3, pp. 412-422 44, 412–422.

Dall'Olmo, G., Gitelson, A.A., 2006. Effect of bio-optical parameter variability and uncertainties in reflectance measurements on the remote estimation of chlorophyll-a concentration in turbid productive waters: modeling results. Applied Optics, Vol. 45, Issue 15, pp. 3577-3592 45, 3577–3592. https://doi.org/10.1364/AO.45.003577

Dattola, L.; Rende, F.S.; Di Mento, R.; Dominici, R.; Cappa, P.; Scalise, S.; Aramini, G.; Oranges, T. 2018. Comparison of Sentinel-2 and Landsat-8 OLI satellite images vs. high spatial resolution images (MIVIS and WorldView-2) for mapping Posidonia oceanica meadows. Proc. SPIE, 10784, 1078419.

de Santi, F., Luciani, G., Bresciani, M., Giardino, C., Lovergine, F.P., Pasquariello, G., Vaiciute, D., de Carolis, G., 2019. Synergistic Use of Synthetic Aperture Radar and Optical Imagery to Monitor Surface Accumulation of Cyanobacteria in the Curonian Lagoon. Journal of Marine Science and Engineering 2019, Vol. 7, Page 461 7, 461. https://doi.org/10.3390/JMSE7120461

Dekker, A.G., 1993. Detection of optical water quality parameters for eutrophic waters by high resolution remote sensing. Management 237.

Del Vecchio, R., Subramanijam, A., 2004. Influence of the Amazon River on the surface optical properties of the western tropical North Atlantic Ocean. Journal of Geophysical Research, 109: C11001.

Dierssen, H.M., 2019. Hyperspectral measurements, parameterizations, and atmospheric correction of whitecaps and foam from visible to shortwave infrared for ocean color remote sensing. Front Earth Sci (Lausanne) 7, 683136. https://doi.org/10.3389/feart.2019.00014

Dierssen, H.M., Bostrom, K.J., Chlus, A., Hammerstrom, K., Thompson, D.R., Lee, Z., 2019. Pushing the limits of seagrass remote sensing in the turbid waters of Elkhorn Slough, California. Remote Sens (Basel) 11. https://doi.org/10.3390/rs11141664

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Dierssen, H.M., Chlus, A., Russell, B., 2015. Hyperspectral discrimination of floating mats of seagrass wrack and the macroalgae Sargassum in coastal waters of Greater Florida Bay using airborne remote sensing. Remote Sens Environ 167, 247–258. https://doi.org/10.1016/j.rse.2015.01.027
Dierssen, H.M., Chlus, A., Russell, B., 2015. Hyperspectral discrimination of floating mats of seagrass wrack and the macroalgae Sargassum in coastal waters of Greater Florida Bay using airborne remote sensing. Remote Sens Environ 167, 247–258. https://doi.org/10.1016/j.rse.2015.01.027
Dierssen, H.M., Kudela, R.M., Ryan, J.P., Zimmerman, R.C., 2006. Red and black tides: Quantitative analysis of water-leaving radiance and perceived color for phytoplankton, colored dissolved organic matter, and suspended sediments. Limnol Oceanogr 51, 2646–2659. https://doi.org/10.4319/LO.2006.51.6.2646

Ding, C., Pu, F., Li, C., Xu, X., Zou, T., Li, X., 2020. Combining Artificial Neural Networks with Causal Inference for Total Phosphorus Concentration Estimation and Sensitive Spectral Bands Exploration Using MODIS. Water (Basel) 12. https://doi.org/10.3390/w12092372

Du, C., Wang, Q., Li, Y., Lyu, H., Zhu, L., Zheng, Z., Wen, S., Liu, G., Guo, Y., 2018. Estimation of total phosphorus concentration using a water classification method in inland water. International Journal of Applied Earth Observation and Geoinformation 71, 29–42. https://doi.org/10.1016/j.jag.2018.05.007

Duan, H., Loiselle, S.A., Zhu, L., Feng, L., Zhang, Y., Ma, R., 2015. Distribution and incidence of algal blooms in Lake Taihu. Aquat Sci 77, 9–16. https://doi.org/10.1007/S00027-014-0367-2/FIGURES/5

Duarte, C.M., Prairie, Y.T., Montes, C., Cole, J.J., Striegl, R., Melack, J., Downing, J.A., 2008. CO2 emissions from saline lakes: A global estimate of a surprisingly large flux. J Geophys Res Biogeosci 113, 4041. https://doi.org/10.1029/2007JG000637

Duarte, C. M. 2017. Reviews and syntheses: hidden forests, the role of vegetated coastal habitats in the ocean carbon budget. Biogeosciences 14, 301–310. https://doi.org/10.5194/bg-14-301-2017.

Ekstrand, S., 1990. Landsat TM based quantification of chlorophyll-a during algae blooms in coastal waters. 13, 1913–1926. https://doi.org/10.1080/01431169208904240

Else, B.G.T., Yackel, J.J., Papakyriakou, T.N., 2008. Application of satellite remote sensing techniques for estimating air-sea CO2 fluxes in Hudson Bay, Canada during the ice-free season. Remote Sens Environ 112, 3550–3562. https://doi.org/10.1016/J.RSE.2008.04.013

Elvidge, C.D.; Dietz, J.B.; Berkelmans, R.; Andréfouët, S.; Skirving, W.; Strong, A.E.; Tuttle, B.T. 2004. Satellite observation of Keppel Islands (Great Barrier Reef) 2002 coral bleaching using IKONOS data. Coral Reefs, 23, 123–132.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Erlandsson, M., Futter, M.N., Kothawala, D.N., Köhler, S.J., 2012. Variability in spectral absorbance metrics across boreal lake waters. Journal of Environmental Monitoring 14, 2643–2652.

ESA, 2021. Outline of all running activities resulting from the Discovery Campaign on Marine Litter.

Fengyang, S., Shuying, Z., Yawena, F., Xinxin, L., Hongkuan, H., 2020. Establishment of a diatom-total phosphorus transfer function for lakes on the Songnen Plain in northeast China. J Oceanol Limnol 38, 1771–1786. https://doi.org/10.1007/s00343-019-9223-5

Fidai, Y.A., Dash, J., Tompkins, E.L., Tonon, T., 2020. A systematic review of floating and beach landing records of Sargassum beyond the Sargasso Sea. Environ Res Commun 2, 122001. https://doi.org/10.1088/2515-7620/ABD109

Fornes, A.; Basterretxea, G.; Orfila, A.; Jordi, A.; Alvarez, A.; Tintore, J. 2006. Mapping Posidonia oceanica from IKONOS. ISPRS J. Photogranmm, 60, 315–322.

Fu, Z., Hu, L., Chen, Z., Zhang, F., Shi, Z., Hu, B., Du, Z., Liu, R., 2020. Estimating spatial and temporal variation in ocean surface pCO2 in the Gulf of Mexico using remote sensing and machine learning techniques. Science of the Total Environment 745. https://doi.org/10.1016/J.SCITOTENV.2020.140965

Gao, Y., Gao, J., Yin, H., Liu, C., Xia, T., Wang, J., Huang, Q., 2015. Remote sensing estimation of the total phosphorus concentration in a large lake using band combinations and regional multivariate statistical modeling techniques. J Environ Manage 151, 33–43. https://doi.org/10.1016/j.jenvman.2014.11.036

Garaba, S.P., Aitken, J., Slat, B., Dierssen, H.M., Lebreton, L., Zielinski, O., Reisser, J., 2018. Sensing Ocean Plastics with an Airborne Hyperspectral Shortwave Infrared Imager. Environ Sci Technol 52, 11699–11707. https://doi.org/10.1021/ACS.EST.8B02855/ASSET/IMAGES/LARGE/ES-2018-02855J_0007.JPEG

Garaba, S.P., Dierssen, H.M., 2018. An airborne remote sensing case study of synthetic hydrocarbon detection using short wave infrared absorption features identified from marine-harvested macro- and microplastics. Remote Sens Environ 205, 224–235. https://doi.org/10.1016/J.RSE.2017.11.023

Garcia-Garin, O., Aguilar, A., Borrell, A., Gozalbes, P., Lobo, A., Penadés-Suay, J., Raga, J.A., Revuelta, O., Serrano, M., Vighi, M., 2020. Who's better at spotting? A comparison between aerial photography and observer-based methods to monitor floating marine litter and marine mega-fauna. Environmental Pollution 258, 113680. https://doi.org/10.1016/J.ENVPOL.2019.113680

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Gerardo, R., de Lima, I.P., 2022. Assessing the potential of Sentinel-2 data for tracking invasive water hyacinth in a river branch. J Appl Remote Sens 16, 014511. https://doi.org/10.1117/1.JRS.16.014511

Ghirardi, N.; Bolpagni, R.; Bresciani, M.; Valerio, G.; Pilotti, M.; Giardino, C. 2019. Spatiotemporal Dynamics of Submerged Aquatic Vegetation in a Deep Lake from Sentinel-2 Data. *Water, 11*, 563.

Giardino, C., Candiani, G., Bresciani, M., Lee, Z.P., Gagliano, S., Pepe, M., 2012. BOMBER: A tool for estimating water quality and bottom properties from remote sensing images. Computers & Geosciences 45 (2012) 313–318.

Gitelson, A., (1992) The peak near 700 nm on reflectance spectra of algae and water relationships of its magnitude and position with chlorophyll concentration. International Journal of Remote Sensing, 13, 3367-3373.

Gitelson, A., Garbuzov, G., Szilagyi, F., Mittenzwey, K.H., Karnieli, A., Kaiser, A., 1993. Quantitative remote sensing methods for real-time monitoring of inland waters quality. Int J Remote Sens 14, 1269–1295. https://doi.org/10.1080/01431169308953956

Gordon, H.R., Brown, O.B., Evans, R.H., Brown, J.W., Smith, R.C., Baker, K.S., Clark, D.K., 1988. A semianalytic radiance model of ocean colour. Journal of Geophysical Research 93, 10909-10924.

