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Developments in Earth observation for the assessment and monitoring of inland, transitional, coastal and shelf-sea waters

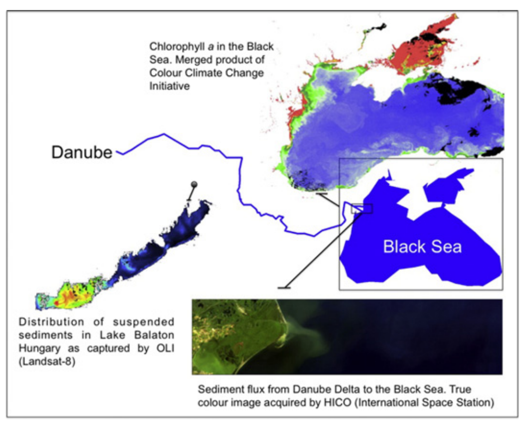
Andrew N. Tyler [a,*], Peter D. Hunter [a], Evangelos Spyrakos [a], Steve Groom [b], Adriana Maria Constantinescu [a,c], Jonathan Kitchen [a]

[a] Biological and Environmental Sciences, School of Natural Sciences, University of Stirling, Stirling FK9 4LA, United Kingdom
[b] Plymouth Marine Laboratory, Prospect Place, The Hoe, Plymouth PL1 3DH, United Kingdom
[c] GeoEcoMar, Str. Dimitrie Onciul, Nr. 23-25, Bucharest, RO 024053, Romania

HIGHLIGHTS

- River-delta–sea systems require integrated approaches to ecological assessment.
- Lack of systematic transboundary monitoring across the Danube catchment
- Remote sensing has shown promise for large-scale assessment but limited application.
- New satellites have potential for synergistic multi-scale operational observation.
- Need for further algorithm development and validation for optically complex waters

GRAPHICAL ABSTRACT



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ABSTRACT

The Earth's surface waters are a fundamental resource and encompass a broad range of ecosystems that are core to global biogeochemical cycling and food and energy production. Despite this, the Earth's surface waters are impacted by multiple natural and anthropogenic pressures and drivers of environmental change. The complex interaction between physical, chemical and biological processes in surface waters poses significant challenges for in situ monitoring and assessment and often limits our ability to adequately capture the dynamics of aquatic systems and our understanding of their status, functioning and response to pressures. Here we explore the opportunities that Earth observation (EO) has to offer to basin-scale monitoring of water quality over the surface water continuum comprising inland, transition and coastal water bodies, with a particular focus on the Danube and Black Sea region. This review summarises the technological advances in EO and the opportunities that the next generation satellites offer for water quality monitoring. We provide an overview of algorithms for the retrieval of water quality parameters and demonstrate how such models have been used for the assessment and monitoring of inland, transitional, coastal and shelf–sea systems. Further, we argue that very few studies have investigated the connectivity between these systems especially in large river–sea systems such as the Danube–Black Sea. Subsequently, we describe current capability in operational processing of archive and near real-time satellite data. We conclude that while the operational use of satellites for the assessment and monitoring of surface waters is still developing for inland and coastal waters and more work is required on the development and

* Corresponding author.

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validation of remote sensing algorithms for these optically complex waters, the potential that these data streams offer for developing an improved, potentially paradigm-shifting understanding of physical and biogeochemical processes across large scale river–sea systems including the Danube–Black Sea is considerable.

1. Introduction

The Earth's surface waters are a fundamental global resource. They are important for biodiversity, fulfil key function in global biogeochemical cycles and are core to food and energy production. However, surface waters face multiple and compounding pressures from changes in land use and climate change, nutrient enrichment, brownification and other natural and anthropogenic driven environmental perturbations operating and interacting over scales ranging from local to global (MEA, 2005; IPCC, 2007; Ormerod et al., 2010). The inherently dynamic and heterogeneous nature of surface waters poses considerable challenges for effective and representative monitoring and assessment via in situ sampling. The limited spatial coverage and temporal frequency of sampling, and differences in the methods and protocols used between laboratories, regions and nations, further constrains our understanding of the state of surface waters and how they are changing locally, regionally and globally scale (e.g. Carvalho et al., 2011; Palmer et al., 2015b).

The use of Earth observation (EO) data acquired from satellites is now becoming increasingly widely used for providing information on a suite of functionally relevant indicators of water quality and ecosystem condition from a local to global scale. This review will explore the potential for basin-scale monitoring of water quality in complex system like the Danube river catchment and Black Sea through EO platforms. Whilst water quality can be measured by a number of physical, biological and chemical water constituents, this contribution will focus on the in-water biogeochemical constituents that can be retrieved from the data from optical EO sensors including chlorophyll-*a* (Chl-*a*), phycocyanin (PC), total suspended matter (TSM), turbidity and coloured dissolved organic matter (CDOM). In addition to those parameters that can be retrieved from optical data, other parameters such as sea surface salinity can be retrieved from spaceborne L-band radar data (e.g. Burrage et al., 2008; Klemas, 2011), while sea surface temperature can be retrieved from the measurements in the thermal infrared between 8 and 14 μm (e.g. MacCallum and Merchant, 2012; Politi et al., 2012; Merchant et al., 2013). This review is restricted to measurements that can be made by optical remote sensing from satellite platforms and will primarily consider Chl-*a*, PC, TSM and CDOM.

Draining an area of land almost twice as large as the Black Sea (801,463 km^2), the Danube River is the world's most international river basin, encompassing 19 countries and is the largest and the most important source of water and sediment entering to the Black Sea basin. It has a mean annual discharge of approximately 205 km^3 $year^{-1}$ (*c*. 60% of the total water runoff in the Black Sea basin) and exports between 36.3 and 52.4 million tons of SPM into the Black Sea per year (*c*. 48% of the total SPM load) (Ludwig et al., 2009; Mikhailov and Mikhailova, 2008). However, over the last few decades the Danube Basin region and the Black Sea have experienced marked declines in water quality, largely due to human activities such as agriculture and industry. The Danube controls the sedimentation on the north-western Black Sea shelf, impacting southwards to the Bosphorus region, as well as down to the deep-sea parts of the basin (Panin and Jipa, 2002). Human activity within the basin results in excessive nutrients inputs into the water bodies within the Danube River Basin (Ludwig et al., 2009; Istvánovics and Honti, 2012; Capet et al., 2013), while significant quantities of sediment are also retained in reservoirs (Rovira et al., 2014) where dams have been constructed. These factors have contributed to pervasive eutrophication and sediment deficit throughout the course of the river and also in the downstream estuarine and coastal areas. In spite of the ecological and socio-economic importance of this iconic river basin system, and the severity of the problems currently faced, integrated space–time studies of water quality are very scarce in this complex multi-component system (Güttler et al., 2013).

Earth observation has the potential to contribute greatly to our ability to observe complex systems like the Danube Delta and its interface with the Black Sea. Earth observation provides a synoptic view of systems that cannot be replicated through field-based sampling and one that can be obtained at relatively high temporal frequencies to build long-term observational records of environmental change. However, many previous studies have shown that the performance of in-waters models for the retrieval of physical and biogeochemical parameters from Earth observation data can vary tremendously between water bodies with very different optical properties and overlying atmospheres (Guanter et al., 2010; Matthews, 2011). The Danube basin and its diversity of water bodies from the large, deep clear water lakes to the south of the Black Forest to the highly turbid environments of the coastal lagoons and waters of the Black Sea will undoubtedly pose a challenge for the operational monitoring of water quality from satellites. In these highly turbid waters, light penetration is also very limited and as such remote sensing data can only provide information on near-surface properties and in situ data and models are required to provide an understanding of vertical structures within the water column.

Morel and Prieur (1977) were the first to formally describe the differences in the optical properties of water bodies identifying two broad classes that they termed “Case-1” and “Case-2” waters. Case-1 waters are best exemplified by the open ocean where water-leaving radiative signals are dominated by phytoplankton and to a lesser extent the presence of low and covarying concentrations of CDOM and detrital matter. By contrast Case-2 waters comprise shelf-sea, coastal and inland waters and are characterised by high and non-covarying concentrations of phytoplankton, TSM and CDOM. The work by Morel and Prieur (1977) was never intended to act as a basis for the classification of optical water types. More recent research has attempted to develop a more useful classification scheme for the identification of optical water types and one that better recognises the variability that exists within Case-1 and, particularly, Case-2 waters.

The ocean colour community have made significant advances in the remote sensing of Case-1 waters (IOCCG, 2000, 2006; Brewin et al., 2013). However, Case-2 waters, now frequently referred to as optically complex waters, present significant challenges for atmospheric correction and retrieval of in-water constituents concentration and many standard ocean colour algorithms perform poorly when applied to these waters (Alikas and Reinart, 2008; Witter et al., 2009; Binding et al., 2010). In recent years considerable effort has been invested in the development and validation of in-water algorithms tailored to optically complex waters and there is a rapidly growing body of literature demonstrating promising results for the retrieval of a range of biogeochemical constituents (Kutser et al., 2005; Kutser et al., 2009; Giardino et al., 2010; Tarrant et al., 2010; Hunter et al., 2010; Matthews et al., 2010; Odermatt et al., 2010; Nechad et al., 2010; Dogliotti et al., 2015; Palmer et al., 2015a, 2015c; Ayana et al., 2015). Many of these studies have focused on individual lakes or small populations of lakes with comparable atmospheric and optical properties and it is almost certain that no single approach will perform adequately over the continuum of surface water bodies. The development of adaptive algorithms offers one potential solution to this challenge (e.g., Dogliotti et al., 2015) but an improved understanding of the performance and applicability of algorithms over different water optical types is also needed.

