



LITERATURE REVIEW OF REMOTE SENSING TECHNOLOGIES FOR COASTAL CHLOROPHYLL-A OBSERVATIONS AND VEGETATION COVERAGE

Part of ReSTEK (Brug af Remote Sensing teknologier til opgørelse af klorofyl-koncentrationer og vegetationsudbredelse i danske kystvande) and DCE Remote sensing in coastal area projects

Technical Report from DCE – Danish Centre for Environment and Energy

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Summary

This report reviews the possibilities of using data from different remote sensing (RS) techniques to supplement the conventional national NOVANA programme for monitoring of water quality (Chlorophyll-a; Chl-a) and submerged aquatic vegetation (SAV; seagrasses and macroalgae) in Danish coastal waters. Strengths, weaknesses and knowledge gaps are discussed and recommendations on future steps for integration of RS techniques for monitoring in Danish coastal waters are provided.

The complex bio-optical characteristics of the Danish coastal waters demand RS sensors that can distinguish between Chl-a from the commonly high levels of coloured dissolved organic matter (CDOM) and total suspended solids (TSS), as well as from sediment reflection and SAV in the nearshore zone.

While most shallow Danish coastal waters are well mixed all year round, areas like the Kattegat, the Belt Sea and the deeper parts of e.g. Limfjorden experience summer stratification, causing the Chl-a signal sensed by RS to only represent the upper part of the water column. As EU's Water and Marine Strategy Framework Directives only require summer data on the mixed layer, stratification is a minor problem. However, near shore bottom reflection is a major issue for most sensors aiming at determining Chl-a in the coastal zone. To overcome this, either high spectral resolution to discriminate this noise is needed, and/or RS data of high spatial resolution, which diminishes the edge effects in the shore zone.

Experiences with RS monitoring of Chl-a have in recent times mostly been based on the European Space Agency's sensor MERIS and the two MODIS sensors from NASA, which were especially adapted to water. With the recently launched and now operational Sentinel 2 MSI and Sentinel 3 OLCI sensors from the European Commission, new possibilities are emerging as these sensors provide higher spatial and temporal resolution and better retrievals in the coastal zone.

The shallow littoral zone around Denmark comprises a complex mixture of seagrasses, macroalgae, benthic filter feeders and soft/hard bottom. To discriminate these benthic features from each other, the data must have a combination of both high spectrally and spatial resolution. While there has been a fast development of RS techniques capable of mapping the distribution and abundance/biomass of seagrasses over the last two decades, no single technology can be recommended to monitor the different parameters and their changes over time. Optimal monitoring of submerged aquatic vegetation requires integration of field observations and different RS techniques.

Vegetation mapping in Denmark has shown promising results using airplane-derived summer orthophotos. The orthophotos are available biennially, and are ordered by the Ministry for other purposes. The optimal use of these orthophotos for nationwide mapping of eelgrass meadows requires some adjustments regarding image processing. At the smaller scale, experience with Red-Green-Blue colour maps (RGB) obtained from drones also provide promising results for mapping eelgrass meadows and floating macro algal mats and is a technique that potentially can supplement validation of larger areas. By contrast, the relatively coarse resolution of freely available satellite data

poses larger challenges for mapping patchy and mixed vegetation, but can be used on a regional scale.

Test and validation of RS derived Chl-a and submerged aquatic vegetation data can be done using data from the existing NOVANA monitoring programme when there is a good match in time and space between ground truth and RS data. Unfortunately, with the current parameters included in the NOVANA programme (2017-2021), it is not possible to validate CDOM and TSS. However, additional Chl-a data for areas less spatial and temporal covered are of high value for water body assessment. RS-derived and NOVANA-derived data on marine vegetation supplement each other nicely in terms of the monitoring parameters they deliver: The NOVANA programme delivers detailed information on the lower depth limit of eelgrass meadows, which is highly sensitive to changes in water clarity and quality and therefore a key indicator of quality status. RS-based assessment of area distribution provides an important supplement to the understanding of the many ecosystem functions and services, provided by eelgrass meadows and other marine forests.

Dansk sammenfatning

Rapporten redegør for mulighederne ved at inddrage forskellige Remote Sensing (RS) teknologier til supplering af det konventionelle nationale NO-VANA-program til overvågning af vandkvalitet (klorofyl-a; Chl-a) og marin vegetation (Submerged Aquatic Vegetation-SAV; ålegræs og makroalger) i danske kystvande. Styrker, svagheder og vidensgab diskuteres kort, og der gives en række anbefalinger til, hvorledes RS-teknikker kan integreres i den fremtidige marine miljøovervågning.

De komplekse bio-optiske egenskaber, som præger de danske kystnære havområder, betyder, at overvågning af Chl-a kræver RS-teknikker og sensorer, som kan adskille Chl-a signaler fra de generelt høje niveauer af opløst farvet organisk stof (CDOM) og totalt suspenderet materiale (TSS), såvel som fra refleksion fra sediment og SAV.

Store dele af de lavvandede kystnære danske havområder er fuldt opblandet hele året, mens lagdeling forekommer om sommeren i Kattegat, dele af Bælt-havet og dybere områder i fx Limfjorden. RS Chl-a signalet repræsenterer derfor kun den øvre vandsøjle i disse områder. Dette er dog ikke et problem i forhold til EU's havstrategi- og vandrammedirektiv, som kun forudsætter sommer Chl-a målinger fra den øvre opblandede del af vandsøjlen. Bundrefleksion er til gengæld et stort problem for de fleste sensorer, der sigter mod at bestemme Chl-a i kystzonen. Dette kan imødekommes enten ved høj spektral opløsning, som kan fjerne denne støj, eller ved RS-data med høj rumlig opløsning, hvorved kanteffekterne i kystzonen mindskes.

Erfaringer med RS-overvågning af Chl-a har hidtil hovedsageligt været baseret på ESA's MERIS sensorer og NASA's MODIS sensorer, som er tilpasset marine observationer. De nyligt lancerede og nu operationelle Sentinel-2 og Sentinel-3 sensorer fra den Europæiske Kommissionen giver nye muligheder for bedre at kunne overvåge kystzonen pga. højere rumlig og tidslig opløsning.

Den lavvandede kystzone omkring Danmark indeholder en kompleks blanding af havgræsser, makroalger, filtrerende organismer samt blød og hård bund. For at kunne skelne disse forskellige bundegenskaber fra hinanden er det nødvendigt at have data med både høj spektral og rumlig opløsning. Selvom der i de sidste to årtier er sket en stor udvikling af tilgængelige RS-teknikker, der er i stand til at kortlægge udbredelse, tæthed og biomasse af ålegræs, kan ingen af teknikkerne anbefales til at stå alene ved overvågning af de forskellige parametre og deres ændringer over tid. Optimal overvågning af SAV kræver en integration af feltobservationer og forskellige RS-teknikker.

Erfaringer med inddragelse af ortofoto fra fly ved vegetationskortlægning i Danmark giver lovende resultater. Disse ortofoto optages hvert andet år, og indkøbes af ministeriet til andre anvendelser. Den optimale anvendelse af ortofoto til landsdækkende kortlægning af ålegræsdekning kræver dog nogle justeringer vedrørende billedbehandling. I mindre målestok giver erfaringer med Red-Green-Blue farvekort (RGB) optaget med droner også lovende resultater for kortlægning af ålegræs og flydende makroalgemåtter og er en teknik, som kan supplere validering til større skalaer. Derimod giver den relativt

grove opløsning af frit tilgængelige satellitdata udfordringer ved kortlægning af tynd og blandet vegetation, men kan bruges på regional skala.

Test og validering af RS Chl-a og SAV data kan udføres ved hjælp af data fra det eksisterende NOVANA overvågningsprogram, såfremt der er en god overensstemmelse i tid og rum mellem ground-truth og RS-data. Det er med de nuværende parametre i NOVANA programmet (2017-21) ikke muligt at kalibrere og validere CDOM og TSS. Men RS-bestemte Chl-a data er af stor værdi, ikke mindst i vandområder med nedsat eller fraværende monitoring i NOVANA-programmet. For marin vegetation supplerer RS-og NOVANA-data hinanden godt, idet NOVANA-programmet leverer detaljerede oplysninger om den nedre dybdegrænse for ålegræs, der er yderst følsom for ændringer i vandets klarhed og -kvalitet og derfor en nøgleindikator for kvalitetsstatus. RS-baseret vurdering af arealfordeling giver et vigtigt supplement til forståelsen for de mange økosystemfunktioner og -tjenester, der leveres af ålegræsenge og andre marine vegetationsområder. Kendskab til arealdækningen er vigtig, da økosystemfunktionerne og -tjenesterne skalerer med deres arealudbredelse.

1 Introduction

Coastal zones and estuaries are the most inhabited areas of the world and almost 30 % of the world's population lives within 100 km distance from the shoreline (Nicholls et al. 2007). About 45 % of the Danish population of ~ 5.6 million lives in the five largest cities, which all are located close to the coast (MST 2012). The coastal ecosystems produce invaluable ecosystem services and are important for human health. The human pressures on the ecosystems are affecting the ability to sustain their services by e.g. agriculture, aquaculture, fishing, construction and industries causing eutrophication, over exploitation of fish resources and pollution (MA 2005; Newton et al. 2014). Actions to mitigate the perturbations have resulted in several international and national environmental programmes, of which many targets to improve the marine environment. International agreements aiming to improve water quality are e.g. EU's Water and Marine Strategy Framework Directives (WFD, MSFD) (European Commission 2000, 2008), the regional Baltic Sea Action Plan (BSAP) from HELCOM (HELCOM 2007) and the OPSAR convention (OSPAR 1992). The frameworks stress the requirement for systematic monitoring and regular reporting of the assessments of the ecosystem or environmental health of the national open, coastal and inland waters. The approaches for assessing the water quality status differ with different methods, but use in general a previously defined baseline, which the observed parameters are tested against, and the Good Ecological/Environmental Status (GES) for each parameter and in total should be reported with the WFD and the MSFD ((Borja et al. 2014; WATERS 2016)). These frameworks and agreements are adopted within the Danish River Basin Management Plans (Vandområdeplaner).

The Basic analysis states the environmental or ecological status as well as changes within each water body. The results from the Basic analysis define the management of the 23 major water regions, which are described in the Danish River Basin Management Plans. The data input to the status assessment is outlined in the National Monitoring and Assessment Programme for the Aquatic and Terrestrial Environments (NOVANA) (Miljøstyrelsen 2017). Hence, the Danish River Basin Management Plans rely on high quality monitoring data with good spatial coverage. As for many other monitoring programmes, the most common methods for measuring water and ecosystem quality are the use of ship-based periodic samplings. The sampling stations or transects included in NOVANA are generally geographically fixed and follow an established periodic scheme with specific sampling intervals that correspond to certain interests, such as seasons, policy regulations or event-driven e.g. phytoplankton spring bloom (Miljøstyrelsen 2017). Collected monitoring data require different levels of post processing: laboratory work by estimation of phytoplankton abundance and nutrient analyses, sorting and categorising benthos or phytoplankton communities, post-analysing by e.g. underwater video recordings of eelgrass and macroalgae abundance, or statistical analyses of e.g. primary production, chlorophyll-a concentrations (Chl-a) from fluorescence data, uncertainty assessment and quality assurance.

The NOVANA programme supports the Danish prioritized requirements, from the WFD, the MSFD as well as the international conventions, providing monitoring data for assessment of pressures, status and changes (Miljøstyrelsen 2017). For a monitoring programme to be successful, the data collected

should form the basis for answering the scientific and political questions regarding how to best assess, manage and when needed, improve the environmental or ecological state of the ecosystems. Models, statistical analyses and assessments provide data on which the conclusions are based. It is therefore fundamental that the data sampling and gathering part of the monitoring programmes are optimized to meet these demands by achieving the best available coverage to be able to identify and understand long-term trends and emerging problems in large areas.