Gordon, H.R., Brown, O.B., Jacobs, M.M., 1975. Computed relationships between the inherent and apparent optical properties of a flat, homogenous ocean. Applied Optics 14, 417-427.

Gower, J, King, S., Borstad, G., Brown, L., 2005. Detection of intense plankton blooms using the 709 nm band of the MERIS imaging spectrometer Detection of intense plankton blooms using the 709 nm band of the MERIS imaging spectrometer. Int J Remote Sens 26. https://doi.org/10.1080/01431160500075857

Gower, J., Hu, C., Borstad, G., King, S., 2006. Ocean Color Satellites Show Extensive Lines of Floating Sargassum in the Gulf of Mexico. IEEE Transactions on Geoscience and Remote Sensing 44, 3619–3625. https://doi.org/10.1109/TGRS.2006.882258

Gower, J., King, S., 2007. Validation of chlorophyll fluorescence derived from MERIS on the west coast of Canada. Int J Remote Sens 28, 625–635. https://doi.org/10.1080/01431160600821010

Gower, J., King, S., 2020. The distribution of pelagic Sargassum observed with OLCI. Int J Remote Sens 41, 5669–5679. https://doi.org/10.1080/01431161.2019.1658240

Gower, J., Young, E., King, S., 2013. Satellite images suggest a new Sargassum source region in 2011. Remote Sensing Letters 4, 764–773. https://doi.org/10.1080/2150704X.2013.796433

Gower, J., Young, E., King, S., 2013. Satellite images suggest a new Sargassum source region in 2011. Remote Sensing Letters 4, 764–773. https://doi.org/10.1080/2150704X.2013.796433

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Gower, J.F., King, S.A., 2011. Distribution of floating Sargassum in the Gulf of Mexico and the Atlantic Ocean mapped using MERIS. Int J Remote Sens 32, 1917–1929. https://doi.org/10.1080/01431161003639660

Gower, J.F.R., Doerffer, R., Borstad, G.A., 1999. Interpretation of the 685nm peak in water-leaving radiance spectra in terms of fluorescence, absorption and scattering, and its observation by MERIS. Int J Remote Sens 20, 1771–1786. https://doi.org/10.1080/014311699212470

Gower, J.F.R.R., King, S.A., 2011. Distribution of floating Sargassum in the Gulf of Mexico and the Atlantic Ocean mapped using MERIS. Int J Remote Sens 32, 1917–1929. https://doi.org/10.1080/01431161003639660

Grayson, R.B., Finlayson, B.L., Gippel, C.J., Hart, B.T., 1996. The potential of field turbidity measurements for the computation of total phosphorus and suspended solids loads. J Environ Manage 47, 257–267. https://doi.org/10.1006/jema.1996.0051

Haarr, M.L., Falk-Andersson, J., Fabres, J., 2022. Global marine litter research 2015–2020: Geographical and methodological trends. Science of the Total Environment 820. https://doi.org/10.1016/J.SCITOTENV.2022.153162

Hedley, J.D., Mumby P.J., 2003. A remote sensing method for resolving depth and subpixel composition of aquatic benthos. Limnology and Oceanography, 48, 480-488.

Hedley, J.D., Roelfsema, C., Phinn S.R., 2009. Efficient radiative transfer model inversion for remote sensing applications. Remote Sensing of Environment, 113, 2527-2532.

Hedley, J. D.; Roelfsema, C.; Brando, V.; Giardino, C.; Kutser, T.; Phinn, S.; Mumby, P.J.; Barrilero, O.; Laporte, J.; Koetz, B. 2018. Coral reef applications of Sentinel-2: Coverage, characteristics, bathymetry and benthic mapping with comparison to Landsat 8, Remote Sensing of Environment, Volume 216, 598-614.

Hedley, J.; Russell, B.; Randolph, K.; Dierssen, H. 2016. A physics-based method for the remote sensing of seagrasses. Remote Sens Environ., 174, 134–147.

Hestir, E. Brando. V.E., Campbell, G., Dekker, A.G., Malthus, T., 2015. The relationship between dissolved organic matter absorption and dissolved organic carbon in reservoirs along a temperate to tropical gradient. Remote Sensing of Environment 156, 395–402.

Hilker, T.; Coops, N.; Wulder, M.; Black, T.A.; Guy, R.D. 2008. The use of remote sensing in light use efficiency based models of gross primary production: A review of current status and future requirements. Sci. Total Environ., 404, 411–423.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Hill, V. J., Zimmermann, R. C., Bissett, W. P., Dierssen, H., Kohler, D. D. R. 2014. Evaluating Light Availability, Seagrass Biomass, and Productivity Using Hyperspectral Airborne Remote Sensing in Saint Joseph's Bay, Florida. Estuaries and Coasts, 37, 1467-1489.

Hirtle, H. & Rencz, A.. (2003). The relation between spectral reflectance and dissolved organic carbon in lake water: Kejimkujik National Park, Nova Scotia, Canada. International Journal of Remote Sensing - Inetrnational Journal of Remote Sensing, 24, 953-967.

Hochberg, E.J., Apprill, A.M., Atkinson, M.J., Bidigare R.R. (2006) Bio-optical modelling of photosynthetic pigments in corals. Coral Reefs, 25, 99-109.

Hochberg, E.J., Atkinson, M.J., Apprill, A., Andréfouët, S., 2004. Spectral reflectance of coral. Coral Reefs 23, 84–95. https://doi.org/10.1007/S00338-003-0350-1

Hoge, F.E., Lyon, P.E. 1996. Satellite retrieval of inherent optical properties by linear matrix inversion of oceanic radiance models: An analysis of model and radiance measurement errors. Journal of Geophysical Research 101, 16631–16648.

Holden, H., LeDrew, E., 1998. Spectral Discrimination of Healthy and Non-Healthy Corals Based on Cluster Analysis, Principal Components Analysis, and Derivative Spectroscopy. Remote Sens Environ 65, 217–224. https://doi.org/10.1016/S0034-4257(98)00029-7

Holden, H., Ledrew, E., 1999. Hyperspectral identification of coral reef features. Int J Remote Sens 20, 2545–2563. https://doi.org/10.1080/014311699212119211

Holden, R.J., Pakula, I.S., Mooney, P.A., 1997. A neuroimmunological model of schizophrenia and major depression: A review. Hum Psychopharmacol 12, 177–201. https://doi.org/10.1002/(SICI)1099-1077(199705/06)12:3<177::AID-HUP869>3.0.CO;2-D

Holligan, P.M., Viollier, M., Dupouy, C., Aiken, J., 1983. Satellite studies on the distributions of chlorophyll and dinoflagellate blooms in the western English Channel. Cont Shelf Res 2, 81–96. https://doi.org/10.1016/0278-4343(83)90009-2

Hoogenboom, H.J., Dekker, A.G., de Haan, J.F., 1998. Retrieval of chlorophyll and suspended matter from imaging spectrometry data by matrix inversion. Canadian Journal of Remote Sensing 24, 144–152. https://doi.org/10.1080/07038992.1998.10855234

Hossen, H., Mahmod, W.E., Negm, A., Nakamura, T., 2022. Assessing Water Quality Parameters in Burullus Lake Using Sentinel-2 Satellite Images. Water Resources 49, 321–331. https://doi.org/10.1134/S0097807822020087, https://doi.org/10.1016/j.rse.2016.03.018, https://doi.org/10.1364/AO.44.000412

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Hu, C., 2022a. Remote detection of marine debris using Sentinel-2 imagery: A cautious note on spectral interpretations. Mar Pollut Bull 183. https://doi.org/10.1016/j.marpolbul.2022.114082

Hu, C., Cannizzaro, J., Carder, K.L., Muller-Karger, F.E., Hardy, R., 2010a. Remote detection of Trichodesmium blooms in optically complex coastal waters: Examples with MODIS full-spectral data. https://doi.org/10.1016/j.rse.2010.04.011

Hu, C., Feng, L., 2016. Modified MODIS fluorescence line height data product to improve image interpretation for red tide monitoring in the eastern Gulf of Mexico. J Appl Remote Sens 11, 012003. https://doi.org/10.1117/1.JRS.11.012003

Hu, C., Feng, L., Hardy, R.F., Hochberg, E.J., 2015. Spectral and spatial requirements of remote measurements of pelagic Sargassum macroalgae. Remote Sens Environ 167, 229–246. https://doi.org/10.1016/J.RSE.2015.05.022

Hu, C., Li, D., Chen, C., Ge, J., Muller-Karger, F.E., Liu, J., Yu, F., He, M.X., 2010b. On the recurrent Ulva prolifera blooms in the Yellow Sea and East China Sea. J Geophys Res Oceans 115. https://doi.org/10.1029/2009JC005561

Hu, C., Muller-Karger, F.E., Taylor, C., Carder, K.L., Kelble, C., Johns, E., Heil, C.A., 2005. Red tide detection and tracing using MODIS fluorescence data: A regional example in SW Florida coastal waters. Remote Sens Environ 97, 311–321. https://doi.org/10.1016/j.rse.2005.05.013

Hu, C., Qi, L., English D.C., Wand, :, Mikelson K., Barnes, B-B-, Pawlik, M.M., Fick, D. (2023) Pollen in the Baltic Sea as viewed from space. Remote Sensing of Environment, 284, 113337.