The ocean colour community have benefited greatly from the long-term data provided by Envisat MERIS (2002–2012) and the still operational, but ageing, MODIS-Aqua and MODIS–Terra sensors. Currently, only a limited number of platforms such as NASA's VIIRS (Visible Infrared Imager Radiometer Suite) on Suomi NPP and OCM-2 on Oceansat-2 have sufficient capability to provide operational ocean colour observations until the next generation of sensors are launched. Of particular interest and relevance are the Sentinel satellites to be launched as part of ESA's Copernicus programme. This will include two Sentinel-2 spacecraft carrying MSI (Multispectral Imager) instruments, the first of which was launched in June 2015 and second is due 2016, and three Sentinel-3 spacecraft with the OLCI (Ocean and Land Colour Instrument) sensor to be launched between early 2016 and 2020 (Table 1). Other new sensors and missions are being developed and launched over the next 5–7 years include: (i) USA's NASA Pre-Aerosol Cloud and ocean Ecosystem (PACE) mission (launch date 2022/23; specifications to be finalised); Japan's JAXA's GCOM-C/SGLI planned for launch in 2016 (2–3 day repeat cycle, 250 m–1 km resolution, 19 multispectral bands from 380 nm to 12.5 μm); (iii) Brazil's INPE/CONAE's SABIA-Mar. mission (two satellites launched around 2020, each with two systems with global coverage 1000 km swath and 1.1 km resolution and regional coverage with a swath of 200 km and 200 m resolution, 16 spectral bands from 380 nm to 11.8 μm); and (iv) South Korea's KIOST GOCI-I & II (launch due in 2019, swath width to be determined but estimated to be between 1200 and 1500 km, 13 multispectral bands between 412 nm and 1240 nm) (IOCCG, 2015). Many of these new and planned satellite sensors have revised band sets that include additional near infrared bands to improve atmospheric correction. Collectively these new sensors will herald a new era for the operational monitoring of inland, coastal and ocean waters from space and will drive innovative science and the development of downstream EO-based services.

This review explores the existing and forthcoming opportunities for water quality monitoring along with the challenges and solutions for retrieving quantitative measures of in-water constituents in optically complex waters. Examples of applications will be presented highlighting the insights that satellite based EO can provide to aid our understanding of surface water status across the continuum from lakes to shelf-seas and how these environments are responding to regional and global environmental change.

2. Earth observation satellites and sensors

Data from satellites have been widely used for the assessment and monitoring of the water quality in inland, transitional, coastal and shelf-sea waters (see Table 1). The vast majority of sensors used for water quality studies are (or were) carried on satellites in sun-synchronous, low-Earth orbits (e.g. Vos et al., 2003; Heim et al., 2005; Wu et al., 2009; Sokoletsky et al., 2011; Lim and Minha, 2015). These platforms typically provide data at a frequency of between 1 to 14 days globally (cloud cover permitting) and at spatial resolutions from a few metres to more than a kilometre. The first dedicated satellite mission for observing the Earth from space was Landsat-1 launched in 1972. The Multispectral Scanner (MSS) instrument carried by Landsat-1 was a relatively rudimentary instrument compared to some of the sensors now in orbit but several authors successfully used the data to derive estimates of water transparency and/or turbidity in lakes and other inland waters (e.g., Gervan and Marshall, 1977). However, the poor spectral and radiometric resolution of the early Landsat-series sensors posed significant challenges for the accurate retrieval of water quality information. It would be some years before satellite data would be used routinely or operationally but these early, pioneering studies starting some 40 years ago, clearly demonstrated the value of being able to retrieve information on water quality over large geographical areas from space (Rogers et al., 1976, 1977; Gervan and Marshall, 1977; Shih and Gervin, 1980; Carpenter and Darpenter, 1983; Graham and Hill, 1983; Raitala et al., 1984).

The first dedicated satellite sensor for global observation of surface waters from space was the Coastal Zone Color Scanner (CZCS) launched in 1978. Importantly, CZCS was the first sensor with a spatial, spectral and radiometric resolution suited for observations over water rather

Table 1
A list of sensors and associated satellite platforms that have been used and are available for the assessment and monitoring of water quality for inland, transitional and coastal waters.

Sensor	Satellite	Resolution				Swath width (km)	Organisation	Data range	Price
		Spectral (nm)	**Temporal (days)**	**Radiometric**	**Spatial (m)**				
PACE	Worldview-3	450–800 (8)	1	14-bit	0.3	13.1	Digital Globe	2014–Present	Payment
Quickbird	Quickbird	450–900 (5)	1–3.5	11-bit	0.7	16.5	Digital Globe	2001–Present	Payment
SPOT 6	SPOT 6	455–890 (4)	01-May	12-bit	1.5	60	CNES	2012–Present	Payment
SPOT 7	SPOT 7	455–890 (4)	01-May	12-bit	1.5	60	CNES	2014–Present	Payment
IKONOS	LM900	445–928 (5)	1	11-bit	3	11.3	Digital Globe	1990–Present	Payment
LISS 4	IRS-P6	520–680 (3)	5	10-bit	5.8	70	ESA	2003–Present	Free
HRG	SPOT 5	480–1750 (5)	02-Mar	8-bit	10	60	CNES	2002–Present	Payment
ETM	Landsat 7	450–2350 (8)	16	8-bit	10	16	USGS	1999–Present	Free
Aster	Terra	520–1165 (14)	16	8-bit	15	60	NASA	2002–Present	Free
OLI	Landsat 8	435–2294 (9)	16	12-bit	15	185	USGS	2013–Present	Free
CHRIS	Proba-1	415–1050 (19)	7	12-bit	18	14	ESA	2001–Present	Free
LISS 3	IRS-P6	520–1700 (4)	24	7-bit	23.5	141	ISRO	2003–Present	Free
Hyperion	EO-1	400–2500 (220)	16	12-bit	30	7.5	NASA	2000–Present	Free
ALI	EO-2	430–2350(9)	16	11-bit	30	37	NASA	2000–Present	Free
HICO	ISS	300–1000 (87)	3	14-bit	100	45	NASA	2003–Present	Free
TIRS	Landsat 8	1060–1251 (2)	16	12-bit	100	185	USGS	2013–Present	Free
MODIS	Terra/Aqua	405–14,385 (36)	16	12-bit	250	2330	NASA	1990–2014	Free
MERIS FS	Envisat	390–1040 (15)	3	16-bit	260	1150	ESA	2002–2013	Free
OCM	IRS-P4	400–900(8)	2	12-bit	360	1420	ISRO	1999–2010	Free
VIIRS	NPP and JPSS	402–11,800 (22)	1	12-bit	370	3000	NASA	2011–Present	Free
WiFS	SeaWiFS	402–885 (8)	2	10-bit	1000	2801	NASA	1997–2010	Free
AVHRR 3	NOAA-18	580–1250 (6)	1	12-bit	1100	3000	GeoEye	2005–Present	Free
MERIS RR	Envisat	390–1040 (15)	3	17-bit	1200	1150	ESA	2002–2013	Free
SEVIRI	METEOSAT	400–1600 (4) 3900–13,400 (8)	0.001	10 bit	1000 3000	Geostationary Centred on Africa	ESA	2004	Free
MCI	Sentinel 2	425–1405 (13)	2 systems 5 days	12 bit	Oct-60	290	ESA	April 2015	Free
OLCI	Sentinel 3	400–1020 (21)	3 systems <2 days	16 bit	300	1270	ESA	January 2016	Free

than the land surface. CZCS was only a proof-of-concept mission but the data provided were unprecedented and unparalleled at the time and as a result have been used in numerous studies on the dynamics of particulate matter and phytoplankton blooms in marine waters including many focused on complex sea-shelf systems (Yoder et al., 1987; Aarup et al., 1989; Fuentes-Yaco et al., 1997). CZCS was primarily designed for ocean colour monitoring and thus the coarse spatial resolution (825 m) of the data was suited only to the observation of very large lake systems. However, a small number of studies also successfully demonstrated that CZCS could be used to retrieve information on water quality in the more optically complex situations found in large continental waters such as Lake Michigan (Mortimer, 1988) and Lake Superior (Li et al., 2004).

The CZCS mission ended in 1986. Unfortunately, there were no immediate successors to the CZCS and its capability was not replaced until the launch of the SeaWiFS (Sea-Viewing Wide Field-of-View Sensor) in 1997. SeaWiFS was arguably the first operational ocean colour satellite mission providing systematic observations over marine waters until 2010. SeaWiFS offered improved spectral and radiometric resolutions but like its predecessor CZCS it captured data at a coarse spatial resolution (1.1 km) that limited its use over inland systems or close to the coast where high spatial complexity exists in near-surface waters. The later launch of MODIS-Terra in 1999 and MODIS-Aqua and MERIS in 2002 improved the spatial resolution of ocean colour data products down to 250–300 m. Importantly, this greatly enhanced our ability to observe spatial and temporal trends in water quality in large lakes, lagoons and coastal waters and numerous studies have demonstrated the potential of such data products for mapping water quality in inland, coastal and shelf-sea systems including water bodies within the Danube basin and the Black Sea (Zibordi et al., 2013; Güttler et al., 2013; Palmer et al., 2015b; Constantine et al., 2016).