Coastal zones are in their nature highly variable and the NOVANA programme covers as much as possible of the spatial and temporal variability under restricted resources. However, a point sample taken during one day may not represent the following day, week, month or season and sometimes also not the nearby areas, especially for pelagic water parameters (Carstensen and Lindegarth 2016). The water samples taken within a waterbody often only represent a small percentage of the total waterbody extent. It is therefore challenging to have a full assessment of e.g. the phytoplankton spatial and temporal variability by measuring the Chl-a based on field measurements. There is therefore a need for additional data that can help characterizing the dynamic changes in time and the spatial variability. Furthermore, a comprehensive and full map of the total coverage of large seascapes of submerged aquatic vegetation (SAV) cannot be achieved due to the restrictions in the *in situ* point monitoring (Vahtmäe et al. 2006).

Monitoring data of the ecosystems reveal different types of information, and the *in situ* data are invaluable for evaluations of the status and long-term changes in ecosystem health enabling analysis of management efforts. Hence, the valuable information from point measurements is of high interest in terms of management. Evaluations and monitoring of the marine forests, such as seagrass meadows and kelp forests, represent key ecosystem functions in the coastal zone, which scale with their distribution area (e.g. (Duarte et al. 2013). Indeed, lacking data on the area distribution of marine forests are identified as a major information gap (Duarte 2017). Monitoring of Chl-a and other water quality parameters gives detailed information on local and regional scales, and depth profiles and phytoplankton communities are important factors for understanding the ecosystems and key factors of changes.

As national and EU-wide demands and regulations on GES assessment are increasing, application of efficient and reliable monitoring methods to assess water quality are of high importance. Hence, using high-resolution remote sensing (RS) data from aircraft, drones or satellites offer a possibility to support traditional monitoring through large-scale SAV mapping (Vahtmäe et al. 2006) and medium- or high-resolution satellite data make it possible to cover larger areas for Chl-a retrieval more frequently (Kratzer et al. 2014, 2016; Harvey et al. 2015). Remote sensing methods are developing fast and recent studies do indicate that they have high potentials to supplement and optimize national marine monitoring programmes (Brockmann et al. 2004; Kratzer et al. 2014; Hossain et al. 2015; Brockmann Geomatics AB 2017). Both the EU's directives and HELCOM recommend a higher implementation of both RS and modelling data for monitoring and assessment activities. Monitoring by remote sensing are expected to provide cost-efficient additional data to fulfil the requirements within the programmes by increase of the number of observations and improving the spatial coverage (Strong and Elliott 2017). However, evaluation and performance assessment of the new techniques, in combination with the existing, are required before full implementation.

1.1 Remote sensing techniques

Monitoring data with high spatial coverage based on the new remote sensing techniques have now become relatively cost-effective and easily available (Strong and Elliott 2017). The technical developments of drone images, aerial orthophotos and satellite remote sensing have been significant and fast over recent years, and we are now in a situation where national monitoring programmes could benefit from this type of data and make use of the higher spatial coverage. The number of remote sensing satellites for Earth Observation (EO) has increased by 66 % during 2016 and currently a bit more than a third of all satellites orbiting the Earth serve the purpose of observing the environmental changes (Lavender 2017). The available data record is large and constantly increasing based mostly on remote sensing sensors developed for land applications. However, there are some previous ones adapted for water, e.g. CZCS, Seastar, Oceansat-2, AQUA, NOAA-SST using sea surface temperature sensors and others for sea level that has been invaluable for large-scale oceanographic understanding and some pioneering ones for measuring water quality, e.g. SeaWiFS. The spatial resolution of a sensor corresponds to the length of the individual quadratic pixels, usually measured in km or m. Some of the current land sensors, e.g. Landsat 6-8 and Sentinel-2, can be used for water applications as well. While satellite remote sensing operates on scales between 10-1000 m resolution, higher spatial resolution can be achieved by aerial or drone-based RS sensors. Aerial orthophotos are detailed geo-corrected images with high spatial resolution, around 10 cm. Images collected by drones provide datasets of geo-based information collected over a short time often with fine spatial resolution of a few cm. Other remote sensing techniques for measuring submerged aquatic vegetation (SAV) are underwater acoustic techniques and both above and underwater lasers (Bučas et al. 2016). Acoustic techniques cover side-scan sonar, single- and multi-beam echo sounder, Acoustic Doppler Current Profiler and Sediment Imager Sonar and different laser techniques (e.g. LIDAR).

The Copernicus remote sensing mission from the European Commission is the largest Earth observation investment in time with a long-term satellite commitment, providing unique opportunities for environmental applications. Copernicus includes a family of satellites for different purposes, including the Sentinels, where the Sentinel-2 and 3 satellites are designed for environmental monitoring and Sentinel-3 specifically for aquatic systems applications. The spatial resolution of Sentinel-2 is 10-60 m while that of Sentinel-3 is 300 m.

The strong absorption of light by water and other inherent constituents make it a challenge both to map the SAV and to retrieve data on Chl-a in surface waters. Therefore, validation (section 3.4) of RS-data is fundamental for uncertainty estimation and for delivering reliable water and sea-bed mapping products by the development of new or adjustments of current algorithms. To validate RS-products, high quality *in situ* data measured in correspondence with satellite- and other RS-overpasses are essential. A major advantage of all types of RS-data is the coherent and consistent data over time. Previous archives can therefore be reprocessed and reanalysed when improvements are made, which facilitates GES assessments of e.g. Chl-a for the full spatial extent of a water body based on previous and current RS-data. Merging data from several sensors enables high temporal and spatial coverage.

1.2 Purpose and aims

The purpose of this report is to provide an overall description and review of the possible RS-techniques that can be used for SAV mapping and Chl-a retrieval in coastal areas. Specifically this literature review aims to:

- Summarise the state-of-the-art regarding the use of RS-technologies for mapping of aquatic vegetation and Chl-a
- Describe the technical procedure for mapping aquatic vegetation areal distribution by RS
- Describe the technical procedure for Chl-a retrieval by satellite sensors
- Discuss possibilities of using data from different RS-techniques to supplement the conventional NOVANA monitoring programme for Danish coastal waters

The review will summarise the knowledge by identifying strengths, weaknesses, research gaps and will define where to go next for a higher implementation of RS-techniques in the monitoring of Danish coastal waters.

2 Space and airborne sensors

Remote sensing sensors are divided into two major types: *active* sensors that emit and receive a signal and *passive* ones that sense the energy reflections and emissions associated with the solar electromagnetic radiation. An example of an active sensor used for aquatic monitoring is Light Detection And Ranging (LiDAR) by which a laser beam emitted from an airplane can be used to detect small-scale topographic features, such as submerged aquatic vegetation (Zavalas et al. 2014). Passive sensors are optical instruments, which register solar radiation reflectance at different wavelengths and thermal sensors that register the emission of thermal infrared radiation. Both passive and active sensors are used for vegetation mapping, but water quality parameters like Chl-a are based on the reflectance spectra received by optical passive sensors. Most experiences about the use of RS-techniques in aquatic environments are based on passive optical sensors, and the following text focuses on these.

The choice of RS-platform and the design of the optical sensors are quite different, depending on their applications. They differ both in spectral and spatial resolution and are categorised based on their characteristics.

Aerial photography is often spatially detailed photos taken by cameras or made up by the RGB (Red-Green-Blue) bands of the sensors. The cameras or sensors can be mounted on aeroplanes or drones, which usually provide images of a very high spatial resolution of down to a few centimetres. *Hyperspectral sensors* (e.g. CASI-Compact Airborne Spectrographic Imager) typically have narrow bands of ~3.5 nm over the full visible spectra, with a spatial resolution of 25 cm. Hyperspectral sensors are usually mounted on aeroplanes and not very commonly mounted on-board satellites, except HICO (Hyperspectral Imager for the Coastal Ocean), which was placed on the International Space Station and used for research purposes. In comparison, *multispectral sensors* are usually situated on satellite platforms. All multispectral sensors have multiple spectral bands of different width and placements. Multispectral *high* spatial resolution sensors (e.g. WorldView 2 & 3, QuickBird and IKONOS) have a high spatial resolution of about 30-80 cm but usually relatively broad and few bands. *Multispectral medium* spatial resolution sensors (e.g. Landsat TM, ETM+ and OLI Sentinel-2 MSI sensor) have slightly lower resolution of about 10-30 m, also typically with broad and fewer bands. However, some of the most recent sensors, such as OLI and MSI, have additional and narrower bands as well. *Multispectral low* spatial resolution sensors (e.g. MERIS and MODIS) have a quite low spatial resolution of 250 to 1000 m, but with much higher spectral resolution and narrower bands. The different placement and width of the spectral bands for some RS-sensors are summarized by (Matthews 2011) (*fig. 1*), where the differences in the band width are clearly seen.

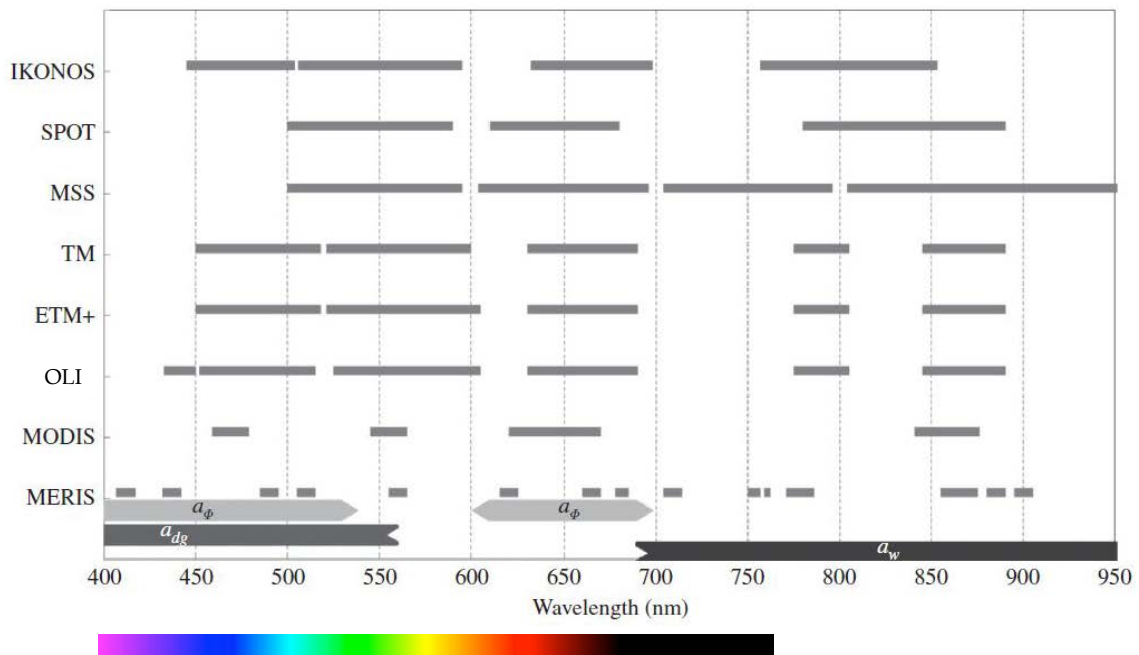


Figure 1. The spectral position of various satellite instruments in relation to the location of the maximum influence of absorption by phytoplankton, a_{ϕ} , particles and humic substances, a_{dg} , and water, a_w . The bands plotted for MODIS are the 250 and 500 m bands. Image from Matthews (2011). An overview and details for recommended sensors to map SAV are presented in *table 1* and for Chl-a in *table 2*.

2.1 Sensor sensitivity and sampling frequency

The electromagnetic sunlight is divided into different types: ultra violet below 390 nm, visible light between 390-750 nm and infrared light above 750 nm. The different wavelengths carry different amounts of energy, and the shorter the wavelength the more energy, the blue light region 390-500 nm carries most energy per photon. The reflectance signal is affected by the wavelength-dependent absorption and scattering, which are different for air, water, particles, phytoplankton and vegetation. Therefore, the total reflectance signal differs significantly, when it comes from water than when coming from land (*fig. 2*). Water absorbs highly in the red and longer wavelengths (620-750 nm), thus reducing the signal detected by the sensor at longer wavelengths (*fig. 2 & 4*). The remote sensing signal carries a mix of information from the object of interest (e.g. eelgrass or Chl-a), the water itself and its constituents, and signals from the atmosphere. Atmospheric signals must be filtered out and an atmospheric correction is generally applied to satellite image data (IOCCG 2010) (see *chapter 3.2 & 3.7*). Similarly, when mapping underwater vegetation from satellite data, signals deriving from the water column in turbid areas usually have to be removed by mathematical modelling. A higher spectral resolution of the sensor, i.e. more and narrower bands (to a certain limit for detection in the visible wavelengths), gives a higher signal-to-noise ratio. Sensors adapted for mapping land vegetation can detect the solar radiation reflected from SAV structures and coverage. To sense the reflectance from either seagrasses or phytoplankton, the spectral band configuration of the sensors must include visible bands and be configured to distinguish between different wavelengths of visible light.