Hu, L., Hu, C., He, M.-X., 2017. Remote estimation of biomass of Ulva prolifera macroalgae in the Yellow Sea-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/). https://doi.org/10.1016/j.rse.2017.01.037

Huang, W.J., Cai, W.J., Castelao, R.M., Wang, Y., Lohrenz, S.E., 2013. Effects of a wind-driven cross-shelf large river plume on biological production and CO2 uptake on the Gulf of Mexico during spring. Limnol Oceanogr 58, 1727–1735. https://doi.org/10.4319/LO.2013.58.5.1727

IOCCG, 2021. Observation of Harmful Algal Blooms with Ocean Colour Radiometry. International Ocean Colour Coordinating Group, Dartmouth, Canada. https://doi.org/10.25607/OBP-1042

Isenstein, E.M., Park, M.H., 2014. Assessment of nutrient distributions in Lake Champlain using satellite remote sensing. J Environ Sci (China) 26, 1831–1836. https://doi.org/10.1016/j.jes.2014.06.019

Janssens, N., Schreyers, L., Biermann, L., van der Ploeg, M., Bui, T.K.L., van Emmerik, T., 2022. Rivers running green: water hyacinth invasion monitored from space. Environmental Research Letters 17, 044069. https://doi.org/10.1088/1748-9326/AC52CA

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Jeffrey, S.W., Wright, S.W., Zapata, M., 2011. Microalgal classes and their signature pigments. Phytoplankton Pigments 3–77. https://doi.org/10.1017/CBO9780511732263.004

Jia, T., Zhang, X., Dong, R., 2019. Long-Term Spatial and Temporal Monitoring of Cyanobacteria Blooms Using MODIS on Google Earth Engine: A Case Study in Taihu Lake. Remote Sensing 2019, Vol. 11, Page 2269 11, 2269. https://doi.org/10.3390/RS11192269

Jimenez-Mariani, C., 2020. Sargassum Monitoring. ESA project Final Report. Reference CLS-ENV-RP-20-0415. p. 47.

Jonsson, A., Åberg, J., Jansson, M., 2007. Variations in p CO2 during summer in the surface water of an unproductive lake in northern Sweden. Tellus B Chem Phys Meteorol 59, 797–803. https://doi.org/10.1111/J.1600-0889.2007.00307.X

Jupp, D.L.B., Kirk, J.T.O., Harris, G.P., 1994. Detection, identification and mapping of cyanobacteria: using remote sensing to measure the optical quality of turbid inland waters. Mar Freshw Res 45, 801–828. https://doi.org/10.1071/MF9940801

Kallio, K., 1999. Absorption properties of dissolved organic matter in Finnish lakes. Proceedings of the Estonian Academy of Sciences, Biology and Ecology 48, 75–83.

Kallio, K., Koponen, S., Pulliainen, J., 2003. Feasibility of airborne imaging spectrometry for lake monitoring - A case study of spatial chlorophyll a distribution in two meso-eutrophic lakes. Int J Remote Sens 24, 3771–3790. https://doi.org/10.1080/0143116021000023899

Kallio, K., Kutser, T., Hannonen, T., Koponen, S., Pulliainen, J., Vepsäläinen, J., Pyhälahti, T., 2001. Retrieval of water quality from airborne imaging spectrometry of various lake types in different seasons. Science of The Total Environment 268, 59–77. https://doi.org/10.1016/S0048-9697(00)00685-9

Kämäri, M., Tarvainen, M., Kotamäki, N., Tattari, S., 2020. High-frequency measured turbidity as a surrogate for phosphorus in boreal zone rivers: appropriate options and critical situations. Environ Monit Assess 192, 1–20. https://doi.org/10.1007/S10661-020-08335-W/FIGURES/6

Karlsson, J., A.K. Bergström, P. Byström, C. Gudasz, P. Rodríguez and C. Hein, 2015. Terrestrial organic matter input suppresses biomass production in lake ecosystems. Ecology **96**. doi:10.1890/15-0515.1

Kauer, T., Arst, H., Nõges, T., Arst, G.-E., 2013. Development and application of a phytoplankton primary production model for well-mixed lakes. Proc. Est. Acad. Sci., 62, 267. https://doi.org/10.3176/proc.2013.4.07.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Kauer, T., Arst, H., Nõges, T., Tuvikene, L., 2009. Estimation of the phytoplankton productivity in three Estonian lakes. Est. J. Ecol., 58, 297, https://doi.org/10.3176/eco.2009.4.05.

Kauer, T., Kutser, T., Arst, H., Danckaert, T., Nõges, T., 2015. Modelling primary production in shallow well mixed lakes based on MERIS satellite data. Remote Sens. Environ. 163, 253–261. https://doi.org/10.1016/j.rse.2015.03.023.

Khalili, M.H., Hasanlou, M., 2019. Harmful algal blooms monitoring using sentinel-2 satellite images. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives 42, 609–613. https://doi.org/10.5194/ISPRS-ARCHIVES-XLII-4-W18-609-2019

Kikaki, A., Karantzalos, K., Power, C.A., Raitsos, D.E., 2020. Remotely Sensing the Source and Transport of Marine Plastic Debris in Bay Islands of Honduras (Caribbean Sea). Remote Sensing 2020, Vol. 12, Page 1727 12, 1727. https://doi.org/10.3390/RS12111727

Kislik, C., Dronova, I., Grantham, T.E., Kelly, M., 2022. Mapping algal bloom dynamics in small reservoirs using Sentinel-2 imagery in Google Earth Engine. Ecol Indic 140, 109041. https://doi.org/10.1016/J.ECOLIND.2022.109041

Knaeps, E., Sterckx, S., Strackx, G., Mijnendonckx, J., Moshtaghi, M., Garaba, S.P., Meire, D., 2021. Hyperspectral-reflectance dataset of dry, wet and submerged marine litter. Earth Syst Sci Data 13, 713–730. https://doi.org/10.5194/essd-13-713-2021

Knudby, A., Nordlund, L. 2011. Remote sensing of seagrasses in a patchy multi-species environment. International Journal of Remote Sensing, 32 (8), 2227-2244.

Koedsin, W.; Intararuang, W.; Ritchie, R.J.; Huete, A., 2016. An Integrated Field and Remote Sensing Method for Mapping Seagrass Species, Cover, and Biomass in Southern Thailand. Remote Sens, 8, 292.

Koivusalo, M., Pukkala, E., Vartianen, T., Jaakola, J.J., Hakulinen, T ., 1997. Drinking water chlorination and cancer – a historical cohort study in Finland. Cancer, Causes, Control, 8, 192-200.

Koll-Egyed, T., Cardille, J.A., Deutsch, E., 2021. Multiple Images Improve Lake CDOM Estimation: Building Better Landsat 8 Empirical Algorithms across Southern Canada. Remote Sens (Basel) 13, 3615. https://doi.org/10.3390/rs13183615

Kortelainen, P., Rantakari, M., Huttunen, J.T., Mattsson, T., Alm, J., Juutinen, S., Larmola, T., Silvola, J., Martikainen, P.J., 2006. Sediment respiration and lake trophic state are important predictors of large CO2 evasion from small boreal lakes. Glob Chang Biol 12, 1554–1567. https://doi.org/10.1111/J.1365-2486.2006.01167.X

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Kovacs, E., Roelfsema, C.; Lyons, M.; Zhao, S.; Phinn, S. 2018. Seagrass habitat mapping: how do Landsat 8 OLI, Sentinel-2, ZY-3A, and Worldview-3 perform?, Remote Sensing Letters, 9:7, 686-695.

Kowalczuk, P., Darecki, M., Zablocka, M., Gorecka, I., 2010. Validation of empirical and semi-analytical remote sensing algorithms for estimating absorption by Coloured Dissolved Organic Matter in the Baltic Sea from SeaWiFS and MODIS imagery. Oceanologia 52, 171-196.

Kremezi, M., Kristollari, V., Karathanassi, V., Topouzelis, K., Kolokoussis, P., Taggio, N., Aiello, A., Ceriola, G., Barbone, E., Corradi, P., 2022. Increasing the Sentinel-2 potential for marine plastic litter monitoring through image fusion techniques. Mar Pollut Bull 182. https://doi.org/10.1016/j.marpolbul.2022.113974

Kritzberg, E. S., E. M. Hasselquist, M. Škerlep, and others. 2020. Browning of freshwaters: Consequences to ecosystem services, underlying drivers, and potential mitigation measures. Ambio 49. doi:10.1007/s13280-019-01227-5

Kritzberg, E.S., 2017. Centennial-long trends of lake browning show major effect of afforestation. Limnol Oceanogr Lett **2**. doi:10.1002/lol2.10041

Kuhwald, K., Schneider von Deimling, J., Schubert, P. R., Oppelt, N., Scales, K. and Lecours, V. 2022. How can Sentinel-2 contribute to seagrass mapping in shallow, turbid Baltic Sea waters?. Open Access Remote Sensing in Ecology and Conservation, 8 (3). pp. 328-346.

Kusari, L., 2022. Turbidity as a Surrogate for the Determination of Total Phosphorus, Using Relationship Based on Sub-Sampling Techniques. Ecological Engineering & Environmental Technology 23, 88–93. https://doi.org/10.12912/27197050/150233

Kutser T., 1997. Estimation of water quality in turbid inland and coastal waters by passive optical remote sensing. Dissertationes Geophysicales Universitas Tartuensis 8, Tartu University Press. 161 pp.

Kutser, T. 2010. Global change and remote sensing of CDOM in arctic coastal waters. *OCEANS'10 IEEE Sydney, OCEANSSYD 2010*.

Kutser, T., 2004. Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing. Limnol Oceanogr 49, 2179–2189. https://doi.org/10.4319/LO.2004.49.6.2179

Kutser, T., 2009. Passive optical remote sensing of cyanobacteria and other intense phytoplankton blooms in coastal and inland waters. Int J Remote Sens 30, 4401–4425. https://doi.org/10.1080/01431160802562305

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Kutser, T., Alikas, K., Kothawala, D.N., Köhler, S.J., 2015a. Impact of iron associated to organic matter on remote sensing estimates of lake carbon content. Remote Sensing of Environment 156, 109–116.

Kutser, T., Arst, H., 1994. A Remote Sensing Reflectance Model of Optically-Active Components of Turbid Waters, In: Johannessen, J.A., Guymer, T.H. (Eds.), Oceanic Remote Sensing And Sea Ice Monitoring, Proceedings Of The Society Of Photo-Optical Instrumentation Engineers (Spie). Pp. 85–91.

Kutser, T., Arst, H., Maekivi, S., 1995. Estimation of water quality by passive optical remote measurements, in: Askne, J. (Ed.), Sensors and Environmental Applications of Remote Sensing. pp. 281–288.