The most recent ocean colour satellite missions such as MERIS and MODIS provide data products at a 300 m spatial resolution every 1–3 days globally. These data provide unparalleled insights into dynamic processes in large lakes, coastal zones and shelf-sea but the coarse resolution of these products restricts their use for studying smaller water bodies. Hence, many studies concerned with small to moderately sized lakes and reservoirs, rivers and estuaries have made use of high spatial resolution data from satellites missions designed for land applications such as those in the Landsat-series (e.g., Tyler et al., 2006; Olmanson et al., 2008). The main disadvantage of the sensors flown on missions such as Landsat is that they were not designed for applications over water bodies and thus the coverage and resolution of their spectral bands and their radiometric sensitivity is sometimes not sufficient to provide accurate retrievals of parameters such as Chl-*a* or CDOM, particularly for lakes with low water-leaving radiance. The potential of current state-of-the-art commercial satellite sensors such as WorldView-2 and -3 for mapping water quality has not been widely explored partly due to the financial costs of acquiring the data, particularly if tasking is required, although costs are likely to decrease overtime as sensors are superseded and archived data volumes increase. However, these platforms offer very high spatial resolution data (<2 m) with sufficient spectral (8 bands between 400 and 1040 nm) and radiometric (11-bit in the visible and near infrared) resolution to enable information on water quality to be retrieved over turbid waters (e.g., Wheeler et al., 2013).

In additional to the data products that are provided by satellite sensors in sun-synchronous, low-Earth orbits some recent studies have also demonstrated the potential of geostationary satellites for high temporal frequency monitoring of coastal and shelf-sea waters. Data from the SEVIRI (Spinning Enhanced Visible and Infrared Imager) instruments on the Meteosat Second Generation (MSG) spacecraft and the GOCI (Geostationary Ocean Color Imager) instrument on the Korean-operated COMS satellite have both recently been used to map changes in water quality in marine waters (Ruddick et al., 2014). The MSG and COMS spacecrafts are in orbit approximately 36,000 km above the Earth. SEVIRI is capable of imaging the hemisphere of the Earth every 15 min at a 3 km resolution, while GOCI provides data at 500 m spatial resolution over a 625,000 km^2 area centred on the Korean Peninsula every 1 h. SEVIRI was not designed primarily for applications over water but several studies have shown the feasibility of retrieving TSM in turbid waters (Neukermans et al., 2009, 2012). The GOCI sensor, however, is specifically designed for ocean colour applications and thus can be used to estimate Chl-*a* concentrations (Wang et al., 2013) and at a spatial resolution that also allows data to be acquired for systems ranging in scale from shelf-seas to large lakes (Lyu et al., 2015).

There are several forthcoming satellite missions due for launch from late-2015 onwards that hold tremendous promise for the assessment and monitoring of water quality in inland, transitional, coastal and shelf-sea waters. Foremost amongst these are the Sentinel-3a and 3b satellites that comprise part of ESA's Copernicus programme (http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus) that will carry the Ocean Land Colour Instrument (OLCI). This sensor has a strong MERIS heritage and will provide daily observations (with 3a and 3b operating in constellation) on inland and ocean water quality with complete global coverage at 300 m spatial resolution. These sensors will replace the capability lost with the failure of Envisat in 2012 and provide continuity in ocean colour observation into the 2020s, at which time they will be succeeded by the Sentinel-3c and 3d follow-up missions with the intention to extend observations until 2030. The planned operational lifetime of the Sentinel-3 series of satellites sets it apart from previous missions as it will provide continuous, systematic and long-term observations for both inland and marine systems.

These missions will be supported by higher spatial resolution data from the Multispectral Instrument (MSI) on-board the Sentinel-2a and 2b satellites scheduled for launch in 2015 and 2016 respectively. In spite of the fact they were primarily designed as land missions, the MSI sensors on the Sentinel-2 series will have sufficient spectral and radiometric resolutions for application over turbid waters but will provide data at a significantly increased spatial resolution (10–60 m). This will afford a much needed ability to observe smaller water bodies from space not previously resolvable from the likes of MERIS, MODIS or the forthcoming Sentinel-3a/b. This capability is already provided to an extent by the Operational Land Imager on Landsat-8 but while it has a much improved radiometric resolution compared to its predecessors its spectral band configuration is not as suitable for application over water bodies, especially for the retrieval of Chl-*a*. Sentinel-2 MSI will also have the advantage of being able to achieve a 5-day revisit frequency when the both satellites are in orbit.

3. Challenges for retrieving in-water constituents

3.1. Context

Inland, estuarine and coastal waters are highly optically complex environments (Morel and Prieur, 1977; IOCCG, 2000) and the water bodies of the Danube basin and Black Sea are no different in this respect. Fig. 1 shows some examples of phytoplankton, non-algal particles and CDOM absorption spectra from three inland waters located in the Hungarian part of the Danube basin. These freshwater systems are located within a few kilometres of each other but show marked variability in the shape and magnitude of their absorption. Many inland and near-shore waters are sporadically dominated by material of biological origin and during such phases these environments typically exhibit phytoplankton absorption spectra similar to the phytoplankton-dominated reservoir shown in Fig. 1. In this situation, the Chl-*a* absorption features near 430 nm and 675 nm and a phycocyanin absorption feature at 620 nm are clearly apparent (Gons, 1999; Babin et al., 2003; Hunter et al., 2008; Mishra and Mishra, 2014).

The contribution of CDOM absorption to the bio-optical properties of inland, transition and near-shore waters is also an important, often dominant, component particularly in rivers, fluvially-influenced lakes

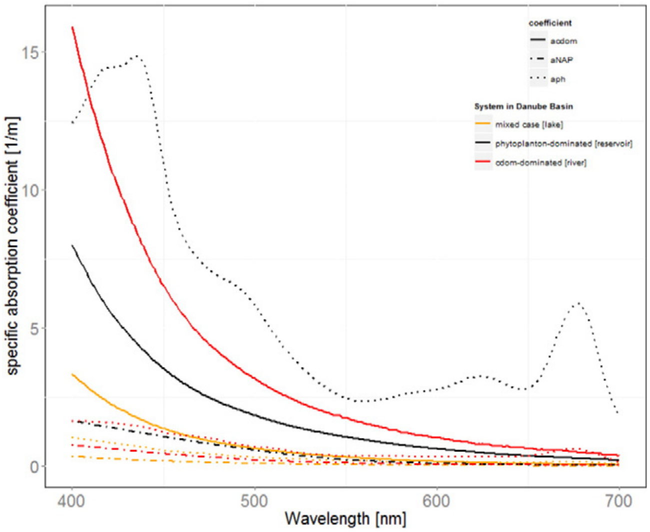

Fig. 1. Examples of absorption coefficients (aCDOM; aNAP and aph) for different systems in the Danube Basin.

and shallow estuaries. High concentrations of CDOM effectively decouples phytoplankton and non-algal particulate matter absorption in the blue (Bricaud et al., 1981; D'Sa and Miller, 2003; Brezonik et al., 2015) and, as a result, CDOM can hinder the accurate estimation of Chl-*a* and TSM from water-leaving radiative signals particularly when algorithms employing blue bands are used for their retrieval (Zhu et al., 2014). Significant variations in the TSM concentration can cause large changes in the magnitude and shape of water-leaving reflectance spectra (Fig. 2). The spectra display an increase in remote sensing reflectance (R_{rs}) with increasing SPM and a change of colour (R_{rs} maxima position) in very turbid rivers. R_{rs} signal appears to be far from zero in the near-infrared wavelengths for the most turbid waters (e.g. Doxaran et al., 2003; Gernez et al., 2014). In such turbid waters, particle scattering dominates the red spectrum confounding the accurate atmospheric correction of satellite data and the retrieval of phytoplankton absorption and pigment concentrations in these wavelengths (Dekker et al., 1997; Lavender et al., 2005; Ruddick et al., 2000; Morel and Bélanger, 2006).

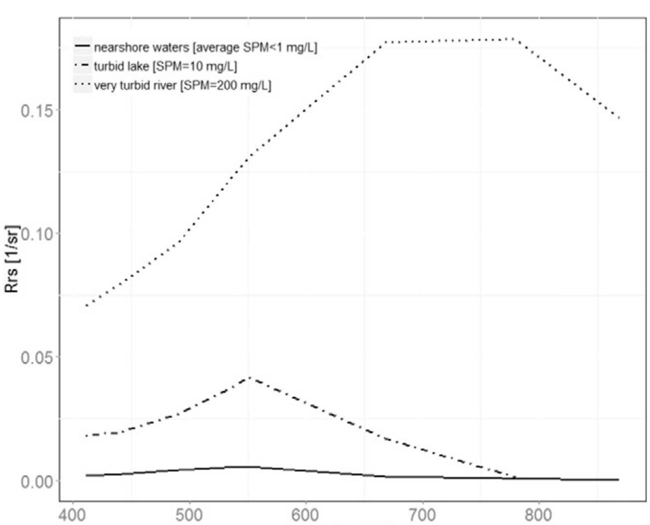

Fig. 2. Examples of water leaving reflectance (R_{rs}) from: a) near-shore waters in the Black Sea (data from the Gloria AERONET station, as displayed on NASA's AERONET web-page) b) a turbid lake in the Danube Basin (unpublished ship borne data collected in July 2013 by University of Stirling in Lake Balaton, Hungary) and c) a very turbid river in the Danube Basin (unpublished ship borne data collected in July 2013 by University of Stirling in River Zala, Hungary).