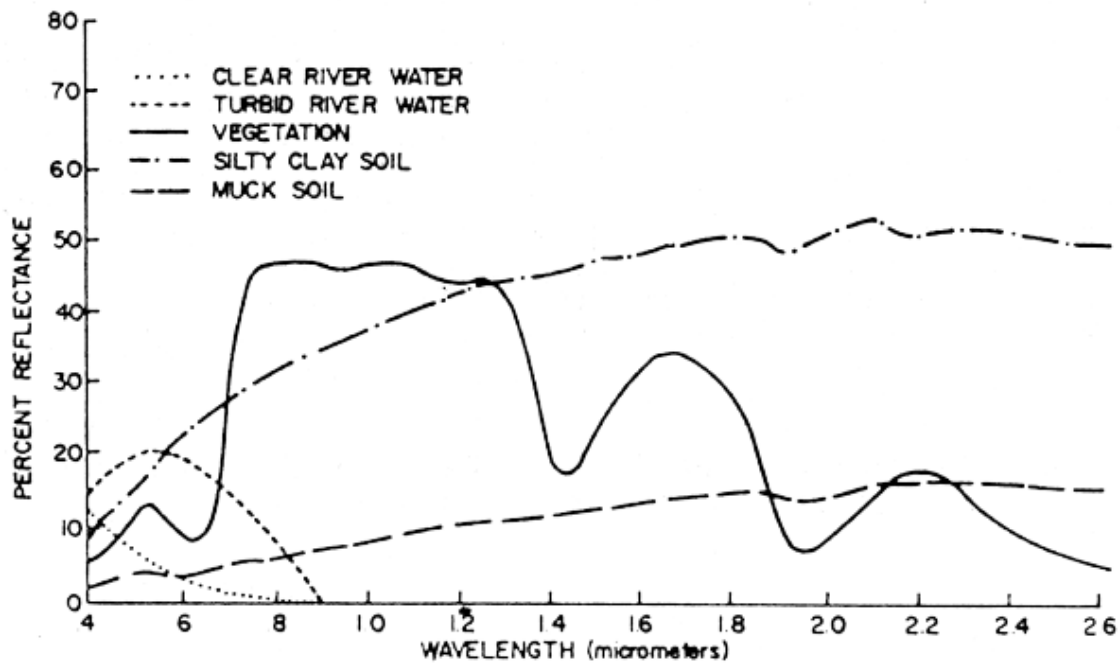


Figure 2. Examples of natural reflectance spectra of clear and turbid coastal waters, vegetation on land and two different types of soils. Note the huge different between the reflectance range between water and land as well as the strength of the signals (FAO 2017).

For satellite Earth observations there is a trade-off between the spatial and temporal resolution. In higher latitudes, the low azimuth angle of the sunlight during the winter months limits the period for satellite-retrieved images to be between March and October. The designs of the sensors also affect the temporal resolution as their distances to the Earth surface or orbits are different. Higher spatial resolution sensors are closer to the Earth, and have a lower revisiting time and measure the same spot every 1-2 weeks. Satellite sensors with medium or low spatial resolution have more frequent revisiting times, typically near-daily. One of the advantages of aerial photography is the ability to control the time of measurements. Therefore, the data samplings are conducted irregularly or periodically by airborne sensors, whereas operational satellite sensors have a repeated fixed overpass period, enabling operational time series studies. However, the presence of clouds or haze in the sky reduces the amount of high-quality cloud-free images, especially in the northern hemisphere. Bad weather and clouds may also postpone scheduled aerial or drone operations, but they might be able to fly underneath the clouds and the collected images can therefore still be of high quality over the areas of interest.

2.2 RS technologies for mapping of submerged aquatic vegetation (SAV)

Remote sensing techniques for mapping of SAV include both active (acoustic and “above” and underwater laser) and passive (optical) sensors. The technologies differ widely in the measurement scale from very local small spatial scale using underwater acoustic methods and photos and videos, to high spatial resolution airplane and drone-borne cameras, hyperspectral scanners, laser techniques (e.g. LIDAR) to multispectral satellite imagery at low spatial resolution (*table 1*). The palette of techniques was recently reviewed in a paper which compared 195 RS-studies coupled with field validation for mapping of seagrasses (Hossain et al. 2015).

2.2.1 Acoustic techniques

Despite the fact that the nature of acoustic backscattering from seagrass is still less understood than that from rock and sediment, over 30 studies have to date applied acoustic methods for seagrass mapping (Hossain et al. 2015). Air pockets in seagrass stems are thought to be a key factor that enables seagrass acoustic detection. Studies have shown that acoustic seagrass sensing is especially effective for both presence/absence mapping and percentage cover mapping in areas of deep water (it operates poorly in shallow water) with high biomass, and it operates well independent of the optical water properties. It is therefore complementary to optical methods (Hossain et al. 2015; Barrell et al. 2015) but possibilities for synoptic measurements over large areas are more limited than that of optical sensing.

2.2.2 Satellite RS techniques

A recent study by (Hoang et al. 2015) provides additional information on the use of satellite imagery. They studied large-scale area distribution of marine SAV using the high-resolution WV2 satellite imagery. Compared to other types of high-resolution satellite data, classification results showed a high level of recognition and ability to differentiate between seagrasses, macroalgae and sand. The optimum depth for classification based on the WV2 satellite was found to be shallower than 3 m, where a good interpretation of eelgrass, and brown and green macroalgae habitats can be provided (Reshitnyk et al. 2014; Hoang et al. 2015). In the more open, deeper and clearer part of the Danish waters, where seagrasses can extend down to 5 to 7 m, and macroalgae even deeper, passive RS-techniques offer little assistance to SAV mapping.

Table 2.1. Overview of operational and project-specific sensors – submerged aquatic vegetation.

Platform	Sensor	Time	Application	Sensor bands	Spatial resolution	Temporal resolution	Availability provider
Satellite Sentinel-2a	MSI (Multispectral Imager)	June 2015-	Land and water	13 spectral bands (443-2190 nm)	10 -20 (60) m	2-3 days	Systematic free European Commission & ESA
Satellite Sentinel-2b	MSI (Multispectral Imager)	July 2016-	Land and water	13 spectral bands (443-2190 nm)	10-20 (60) m	2-3 days	Systematic free European Commission & ESA
Satellite Landsat series 6-7	TM/ ETM+	October1993 April 1999	Land (water)	5 spectral bands			Systematic free NASA
Satellite Landsat 8	OLI (Operational Land Imager)	February 2013-	Land and water	9 spectral bands (435-1384 nm)	15/30 m	16 days	Systematic free NASA
Satellite Worldview2	Multispectral	October 2009-	Land and water	8 spectral bands (443-1050 nm)	2 m	1 day	On-request, Commercial
Airplane e.g. CASI	Multispectral	-	Land and water	Variable	375 m (5 bands) 750 m (16 bands)	-	On- request, Commercial
Drones Different optical cameras	Multispectral	-	Land and water	Variable	Variable	-	On request, Commercial
LIDAR	-	-	Land and water	Variable	Radar	-	On request, Commercial
Acoustic	-	-	Land and water	Variable	Eco sound	-	On request, Commercial

2.2.3 Summary of RS for SAV mapping

According to (Hossain et al. 2015), there has been a revolution over the last two decades in the application of RS-techniques for mapping parameters interesting for monitoring, such as the distribution, abundance/biomass of particularly seagrasses and to a smaller extent macroalgae. A take-home message from the review is that no single technology is fit to monitor all the different parameters and their changes over time. Optimal monitoring of submerged aquatic vegetation requires integration of field observations and different RS-techniques (Hossain et al. 2015). As an example, while photos from airplanes and drones have great advantage when it comes to acquiring detailed high-resolution characteristics of shallow water habitats, the fine spatial scale has the disadvantage of a much lower areal cover compared to data obtained from satellites such as Sentinel-2 and WorldView-2 (WV2). In addition, most drones and regularly sampled orthophotos from airplanes do not provide the spectral resolution required to discriminate subtle features of the benthic habitats (Hossain et al. 2015). Still, their high spatial resolution may compensate for the lower spectral resolution of aerial photos. Therefore, a synergistic use of both airborne and spaceborne sensors can compensate for the gaps in spectral or spatial resolution.

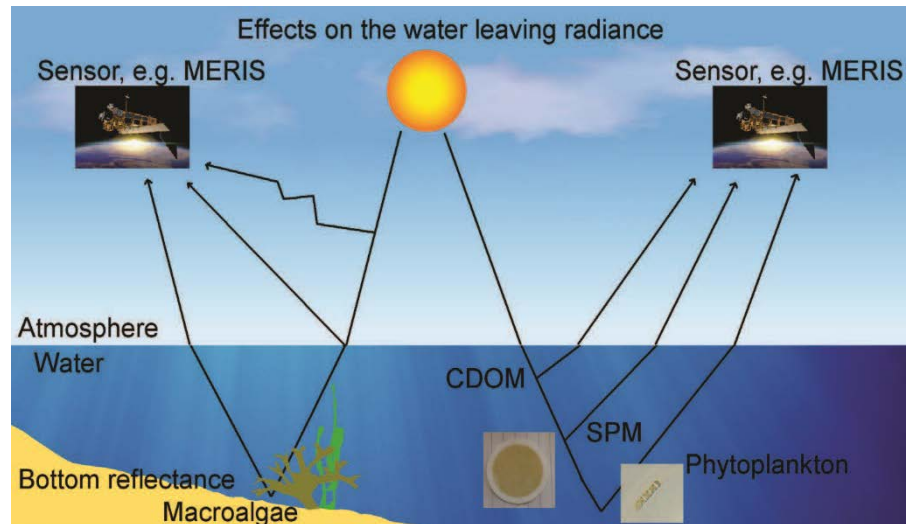
2.3 RS-technologies for water quality monitoring

The colour of the light reflected from the open sea is a result of the light absorbing and light scattering components of the water body, also referred to as the inherent optical properties (IOP) of the water. Besides the optical characteristics of pure water itself, the IOPs are defined by three main optical components categorized into phytoplankton pigments (dominated by Chl-a), the total suspended solids inorganic and organic suspended material (TSS) arising from resuspension or run-off, the coloured part of the dissolved organic matter (CDOM) originating from the decomposition of both terrestrial and marine organic matter. The spectral signals from the in-water constituents (also called bio-optical components) vary over the visible wavelengths together with water itself, making it more challenging to retrieve the information from the electromagnetic reflectance. Due to the complexities of these optical conditions, there is a higher demand on the spectral resolution for RS-sensors used for water quality measurements compared to vegetation monitoring as the signal to noise ratio is much lower. The combination of the spectral bands need to cover a broad total range in the visible wavelengths as well as the individual bands should be wavelength-specific, i.e. narrow, in order to distinguish between the different spectral responses from the bio-optical constituents (IOCCG 2000, 2010).

In open seawaters, the colour of the sea varies mostly with the abundance of phytoplankton measured as Chl-a, as both the CDOM and TSS originate from the phytoplankton and then co-varies with the Chl-a concentrations. However, in coastal water bodies, the colour and transparency of the water column depend on the independent light interactions with all constituents within the water. The Chl-a, CDOM and TSS can vary independently as the origin of both CDOM and TSS originates from other sources than phytoplankton. Also the reflectance from the bottom may have an influence on the water-leaving signal in shallow waters (IOCCG 2000; Harvey 2015). The water-leaving reflectance is the results of an integrated value over all parameters found within the depth penetration of the light signal. As a rule of thumb, the depth penetration of the water-leaving reflectance is usually said to be around the Z_{90} depth (to depth at which 90 % of the water-leaving reflectance has penetrated

the water), estimated to be around 7 m in turbid coastal waters (compared to 30 m in clear oligotrophic waters). Since the satellite sensor is passive, it depends of the amount and angle of the solar radiation. When the angle of the incoming light (azimuth angle of the sun) is low, as during the winter months in Denmark, the major part of the light is absorbed and scattered in the atmosphere and too little of the reflectance can reach the sensor (IOCCG 2000). Hence, optical RS-images are available from about February to November.