Kutser, T., Arst, H., Mäekivi, S., Kallaste, K., 1998c. Estimation of the water quality of the Baltic Sea and some lakes in Estonia and Finland by passive optical remote sensing measurements on board a vessel. Lakes and Reservoirs; Research and Management 3, 53-66.

Kutser, T., Arst, H., Maekivi, S., Leppanen, J.M., Blanco, A., 1997. Monitoring of algae blooms by optical remote sensing, in: Spiteri, A. (Ed.), Remote Sensing `96: Integrated Applications For Risk Assessment And Disaster Prevention For The Mediterranean. Pp. 161–166.

Kutser, T., Arst, H., Miller, T., Käärmann, L., Milius, A., 1995b. Telespectrometrical estimation of water transparency, chlorophyll-a and total phosphorus concentration of Lake Peipsi. Int J Remote Sens 16, 3069–3085. https://doi.org/10.1080/01431169508954609

Kutser, T., Blanco, A., Arst, H., 1996. Evaluation of remote sensing algorithms for the retrieval of optically-active components in turbid natural waters, in: IGARSS `96 - 1996 International Geoscience And Remote Sensing Symposium: Remote Sensing For A Sustainable Future, Vols I - IV. pp. 76–78.

Kutser, T., Casal Pascual, G., Barbosa, C., Paavel, B., Ferreira, R., Carvalho, L. Toming, K., 2016a. Mapping inland water carbon content with Landsat 8 data. International Journal of Remote Sensing 37, 2950-2961.

Kutser, T., Eloheimo, K., Hannonen, T., Harma, P., Kirkkala, T., Koponen, S., Pullianen, J., Pyhalahti, T., 1998a. Monitoring of coastal waters of the Baltic Sea by airborne imaging spectrometer AISA, in: Brebbia, C.A. (Ed.), Environmental Coastal Regions. pp. 123–134.

Kutser, T., Hannonen, T., Kallio, K., Koponen, K., Pulliainen, J., Pyhalahti, T., Servomaa, H., 1998b. Monitoring of turbid coastal and inland waters by airborne imaging spectrometer AISA, in: Stein, T.I. (Ed.), IGARSS '98. Sensing and Managing the Environment. 1998 IEEE International

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Geoscience and Remote Sensing. Symposium Proceedings. (Cat. No.98CH36174), IEEE International Symposium on Geoscience and Remote Sensing (IGARSS). IEEE, pp. 2597–2599 vol.5. https://doi.org/10.1109/IGARSS.1998.702290

Kutser, T., Hedley, J., Giardino, C., Roelfsema, C., Brando, V.E., 2020. Remote sensing of shallow waters-A 50 year retrospective and future directions. Remote Sensing of Environment 240, 111619. https://doi.org/10.1016/j.rse.2019.111619

Kutser, T., Herlevi, A., Kallio, K., Arst, H., 2001. A hyperspectral model for interpretation of passive optical remote sensing data from turbid lakes. The Science of the Total Environment 268, 47-58.

Kutser, T., Jupp, D.L.B., 2006. On the possibility of mapping living corals to the species level based on their optical signatures. Estuar Coast Shelf Sci 69, 607–614. https://doi.org/10.1016/j.ecss.2006.05.026

Kutser, T., Ligi, M. Browning of the world largest lakes. In preparation.

Kutser, T., Metsamaa, L., Strömbeck, N., Vahtmäe, E., 2006a. Monitoring cyanobacterial blooms by satellite remote sensing. Estuar Coast Shelf Sci 67, 303–312. https://doi.org/10.1016/J.ECSS.2005.11.024

Kutser, T., Miller, I., Jupp, D.L.B., 2002. Mapping coral reef benthic habitat with hyperspectral space borne sensor. Proceedings of Ocean Optics XVI, Santa Fe, USA. (CD-ROM)

Kutser, T., Miller, I., Jupp, D.L.B., 2006. Mapping coral reef benthic substrates using hyperspectral space-borne images and spectral libraries. Estuar Coast Shelf Sci 70, 449–460. https://doi.org/10.1016/j.ecss.2006.06.026

Kutser, T., Paavel, P. Verpoorter, C., Ligi, M., Soomets, T., Toming, K., Casal, K., 2016b. Remote Sensing of black lakes and using 810 nm reflectance peak for retrieving water quality parameters of optically complex waters. Remote Sensing, 8, 497, doi:10.3390/rs8060497.

Kutser, T., Pierson, D.C., Kallio, K.Y., Reinart, A., Sobek, S., 2005. Mapping lake CDOM by satellite remote sensing. Remote Sens Environ 94, 535–540. https://doi.org/10.1016/J.RSE.2004.11.009

Kutser, T., Pierson, D.C., Tranvik, L., Reinart, A., Sobek, S., Kallio, K., 2005a. Using satellite remote sensing to estimate the coloured dissolved organic matter absorption coefficient in lakes. Ecosystems 8, 709–720.

Kutser, T., Vahtmäe, E., Martin, G., 2006. Assessing suitability of multispectral satellites for mapping benthic macroalgal cover in turbid coastal waters by means of model simulations. Estuar Coast Shelf Sci 67, 521–529. https://doi.org/10.1016/j.ecss.2005.12.004

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Kutser, T., Verpoorter, C., Paavel, B., Tranvik, L.J., 2015. Estimating lake carbon fractions from remote sensing data. Remote Sens Environ 157, 138–146. https://doi.org/10.1016/J.RSE.2014.05.020

Kutser, T., Verpoorter, C., Paavel, B., Tranvik, L.J., 2015b. Estimating lake carbon fractions from remote sensing data. Remote Sensing of Environment 157, 138–146.

Laffoley, D.d'A. & Grimsditch, G. (eds). 2009. The management of natural coastal carbon sinks. IUCN, Gland, Switzerland. 53 pp

Lancelot, C., 1995. The mucilage phenomenon in the continental coastal waters of the North Sea. Science of The Total Environment 165, 83–102. https://doi.org/10.1016/0048-9697(95)04545-C

Lannergård, E.E., Ledesma, J.L.J., Fölster, J., Futter, M.N., 2019. An evaluation of high frequency turbidity as a proxy for riverine total phosphorus concentrations. Science of The Total Environment 651, 103–113. https://doi.org/10.1016/J.SCITOTENV.2018.09.127

Lavender, S.J., Groom, S.B., 2001. The detection and mapping of algal blooms from space. 22, 197–201. https://doi.org/10.1080/014311601449899

Lazzarino, J.K., Bachmann, R.W., Hoyer, M. v., Canfield, D.E., 2009. Carbon dioxide supersaturation in Florida lakes. Hydrobiologia 627, 169–180. https://doi.org/10.1007/S10750-009-9723-Y/TABLES/4

Lee, Z.P., Carder, K. L., Arnone, R. A., 2002. Deriving inherent optical properties from water color: A multiband quasi-analytical algorithm for optically deep waters. Applied Optics 41, 5755–5772.

Lesser, M.P., Mobley, C.D., 2007. Bathymetry, water optical properties, and benthic classification of coral reefs using hyperspectral remote sensing imagery. Coral Reefs, 26, 819–829.

Liu, G., Li, S., Song, K., Wang, X., Wen, Z., Kutser, T., Jacinthe, P.-A., Shang, Y., Lyu, L., Fang, C., Yang, Y., Yang, Q., Zhang, B., Cheng, S., Hou, J., 2021. Remote sensing of CDOM and DOC in alpine lakes across the Qinghai-Tibet Plateau using Sentinel-2A imagery data. J Environ Manage 286, 112231. https://doi.org/10.1016/j.jenvman.2021.112231

Liu, J., Zhang, Y., Yuan, D., Song, X., 2015. Empirical Estimation of Total Nitrogen and Total Phosphorus Concentration of Urban Water Bodies in China Using High Resolution IKONOS Multispectral Imagery. Water (Basel) 7, 6551–6573. https://doi.org/10.3390/w7116551

Liu, M., Ling, H., Wu, D., Su, X., Cao, Z., 2021. Sentinel-2 and Landsat-8 Observations for Harmful Algae Blooms in a Small Eutrophic Lake. Remote Sensing 2021, Vol. 13, Page 4479 13, 4479. https://doi.org/10.3390/RS13214479

Liu, R., Xiao, Y., Cui, T., An, J. 2022. Red tide detection based on high spatial resolution broad band optical satellite data. ISPRS Journal of Photogrammetry and remote sensing, 184, 131-147.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Liu, R., Xiao, Y., Ma, Y., Cui, T., An, J., 2022. Red tide detection based on high spatial resolution broad band optical satellite data. ISPRS Journal of Photogrammetry and Remote Sensing 184, 131–147. https://doi.org/10.1016/J.ISPRSJPRS.2021.12.009

Liu, R.J., Liu, R.J., Zhang, J., Cui, B.G., Ma, Y., Song, P.J., An, J.B., 2019. Red tide detection based on high spatial resolution broad band satellite data: A case study of GF-1. J Coast Res 90, 120–128. https://doi.org/10.2112/SI90-015.1

Lu, S., Deng, R., Liang, Y., Xiong, L., Ai, X., Qin, Y., 2020. Remote Sensing Retrieval of Total Phosphorus in the Pearl River Channels Based on the GF-1 Remote Sensing Data. Remote Sens (Basel) 12, 1420. https://doi.org/10.3390/rs12091420

Lu, Y., Shi, J., Hu, C., Zhang, M., Sun, S., Liu, Y., 2020. Optical interpretation of oil emulsions in the ocean – Part II: Applications to multi-band coarse-resolution imagery. Remote Sens Environ 242, 111778. https://doi.org/10.1016/j.rse.2020.111778

Lyons, M.B.; Phinn, S.R.; Roelfsema, C.M. 2012. Long term land cover and seagrass mapping using Landsat and object-based image analysis from 1972 to 2010 in the coastal environment of South East Queensland, Australia. ISPRS J. Photogramm. Remote Sens., 71, 34–46.