The development and testing of algorithms for the retrieval of selected water quality properties over oceanic water over the last decade has led to high quality ocean colour products. Traditionally, biogeochemical parameters such as Chl-*a*, CDOM and TSM are estimated using empirical models derived from statistical regression between water-leaving radiances or reflectances and the concentration of these parameters. Many of these algorithms have found applications in optically complex waters (e.g. Ali et al., 2014; Bélanger et al., 2008; Kowalczuk et al., 2010; Matthews et al., 2010; Tyler et al., 2006). Regionally-specific implementations and adaptations of already existing algorithms are also common in the literature (Budd and Warrington, 2004; Li et al., 2004; Yacobi et al., 2011; Palmer et al., 2015a, 2015c). Similarly, much effort has been devoted to the development of new retrieval algorithms for optically complex waters (Duan et al., 2010; Wang et al., 2011; Spyrakos et al., 2011; Lah et al., 2014; Dogliotti et al., 2015). The expansion in the use of powerful inversion methods such as neural networks, the availability of in-situ data though dedicated databases such as MERMAID (http://mermaid.acri.fr) and LIMNADES (http://www.globolakes.ac.uk) and the improvement in quantity, quality and availability of Earth observation data have contributed to a growing list of retrieval algorithms. The advances in optical sensor design, bio-optical algorithms and validation methods have also supported the retrieval of a wide range of new water quality parameters (e.g. phycocyanin, particulate organic carbon, phytoplankton size distribution) (Simis et al., 2005; Nair et al., 2008; Allison et al., 2010; Ciotti and Bricaud, 2006; Hunter et al., 2010; Brewin et al., 2011; Sun et al., 2013).

This section outlines the available water quality retrieval algorithms and atmospheric correction models that have been used or tested in near-shore and inland waters and provide some insights on their applications to systems such as the Danube Basin and the Black Sea. A comprehensive list and comparison of algorithms for the estimation of biogeochemical water quality parameters and atmospheric correction models in waters with high optical complexity can be found in Acker et al. (2005); Matthews (2011); Odermatt et al. (2012); Blondeau-Patissier et al. (2014) and Zhu et al. (2014).

3.2. Constituent retrieval

Many of the algorithms for estimating water constituent concentrations from EO data have been developed targeting the characteristics of a specific sensor (e.g. Doerffer and Schiller, 2007; Yi and An, 2014). This does not always restrict their applicability to other sensors since in several cases they can be re-trained or have the location of the input bands shifted to the closest wavelength available (Gitelson et al., 2009; Moses et al., 2009; Lesht et al., 2013). For example, the near-infrared to red reflectance ratio which was suggested by Dall'Olmo et al. (2005) for estimating Chl-*a* in turbid productive waters has been applied using the corresponding bands of SeaWiFS, MODIS, MERIS and HICO (Gitelson et al., 2006, 2007, 2011). In a recent study, Nechad et al. (2010) developed a generic algorithm for the retrieval of SPM from any optical sensor using one band in the red to NIR part of the spectra. This model can also consider bidirectional effects and has been shown to be robust in moderate values of SPM. This type of approach could be particularly useful in a complex system such as the Danube basin and the Black Sea where multi-sensor approaches seem to be required to handle the variable scale of its component waters. While the removal of the atmosphere from the total signal measured by a space-borne sensor is still considered challenging over inland and near-shore waters, in turbid systems with high signal-to-noise some algorithms can compute water biogeochemical properties successfully from top-of-atmosphere radiances (Gower et al., 2004) or Rayleigh-corrected reflectances (Matthews et al., 2012).

Satellite observations over near-shore and inland aquatic systems are challenging, not only because of high complexity in the optical properties of the water column but also in the overlying continental atmosphere. The effective retrieval of the water properties by remote sensors is partly hindered by the contribution of the atmosphere (due absorption and scattering by gas molecules and aerosols) to the signal recorded by the sensors. Classic methods for aerosol retrieval and atmospheric correction of EO data over water are based on the assumption that water-leaving radiance is negligible in the infrared (IR) (Gordon and Wang, 1994). However, this assumption is normally not valid for coastal and inland waters (Doron et al., 2011). Dust aerosols in closed seas such as the Black Sea can result in the underestimation of water-leaving radiance from satellite platforms in the visible especially for shorter wavelengths (Banzon et al., 2009).

The methods for aerosol retrieval and atmospheric correction used over near-shore and inland waters can be roughly grouped into water-specific models (e.g., Case-2 Regional Processor: Doerffer and Schiller, 2008; CoastColour: Brockmann Consult, 2014; Modular Inversion and Processing System: Heege and Fischer, 2004; Management Unit of the North Sea Mathematical Models (MUMM) algorithm: Ruddick et al., 2000; ACOLITE: Vanhellemont and Ruddick, 2015; Free University Berlin (FUB) algorithm: Schroeder et al., 2007; Short-wave infrared (SWIR)-based iterative algorithms: Wang, 2007; Zhang et al., 2014b; Combined NIR–SWIR: Wang and Shi, 2007) and adapted land-surface models (SCAPE-M: Guanter et al., 2009; Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH): ITT Visual Information Solutions, 2009; Atmospheric/Topographic Correction for Satellite Imagery (ATCOR): Richter and Schlapfer, 2014). Since water-specific models consider water spectra at the lower boundary, significant errors may be introduced in the atmospheric correction over the highly dynamic and often complex near-shore and inland waters (Vidot and Santer, 2003; Goyens et al., 2013). On the other hand, land-surface models do not embrace any assumptions on the water spectra but they experience other shortcomings (e.g., assumptions on atmospheric homogeneity) and introduce large uncertainties over clear waters (Guanter et al., 2009; Jaelani et al., 2013).

Remote sensing reflectance data in waters with high level of optical complexity are affected by the concentration of different optically active constituents and, as such, a single algorithm is unlikely to perform adequately in all situations. Some algorithm developers have tried to tackle this issue by predefining the limits to the applicability in their models. These limits are normally applied to the reflectance values or the concentrations of the water constituents (Stumpf and Tyler, 1988; Kutser et al., 2006; Du et al., 2008). However, the concentrations of the different water parameters are usually not known *a priori*. For regionally-specific algorithms some attempts have been made to set limits on the Chl-*a* concentrations based on expected the values for the region (Rosado-Torres, 2008). Another recent approach has been to develop a single band semi-analytical algorithm using reflectance at 645 nm to 859 nm with a switching scheme to improve globally applicability for retrieving turbidity, which is almost independent IOPs of different particle types (Dogliotti et al., 2015). The advantage of this approach is that a regionally derived turbidity/TSM ratio can be used to convert from turbidity to estimates of TSM. More sophisticated approaches, particularly for Chl-*a* include fuzzy c-means classification of satellite-derived data (Spyrakos et al., 2011; Moore et al., 2014) and development of cluster-specific retrieval algorithms (González Vilas et al., 2011). For those algorithms based on machine learning techniques, the range in the variation in the training dataset can define these thresholds.

In order to facilitate convenient comparisons, existing in-water models for the estimation of biogeochemical properties from remotely sensed data in optically complex waters were categorised here into three groups based on their retrieval approach. The first group comprises those algorithms whose performance and applicability is strongly driven by the shape and magnitude of the water-leaving radiative signal. The most common type of in-water algorithm are those based on a single band or the difference or ratio between two bands derived based on statistical relationships with the measured concentrations of Chl-*a* or other in-water constituents (e.g. Morel and Prieur, 1977; Gitelson et al., 1985; Hoge et al., 1987; Stumpf and Tyler, 1988; Dekker et al., 1991; Oki and Uasuoka, 2002; Dall'Olmo et al., 2005), SPM (e.g. Curran and Novo, 1988; Dekker et al., 2001; Doxaran et al., 2002) and CDOM (e.g. D'Sa and Miller, 2003; Del Castillo and Miller, 2008; Mannino et al., 2008; Ficek et al., 2011). Combinations of more spectral bands have been also introduced in band ratio algorithms with variable results in order to account for the confounding effects of other optically active constituents (Dall'Olmo et al., 2003; Dall'Olmo and Gitelson, 2006; Gitelson et al., 2007; Le et al., 2009). In parallel, research in optically complex waters has focused on the pursuit of particular signal attributes (e.g., peak position and height) of the water-leaving radiative signal that appear to be unique to a specific parameter such as Chl-*a* fluorescence (Esaias et al., 1998; Gower et al., 1999; Matthews et al., 2012). One of the apparent limitations of this type of approaches is the need for well-defined features in the water-leaving radiative spectra and in situations of low concentrations of the water constituents and poor atmospheric correction this requirement is not always fulfilled. In addition, re-tuning to specific conditions is normally necessary if the models are to be applied to new regions. Despite the limitations, these algorithms are usually easy to implement and regionally robust.

The second group of algorithms comprise those are strongly driven by an understanding of the relationships between *inherent optical properties* (IOPs) (i.e., absorption, scattering and fluorescence) and the water-leaving radiative signal through the use of physics-based bio-optical models. Several inversion techniques (e.g., spectral optimization, linear and non-linear matrix inversion) have been developed for retrieve IOPs and to relate these to in-water biogeochemical properties (Hoge and Lyon, 1996; Garver and Siegel, 1997; Lee et al., 1999, 2002; Carder et al., 1999; Maritorena et al., 2002; Heege and Fischer, 2004; Smyth et al., 2006; Santini et al., 2010; Giardino et al., 2012; Werdell et al., 2013). Although, these models are physic-based many rely on empirical assumptions, while others require knowledge of the specific IOPs (SIOPs; i.e., absorption or scattering per unit mass) (Brando and Dekker, 2003). The output of these algorithms typically includes the three main optically active constituents, while more recent implementations also retrieve variables such as phycocyanin (Mishra and Mishra, 2013; Li et al., 2015). This inverse modelling approach has often shown better retrieval capabilities than the empirical, data-driven algorithms (Huang et al., 2013). However, some of them still suffer from drawbacks such as their dependency on the initial parameterisation and the fact that the inversion process itself is an ill-posed problem (IOCCG, 2000).