Figure 3. Illustration of the factors influencing the water-leaving radiance detected by the RS-sensor, the remote sensing reflectance and the retrieval of the water quality products. The water-leaving radiance changes with the surface roughness, scattering and absorption in the atmosphere and in water. TSS, phytoplankton and water itself as well as the absorption by CDOM cause the scattering and absorption in water. Bottom reflectance or absorption and reflectance from macro algae may influence the radiance. Figure from Harvey (2015).



A schematic illustration of the parameters influencing the water-leaving radiance is shown in figure 3 and schematic examples of water-leaving reflectance spectra are shown in figure 4a, where the difference between coastal and clear open water leaving (or remote sensing) reflectance is seen. The reflectances increase with higher TSS concentrations as well as high Chl-a, whereas more CDOM absorption reduces the amplitude of the reflectance spectra. All bio-optical components affect the total absorption and figure 4b shows some typical absorption and scattering spectra for coastal waters. Other parameters than the water-leaving reflectance and the bio-optical components, are available from satellite RS data such as the light attenuation, (K_d or Secchi depth) and turbidity. Information can also be retrieved on specific inherent optical properties such as absorption and scattering of light due to particles and dissolved matter at certain wavelengths or in total (IOCCG 2000, 2006). True RGB water colour, which is the true visible colour from the red, blue and green light, is also an optional parameter (Woerd and Wernand 2015).

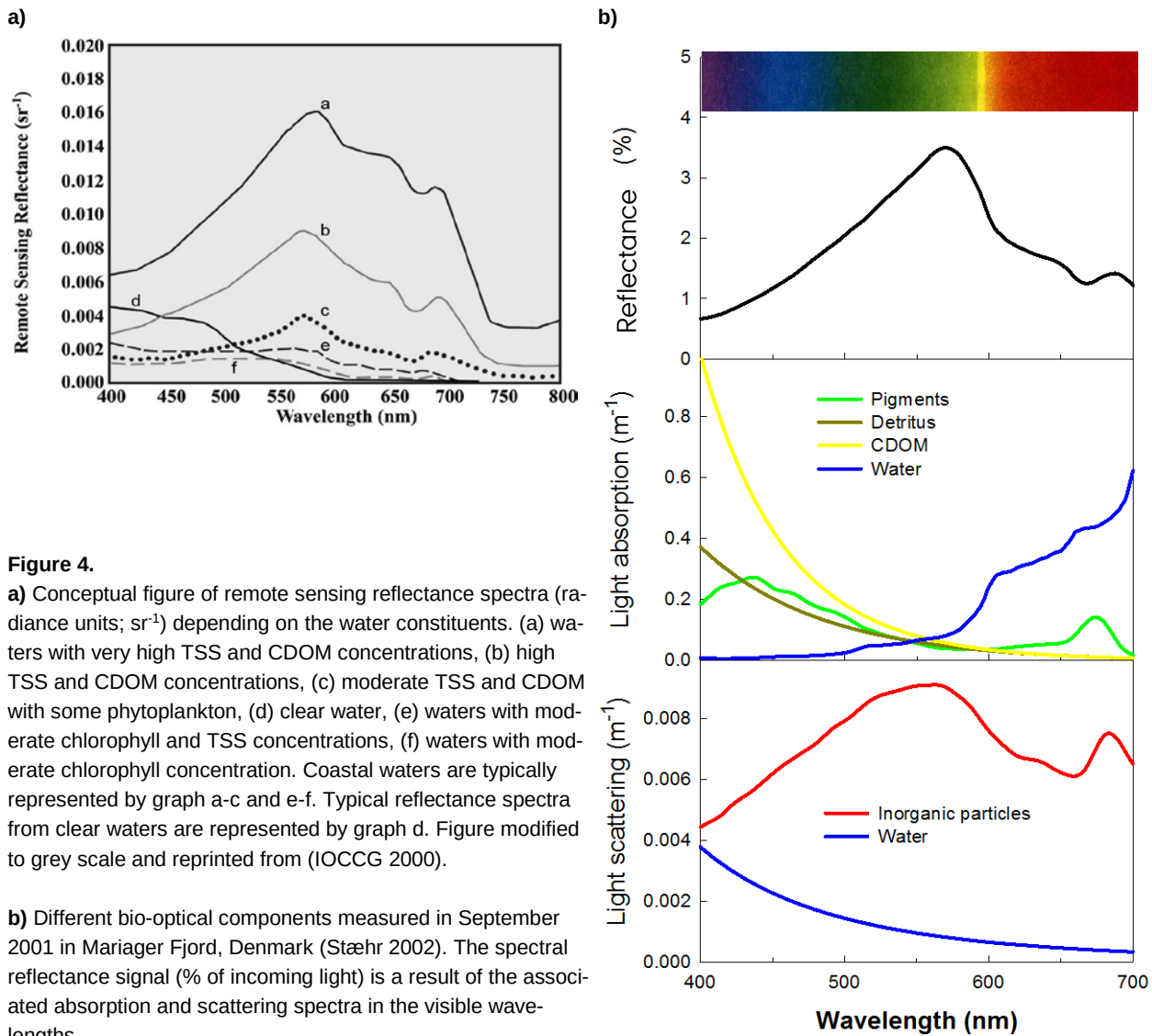


Figure 4.

a) Conceptual figure of remote sensing reflectance spectra (radiance units; sr^{-1}) depending on the water constituents. (a) waters with very high TSS and CDOM concentrations, (b) high TSS and CDOM concentrations, (c) moderate TSS and CDOM with some phytoplankton, (d) clear water, (e) waters with moderate chlorophyll and TSS concentrations, (f) waters with moderate chlorophyll concentration. Coastal waters are typically represented by graph a-c and e-f. Typical reflectance spectra from clear waters are represented by graph d. Figure modified to grey scale and reprinted from (IOCCG 2000).

b) Different bio-optical components measured in September 2001 in Mariager Fjord, Denmark (Stæhr 2002). The spectral reflectance signal (% of incoming light) is a result of the associated absorption and scattering spectra in the visible wavelengths.

2.3.1 Satellite remote sensing sensors

Several satellite sensors are currently being used for water quality estimations. Common for these is that their spectral design and accuracy determine what they can be applied for. The most relevant operational RS-satellite sensors suitable for water quality applications are described below and a more comprehensive list is found in *table 2*.

The **MODIS** (The MODerate resolution Imaging Spectroradiometer) is a twin-sensor constellation on board the two NASA satellite platforms Terra and Aqua. Terra was launched in 1999 and Aqua in 2002. Even though both sensors are well beyond their expected lifetime with significant resulting sensor degradation affecting the retrieval accuracies, they are still delivering relatively high quality data. The MODIS sensors have a high spectral resolution adapted for clear waters, but neither the spectral nor the spatial resolution (1000 m) is suitable for coastal applications and turbid waters.

The Visible Infrared Imaging Radiometer Suite (**VIIRS**) from NASA and NOAA is placed on board the Finnish satellite Suomi National Polar Orbiting Partnership (SNPP). VIIRS is mainly designed to measure climate change and

land vegetation, but is also used for water applications with good results due to its high spectral resolution, with similar, but two fewer bands in the visible compared to MODIS.

Table 2. Overview of satellite RS mission sensors for water quality

Satellite/Sensor	Time	Application	Sensor bands	Spatial resolution	Temporal resolution	Availability Provider
Current missions						
Terra & Aqua / MODIS (Moderate Resolution Imaging Spectrometer)	1999-2002-	Land and water	36 spectral bands (405-14385 nm)	250 m (bands 1-2) 500 m (bands 3-7) 1000 m (bands 8-36)	1-2 days	Systematic free NASA
Sentinel-2a / MSI (Multispectral Imager)	June 2015-	Land and water	13 spectral bands (443-2190 nm)	10-20 (60) m	2-3 days	Systematic free European Commission & ESA
Sentinel-2b / MSI (Multispectral Imager)	July 2016-	Land and water	13 spectral bands (443-2190 nm)	10-20 (60) m	2-3 days	Systematic free European Commission & ESA
Landsat 8 / OLI (Operational Land Imager)	February 2013-	Land and water	8 spectral bands (435-1384 nm)	30 m	16 days	Systematic free NASA
Sentinel-3a / OLCI (Ocean and Land Colour Instrument)	February 2016-	Land and water	21 spectral bands (400-1020 nm)	300 m	1-2 days	Systematic free European Commission & ESA
Sentinel-3b/ OLCI (Ocean and Land Colour Instrument)	<i>To be launched in 2018</i>	Land and water	21 spectral bands (400-1020 nm)	300 m	1-2 days	Systematic free European Commission & ESA
Suomi NPP / VIIRS (Visible Infrared Imaging Radiometer Suite)	2011-	Land and water	22 spectral bands (410-1250 nm)	375 m (5 bands) 750 m (16 bands)	~2 days	Systematic free NASA
Previous missions						
ENVISAT / MERIS (Medium Resolution Imaging Spectrometer)	2002-2012	Land and water	15 spectral bands (412-1020 nm)	300 m	2-3 days	Systematic free ESA
ISS / HICO (The Hyperspectral Imager for the Coastal Ocean)	2009-2014	Coastal water	Hyperspectral 5.73 nm bands (380-960nm)	96 m	-	Free (scenes taken for dedicated research projects)
Planned missions						
PACE MISSION / OCI (Ocean Color Instrument)	<i>The OCI sensor within the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) mission will build on the legacy of previous NASA ocean colour sensors; SeaWiifs, MODIS and VIIRS.</i>					
HyspIRI MISSION (Hyperspectral Infrared Imager)	<i>The HyspIRI mission from NASA includes a hyperspectral spectrophotometer of 10 nm bands between 380 - 2500 nm, with a spatial resolution of 60 m and 19 days revisiting time.</i>					

The Copernicus satellite **Sentinel-3A** houses **OLCI** (Ocean and Land Colour Instrument), which is a sensor especially adapted to detect the reflectance signal from water (Donlon et al. 2012). The OLCI instrument is directly based on the Medium Resolution Imaging Spectrometer (**MERIS**) from the European Space Agency, which was launched on-board the ENVISAT satellite 2002 (Dorffner 2002). Sentinel-3A was launched in 2016 and will be followed by Sentinel-3B in 2018 (~18 month's difference). The revisit time of the twin constellation will be ~1 day over Denmark and the spatial resolution is 300 × 300 m, which is both a high temporal and moderate spatial resolution, considering operational aquatic missions. The 300 m resolution makes OLCI suitable for monitoring coastal areas, and the high spectral resolution makes it possible to retrieve water quality products from turbid and murky waters found in Danish coastal zones and estuaries. It also enables a more frequent retrieval of high quality images free of clouds. The 300 m spatial resolution is the highest currently obtained for operational water-adapted satellite sensors.

The Multispectral Imager (**MSI**) is the optical sensor on-board the **Sentinel2-A and B satellites** (launched 2015 and 2017). It has a lower spectral resolution (fewer and broader bands) than OLCI, but a much higher spatial resolution of 10-60 m. Sentinel-2 was originally designed for land use but has shown to be successful also for water applications. This makes it possible to retrieve data much closer to land and to dissolve features in much higher detail compared to e.g. Sentinel-3 data from OLCI. The twin constellation of the Sentinel-2 satellites has an operational revisiting day of about 2-3 days over Denmark, enabling the possibility to monitor rapid water quality changes in the coastal zones in a higher resolution on cloudless days. MSI has an extra narrow band in the blue (443 nm) which makes it more suitable for water applications.