Lyu, H., Wang, Y., Jin, Q., Shi, L., Li, Y., Wang, Q., 2017. Developing a semi-analytical algorithm to estimate particulate organic carbon (POC) levels in inland eutrophic turbid water based on MERIS images: A case study of Lake Taihu. International Journal of Applied Earth Observation and Geoinformation 62, 69–77. https://doi.org/10.1016/J.JAG.2017.06.001

Lyzenga, D. R. 1978. Passive remote sensing techniques for mapping water depth and bottom features. Appl. Opt. 17(3), 379–383.

Magnus, P., Jaakola, J.J., Skrondal, A., Alexander, J., Becher, G., Krog, T., et al., 1999. Water chlorination and birth defects. Epidemiology, 10, 513-520.

Mannino, A., Novak, M.G., Hooker, S.B., Hyde, K., Aurin, D., 2014. Algorithm development and validation of CDOM properties for estuarine and continental shelf waters along the northeastern U.S. coast. Remote Sens Environ 152, 576–602. https://doi.org/10.1016/J.RSE.2014.06.027

Mannino, A., Russ, M.E., Hooker, S.B., 2008. Algorithm development and validation for satellite-derived distributions of DOC and CDOM in the U.S. Middle Atlantic Bight. J Geophys Res Oceans 113, 7051. https://doi.org/10.1029/2007JC004493

Maritorena, S., 2007. Remote sensing of the water attenuation in coral reefs: a case study in French Polynesia. 17, 155–166. https://doi.org/10.1080/01431169608948992

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Marmorino, G.O., Miller, W.D., Smith, G.B., Bowles, J.H., 2011. Airborne imagery of a disintegrating Sargassum drift line. Deep Sea Res 1 Oceanogr Res Pap 58, 316–321. https://doi.org/10.1016/j.dsr.2011.01.001

Martin, C., Zhang, Q., Zhai, D., Zhang, X., Duarte, C.M., 2021. Enabling a large-scale assessment of litter along Saudi Arabian red sea shores by combining drones and machine learning. Environmental Pollution 277. https://doi.org/10.1016/j.envpol.2021.116730

Martinez-Vicente, V. The need for a dedicated marine plastic litter satellite mission. Nat Rev Earth Environ 3, 728–729 (2022). https://doi.org/10.1038/s43017-022-00360-2

Martinez-Vicente, V., Biermann, L., Mata, A., 2020. Optical Methods for Marine Litter Detection (OPTIMAL) - Final Report.

Martínez-Vicente, V., Clark, J.R., Corradi, P., Aliani, S., Arias, M., Bochow, M., Bonnery, G., Cole, M., Cózar, A., Donnelly, R., Echevarría, F., Galgani, F., Garaba, S.P., Goddijn-Murphy, L., Lebreton, L., Leslie, H.A., Lindeque, P.K., Maximenko, N., Martin-Lauzer, F.R., Moller, D., Murphy, P., Palombi, L., Raimondi, V., Reisser, J., Romero, L., Simis, S.G.H., Sterckx, S., Thompson, R.C., Topouzelis, K.N., van Sebille, E., Veiga, J.M., Vethaak, A.D., 2019. Measuring Marine Plastic Debris from Space: Initial Assessment of Observation Requirements. Remote Sensing 2019, Vol. 11, Page 2443 11, 2443. https://doi.org/10.3390/RS11202443

Matos Valerio, A. de, Kampel, M., Vantrepotte, V., Ward, Nicholas D, Oliveira Sawakuchi, H., Fernanda Silva Less, D. da, Neu, V., Cunha, A., Richey, J., Kaplan, L.A., Findlay, S., Hopkinson, C.S., Marti, E., Packman, A.I., Newbold, J.D., Sabater, F., Ward, N D, Bianchi, T.S., Medeiros, P.M., Seidel, M., Richey, J.E., Keil, R.G., Sawakuchi, H.O., 2018. Using CDOM optical properties for estimating DOC concentrations and pCO2 in the Lower Amazon River. Optics Express, Vol. 26, Issue 14, pp. A657-A677 26, A657–A677. https://doi.org/10.1364/OE.26.00A657

Maximenko, N., Corradi, P., Law, K.L., Sebille, E. van, Garaba, S.P., Lampitt, R.S., Galgani, F., Martinez-Vicente, V., Goddijn-Murphy, L., Veiga, J.M., Thompson, R.C., Maes, C., Moller, D., Löscher, C.R., Addamo, A.M., Lamson, M., Centurioni, L.R., Posth, N., Lumpkin, R., Vinci, M., Martins, A.M., Pieper, C.D., Isobe, A., Hanke, G., Edwards, M., Chubarenko, I.P., Rodriguez, E., Aliani, S., Arias, M., Asner, G.P., Brosich, A., Carlton, J.T., Chao, Y., Cook, A.M., Cundy, A., Galloway, T.S., Giorgetti, A., Goni, G.J., Guichoux, Y., Hardesty, B.D., Holdsworth, N., Lebreton, L., Leslie, H.A., Macadam-Somer, I., Mace, T., Manuel, M., Marsh, R., Martinez, E., Mayor, D., le Moigne, M., Jack, M.E.M., Mowlem, M.C., Obbard, R.W., Pabortsava, K., Robberson, B., Rotaru, A.E., Spedicato, M.T., Thiel, M., Turra, A., Wilcox, C.,

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

2019. Towards the integrated marine debris observing system. Front Mar Sci 6. https://doi.org/10.3389/FMARS.2019.00447

McDonald, T. A., and H. Komulainen, 2005. Carcinogenicity of the chlorination disinfection by-product MX. J Environ Sci Health C Environ Carcinog Ecotoxicol Rev **23**. doi:10.1080/10590500500234988

McKinna, L.I.W (2015) Three decades of ocean-color remote-sensing Trichodesmium spp. In the World's oceans: A review. Progress in Oceanography, 131, 177-199.

Melendez-Pastor, I., Isenstein, E.M., Navarro-Pedreño, J., Park, M.H., 2019. Spatial variability and temporal dynamics of cyanobacteria blooms and water quality parameters in Missisquoi Bay (Lake Champlain). Water Supply 19, 1500–1506. https://doi.org/10.2166/WS.2019.017

Meyer-Jacob, C., N. Michelutti, A.M. Paterson, B.F. Cumming, W. Keller, and J. P. Smol, 2019. The browning and re-browning of lakes: Divergent lake-water organic carbon trends linked to acid deposition and climate change. Sci Rep **9**. doi:10.1038/s41598-019-52912-0

Miller, R. J., Reed, D. C., Brzezinski, M. A. 2011. Partitioning of primary production among giant kelp (Macrocystis pyrifera), understory macroalgae, and phytoplankton on a temperate reef. Limnol. Oceanogr. 56:119-132.

Millie, D.F., Schofield, O.M.E., Kirkpatrick, G.J., Johnsen, G., Evens, T.J., 2002. Using absorbance and fluorescence spectra to discriminate microalgae. Eur J Phycol 37, 313–322. https://doi.org/10.1017/S0967026202003700

Minor, E.C., and A.R. Oyler, 2021. Dissolved organic matter in large lakes: a key but understudied component of the carbon cycle. Biogeochemistry. doi:10.1007/s10533-020-00733-z

Mobley, C.D., Sundman, L.K., Davis, C.O., Bowles, J.H., Downes, T.V., Leathers, R.A., Montes, M.J., Bissett, W.P., Kohler, D.D., Reid, R.P., 2005. Interpretation of hyperspectral remote-sensing imagery by spectrum matching and look-up tables. Applied Optics 44, 3576–3592.

Mol, B. van, Ruddick, K., Astoreca, R., Park, Y., Nechad, B., 2007. Optical detection of a Noctiluca Scintillans bloom. EARSeL eProceedings 6 130–137.

Molot, L.A., Dillon, P.J., 1997. Colour – mass balances and colour – dissolved organic carbon relationships in lakes and streams in central Ontario. Cananadian Journal of Fisheries and Aquatic Sciences 54, 2789–2795.

Monteith, D.T., J.L. Stoddard, C.D. Evans, and others, 2007. Dissolved organic carbon trends resulting from changes in atmospheric deposition chemistry. Nature **450**. doi:10.1038/nature06316

Monteith, J.L. 1972. Solar Radiation and Productivity in Tropical Ecosystems. J. Appl. Ecol., 9, 747–766.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Morales-Pineda, M., Cõzar, A., Laiz, I., Úbeda, B., Gálvez, J.A., 2014. Daily, biweekly, and seasonal temporal scales of pCO_2 variability in two stratified Mediterranean reservoirs. J Geophys Res Biogeosci 119, 509–520. https://doi.org/10.1002/2013JG002317

Morales-Pineda, M., Cõzar, A., Laiz, I., Úbeda, B., Gálvez, J.A., 2014. Daily, biweekly, and seasonal temporal scales of pCO_2 variability in two stratified Mediterranean reservoirs. J Geophys Res Biogeosci 119, 509–520. https://doi.org/10.1002/2013JG002317

Moy, K., Neilson, B., Chung, A., Meadows, A., Castrence, M., Ambagis, S., Davidson, K., 2018. Mapping coastal marine debris using aerial imagery and spatial analysis. Mar Pollut Bull 132, 52–59. https://doi.org/10.1016/J.MARPOLBUL.2017.11.045

Nydahl, A. C., M. B. Wallin, L. J. Tranvik, and others. 2019. Colored organic matter increases CO_2 in meso-eutrophic lake water through altered light climate and acidity. Limnol Oceanogr **64**. doi:10.1002/lno.11072

O'Shea, R.E., Pahlevan, N., Smith, B., Bresciani, M., Egerton, T., Giardino, C., Li, L., Moore, T., Ruiz-Verdu, A., Ruberg, S., Simis, S.G.H., Stumpf, R., Vaičiūtė, D., 2021. Advancing cyanobacteria biomass estimation from hyperspectral observations: Demonstrations with HICO and PRISMA imagery. Remote Sens Environ 266, 112693. https://doi.org/10.1016/J.RSE.2021.112693

Odermatt, D., Gitelson, A., Brando, V.E., Schaepman, M (2012) Review of constituent retrieval in optically deep and complex waters from satellite imagery. Remote Sensing of Environment, 118, 116-126.