The third type of retrieval algorithm comprises those models based on machine learning approaches. Machine-learning algorithms were introduced in image processing as powerful alternatives for the retrieval of water properties due to their ability to approximate a set of input data to the corresponding output and the limited assumptions required (Thiria et al., 1993). Machine-learning algorithms that have been used in optically complex waters are based mainly on neural networks techniques (Keiner and Yan, 1998; Dzwonkowski and Yan, 2005; Doerffer and Schiller, 2007; González Vilas et al., 2011, 2014) but examples also include support vector machines (Matarrese et al., 2008) and hybrid active learning models (Shahraiyni et al., 2009). These approaches appear to be robust to noise and to allow the application of complex bi-directional radiative transfer models providing stable numerical outputs. They have shown good prediction capabilities in coastal (Spyrakos, 2012) and inland waters (Odermatt et al., 2010) and they are often accompanied with the improvement of the EO products by reducing residual atmospheric correction errors. Since these models are strongly driven by the data, a large representative training set is often required. Nevertheless, extending the training range can result in poorer accuracies and increased computational times. Machine-learning algorithms based on simulated datasets have been widely used to address this issue; however, they still fail to provide accurate results in regional and atypical situations (e.g. Spyrakos et al., 2011;

Palmer et al., 2015a, 2015c). Moreover, careful selection of the initial inputs and parameterisation of these models are necessary to avoid imprecision in the prediction of the output and over-fitting.

4. Inland freshwaters

The application of remote sensing for the assessment and monitoring of inland waters has developed markedly over recent decades particularly since the launch of the Terra- and Aqua-MODIS and Envisat MERIS sensors in 1999 and 2002 respectively. Numerous studies have demonstrated the potential of Earth observation for providing information on key water quality parameters including Chl-*a*, measures of water transparency (e.g., Secchi depth, K_d), turbidity, TSM concentrations and CDOM. The spatial coverage and temporal sampling frequency achievable with remote sensing can provide novel insights into dynamic processes in inland waters that cannot be easily captured through more in situ sampling or even from instrumented buoys (Palmer et al., 2015b).

Many studies have derived estimates of the Secchi depth from satellite data. Most algorithms for the estimation of Secchi depth take advantage of the bands in red because as water clarity decreases, the water-leaving radiative signal in the red spectrum usually increases (Matthews, 2011). The retrieval of Secchi depth can also be achieved successfully using relatively broad spectral bands and thus many studies have capitalised on Landsat-MSS/-TM/-ETM+/-OLI data as they offer high spatial resolution (30 m) suitable for application to moderately sized lakes and reservoirs. For example, Duan et al. (2009) used red band algorithms to successfully retrieve Secchi depth in two Chinese lakes and achieved good agreement ($R^2 \geq 0.72$) against measured *in situ* values.

There are also a relatively large number of studies dedicated to the retrieval of TSM in inland waters, using sensors ranging from Landsat-TM/ETM+/OLI to ocean colour sensors such as MERIS and MODIS. This reflects the fact that TSM is arguably the most straightforward in-water constituent to retrieve from remote sensing data. In similar fashion to algorithms for turbidity, reflectance in red bands is often used in TSM retrieval algorithms (Matthews, 2011) although many different approaches have been used including ratios of reflectance in the green and infrared. Gitelson et al. (1993) developed an algorithm based on reflectance in the red that was effective in retrieving TSM in lakes for concentrations up to 66 mg/L. In extremely turbid waters (TSM > 100 mg/L) such as rivers and estuaries, nonlinearity in the relationship between water-leaving reflectance and the TSM concentration is often observed. To counter such effects, recent research has shown that the signals in the SWIR (c. 1070 nm) demonstrate greater linearity with TSM and are less prone to saturation (Knaeps et al., 2012) at very high turbidity.

Chl-*a* is the main light harvesting pigment in most phytoplankton and is widely accepted to provide an accurate indication of phytoplankton biomass in inland, coastal and ocean waters. There is an extensive literature demonstrating that Chl-*a* can be retrieved over from water-leaving radiative signals. In large lakes, Chl-*a* can be retrieved using ocean colour satellite data from sensors such as MODIS and MERIS. Palmer et al. (2015b)used MERIS data to map changes in the Chl-*a* concentration in Lake Balaton (Hungary) over a 5-year period with a high accuracy ($R^2 = 0.87$, RSE 4.19 mg m^{-3} (30.75%)). Fig. 3 shows monthly composited mapped Chl-*a* products for Lake Balaton, Hungary derived from the MPH algorithm (Matthews et al., 2012). The spectral and radiometric resolutions of MERIS and MODIS are well suited for the retrieval of Chl-*a* in inland waters but their coarse spatial resolution limits their application to smaller water bodies. Higher resolution satellite data from sensors such as Landsat-TM/ETM+ has been used to retrieve estimates of Chl-*a* in smaller lakes. Tyler et al. (2006), for example, used Landsat-TM data to estimate the concentration of Chl-*a* in Lake Balaton. Tebbs et al. (2013) used Landsat ETM+ data to retrieve estimates of Chl-*a* in Lake Bogoria in the Kenyan Rift Valley at concentrations up to 800 mg m^{-3}. However, the poor spectral and radiometric resolutions of the Landsat sensors limits their application to lakes with high turbidity and, although the recently launched OLI sensor on Landsat-8 has a greatly improved radiometric resolution, its spectral channels are arguably less suited to Chl-*a* retrieval than its predecessors (Vanhellemont and Ruddick, 2015).

In addition to retrieving estimates of the bulk Chl-*a* concentration, numerous studies have now also demonstrated the feasibility of obtaining information on the abundance of cyanobacteria through the detection and quantitative retrieval of the diagnostic phycocyanin pigment. Phycocyanin has a major absorption maximum near 620 nm. The MERIS sensor carried by Envisat had a spectral channel centred close to at 620 nm and several studies have developed and tested algorithms to retrieve phycocyanin absorption and concentrations from MERIS data. Riddick et al. (in review) used MERIS data to map seasonal changes in the concentration of phycocyanin in Lake Balaton and were able to demonstrate not only good retrieval accuracy ($R^2 = 0.71$, mean absolute percentage error (MAPE) = 62%) but also a strong relationship between the retrieved phycocyanin concentration and the abundance of cyanobacteria as estimated from standard cell counts. This approach has been further demonstrated by Wheeler et al. (2013) and Qi et al. (2014) amongst others. However, following the failure of MERIS in 2012, currently only the OCM-2 (Ocean Colour Monitor) sensor on the OceanSat-2 satellite has the potential to retrieve phycocyanin concentrations, although it coarse spatial resolution of 360 m means it is also restricted to application over large lakes (Dash et al., 2011). The potential to discriminate other phytoplankton groups beyond cyanobacteria has not been examined for inland waters, although algorithms for the identification of other toxic bloom-forming species such as red tide dinoflagellates have been developed for marine waters (e.g., Siswanto et al., 2013).

CDOM is arguably the most challenging in-water constituent to retrieve from remote sensing data. CDOM is non-scattering and has very high absorption in the blue and green spectral regions. Consequently, increases in CDOM concentration result in a decrease in the water-leaving signal and an increase in the signal-to-noise ratio. Changes in the water-leaving signal due to variability in CDOM are thus difficult to resolve, particularly with sensors with poor radiometric resolution. The need for a highly accurate atmospheric correction, particularly at blue wavelengths, is also a challenge to the development of operational approaches for CDOM retrieval in inland waters. Campbell et al. (2011) used an analytical algorithm applied to MERIS data to successfully retrieve CDOM in the Burdekin Falls Dam in Northern Australia with a mean bias of 0.12 m^{-1}. Zhu et al. (2014) provide the most comprehensive assessment of CDOM algorithms for inland waters published thus far with an evaluation of 15 different models. The performance of the models varied greatly with R^2 varying from 0.01 to 0.89 and RMS errors from 0.29 to 1.43 m^{-1} for CDOM absorption coefficients ranging from 0.11 to 8.46 m. However, the coarse spatial resolutions of ocean colour sensors are, as previously discussed, prohibitive to applications over small lakes. The retrieval of CDOM from sensors such as Landsat TM/ETM+ has proven unreliable, largely due to the poor spectral and radiometric resolution of these sensors; thus far only a very limited number of studies have successfully retrieved CDOM from Landsat or similar data products (e.g. Kutser et al., 2005; Kutser, 2012) and then only for lakes covering very large DOC concentration gradients.