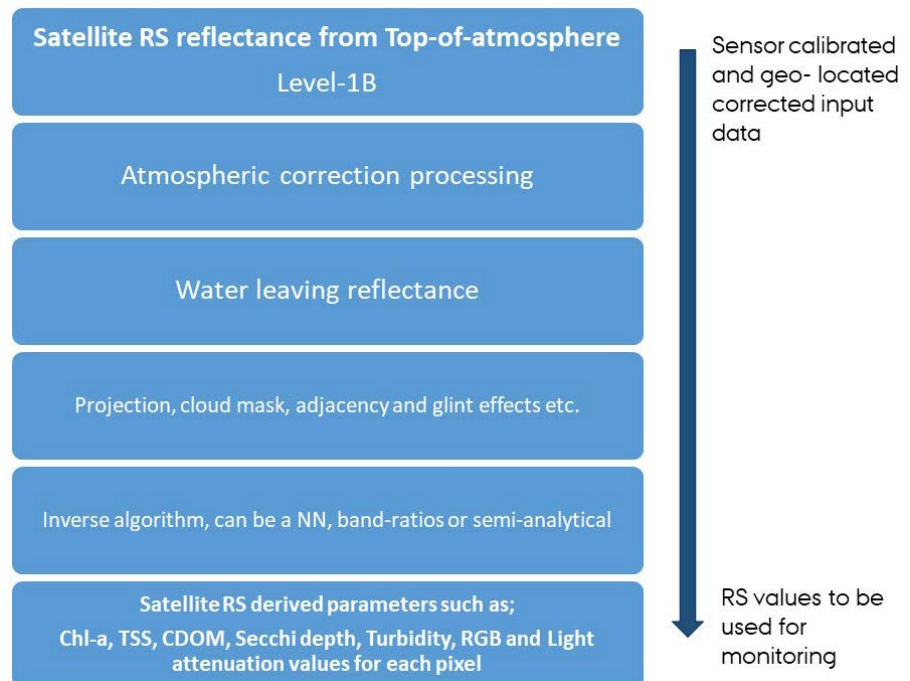
The Operational Land Imager (**OLI**) on-board the NASA satellite Landsat-8 is very similar to the MSI sensor, including an extra narrow band in the blue (435 – 451 nm) for coastal applications. Landsat-8 has a spatial resolution of 30 m and a revisiting time of 16 days. Compared to past Landsat instruments, OLI is more reliable and provides improved performance due to the enhanced signal-to-noise ratio making it possible to use it for water applications.

3 General considerations for RS-monitoring

3.1 Satellite RS-reflectance processing

To retrieve Chl-a or vegetation data derived from RS, the signal that has reached the satellite sensor needs to be processed in several ways. As discussed earlier in chapter 2.3, the RS-signal has interacted with the water and the constituents within, so the remote sensing reflectance can be expressed as a function of the concentrations of the various substances present in the water column. To retrieve satellite data for vegetation and water quality, there are two ways of modelling: forward model and inverse model. Forward modelling is when the remote sensing spectral reflectance at the top-of-atmosphere is predicted based on a quantitative description of the reflection, scattering and absorption properties of the optical components both in air and water (Kirk 1994). Inverse modelling is when the IOPs and concentrations of the in-water constituents or vegetation are derived from the reflectance spectra detected by the satellite. In the forward model, all parameters affecting the reflectance signal need to be accounted for and solved by mathematical calculations and modelling (IOCCG 2006; Kirk 1994), i.e. the inherent optical properties (scattering and absorption of both aerosols and water constituents) and the apparent optical properties. The inverse approach is much more difficult to solve than the forward approach, as it is done by radiative transfer theory. The solutions for the inverse model are included in the RS-algorithms either by semi-analytical approaches or neural network solutions among others (IOCCG 2006). The different processing steps are shown in a conceptual model in *figure 5* and the steps and factors influencing the retrieval are described below.

Figure 5. Conceptual model of processing steps for RS-reflectance data using the inverse modelling approach.



3.2 Atmospheric correction

Correction for atmospheric disturbance is a first important step in the analysis of all satellite and airplane RS-techniques based on passive, optical sensors. Application of a correct atmospheric correction filter (i.e. algorithms designed for the correction of absorption and scattering caused by aerosols) is basically a way to filter out the noise from the atmosphere, so that the water-leaving reflectance remains. It is estimated that the reflectance signal from water (the signal to noise ratio) is 10 % in clear oceanic waters. By contrast, in CDOM-dominated waters, like the Baltic Sea, less than 1 % (sometimes only up to 0.4 %) of the top of atmosphere (TOA) signal that reaches the sensor carries information about the water (IOCCG 2010). Hence, 90-99.6 % of the light is not reflected back into space. It is instead absorbed or scattered by the water or in the atmosphere. The results from the atmospheric correction algorithms need to be filtered out for erroneous pixels showing anomalies by applying a set of different flags; e.g. clouds, land, sun glint, sun angle, uncertainty (low confidence), out of range reflectance etc. (Doerffer and Schiller 2007; Brockmann et al. 2016). An adjacency correction is often applied in coastal areas, correcting for possible land effects influencing the water-leaving reflectance over mixed water pixels (Santer and Zagolski 2008; Sterckx et al. 2015).

3.3 Bottom effects

The effects from the bottom on the spectral signal can be substantial in shallow areas. This is utilized within vegetation mapping, where the spectral features of e.g. sand are used to distinguish between areas with sand and eelgrass. On the other hand, when assessing the water quality, the effects of the bottom are a disturbance, limiting the areas where accurate RS-data can be retrieved. There are algorithms to deal with these issues but the natural patchiness of SAV and bottom substrate has made operational processing difficult (Mouw et al. 2015). The spatial resolution needs to be finer and the spectral resolution needs to be hyperspectral, and no current RS-satellite sensors with this combination are available.

3.4 Validation and match-up

Validation of marine remote sensing data requires *in situ* data measured at the corresponding time and place. For ocean colour data (e.g. radiometric, absorption and scattering measurements), the field data should be sampled simultaneously with overpassing of relevant satellites. Also bio-optical data affecting the light within the water columns (Chl-a, TSS and CDOM) should optimally be sampled at the same time. A validation match-up should optimally be done within a 30 min to 2 hours window from the satellite overpass for 300 m resolution to avoid moving of water masses (Zibordi et al. 2009; Beltrán-Abaunza et al. 2014), and even shorter time for higher resolution sensors such as Sentinel-2 MSI. By using validation and match-up data, the satellite products can be directly evaluated and compared to *in situ* measurements (D'Alimonte et al. 2011; Attila et al. 2013; Kallio et al. 2014; Beltrán-Abaunza et al. 2014). Validation of SAV has a more relaxed time window, as most of the vegetation is stationary and match-ups conducted during the same season should therefore be sufficient, except when the aim is to monitor the distribution of opportunistic macro algal mats, which are highly dynamic. Ongoing NOVANA sampling for Chl-a and submerged aquatic vegetation can to some extent provide valuable data for validation, if there is a good match in time and space. However, the NOVANA programme does not enable calibration and validation of RS products and does not include CDOM, TSS or IOPs but do provide data

on Chl-a, K_d and Secchi depth. To enhance the use of RS data to determine these important water quality parameters, it is therefore recommended to both commit and invest in independent validation campaigns for gathering of RS validation data and expand the monitoring programme to enable more frequent comparisons. A way to increase the amount of *in situ* data to use for comparisons could be that all monitoring ships, regardless of position, when the sky is clear or with distinct cumulus clouds, were to stop correspondently to a satellite overpass to conduct a match-up sampling. The satellite overpasses are easy to predict and can thus be included in the sampling schedule.

3.5 Optical water types

As a result of major changes in land-use and increased loading of nutrients, dissolved and particulate matter from land to sea, the optical conditions of the Danish coastal areas have changed dramatically over the last century (Pedersen et al. 2014). Water clarity has decreased, leading to reductions in Secchi depths and eelgrass distribution. The decreased light attenuation is caused especially by an increase in particulate and dissolved organic matter, in a combination with increased phytoplankton. However, the contribution from phytoplankton is very limited compared to the strong absorption by organic matter. Efforts to mitigate the negative disturbances since the 80s have resulted in an overall improved ecological status with reduced nutrient concentrations. This has led to a decrease in Chl-a concentrations, an increased water clarity and an initial increase in the depth limits of eelgrass as well as in the distribution and cover of macro algae (Riemann et al. 2016). However, the same issues remain and new ones arise.

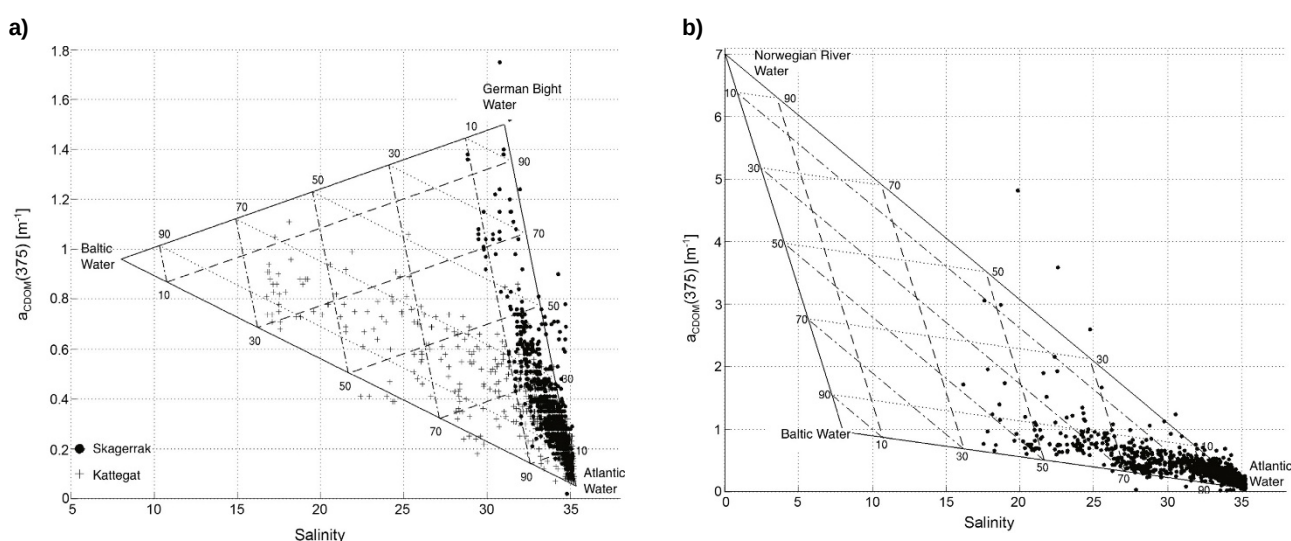


Figure 6. Graphs showing the CDOM absorption vs salinity in April for all years 1996-2000 and all depths. a) From the Kattegat, the southern part of the Skagerrak and off the Jutland west coast. The triangle shows the Danish water types. b) from the northern part of the Skagerrak, with the Norwegian triangle of water types. Images from (Kristiansen and Aas 2015).

Besides these longer-term anthropogenic changes, the optical characteristics of the Danish coastal waters are to a high extent naturally defined by the proximity and influence from the Baltic Sea and the North Sea. The low saline Baltic Sea water masses contain high concentrations of dissolved organic matter, which increases the light attenuation. The high CDOM loads absorb the light in the blue part of the spectrum (figure 3), reducing both the light attenuation and the reflectance that can be detected by the RS-sensors. The full saline North Sea waters have naturally lower CDOM loads. Both the CDOM and salinity ranges for Danish waters are variable with 0-35 in salinity and 0.05-

7.00 m^{-1} in CDOM absorption at 375 nm (Kristiansen and Aas 2015). The high variability of the water masses is illustrated by the summary plots from (Kristiansen and Aas 2015)) (figure 6). CDOM contributes significantly to the attenuation of light in most of the Danish coastal and Baltic Sea waters, where CDOM absorbs more light than phytoplankton and TSS (Ferrari and Dowell 1998; Kratzer and Tett 2009).

Water masses can be divided into different optical water types depending on their optical characteristics. The optical water types (OWT) in this study are defined based on their reflectance spectra, which are directly influenced by their different bio-optical concentrations and optical characteristics ((Hieronymi et al. 2017). The map from 20 July 2016, derived from Sentinel 3-A/OLCI ((Hieronymi et al. 2017), clearly illustrates the vast difference among different OWTs, notably the Danish open sea and coastal waters (figure 7). It is therefore a challenge to apply general RS-algorithms for Danish waters. The combination of CDOM loads together with high turbidity and, at times, high Chl-a concentration in coastal areas requires a high technical performance of the sensors to be able to distinguish between the reflectance signals.