Ogashawara, I., 2019. The use of sentinel-3 imagery to monitor cyanobacterial blooms. Environments - MDPI 6. https://doi.org/10.3390/environments6060060

Olivé, I., Silva, J., Costa, M. M., Santos, R. 2016. Estimating seagrass community metabolism using benthic chambers: the effect of incubation time. Estuaries and Coasts 39:138-144.

Olsen, A., Triñanes, J.A., Wanninkhof, R., 2004. Sea-air flux of CO_2 in the Caribbean Sea estimated using in situ and remote sensing data. Remote Sens Environ 89, 309–325. https://doi.org/10.1016/J.RSE.2003.10.011

Öström, B., 1975. Fertilization of the baltic by nitrogen fixation in the Blue-Green AlgaNodularia Spumigena. Remote Sens Environ 4, 305–310. https://doi.org/10.1016/0034-4257(75)90026-7

Ouyang, Z., Shao, C., Chu, H., Becker, R., Bridgeman, T., Stepien, C.A., John, R., Chen, J., 2017. The Effect of Algal Blooms on Carbon Emissions in Western Lake Erie: An Integration of Remote Sensing and Eddy Covariance Measurements. Remote Sensing 2017, Vol. 9, Page 44 9, 44. https://doi.org/10.3390/RS9010044

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Pahlevan, N., Smith, B., Alikas, K., Anstee, J., Barbosa, C., Binding, C., Bresciani, M., Cremella, B., Giardino, C., Gurlin, D., Fernandez, V., Jamet, C., Kangro, K., Lehmann, M.K., Loisel, H., Matsushita, B., Hà, N., Olmanson, L., Potvin, G., Simis, S.G.H., VanderWoude, A., Vantrepotte, V., Ruiz-Verdù, A., 2022. Simultaneous retrieval of selected optical water quality indicators from Landsat-8, Sentinel-2, and Sentinel-3. Remote Sens Environ 270, 112860. https://doi.org/10.1016/J.RSE.2021.112860

Palmer, S.C. J., Kutser, T., Hunter, P.D., 2015. Remote sensing of inland waters: Challenges, progress and future directions. Remote Sensing of Environment 157, 1–8.

Pawlik, M.M., Ficek, D., 2022. Validation of measurements of pine pollen grain concentrations in Baltic Sea waters. Oceanologia 64, 233–243. https://doi.org/10.1016/J.OCEANO.2021.11.001

Peperzak, L., Colijn, F., Gieskes, W.W.C., Peeters, J.C.H., 1998. Development of the diatom- Phaeocystis spring bloom in the Dutch coastal zone of the North Sea: the silicon depletion versus the daily irradiance threshold hypothesis. J Plankton Res 20, 517–537. https://doi.org/10.1093/plankt/20.3.517

Phinn, S.R.; Roelfsema, C. M., Mumby, P.J. 2012. Multi-scale, object-based image analysis for mapping geomorphic and ecological zones on coral reefs, International Journal of Remote Sensing, 33:12, 3768-3797.

Pierson, D.C., Strombeck, N., 2001. Estimation of radiance reflectance and the concentrations of optically active substances in Lake Malaren, Sweden, based on direct and inverse solutions of a simple model. The Science of the Total Environment 268, 171-188.

Pu, R.; Bell, S. 2013. A protocol for improving mapping and assessing of seagrass abundance along the West Central Coast of Florida using Landsat TM and EO-1 ALI/Hyperion images. ISPRS J. Photogramm. Remote Sens., 83, 116–129.

Qi, L., Hu, C., 2021. To what extent can Ulva and Sargassum be detected and separated in satellite imagery? Harmful Algae 103, 102001. https://doi.org/10.1016/j.hal.2021.102001

Qi, L., Hu, C., Mikelsons, K., Wang, M., Lance, V., Sun, S., Barnes, B.B., Zhao, J., van der Zande, D., 2020. In search of floating algae and other organisms in global oceans and lakes. Remote Sens Environ 239, 111659. https://doi.org/10.1016/j.rse.2020.111659

Qi, L., Hu, C., Wang, M., Shang, S., Wilson, C., 2017. Floating Algae Blooms in the East China Sea. Geophys Res Lett 44, 11,501-11,509. https://doi.org/10.1002/2017GL075525

Qiao, Z., Sun, S., Jiang, Q., Xiao, L., Wang, Y., Yan, H., 2021. Retrieval of Total Phosphorus Concentration in the Surface Water of Miyun Reservoir Based on Remote Sensing Data and Machine Learning Algorithms. Remote Sens (Basel) 13. https://doi.org/10.3390/rs13224662

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Quibell, G., 1992. Estimating chlorophyll concentrations using upwelling radiance from different freshwater alga] genera. Int J Remote Sens 13, 2611–2621. https://doi.org/10.1080/01431169208904067

Rahman, A.F., Aslan, A., 2016. Detecting red tide using spectral shapes. International Geoscience and Remote Sensing Symposium (IGARSS) 2016-November, 5856–5859. https://doi.org/10.1109/IGARSS.2016.7730530

Richardson, L.L., **1996**. Remote sensing of algal bloom dynamics. Bioscience 46, 492–501. https://doi.org/10.2307/1312927

Rodgers, K. L., Rees, T. A. V., Shears, N. T. 2015. A novel system for measuring in situ rates of photosynthesis and respiration of kelp. Mar. Ecol. Prog. Ser. 528:101-115

Rodríguez-Benito, C. v., Navarro, G., Caballero, I., 2020. Using Copernicus Sentinel-2 and Sentinel-3 data to monitor harmful algal blooms in Southern Chile during the COVID-19 lockdown. Mar Pollut Bull 161. https://doi.org/10.1016/j.marpolbul.2020.111722

Roelfsema, C.; Phinn, S.; Jupiter, S.; Comley, J.; Albert, S. 2013. Mapping coral reefs at reef to reef-system scales, 10s–1000s km^2, using object-based image analysis, International Journal of Remote Sensing, 34:18, 6367-6388.

Rossini, M.; Cogliati, S.; Meroni, M.; Migliavacca, M.; Galvagno, M.; Busetto, L.; Cremonese, E.; Julitta, T.; Siniscalco, C.; di Cella, U.M.; et al. 2012. Remote sensing-based estimation of gross primary production in a subalpine grassland. Biogeosciences, 9, 2565–2584.

Salgado-Hernanz, Paula M, Bauzà, J., Alomar, C., Compa, M., Romero, L., Deudero, S., 2021. Assessment of marine litter through remote sensing: recent approaches and future goals. https://doi.org/10.1016/j.marpolbul.2021.112347

Salgado-Hernanz, Paula M., Bauzà, J., Alomar, C., Compa, M., Romero, L., Deudero, S., 2021a. Assessment of marine litter through remote sensing: recent approaches and future goals. Mar Pollut Bull 168, 112347. https://doi.org/10.1016/J.MARPOLBUL.2021.112347

Salgado-Hernanz, Paula M., Bauzà, J., Alomar, C., Compa, M., Romero, L., Deudero, S., 2021b. Assessment of marine litter through remote sensing: recent approaches and future goals. Mar Pollut Bull 168. https://doi.org/10.1016/j.marpolbul.2021.112347

Sathyendranath, S., Cota, G., Stuart, V., Maass, H., Platt, T., 2001. Remote sensing of phytoplankton pigments: a comparison of empirical and theoretical approaches. Int. J. Remote Sensing 22, 249–273.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Sathyendranath, S., Subba Rao, D. v., Chen, Z., Stuart, V., Platt, T., Bugden, G.L., Jones, W., Vass, P., 1997. Aircraft Remote Sensing of Toxic Phytoplankton Blooms: A Case Study from Cardigan River, Prince Edward Island. http://dx.doi.org/10.1080/07038992.1997.10874674 23, 15–23.

Sayers, M.J., Grimm, A.G., Shuchman, R.A., Bosse, K.R., Fahnenstiel, G.L., Ruberg, S.A., Leshkevich, G.A., 2019. Satellite monitoring of harmful algal blooms in the Western Basin of Lake Erie: A 20-year time-series. J Great Lakes Res 45, 508–521. https://doi.org/10.1016/J.JGLR.2019.01.005

Schalles, J.F., Yacobi, Y.Z., 2000. Remote detection and seasonal patterns of phycocyanin, carotenoid and chlorophyll pigments in eutrophic waters. Ergebnisse Der Limnologie 55, 153–168.

Shang, W., Jin, S., He, Y., Zhang, Y., Li, J., 2021. Spatial-Temporal Variations of Total Nitrogen and Phosphorus in Poyang, Dongting and Taihu Lakes from Landsat-8 Data. Water (Basel) 13. https://doi.org/10.3390/w13121704

Siegel, H., Gerth, M., Neumann, T., Doerffer, R., 1999. Case studies on phytoplankton blooms in coastal and open waters of the Baltic Sea using Coastal Zone Color Scanner data. http://dx.doi.org/10.1080/014311699212713 20, 1249–1264.