5. Transitional and coastal waters

Transitional waters are 'bodies of surface water in the vicinity of river mouths which are partially saline in character as a result of their proximity to coastal waters but which are substantially influenced by freshwater flows. If riverine dynamics occur in a plume outside the coastline because of high and strong freshwater discharge, the transitional water may extend into the sea area' (EC, 2000). Deltas, estuaries, gulfs with freshwater input, lagoons and salt marshes can all be considered transitional environments. Transitional and near-shore coastal

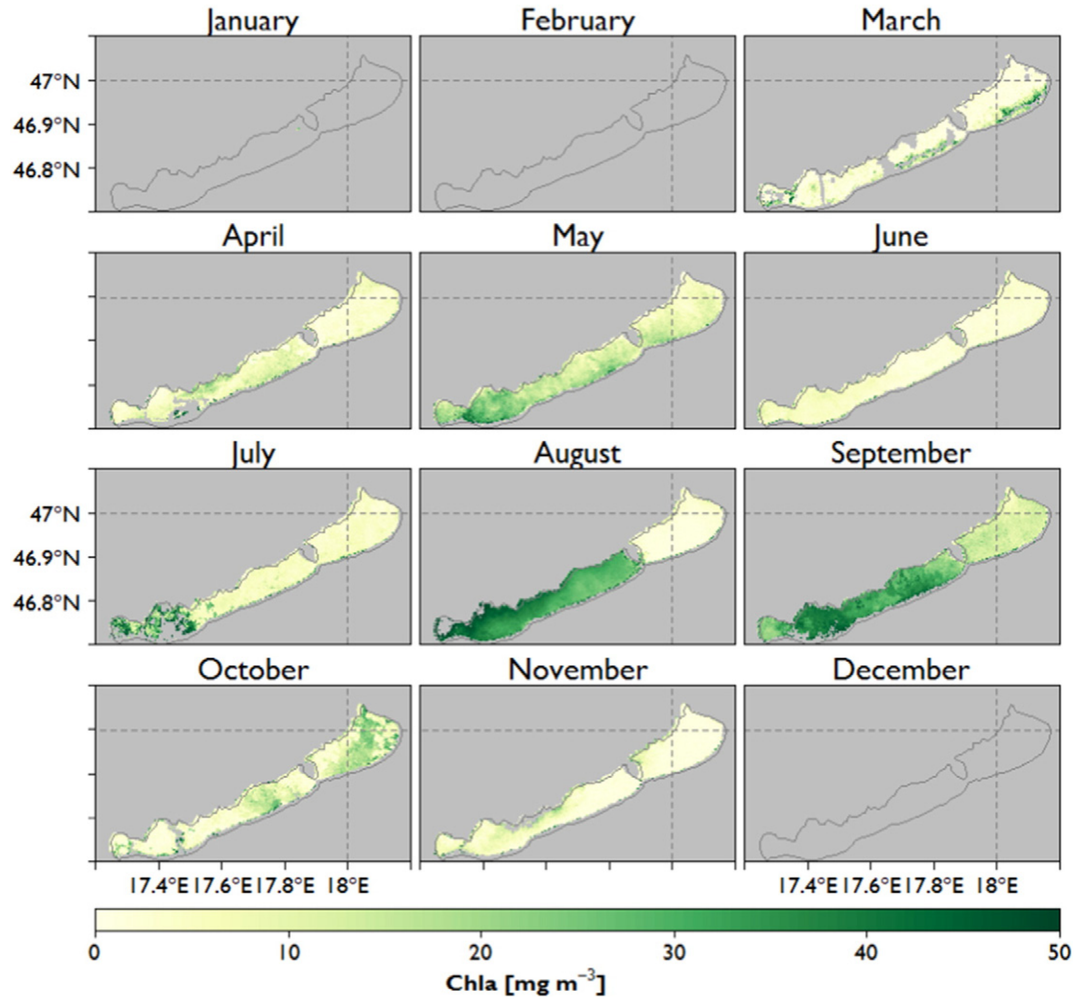

Fig. 3. Example of MERIS derived monthly integrated time series of Chl-*a* from Lake Balaton. Figures reproduced courtesy of Carsten Brockman from the ESA funded Diversity II project.

waters often share common characteristics regarding optical properties and physical processes. Transitional and coastal systems represent spatially and temporally complex environments, largely as a result of the dynamic interaction of the physical and biological factors (e.g. Yang et al., 2013; Petus et al., 2014) that are compounded still further by the variation in tides and variations in freshwater discharge from the catchment.

Whilst macro-tidal estuaries tend to be more extreme in their dynamic behaviour, microtidal systems including lagoons, and deltas exhibit spatial and temporal heterogeneity as a result of the subtle balance between sediment inflow from inland waters or the sea and sediment outflow originated by wind erosion and tidal currents (Volpe et al., 2011). River plumes discharging into coastal areas, either in the vicinity of an estuary or delta, represent the main pathways from the continent to the ocean and the main transport mechanism for nutrients, sediments and land-based pollutants into the coastal waters (Dagg et al., 2004). The SPM exported by turbid rivers in the sea, directly affects phytoplankton productivity, nutrient dynamics and the transport of pollutants in coastal zones (Doxaran et al., 2009).

EO data are an important source of synoptic observations of coastal and transitional aquatic systems. Much research has been published on the use of data from multiple satellite sensors (e.g. MODIS, MERIS, Landsat) that offer the necessary spatial resolution and/or sensor sensitivity for mapping and assessing spatial and temporal variation of water quality and sediment flux (e.g. Burrage et al., 2008; Doxaran et al., 2009; Salama et al., 2012; Chen et al., 2013, 2014; Eleveld et al., 2014; Karageorgis et al., 2014, 2009; Keith, 2014; Loisel et al., 2014; Mendes et al., 2014; Salama and Su, 2010, 2011; Tian et al., 2014; Zhang et al., 2014a, 2014b; Cai et al., 2015; Schaeffer et al., 2015). The main parameters assessed by EO include the phytoplankton Chl-*a* concentration and SPM. Both variables are measures of water turbidity and thus allow for the delineation of dynamic features such as river plumes that provide important insights into ecosystem function. Such studies have also been able to identify long-term seasonal changes in the turbidity patterns, their relationship with physical drivers (hydrological conditions, wind, waves, tide), and monitor river plume dynamics, sediment dynamics and associated phenomena (re-suspension/deposition) and any environmental changes (e.g., Neil et al., 2012).

6. Remote sensing of the Danube and Black Sea

The Danube system encompasses a complex mosaic of river channels, lakes and lagoons, discharging suspended particles tens of kilometres into the coastal and sea-shelf waters of the Black Sea (Güttler et al., 2013) and influence the biogeochemical properties of the shelf-sea system (Friedrich et al., 2014) and has impacts as far as the Turkish coast (Tsiaras et al., 2008). The sheer size of the system and scarcity of *in situ* data means that remote sensing data are likely to become increasingly important for providing synoptic observations on the state of the system and its evolution over time. In order to resolve spatially and temporally dynamic processes, particularly at the interface between the freshwaters of the Daunbe river and the marine waters of the Black Sea, observations are needed at medium to high spatial resolutions and also at high temporal sampling frequency (Doxaran et al., 2009). This presents a challenge at present because although the temporal resolution of ocean colour platforms are of the order of 1–3 days globally, their spatial resolution is only suitable for observing the coastal and shelf-sea area and some of the larger coastal lagoons and lakes. Those platforms capable of providing high spatial resolution data such as Landsat-7 TM and -8 OLI have significantly reduced temporal sampling frequencies (8–14 d) (Fig. 4) and while they can provide insights into the seasonal dynamics of the system they might not be able to sufficiently capture the occurrence and effect of more episodic events (e.g., high rainfall floods, storms, phytoplankton blooms).

This will be partly addressed once the Sentinel-2 and Sentinel-3 satellite constellations are operational and providing data synergistically on a 1-day and 5-day repeat cycle globally and at spatial resolutions of 10–60 m and 300 m respectively. The 16-bit radiometric resolution of OLCI should provide at least comparable performance to MERIS in terms of the dynamic range for constituent retrieval and improved performance over predecessors such as MODIS. The lower 12-bit resolution of the Sentinel-2 MSI sensors, coupled with their 10–20 m spatial resolution in many of the visible and near-infrared bands, will result in a lower signal-to-noise ratio at its native resolution than achievable with OLCI. Thus spatial and temporal binning of the data will probably be required to achieve the desired performance for retrieval of parameters such as Chl-*a* and TSM.

The imminent availability of these new data streams from the ESA Sentinels and other forthcoming platforms will provide new opportunities to observe dynamic processes in the Danube system from space, including: (i) the variation in plume extent from the Danube sediment laden waters into the Black Sea; (ii) the connectivity between the channels of the delta and the delta lakes and lagoons; and (iii) the frequency and spatial extent of events such as flooding and eutrophication including the connectivity phenology of events at the local and regional catchment scale The use of archive data can also fill in the gaps in infrequent monitoring and provide a fuller interpretation of the magnitude and impact of events and processes. Surprisingly, there have been relatively few studies undertaken thus far that have used remote sensing data to study biogeochemical processes in the Danube–Black Sea region. Those studies that have been undertaken have largely focused on mapping spatial and temporal variation in suspended particles and turbidity and even here the publications are sparse (Constantine et al., 2016) within the system and can be broadly grouped into:

(i) those studies focused on the Danube River and the dynamics of the sediment plume and its seasonal variability (e.g., Constantine et al., 2016; Güttler et al., 2013; Karageorgis et al., 2009);
(ii) those studies that sought to map in-water optical properties and constituents and their distribution to assess environmental interactions in the wider northwest Black Sea and to use the observations to improve ecosystem models, including CDOM (Barale et al., 2002), Chl-*a* (Tsiaras et al., 2008) and particle size (Karageorgis et al., 2014).