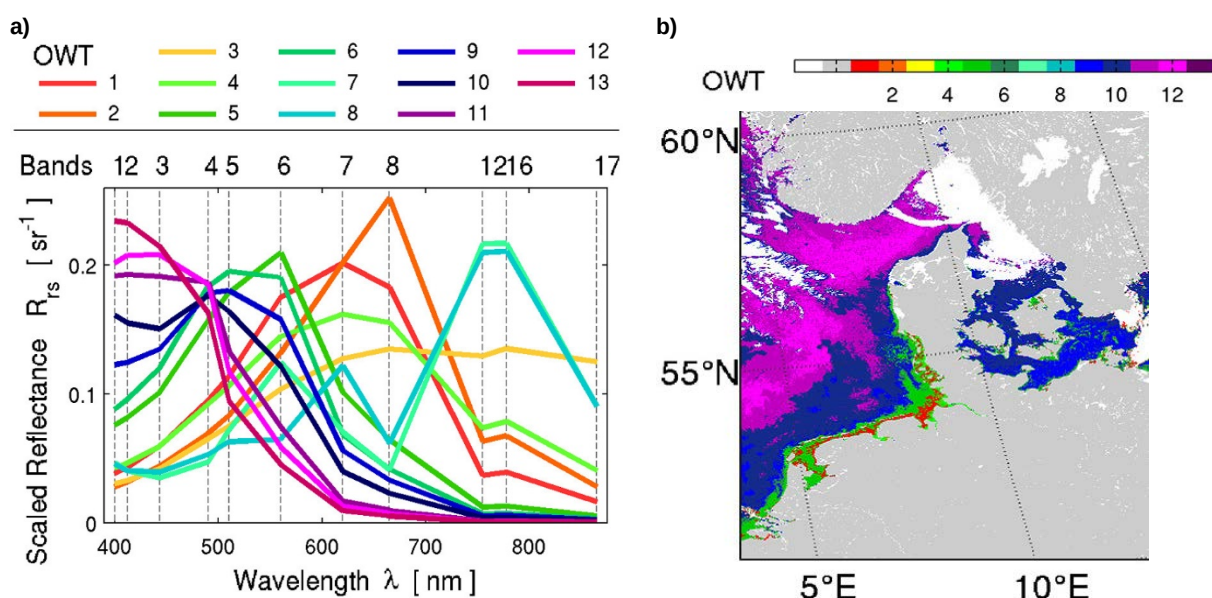


Figure 7. a) Brightness-scaled remote sensing reflectances for 13 classes of optical water types (OWT). The utilized OLCI bands are marked by dotted lines. b) Example of algorithm (ONNS) applied to an OLCI scene to define the optical water classes (20 July 2016). The grey colour marks land areas, white shows the cloud mask above water and inland waters, and the other colours correspond to the spectra of water types. Images (Hieronymi et al. 2017).

3.6 Procedures for vegetation mapping

As highlighted in *chapter 2.2*, a large number of RS-techniques are available for vegetation mapping and all of those could, potentially, be relevant for Danish coastal waters. However, the coarse resolution of the satellite data that is currently freely available limits their capacity to distinguish and map patchy and mixed vegetation types and therefore also limits their potential in providing precise area cover of such vegetation. Aerial photos having high spatial resolution, therefore currently seem like the best option for mapping of marine vegetation in Danish coastal waters even though the methods need further development (Ørberg et al. 2018). Satellite RS-data can be used on a regional basis and when high-resolution satellite images are rendered freely available, these should have the combined capacity of large spatial cover and

fine spatial resolution potentially making satellites the superior method in the future for SAV areal mapping.

A newly started European research project (<http://www.bonus-ecomap.eu/>), with Danish participation will test and compare a whole range of different RS-methods, both acoustic and optical, in a Danish test area.

3.7 Procedures for Chl-a mapping

Chl-a concentrations in surface waters are based on RS-algorithms, which utilize the spectral information in the atmospheric-corrected remote sensing reflectance spectra. It is important that the reflectance spectra used for the Chl-a algorithms are as accurate as possible for the water body of interest. For clear waters, like the North Sea, empirical band ratio algorithms between the blue and the green bands or optimized semi-analytical algorithms are usually sufficient (Tilstone et al. 2017), while they tend to fail in complex coastal waters (IOCCG 2000). Hence, algorithms based on neural networks (NN) usually performs better for Chl-a retrieval in waters similar to Danish waters (IOCCG 2000). The NNs within the algorithms are trained with large datasets of empirical bio-optical and reflectance relationships, typically covering large simulated concentration ranges, e.g. as in the FUB processor from (Schroeder et al. 2007) with Chl-a trained to be between 0.05-50 $\mu\text{g l}^{-1}$, TSS 0.05-50 g m^{-3} and $\text{CDOM}_{(443 \text{ nm})}$ 0.005-1 m^{-1} . The most commonly applied atmospheric and in-water algorithms for MERIS are the standard algorithm MEGS (Schiller and Doerffer 2005) and the Case 2 regional processor C2R (Doerffer and Schiller 2007), with the recently updated version Case 2 regional Coast Colour, C2RCC (Brockmann et al. 2016). The C2RCC processor include an extreme net with e.g. CDOM absorption range up to 60 m^{-1} and particulate scatter of up to 590 m^{-1} (Brockmann et al. 2016). For MODIS data the most used algorithms are the Ocean Color Chlorophyll OC4.v6 (O'Reilly et al. 1998; Werdell 2010) and the OC5 (Gohin et al. 2002). The OC algorithms are also applied to MERIS data. A schematic figure of the NN and a flow chart for the processing steps of the C2RCC processor are shown below, where the IOPs of the water constituents are fed into a bio-optical model (*figure 8a*) and used in the NN (*figure 8b*), producing water quality products.

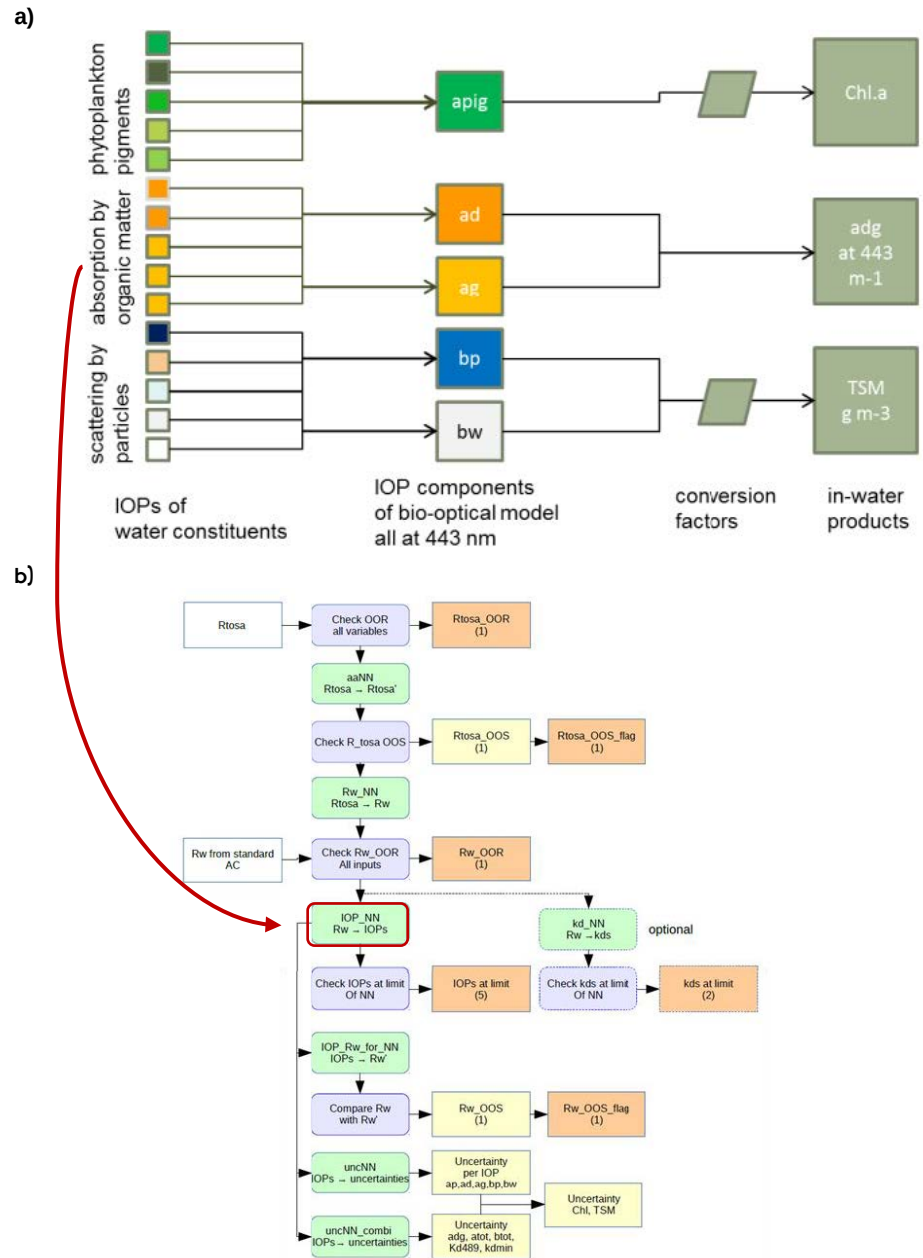


Figure 8. a) Schematic image of the bio-optical model for the C2R NN (Brockmann et al. 2016). b) Flow chart of the processing steps for the C2RCC processors. See Brockmann et al. (2016) for details.

(Mouw et al. 2015) have recently summarised the current challenges and recommendations for ocean colour missions. There are issues that need to be solved, and the Chl-a retrieval is listed as one. The band ratio and band difference algorithms have an advantage in the tolerance against errors in the RS-reflectances, but the blue bands can rarely be used in coastal areas due to the low reflectance in the blue and strong CDOM absorption influencing the Chl-a signal. This may lead to misinterpretations of the actual changes in Chl-a. Therefore, it is recommended to apply semi-analytical or NN algorithms which minimise the effects of CDOM. Other uncertainty issues relate to poor atmospheric correction and *in situ* sampling for validation and comparisons. The main challenge is the need for more data about the inherent (absorption and scattering) and apparent optical properties (AOP, e.g. light attenuation) in order to have a substantial dataset to be able to further develop the RS-algorithms. Many of these type of data are in need of full characterization for bio-optical and radiative transfer models and are listed in *table 3*. The *in situ*

optical parameters needed are currently not sampled regularly over sufficient spatial and temporal scales. If those were included within regular monitoring programmes, instead of solely in dedicated research projects, the possibilities to develop the RS-algorithms would increase dramatically. This would be a positive feedback loop, as the use of RS-algorithms for the current monitoring programme could be adjusted and improved. The fixed optical sensor on-board stationary buoys e.g. BOUSSOLOUE and the AERONET-OC stations have proven to provide invaluable *in situ* data for sensor validation, calibration and algorithm development.

The NN approach has been adjusted to allow processing of both Landsat-8 OLI and Sentinel-2 MSI data and initial tests are quite promising (DHI GRAS internal activities, unpublished). Alternative approaches, relying either on information from the reflectance data within the image, such as ACOLITE (Atmospheric Correction for High-Resolution Satellites) from the Royal Belgian Institute of Natural Sciences (Vanhellemont and Ruddick 2016) or look-up tables of IOPs based, such as iCOR atmospheric correction from Vito in Belgium have also shown promising results for the high resolution sensors.

Table 3. Overview of satellite RS mission sensors for water quality.