Simis, S.G.H., Peters, S.W.M., Gons, H.J., 2005. Remote sensing of the cyanobacterial pigment phycocyanin in turbid inland water. Limnol Oceanogr 50, 237–245. https://doi.org/10.4319/LO.2005.50.1.0237

Simis, S.G.H., Ruiz-Verdú, A., Domínguez-Gómez, J.A., Peña-Martinez, R., Peters, S.W.M., Gons, H.J., 2007. Influence of phytoplankton pigment composition on remote sensing of cyanobacterial biomass. Remote Sens Environ 106, 414–427. https://doi.org/10.1016/J.RSE.2006.09.008

Sobek, S., Tranvik, L.J., Cole, J.J., 2005. Temperature independence of carbon dioxide supersaturation in global lakes. Global Biogeochem Cycles 19, 1–10. https://doi.org/10.1029/2004GB002264

Song, K., Li, L., Li, S., Tedesco, L., Hall, B., Li, Z., 2012. Hyperspectral retrieval of phycocyanin in potable water sources using genetic algorithm-partial least squares (GA-PLS) modeling. International Journal of Applied Earth Observation and Geoinformation 18, 368–385. https://doi.org/10.1016/j.jag.2012.03.013

Song, K., Li, L., Tedesco, L.P., Li, S., Hall, B.E., Du, J., 2014. Remote quantification of phycocyanin in potable water sources through an adaptive model. ISPRS Journal of Photogrammetry and Remote Sensing 95, 68–80. https://doi.org/10.1016/j.isprsjprs.2014.06.008Song, K., Li, Lin, Li, S., Tedesco, L., Hall, B., Li, Linhai, 2012. Hyperspectral Remote Sensing of Total Phosphorus (TP) in Three Central Indiana Water Supply Reservoirs. Water Air Soil Pollut 223, 1481–1502. https://doi.org/10.1007/s11270-011-0959-6

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Song, X., Bai, Y., Cai, W.J., Arthur Chen, C.T., Pan, D., He, X., Zhu, Q., 2016. Remote sensing of sea surface pCO2 in the Bering sea in summer based on a mechanistic semi-analytical algorithm (MeSAA). Remote Sens (Basel) 8. https://doi.org/10.3390/RS8070558

Soomets, T., Kutser, T., Wüest, A., Bouffard, D., 2019. Spatial and temporal changes of primary production in a deep peri-alpine lake. Inl. Waters 9, 49–60. https://doi.org/10.1080/20442041.2018.1530529.

Soomets, T., Uudeberg, K., Kangro, K., Jakovels, D., Brauns, A., Toming, K., Zagars, M., Kutser, T., 2020. Spatio-Temporal Variability of Phytoplankton Primary Production in Baltic Lakes Using Sentinel-3 OLCI Data. Remote Sens. 12, 2415, https://doi.org/10.3390/rs12152415.

Stumpf, R. P.; Holderied, K. and Sinclair, M. 2003. Determination of water depth with high resolution satellite imagery over variable bottom types. Limnol. Oceanogr. 48, 547–556.

Stumpf, R.P., Tyler, M.A., 1988. Satellite detection of bloom and pigment distributions in estuaries. Remote Sens Environ 24, 385–404. https://doi.org/10.1016/0034-4257(88)90014-4

Subramaniam, A., Carpenter, E.J., 1994. An empirically derived protocol for the detection of blooms of the marine cyanobacterium Trichodesmium using CZCS imagery. 15, 1559–1569. https://doi.org/10.1080/01431169408954191

Sun, D., Chen, Y., Wang, S., Zhang, H., Qiu, Z., Mao, Z., He, Y., 2021. Using Landsat 8 OLI data to differentiate Sargassum and Ulva prolifera blooms in the South Yellow Sea. International Journal of Applied Earth Observation and Geoinformation 98. https://doi.org/10.1016/j.jag.2021.102302

Sun, D., Li, Y., Wang, Q., Le, C., Huang, C., Shi, K., 2011. Development of optical criteria to discriminate various types of highly turbid lake waters. Hydrobiologia 669, 83–104. https://doi.org/10.1007/S10750-011-0652-1

Sun, D., Li, Y., Wang, Q., Le, C., Lv, H., Huang, C., Gong, S., 2012. A novel support vector regression model to estimate the phycocyanin concentration in turbid inland waters from hyperspectral reflectance. Hydrobiologia 680, 199–217. https://doi.org/10.1007/S10750-011-0918-7

Sun, D., Qiu, Z., Li, Y., Shi, K., Gong, S., 2014. Detection of Total Phosphorus Concentrations of Turbid Inland Waters Using a Remote Sensing Method. Water Air Soil Pollut 225. https://doi.org/10.1007/s11270-014-1953-6

Sun, X., Zhang, Yunlin, Shi, K., Zhang, Yibo, Li, N., Wang, W., Huang, X., Qin, B., 2022. Monitoring water quality using proximal remote sensing technology. Science of The Total Environment 803, 149805. https://doi.org/10.1016/J.SCITOTENV.2021.149805

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Suwandana, E., Kawamura, K., Sakuno, Y., Evri, M., Lesmana, A.H., 2012. Hyperspectral Reflectance Response of Seagrass (Enhalus acoroides) and Brown Algae (Sargassum sp.) to Nutrient Enrichment at Laboratory Scale. 28, 956–963. https://doi.org/10.2112/JCOASTRES-D-11-00222.1

Tassan, S., 1995. SeaWiFS potential for remote sensing of marine Trichodesmium at sub-bloom concentration. 16, 3619–3627. https://doi.org/10.1080/01431169508954650

Thamaga, K.H., Dube, T., 2019. Understanding seasonal dynamics of invasive water hyacinth (Eichhornia crassipes) in the Greater Letaba river system using Sentinel-2 satellite data. GIsci Remote Sens 56, 1355–1377. https://doi.org/10.1080/15481603.2019.1646988

Themistocleous, K., Papoutsa, C., Michaelides, S., Hadjimitsis, D., 2020. Investigating detection of floating plastic litter from space using sentinel-2 imagery. Remote Sens (Basel) 12. https://doi.org/10.3390/RS12162648

Tian, Y.Q., Yu, Q., Zimmerman, M.J., Flint, S., Waldron, M.C., 2010. Differentiating aquatic plant communities in a eutrophic river using hyperspectral and multispectral remote sensing. Freshw Biol 55, 1658–1673. https://doi.org/10.1111/j.1365-2427.2010.02400.x

Toming, K., Kutser, T., Laas, A., Sepp, M., 2016. Mapping lake water quality parameters with Sentinel-2 MSI imagery. Remote Sensing, 8, 640, doi:10.3390/rs8080640.

Topouzelis, K., Papageorgiou, D., Karagaitanakis, A., Papakonstantinou, A., Ballesteros, M.A., 2020a. Plastic Litter Project 2019: Exploring the Detection of Floating Plastic Litter Using Drones and Sentinel 2 Satellite Images. International Geoscience and Remote Sensing Symposium (IGARSS) 6329–6332. https://doi.org/10.1109/IGARSS39084.2020.9324548

Topouzelis, K., Papageorgiou, D., Karagaitanakis, A., Papakonstantinou, A., Ballesteros, M.A., 2020b. Remote sensing of sea surface artificial floating plastic targets with Sentinel-2 and unmanned aerial systems (plastic litter project 2019). Remote Sens (Basel) 12. https://doi.org/10.3390/rs12122013

Topouzelis, K., Papageorgiou, D., Suaria, G., Aliani, S., 2021. Floating marine litter detection algorithms and techniques using optical remote sensing data: A review. Marine Pollution Bulletin, 170, 112675. https://doi.org/10.1016/j.marpolbul.2021.112675

Topouzelis, K., Papakonstantinou, A., Garaba, S.P., 2019. Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018). International Journal of Applied Earth Observation and Geoinformation 79, 175–183. https://doi.org/10.1016/j.jag.2019.03.011

Traganos D, Reinartz P. 2018a. Mapping Mediterranean seagrasses with Sentinel-2 imagery. Mar Pollut Bull. Sep;134,197-209.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Traganos, D.; Reinartz, P., 2018b. Machine learning-based retrieval of benthic reflectance and Posidonia oceanica seagrass extent using a semi-analytical inversion of Sentinel-2 satellite data, International Journal of Remote Sensing.

Tranvik, L.J., 1990. Bacterioplankton growth on fractions of dissolved organic carbon of different molecular weights from humic and clear waters. Applied and Environmental Microbiology 56, 1672–1677.

Tranvik, L.J., Downing, J.A., Cotner, J.B., Loiselle, S.A., Striegl, R.G., Ballatore, T.J., Dillon, P., Finlay, K., Fortino, K., Knoll, L.B., Kortelainen, P.L., Kutser, T., Larsen, S., Laurion, I., Leech, D.M., Leigh McCallister, S., McKnight, D.M., Melack, J.M., Overholt, E., Porter, J.A., Prairie, Y., Renwick, W.H., Roland, F., Sherman, B.S., Schindler, D.W., Sobek, S., Tremblay, A., Vanni, M.J., Verschoor, A.M., von Wachenfeldt, E., Weyhenmeyer, G.A., 2009. Lakes and reservoirs as regulators of carbon cycling and climate. Limnol Oceanogr 54, 2298–2314. https://doi.org/10.4319/LO.2009.54.6_PART_2.2298

Tranvik, L.J., J.J. Cole, and Y.T. Prairie, 2018. The study of carbon in inland waters–from isolated ecosystems to players in the global carbon cycle. Limnology And Oceanography Letters 3. doi:10.1002/lol2.10068

Trevisan, G. v., Forsberg, B.R., 2007. Relationships among nitrogen and total phosphorus, algal biomass and zooplankton density in the central Amazonia lakes. Hydrobiologia 586, 357–365. https://doi.org/10.1007/s10750-007-0705-7

UNEP (United Nations Environment Programme), 2021. From pollution to solution: a global assessment of marine litter and plastic pollution, New Scientist.

Vahtmäe, E., Kotta, J., Argus, L., Kotta, M., Kotta, I., Kutser, T. (2022) A model-based assessment of canopy-scale oroductivity for the Baltic Sea benthic vegetation using environmental variables and spectral indices. Remote Sensing, 14, 158.

Vahtmäe, E., Kotta, J., Lõugas, L., Kutser, T., 2021. Mapping spatial distribution, percent cover and biomass of benthic vegetation in optically complex coastal waters using hyperspectral CASI and multispectral Sentinel-2 sensors. International Journal of Applied Earth Observations and Geoinformation, 102, 102444.

Vahtmäe, E., Kutser, T., 2013. Classifying the Baltic Sea shallow water habitats using image-based and spectral library methods. Remote Sens. 5, 2451–2474.