The erosion, transport and deposition of suspended particles are some of the key processes influencing the state and behaviour of the Danube system and the coastal and shelf-sea waters of the Black Sea. The Danube is the major source of water and sediment for the Black Sea and the processes that govern the transport of suspended particles from the Danube Delta into the Black Sea are incredibly complex. Historically, damming and channel dredging have reduced the sediment input leading to degradation and erosion of the delta and the coastal environment (Panin and Jipa, 2002). At the same time, intensification of land use has had the opposite effect (McCarney-Castle et al., 2011) and together, these influences along with climate change drivers control the fluvial transfer and variability across the basin. The turbid waters of the Danube mix with the brackish waters of the Black Sea over a large area as the Danube river splits into three main channels are Chilia (north) with a secondary delta (situated in Ukraine), Sulina (middle) and Sfantu Gheorghe (south) over the deltaic plain. The tidal variations are small in the Black Sea (c. 7 to 12 cm; Giosan, 2007) and as such the interaction between the wind, waves and currents largely shape the hydrodynamic processes governing sediment transport in the transitional zone.

Güttler et al. (2013) used a multi-sensor approach, combining observations from five difference satellites from ALOS AVNIR-2 at 10 m spatial resolution, through Landsat-7 TM/ETM+ at 30 m spatial resolution up to Envisat MERIS at 300 m resolution, to study the spatial and temporal dynamics of sediment in the Danube Delta and Black Sea and obtain insights into the relative importance of hydrodynamic and meteorological processes in shaping sediment transport through the system. Interestingly, they showed that sediment dynamics in the coastal zone are largely shaped by the interactions between hydrodynamical and meteorological processes, whereas phytoplankton growth is increasingly important to the turbidity of the coastal lagoons and deltaic lakes. They were also able to show that the Danube plume can extend some 70 km into the Black Sea under specific hydrodynamic conditions. This study exemplifies the potential for using satellite observations acquired at different spatial and temporal resolutions in a synergistic manner to provide otherwise unobtainable insights into the dynamics of the Danube river basin and Black Sea. Sentinel-2a MSI and Landsat-8 OLI are already providing high spatial resolution data and will soon be complemented by the higher frequency observations from Sentinel-3a OLCI. Landsat-8 imagery, for instance, has the spatial and radiometric resolution to map the TSM concentrations within the river channels, deltaic lakes and Black Sea coastal environment (Fig. 4).

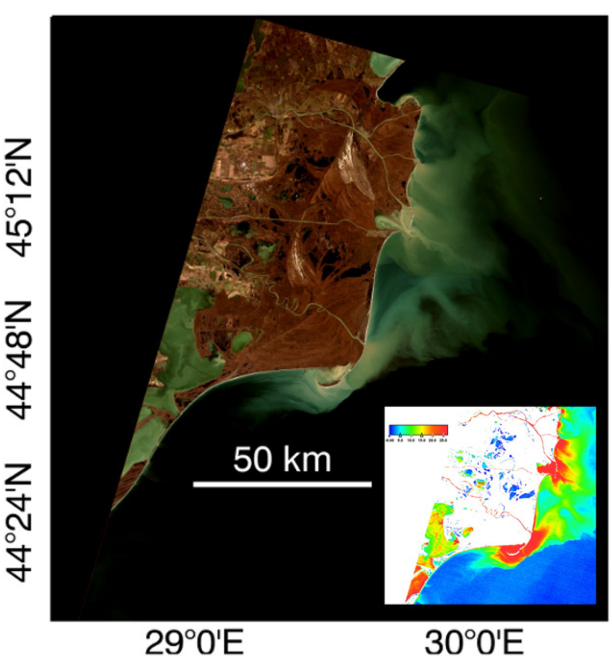

Fig. 4. Landsat-8 image showing the complex turbidity pattern as a result of the Danube discharging through the Danube Delta into the Black Sea and the variable connectivity with lakes in the delta. Image acquired on the 24 December 2014 (NASA/USG Landsat 8 OLI: RGB — Rayleigh corrected). Inset: SPM concentration (g m^3) in the Danube Delta and Black Sea on the 24 December 2014. SPM estimated using the 665 nm band from the Rayleigh corrected Landsat-8 image (after Nechad et al., 2010).

The Danube is known to exert a strong influence over the Black Sea system, but again our understanding of the interaction between these systems remains limited. There have been several studies that have used satellite data to examine the optical properties and biogeochemical processes of the shelf-sea and pelagic zones of the Black Sea. The use of Earth observation for monitoring and assessment of marine systems is far more advanced than for inland and transitional waters and operational services are already available. Broadly speaking, monitoring of the Black Sea from Earth-observing satellites can be split into two approaches:

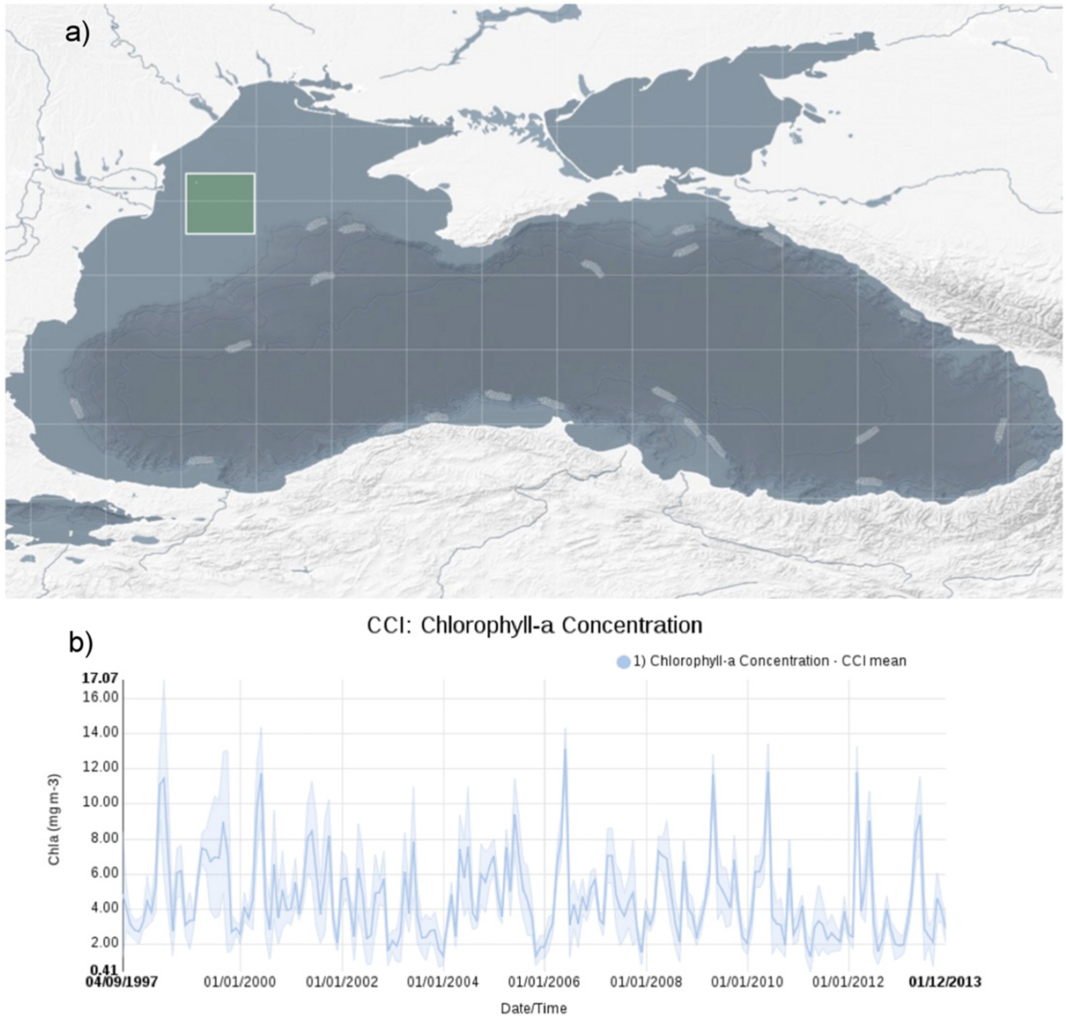

Fig. 5. a) OC CCI web-based visualisation portal with b) time series (1998–2013) of Chl-*a* for a box on the northwest shelf close to the Danube Delta.

near-real time (NRT), where the data are delivered to end-users as soon as possible after the satellite has passed over the site (typically same day), and reprocessing (REP) mode where a long time series is processed using consistent data processing methods.

Near-real time data can be used for guiding *in situ* sampling, for instance, to find the location of the highest concentrations of phytoplankton or suspended particles, or could be used to update a numerical model to make short-term forecasts, such as the development of a harmful algal bloom. Reprocessed time series, by contrast, can be used to find the interannual variability for an area (Kopelevich et al., 2013), to detect anomalous events (e.g. McQuatters-Gollop et al., 2008), changes in phenology (Palmer et al., 2015b), or to compare with a long-term run of a numerical model. The European Copernicus programme is implementing the Copernicus Marine Environment Monitoring Service (CMEMS) (http://marine.copernicus.eu/) that provides data for both NRT and REP purposes. MCS will be established in 2015 following development of the precursor service through the MyOcean project. Satellite data for the Black Sea are available from the Thematic Assembly Centres which produce a series of data products including ocean colour, sea-surface temperature, and sea-level while also providing *in situ* data; these data are used by end-users as well as the dedicated Black Sea Monitoring and Forecasting Centre.

NRT ocean colour data for the Black Sea are produced by CNR, Italy and currently (March 2015) rely on the Aqua-MODIS and VIIRS sensors and include Chl-*a* computed with the regional algorithm of Kopelevich et al. (2013) and "optics" products which include R_{rs} at 412, 443, 488, 531, 547, 667, and 869 nm and the diffuse attenuation coefficient at 490 nm ($K_d = 490$).