Apparent optical properties	Acronym	Included in NOVANA	Inherent optical properties	Acronym	Included in NOVANA	Biogeochemical optical parameters	Acronym	Included in NOVANA
RS reflectance	$R_{rs(\lambda)}$	No	Total absorption	$a(\lambda)$	No	Chl-a	Chl-a	Yes
Diffuse light attenuation	$K_d(\lambda)$	Yes	CDOM absorption	$a_{CDOM(\lambda)}$	No	Total Suspended Solids	TSS	To some extent
Euphotic zone depth	$Z_{1\%}$	No	Non algal particles absorption	$a_{NAP(\lambda)}$	No	Suspended Particulate Inorganic Matter	SPIM	No
Photosynthetic active radiation	$K_d(PAR)$	Yes	Phytoplankton absorption	$a_{ph(\lambda)}$	No	Suspended Particulate Organic Matter	SPOM	No
			Total backscatter	$bbp(\lambda)$	No	Dissolved Organic Matter	DOM	Yes

4 Experiences with RS-monitoring of Danish coastal waters

4.1 Vegetation mapping

4.1.1 Experiences with vegetation mapping based on aerial photos from planes and drones

Aerial photos from planes have been used in a number of cases for mapping the distribution of marine vegetation, particularly eelgrass, in selected coastal Danish areas. For example 'the Authorities' Control and Monitoring Programme' in connection with the establishment of Øresundsbroen across Øresund monitored the vegetation in Øresund before, during and after the establishment of the Fixed Link, including the area distribution of *Zostera marina* (eelgrass) and of *Ruppia spp.* (tasselweed). The vegetation was determined by means of aerial photography and subsequent image analysis (Krause-Jensen et al. 2001). For this purpose, approximately 1.500 pictures were taken by plane with an image overlap of about 40 % and at a resolution of 15-30 cm per pixel. After geo-rectification of the images, a classification analysis was carried out of the spectral composition (Red-, Green- and Blue- (RGB) signals) of aerial photos in training areas where vegetation type, cover and depth were known from paravane diving along transect lines. The image analysis was carried out using Discriminant Function Analysis to correlate the observed vegetation type with the colour value measured by the aerial photos. Another part of the training areas was used for validation. On this basis, the analysis provided a correct assessment of 'eelgrass', other seagrasses such as *Ruppia maritima* or 'tasselweed' in 83 % of the cases and estimated an overall area distribution of 140 km² eelgrass and 36 km² tasselweed in Øresund in year 2000 (Krause-Jensen et al. 2001).

Eelgrass mapping based on aerial photos and subsequent image analysis was also part of the national marine monitoring programme over a short period in the late 1990s. The areas mapped during this subprogram as well as through other initiatives were summarised in a report from 2009 (Josefson et al. 2009). However, the method was not sufficiently well-developed (e.g. with large uncertainties in assessing vegetation cover particularly in areas with mixed bottom) and not sufficiently cost-efficient (e.g. since it required specific flight time), so the sub-programme was discontinued during an exercise of economic cutback. Currently, aerial photos and image analyses are included in the marine part of NOVANA, solely for the Wadden Sea area. Here, flights with low-flying height are conducted, images are manually rectified and areas covered with eelgrass are visually delineated. The analyses based on aerial photographs are calibrated against field surveys. The resulting information on status and trends in the areal distribution of eelgrass in the Wadden Sea has recently been compiled in an updated status report for the Wadden Sea (Dolch et al. in press). Mapping of eelgrass areas from aerial photos in the monitoring programmes mentioned above, all required special flight time since the aerial photos obtained were used solely for the assessment of marine vegetation, rendering the programmes costly. However, summer-orthophotos covering the entire country are recorded bi-annually for other purposes and may offer possibilities for large-scale eelgrass mapping.

Compared to airplanes and satellites, drones can provide information at a much higher spatial resolution of down to a few cm² per pixel. This high resolution makes it possible to obtain detailed information on the benthic vegetation, especially in shallow clear waters. A pilot study from Odense Fjord, Denmark, showed that drones provided detailed information on the density and areal distribution of seagrasses (*Zostera marina*) and dominant macroalgae (*Fucus vesiculosus*) and opportunistic fast growing macroalgae growing within the seagrass meadows (Svane et al. 2016). Drone-based colour photos could even be used to distinguish between reproductive shoots and purely vegetative shoots of *Z. marina*. Under such optimal conditions, the requirements for ground truth data become less of an issue, compared to coarser data obtained from airplanes and satellites. Drones do provide a high level of flexibility in terms of when and where to record data, making it possible to monitor and assess responses to sudden storm events.

The high spatial resolution acquired when drones are applied at low height (< 30 m) comes at the expense of a limited areal coverage. Monitoring of areas at the landscape scale would typically require drone photos taken at around 100 m height thus reducing the spatial resolution considerably. Experiences from drone-mapping of opportunistic fast growing macroalgae (*Ulva lactuca*) in Danish waters indicate that drone transects should have an overlap of 90 % to ensure sufficient coverage (Michael Bo Rasmussen pers com). Gathering a coherent RGB image of a larger area based on drone data therefore involves a substantial effort into stitching a large series of smaller images together according to georeferenced data points, requiring a very systematic and specialized analysis. Fortunately, this time-demanding procedure has been greatly automatized as access to huge data storage facilities has increased.

4.1.2 Experience with vegetation mapping based on aerial photos from planes – the special case of the national orthophoto dataset

Bi-annual nationwide summer-orthophoto image mosaic datasets are available via agreements made between the national mapping and data agency, SDFF, and a set of Danish public sector organisations, including the Ministry of Environment and Food of Denmark and Aarhus University. So far, no systematic analyses have been available on the potentials of using aerial orthophotos for large-scale eelgrass mapping or the possibility of improving the data material to better fit this purpose. However, the DCE project 'Eelgrass area distribution' has, through 2017, explored this potential (Ørberg et al. 2018). The special case with 'summer orthophotos' (SOF) is that these images provide a unique long-term dataset, namely, repeated (1954, 1995, 1999, 2002 and onwards biennial datasets) national image coverages made with very high spatial resolution imaging (typically 15-20 cm pixels) in relatively short time periods (2 months) on each occasion. SOFs are not acquired primarily for advanced digital analysis, let alone for advanced digital mapping of eelgrass in coastal water. Rather, their primary purpose is for visual application, as backdrop to other spatial data, as publicity purposes for planning of outdoor activities and for visual interpretation with manual digitisation. However, it has previously been noted for several Danish coastal locations that these image data appear to represent a basis for mapping the distribution of eelgrass. Hence, a pioneer study applied selected orthophotos to establish time series from the 1940s to the 2000s to estimate trends in eelgrass areas in selected Danish fjords/coastal areas (Frederiksen et al. 2004). Furthermore, several recent projects have demonstrated that it is possible to apply automated digital analyses to the Danish orthophoto image data for mapping of, for example,

terrestrial coastal habitats (e.g. (Juel et al. 2015)). As such, given their national coverage, temporal and spatial resolution qualities, the questions are valid as (a) to what extent do they enable wider area mapping of eelgrass? and (b) what data interpretation, processing and analysis issues are relevant to their general use for spatial detailed eelgrass mapping?

The 2018 DCE-project analysed the most recent orthophoto series (2012-2016) for four selected areas having sufficient image quality and representing important eelgrass distribution areas: Nibe-Gjøl Bredning in Limfjorden, Saltholm incl. the Øresund coast facing Saltholm, the south Funen Archipelago and Roskilde Fjord. Reference data on eelgrass observations in points along transects under NOVANA were used to define a set of training areas and validation areas with/without known eelgrass cover. Then classification analysis was carried out based on the spectral composition (Red, Blue and Green (RGB) signals) of aerial photos in the training areas using two different image analysis techniques, namely Linear Discriminant Analysis (LDA) and Maximum Likelihood Classification (MLC). The developed models were subsequently validated based on reference data information in validation areas.

Overall, the project showed a large capacity for mapping shallow-water eelgrass meadows based on orthophotos in the selected areas where eelgrass is the dominant vegetation type (Ørberg et al. 2018). The mapping proved the highest level of correspondence with *in situ* data in relatively shallow waters where the image contrast is largest. The uncertainty of classification, however, increased at depth due to lower image contrast. It is potentially possible to expand the image analyses to include areas with more mixed vegetation if suitable training classes/areas are included. While the DCE-project mapped eelgrass down to 2.5 m in fjord areas and to 5 m along open coast areas, it is also potentially possible to fine-tune the depth resolution of the model depending on actual depth/light conditions of the study areas. Moreover, the study provides recommendations for optimised workflow for a national eelgrass mapping. The results are encouraging given the availability of orthophotos with large national coverage, high resolution, biannual repetition and long-time series, potentially allowing analyses of trends and reference distribution areas.

The DCE project, however, also pointed at important limitations in the current orthophoto-deliveries including incomplete image coverage of coastal waters and the lacking of colour normalization for coastal waters (Ørberg et al. 2018). These limitations could be overcome through new consortium agreements with the supplier of orthophotos since a much larger image coverage is actually available over coastal waters. Even maps with colour normalization are available as can be seen in the aerial photos of the current 'krak.dk'-maps, which are based on orthophotos from 2016. On this basis, the project team approached the orthophoto consortium to advocate for optimised image coverage and quality for coastal waters. Use of a pole filter may also reduce the problem of sunglint speckles on the water surface, which otherwise have to be corrected in an image analysis process (Ørberg et al. 2018).

Important to note is that test and validation of image analyses of any kind require reference data on vegetation type/coverage and years matching the image data. The DCE study showed that NOVANA data suit this purpose well. Overall, the vegetation surveys under NOVANA and the analyses of eelgrass area distribution based on orthophotos suit each other really well since NOVANA supplies not solely reference data on vegetation type/cover

but also precise information on depth limits of the vegetation, which is an additional key monitoring parameter given its sensitivity to water clarity and, hence, water quality. Conversely, mapping of area distribution based on image analysis of orthophotos potentially could be a valuable supplement to NOVANA monitoring since the many ecological functions of eelgrass and associated ecological services are directly coupled to the distribution area.

4.2 Water quality monitoring (Chl-a)

Most studies relevant for Danish coastal waters have so far used MERIS data. This is for two reasons: the high spectral resolution of the sensor and the higher spatial resolution enabling measures closer to the shore (Kratzer and Vinterhav 2010). Results from MODIS are also relevant but for Chl-a, the coarser spatial resolution of 1 km restricts the studies to more open waters. The optical complexity with low reflectance in the blue region (due to high CDOM absorption in Danish coastal areas), makes it difficult to draw general conclusions based on studies for other areas. The use and development of regional algorithms are usually applied for optical complex waters.

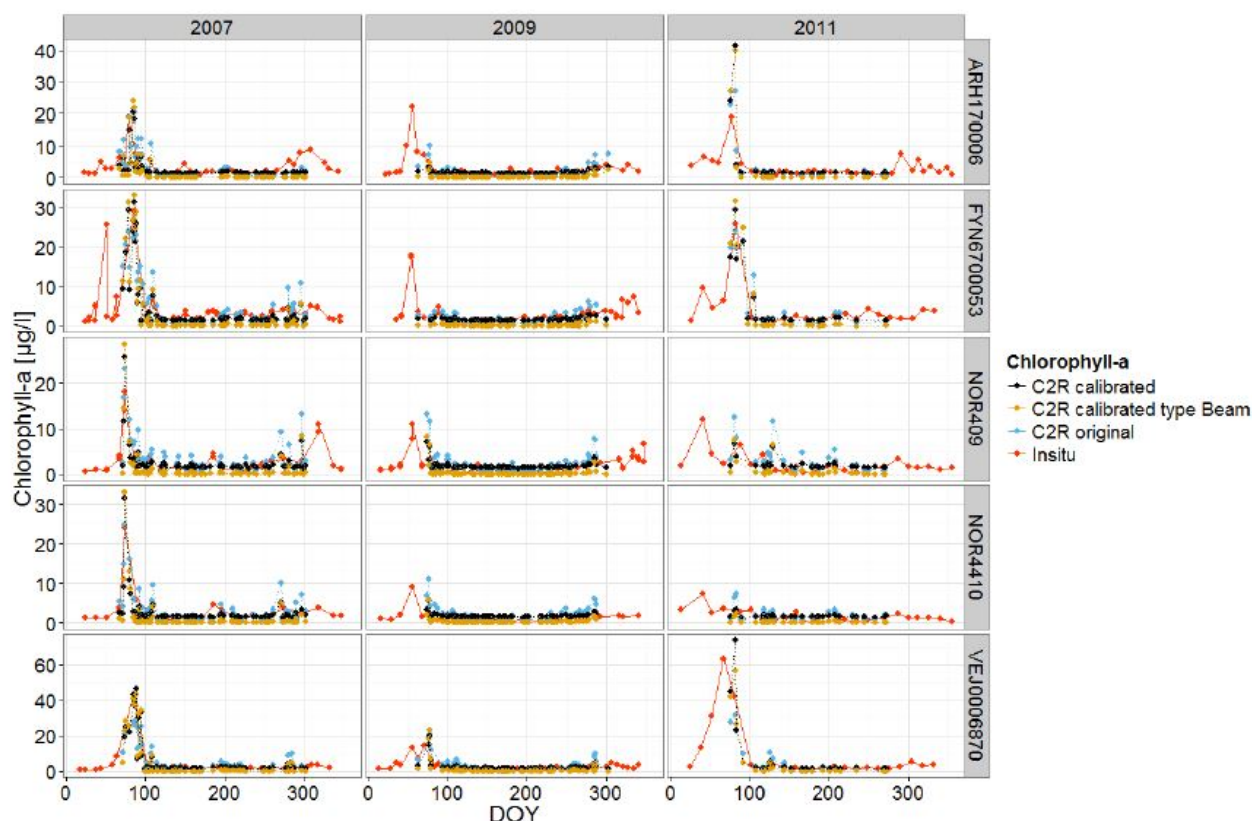


Figure 9. Danish time-series of chlorophyll-a concentration derived from MERIS with the C2R processor. Original values as well as calibrated values and *in-situ* measurements are shown for selected stations for the years 2007, 2009 and 2011. C2R: Case 2 Regional version 1.6.2, DOY: Day of Year. Image from (Poser et al. 2015).