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Vahtmäe, E., Kutser, T., Martin, G., Kotta, J., 2006. Feasibility of hyperspectral remote sensing for mapping benthic macroalgal cover in turbid coastal waters - a Baltic Sea case study. Remote Sens Environ 101, 342–351. https://doi.org/10.1016/j.rse.2006.01.009

Vahtmäe, E., Kutser, T., Paavel, B., 2020. Performance and Applicability of Water Column Correction Models in Optically Complex Coastal Waters. Remote sensing, 12, 1861.

Valerio, A.M., Kampel, M., Ward, N.D., Sawakuchi, H.O., Cunha, A.C., Richey, J.E., 2021. CO2 partial pressure and fluxes in the Amazon River plume using in situ and remote sensing data. Cont Shelf Res 215, 104348. https://doi.org/10.1016/J.CSR.2021.104348

Veettil, B.K., Ward, R.D., Lima, M.D.A.C., Stankovic, M., Hoai, P.N., Quang, N.X., 2020. Opportunities for seagrass research derived from remote sensing: A review of current methods. Ecol Indic 117, 106560. https://doi.org/10.1016/j.ecolind.2020.106560

Verpoorter, C., Kutser, T., Tranvik, L.J., Seekell, D., 2014. A Global Inventory of Lakes Based on High-Resolution Satellite Imagery. Geophysical Research Letters 41, 6396–6402.

Vertucci, A., Likens, G.E., 1989. Spectral reflectance and water quality of Adirondack mountain region lakes. Limnolology and Oceanography 34, 1656-1672.

Wang, G., Zhang, B., Li, J., Zhang, H., Shen, Q., Wu, D., Song, Y., 2011. Study on monitoring of red tide by multi-spectral remote sensing based on HJ-CCD and MODIS. Procedia Environ Sci 11, 1561–1565. https://doi.org/10.1016/j.proenv.2011.12.235

Wang, M., Hu, C., 2016. Mapping and quantifying Sargassum distribution and coverage in the Central West Atlantic using MODIS observations. Remote Sens Environ 183, 350–367. https://doi.org/10.1016/J.RSE.2016.04.019

Wang, M., Hu, C., 2021. Automatic Extraction of Sargassum Features from Sentinel-2 MSI Images. IEEE Transactions on Geoscience and Remote Sensing 59, 2579–2597. https://doi.org/10.1109/TGRS.2020.3002929

Wang, M., Hu, C., Barnes, B.B., Mitchum, G., Lapointe, B., Montoya, J.P., 2019. The great Atlantic Sargassum belt. Science (1979) 364, 83–87. https://doi.org/10.1126/SCIENCE.AAW7912

Wang, M., Hu, C., Cannizzaro, J., English, D., Han, X., Naar, D., Lapointe, B., Brewton, R., Hernandez, F., 2018. Remote Sensing of Sargassum Biomass, Nutrients, and Pigments. Geophys Res Lett 45, 12,359-12,367. https://doi.org/10.1029/2018GL078858

Wen, Z., Shang, Y., Lyu, L., Li, S., Tao, H., Song, K., 2021. A review of quantifying pco2 in inland waters with a global perspective: Challenges and prospects of implementing remote sensing technology. Remote Sens (Basel) 13. https://doi.org/10.3390/RS13234916

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Wetzel, R.G. (2001) Limnology; Lake and river ecosystems (3rd ed.) Elsevier, 1006 pp.

Whiteside, A., Dupouy, C., Singh, A., Frouin, R., Menkes, C., Lefèvre, J., 2021. Automatic Detection of Optical Signatures within and around Floating Tonga-Fiji Pumice Rafts Using MODIS, VIIRS, and OLCI Satellite Sensors. Remote Sensing 2021, Vol. 13, Page 501 13, 501. https://doi.org/10.3390/RS13030501

Wicaksono, P., Hafizt, M. 2013. Mapping seagrass from space: Addressing the complexity of seagrass LAI mapping. European Journal of Remote Sensing, 46, 18-39.

Wicaksono, P.; Aryaguna, P.A.; Lazuardi, W. 2019. Benthic Habitat Mapping Model and Cross Validation Using Machine-Learning Classification Algorithms. *Remote Sens.*, *11*, 1279.

Wilson, K.L.; Wong, M.C.; Devred, E. 2022. Comparing Sentinel-2 and WorldView-3 Imagery for Coastal Bottom Habitat Mapping in Atlantic Canada. *Remote Sens.*, *14*, 1254.

Woolway, R. I., and C. J. Merchant. 2019. Worldwide alteration of lake mixing regimes in response to climate change. Nat Geosci **12**. doi:10.1038/s41561-019-0322-x

Wrigley, R.C., Horne, A.J., 1974. Remote sensing and lake eutrophication. Nature 1974 250:5463 250, 213–214. https://doi.org/10.1038/250213a0

Wu, C., Wu, J., Qi, J., Zhang, L., Huang, H., Lou, L., Chen, Y., 2010. Empirical estimation of total phosphorus concentration in the mainstream of the Qiantang River in China using Landsat TM data. Int J Remote Sens 31, 2309–2324. https://doi.org/10.1080/01431160902973873

Xenopoulos, M. A., R. T. Barnes, K. S. Boodoo, and others. 2021. How humans alter dissolved organic matter composition in freshwater: relevance for the Earth's biogeochemistry. Biogeochemistry **154**. doi:10.1007/s10533-021-00753-3

Xiao, Y., Liu, R., Kim, K., Zhang, J., Cui, T., 2022. A Random Forest-Based Algorithm to Distinguish Ulva prolifera and Sargassum from Multispectral Satellite Images. IEEE Transactions on Geoscience and Remote Sensing 60. https://doi.org/10.1109/TGRS.2021.3071154

Xiong, J., Lin, C., Cao, Z., Hu, M., Xue, K., Chen, X., Ma, R., 2022. Development of remote sensing algorithm for total phosphorus concentration in eutrophic lakes: Conventional or machine learning? Water Res 215. https://doi.org/10.1016/j.watres.2022.118213

Xiong, J., Lin, C., Ma, R., Cao, Z., 2019. Remote Sensing Estimation of Lake Total Phosphorus Concentration Based on MODIS: A Case Study of Lake Hongze. Remote Sens (Basel) 11. https://doi.org/10.3390/rs11172068

Yacobi, Y.Z., Gitelson, A., Mayo, M., **1995.** Remote sensing of chlorophyll in Lake Kinneret using highspectral-resolution radiometer and Landsat TM: spectral features of reflectance and

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

algorithm development. J Plankton Res 17, 2155–2173. https://doi.org/10.1093/PLANKT/17.11.2155

Yamano, H.; Tamura, M. 2004. Detection limits of coral reef bleaching by satellite remote sensing: Simulation and data analysis. Remote Sens. Environ., 90, 86–103.

Yan, X., Ma, J., Li, Z., Ji, M., Xu, J., Xu, X., Wang, G., Li, Y., 2021. CO2 dynamic of Lake Donghu highlights the need for long-term monitoring. Environmental Science and Pollution Research 28, 10967–10976. https://doi.org/10.1007/S11356-020-11374-Y/FIGURES/6

Yang, R., Xu, Z., Liu, S., Xu, Y.J., 2019. Daily pCO 2 and CO 2 flux variations in a subtropical mesotrophic shallow lake. https://doi.org/10.1016/j.watres.2019.01.012

Yu, X., Wang, Y., Liu, Xiangyang, Liu, Xin, 2017. Remote sensing estimation of carbon fractions in the Chinese Yellow River estuary. 36, 202–210. https://doi.org/10.1080/1064119X.2017.1297876

Yunus, A.P., Dou, J., Song, X., Avtar R. 2019. Improved Bathymetric Mapping of Coastal and Lake Environments Using Sentinel-2 and Landsat-8 Images. Sensors (Basel). Jun 21;19(12):2788.

Yunus, A.P., Dou, J., Sravanthi, N., 2015. Remote sensing of chlorophyll-a as a measure of red tide in Tokyo Bay using hotspot analysis. Remote Sens Appl 2, 11–25. https://doi.org/10.1016/j.rsase.2015.09.002

Zeng, S., Lei, S., Li, Y., Lyu, H., Dong, X., Li, J., Cai, X., 2022. Remote monitoring of total dissolved phosphorus in eutrophic Lake Taihu based on a novel algorithm: Implications for contributing factors and lake management. Environmental Pollution 296. https://doi.org/10.1016/j.envpol.2021.118740

Zhang, C; Selch, D.; Xie, Z.; Roberts, C.; Cooper, H.; Chen, G. 2013. Object-based benthic habitat mapping in the Florida Keys from hyperspectral imagery. Estuarine, Coastal and Shelf Science, 134, 88-97.

Zhang, Linshan, Zhang, Lifu, Cen, Y., Wang, S., Zhang, Y., Huang, Y., Sultan, M., Tong, Q., 2022. Prediction of Total Phosphorus Concentration in Macrophytic Lakes Using Chlorophyll-Sensitive Bands: A Case Study of Lake Baiyangdian. Remote Sens (Basel) 14. https://doi.org/10.3390/rs14133077

Zhou, S., Kaufmann, H., Bohn, N., Bochow, M., Kuester, T., Segl, K., 2022. Identifying distinct plastics in hyperspectral experimental lab-, aircraft-, and satellite data using machine/deep learning methods trained with synthetically mixed spectral data. Remote Sens Environ 281. https://doi.org/10.1016/j.rse.2022.113263

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.

Zhu, W., Yu, Q., Tian, Y., Becker, B.L., Zheng, T., Carrick, H.J., 2014. An assessment of remote sensing algorithms for colored dissolved organic matter in complex freshwater environments. Remote Sensing of Environment 140, 766–778.

Zimba, P. v., Gitelson, A., 2006. Remote estimation of chlorophyll concentration in hyper-eutrophic aquatic systems: Model tuning and accuracy optimization. Aquaculture 256, 272–286. https://doi.org/10.1016/J.AQUACULTURE.2006.02.038

Water-ForCE is a CSA that has received funding form the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 101004186.