The REP data makes use of the state of the art Ocean Colour Climate Change Initiative (OC CCI) product, which is produced by merging data from SeaWiFS, MODIS-Aqua and MERIS, de-biasing MODIS and MERIS with respect to SeaWiFS as a reference sensor. Likewise, data are available as Chl-*a* and optical products at 4 km resolution. A regional version of this product is produced by CNR using OC CCI level 2 data as input with the algorithm of Kopelevich et al. (2013) to compute Chl-*a*. The existing 4 km resolution product will be shortly superseded with a 1 km version while other new regional algorithms (Zibordi et al., 2014) will be investigated. Furthermore, Level 4 products are being produced that use the DINEOF approach (Beckers and Rixen, 2003) to "gap fill" cloud covered areas.

A key issue with EO data is ease of access: often users need a time series for a given location or a single image, or may wish to compare ocean colour data with sea-surface temperature images, or compare EO data with model output. Ideally, this analysis could be accomplished without having to download the entire data archive. Recent work in the OC CCI project and an EC FP7 project called Operational Ecology has enabled development of a web-based visualisation portal with simple data analysis and comparison tools. The EO portal (http://www.oceancolour.org) contains the OC CCI data whilst model output provided by the Institute of Marine Science at the Middle East Technical University (METU) is available at http://portal.marineopec.eu. Fig. 5 shows a time series of Chl-*a* (using the global Chl-*a* algorithm) for a small box on the

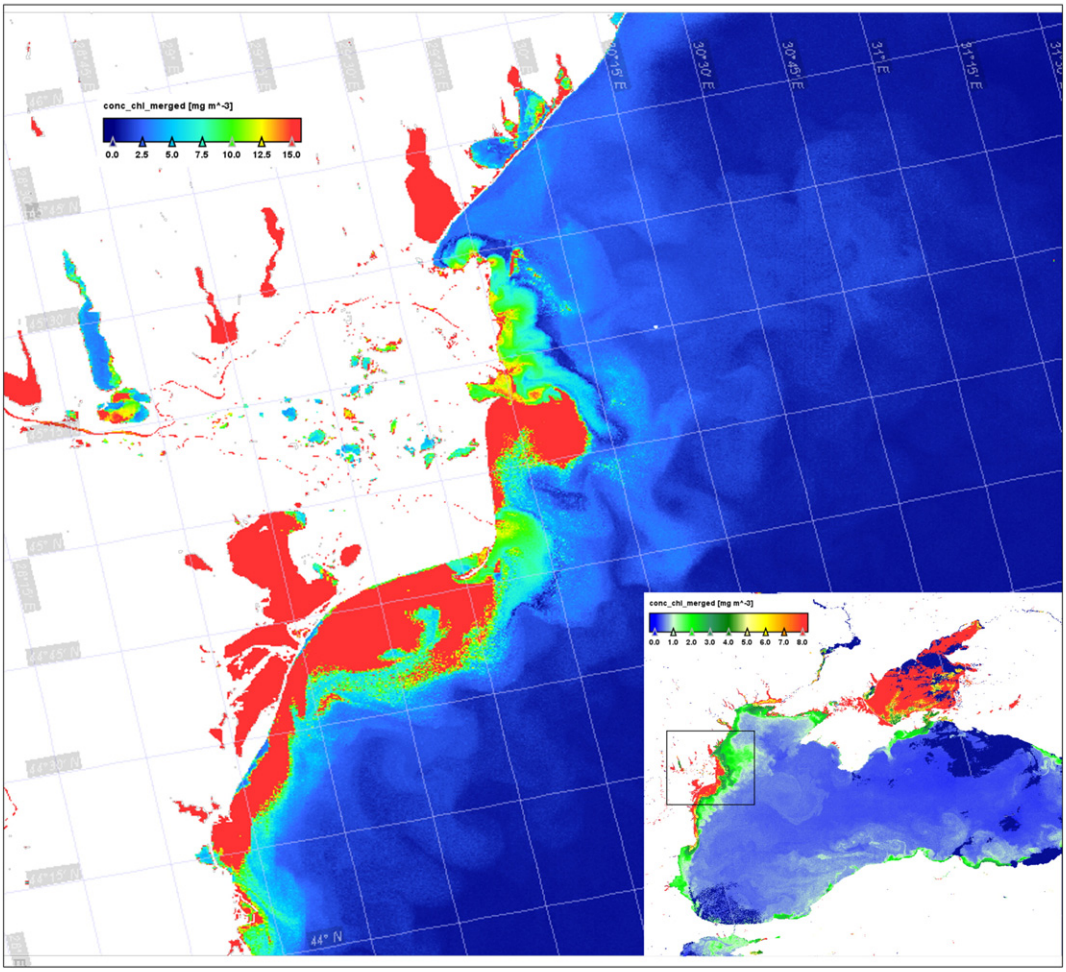

Fig. 6. MERIS full resolution image showing chl a for Danube Delta; inset whole swath.

northwest shelf region. The system can be used for simple analyses: for example, R_{rs} data were extracted for a box in the Black Sea western gyre and used with the Case-1/Case-2 classification method of Lee and Hu (2006) to show that the region is Case-1 most of the time when considering turbidity (measured by $R_{rs}555$) but can be considered Case-2 permanently with regard to CDOM absorption as indicated by the $R_{rs}412/R_{rs}443$ ratio. The two portals will be merged shortly with both model and EO data available in one place.

The European Copernicus programme includes planned launches of the OCLI (on board the Sentinel-3 series of spacecraft) with the first launch expected in late 2015. Sentinel-3 OLCI will provide ocean colour imagery at 300 m, similar to MERIS full resolution data; however, unlike MERIS, OLCI 300 m data will be global and since there will be three Sentinel-3 platforms operational at any time the frequency will be superior to MERIS. An ESA project CoastColour (www.coastcolour.org) re-processed the entire MERIS 300 m data set and the Black Sea is one of the user specified areas. Fig. 6 shows the detail possible even with the 300 m resolution, revealing significant contrast in the eutrophic status of lakes within the Danube Delta. A number of pixels within the main branches of the River Danube through the Delta are also resolved.

7. Conclusions

The world's surface waters remain at risk from a range of natural and anthropogenic environmental pressures. One of the limiting factors on understanding the consequences of these pressures is the lack of consistent data collected systematically and at a sufficient spatial resolution and temporal frequency to allow greater understanding of the connectivity of surface waters through the ecological compartments that comprise the river–shelf-sea continuum. There are a number of Earth observation missions planned that will lead to step change in our ability to monitor inland, coastal and transitional waters. The forthcoming generation of satellites, such as ESA's Sentinel 2 and -3 missions have the potential to provide comprehensive observational capacity for large river–sea systems such as the Danube–Black Sea. Numerous examples exist demonstrating the successful application of EO data to the characterisation and monitoring of lake, rivers transitional and coastal waters and multi-sensor approaches (MERIS, MODIS, SeaWiFS) have been used to extend time series at high temporal frequency (weekly to monthly) data back into the 1990s. Collectively these examples demonstrate the exciting potential that satellite data archives from past missions allied to observations from current and forthcoming platforms have to offer, particularly when such data are used synergistically and merged to develop consistent long-term climatologies.

The studies highlighted in this contribution demonstrate that a range of regionally-tuned or adaptive algorithms for the retrieval of optical and biogeochemical properties can be used to observe the dynamic behaviour of large, complex river basins and their interface with marine systems. Despite the number of applications of EO data to inland systems, coastal and shelf-sea systems, this review has highlighted that very few look across these environmental systems and the general applicability of these approaches in a multi-component system like the Danube basin and its interface with the Black Sea has yet to be fully explored. Furthermore, application of EO to the Danube River-Delta–Sea system have focussed primarily on sediment only.

To become operational, improvements in cross-platform the atmospheric correction of satellite data over turbid waters are urgently need and further effort is required to quantify and better constrain the uncertainties on the performance of in-water models in the different optical water types (e.g. high phytoplankton biomass, sediment-laden, CDOM dominated) that can be found in any of the components that contribute to these systems. To facilitate the development and selection of algorithms, a much improved understanding of the sources and magnitude of the variability in the SIOPs of these water types is needed to better understand their contribution to the water-leaving radiative signal and to better constrain the uncertainties in model parameterisation and the generated data products. In systems like the Danube and Black Sea that are likely to exhibit significant variability in the optical properties of the various water bodies, approaches must be developed that can allow dynamic selection of in-water and atmospheric models in space and time to optimise performance and minimise product uncertainties. Allied to this is a need for high quality in situ data, measured using community-endorsed protocols to facilitate algorithm development and validation. This is especially challenging in multi-national river–sea systems such as the Danube.

In spite of these challenges, Earth observation data are being processed and reprocessed on an operational basis and, due to rapid improvements in computing power, NRT monitoring of inland, transitional, coastal and shelf-sea waters is now a realistic ambition. These data are sufficiently reliable to reveal new insights into the connectivity between the changes occurring within and across the catchment and the resulting downstream impacts in the highly dynamic transitional, coastal and shelf-sea environments. Collectively, these data will yield new spatially resolved insights into the highly dynamic processes that shape the structure and function of inland, transitional, coastal and shelf-sea ecosystems and open a window of opportunity to better understand the response and sensitivity of our surface waters to natural and anthropogenic pressures.

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