However, previous experiences are important and relevant to continue to build upon, especially from studies in similar water types as the Danish. The accuracy of Chl-a retrieval depends largely upon: 1) the atmospheric correction, 2) if adjacency effects have been corrected for and 3) if in-water algorithms adapted for coastal waters have been applied. As the applicability varies depending on the optical properties of the water body, it is important to evaluate the performance under environmental conditions that are comparable with those where the RS-techniques are expected to be applied. It is important

to calculate both the systematic and the random errors by e.g. the mean normalized bias (MNB) and the root mean square error (RMSE), respectively, when assessing the accuracy of Chl-a RS-retrieval against *in situ* measurements. The systematic errors for *in situ* data are as important to assess and evaluate (JCGM 2008; Carstensen and Lindegarth 2016). Evaluation of the Danish time series (figure 9) between RS and *in situ* data gives a visual view of the performance in order to follow the timing of changes and evaluate if they are accurately detected by the different methods (Poser et al. 2015; Harvey et al. 2015; Kratzer et al. 2016; Cristina et al. 2016; Beltrán-Abaunza et al. 2017).

The performance of the algorithms to derived RS-based Chl-a can be estimated by comparing the RS-data to *in situ* Chl-a values. Results from studies carried out in waters similar to Denmark are presented below. The general accuracy for Chl-a retrieval for the southern, west and east Baltic Sea (with similar waters as the eastern Danish coastal areas), measured by the correlation coefficient, r , varies between $r = 0.25-0.76$, MNB = 8-56 % and RMSE = 37-115 % for different types of neural network algorithms (e.g. FUB, MEGS, C2R) (Attila et al. 2013; Beltrán-Abaunza et al. 2014; Harvey et al. 2015). A recent study by (Ligi et al. 2017) tests the applicability of band ratio or empirical algorithms for reflectance data for Chl-a retrieval on simulated RS-datasets with highly variable results. Thus correlation (r) between measured Chl-a concentrations and those calculated from RS was $r = 0.07-0.74$, with an associated Root Mean Square of Error (RMSE) of 16-59 % and a mean normalised bias (MNB) of 75-149 %. The high variabilities were explained by seasonality, dynamic coastal waters with high variability in the water constituents, both spatially and temporally, use of monitoring datasets instead of validation match-up datasets. Bloom events are pointed out as a source of discrepancies. In (Pitarch et al. 2016), Chl-a retrieval from the Glob Colour dataset (merged 15 years RS data from MERIS, MODIS, SeaWiFS, and VIIRS) was used with four types of algorithms for both Baltic Sea waters as well as Kattegat and Skagerrak waters. The standard algorithms needed to be adjusted before an unbiased estimation of the basin-average Chl-a was obtained, with a general $r = 0.67$, MNB = 60 % and RMSE = 136 % and $r = 0.61$, MNB = 59 and RMSE = 135 for the Baltic proper and $r = 0.58$, MNB = 58 % and RMSE = 133 % for Kattegat and Skagerrak.

In a recent study by DHI GRAS, different RS algorithms were tested in six Danish coastal areas using NOVANA monitoring data under the framework of the AQUA-USERS project (Poser et al. 2015). The retrieval of Chl-a values from RS was comparable to the *in situ* data, but somewhat overestimated for higher concentrations for two of the tree algorithms. This was adjusted for by applying a local adjustment of coefficients for the Chl-a algorithms. After the adjustment of the algorithm, the results were improved with a better correlation between measured and RS-detected Chl-a ($r = 0.95-0.97$), a lower bias (MNB = 1.04-1.91) and a low error (RMSE = 1.60- 2.96) compared to before adjustment of the RS-algorithms ($r = 0.87-0.95$, MNB = 1.62-2.07 and RMSE = 2.96-4.94). Hence, both the bias and systematic errors decreased, meaning that the RS-derived Chl-a was more in coherence with the *in situ* data. The adjusted C2R algorithm was chosen for further studies (Poser et al. 2015). The same algorithm was used in another study, where the Chl-a fluorescence retrieval from the Ferrybox on-board the Oslo-Kiel ferry (operated by NIVA) was compared to MERIS and MODIS data (Andersen et al. 2017). The MODIS Chl-a data were retrieved by the OC3 algorithm, which is known to have high discrepancies in high CDOM waters (Matthews 2011; Pitarch et al. 2016). The

results based on data from 2009-2016 were quite variable for the different stations with low correlations of only $r = 0.2$ (low range of Chl-a values) to very good ones with $r = 0.79$. The Ferrybox data is Chl-a fluorescence, which is known to be problematic for RS-comparisons (Doerffer 2002). Regional MODIS Chl-a empirical band ratio algorithms for the Gulf of Finland have been tested by (Vazyulya et al. 2014) with promising results that might be applicable for Danish waters as well. The choice of algorithms comes down to the chosen sensor and the specific application. One that works well for Chl-a might not be the best choice for TSS, CDOM or light attenuation. It is therefore important to choose carefully and generally not apply algorithms adopted to open sea and clear waters for coastal applications.

Once the RS Chl-a retrieval is accurate and validated the data can be used to support monitoring and water quality assessments. There are good examples of the use of RS for water quality assessment. The ecological status within the WFD and MSFD was well evaluated based on RS-data for the Bay of Biscay (Gohin et al. 2008; Novoa et al. 2012), the Baltic Sea (Philipson et al. 2009; Kratzer et al. 2014), the Atlantic Ocean (Cristina et al. 2015) as well as in examples from boreal and alpine lakes (Alikas et al. 2015). In a recent Danish OSPAR Chl-a assessment, RS-data were used to fill in the data gaps for the North Sea (Andersen et al. 2016). Common for these studies are the results which show an increase in spatial and temporal coverage when using RS-data as an additional source for water quality assessment. The use of RS-data within ecological and environmental assessments on water body level has so far not been used a lot, but there is a growing tendency. As an example the latest and the upcoming Swedish water quality assessment will partly be based on RS-data (Brockmann Geomatics AB 2017). Also the Dutch national monitoring program has included Satellite RS data since 2016 (Blauw 2017a).

When applying RS-data within monitoring, it can be included at different levels. Single daily images can be used as a complement to *in situ* measurements in order to follow the spatial and temporal changes, as well as developments of algae blooms (Harvey et al. 2015; Beltrán-Abaunza et al. 2017). The daily images can be merged into averages per week, month, season, year or assessment period, as done in Sweden between 2009-2011, based on MERIS data (Brockmann Geomatics AB 2017). The Chl-a values for an assessment period can then be used for the Chl-a status assessment per water body or the RS-data can be used in a combination with other methods for filling out gaps and to increase the amount of data on which to base an assessment. The spatial differences over time are well-illustrated by RS-data, and areas of high variability or anomalies towards a known state or threshold can be identified and evaluated (Beltrán-Abaunza et al. 2017). This is commonly presented for the yearly ice-cover in the polar regions, but can be applied to any RS-parameter.

4.2.1 General considerations for RS Chl-a retrieval

The results from coastal areas based on MERIS data have proven the methods to be accurate enough when appropriate or adjusted algorithms are applied. However, the implementation of RS-data within European national monitoring programmes is still lacking behind, but are applied in some countries like Sweden, the Netherlands, England and Belgium. One of the reasons has been the unfortunate gap in the sensor launch between the end of MERIS (2012) and delayed launch of Sentinel3 OLCI (2016). As the operational phase of OLCI only became available in late 2016, published studies focusing on coastal

applications of OLCI are still rare, although there is an intense ongoing research with high expectations for the applications of the instrument within the RS-community. The need for complete spectral and radiometric accuracy of the sensor is crucial for applying any RS-algorithms, and the radiometric uncertainty for match-ups should be lower than $\pm 1\%$ in the blue and green spectral regions in oceanic waters (Zibordi et al. 2017).

Since the OLCI sensor builds on the legacy of MERIS, with similar but improved spectral and band design, direct applications of MERIS methods should be feasible for OLCI as well. However, OLCI is still in its starting phase and the spectral and radiometric models are still being adjusted by vicarious calibration (calibration of the RS-sensor) and later reprocessing in order to improve the sensor's accuracy. The relative error of the spectral measurements made by the OLCI sensor is overall between 0.4 % and 1.4 %, depending on wavelength (ESA 2016). OLCI data has only been available since May 2017 and the match-up data for validation are very scarce and mostly based on the summer months. It has been observed that the Sentinel-3 OLCI product performs worse than MERIS in turbid coastal waters and that the Chl-a concentrations are underestimated. A first validation of Sentinel-3 OLCI in the south and eastern Baltic Sea has been performed by (Toming et al. 2017). The standard processor for OLCI, the C2RCC (adjusted NN of the C2R for higher ranges of bio-optical data (Brockmann et al. 2016), and several band algorithms were tested. The results showed that there were problems with the absorption and scattering coefficients as well as the concentrations of Chl-a from the C2RCC processor, but the reflectance spectra was well validated for non-bloom conditions. The use of band ratio algorithms performed relatively well. Available band combinations can be applied on both Sentinel-3 OLCI and Sentinel-2 MSI sensors. The study by Brockmann et al. (2016) concludes that there is a need for a processor specially adapted to high CDOM waters that can retrieve the reflectance accurate enough in the blue parts of the spectrum. The results from a very recent validation study in the Dutch and Belgian waters confirm this, with poor results for the OLCI NN, but better for the reflectance (Blauw 2017b). These issues will be solved with time, as the algorithms are tested, refined and tuned. It is still possible to use the algorithms and apply local correction factors to increase the accuracy.

The sentinel-2A & B satellites have potential to retrieve water quality data over smaller water bodies with its spatial resolution of 10-60 m, with a revisiting time of 2-3 days in Denmark. The several band ratio algorithms used for Chl-a retrieval, recently tested by (Ligi et al. 2017), (Gernez et al. 2017) and (Toming et al. 2016), can be applied to Sentinel-2 MSI sensors with promising results in clear waters and in eutrophic murky lakes. The application of the band ratio between band 5 and 4 or 6 should also be applicable in Danish coastal waters, but has not yet been tested and evaluated.

5 Conclusions and recommendations

The large effort and the recent developments put into highly specific and advanced satellite RS has dramatically improved the operational possibilities of applying RS within coastal marine monitoring. Today, we are able to follow the dynamics in the coastal zones by using a combination of different sensors. The breakthrough decisions from ESA and NASA to provide the RS-data free of charge have really opened up for this to happen. For vegetation, mapping the rapid development of technical methods and new instruments such as drones and high-resolution optical photos provides us with new data and new possibilities. These opportunities can help to improve the monitoring programmes by adding other types of data efficiently in a cost-effective manner.

However, to be ready for full implementation within the NOVANA monitoring programme, there are still some issues that need to be solved. For RS Chl-a retrieval, the most crucial issue is to test the Sentinel-2 MSI and Sentinel-3 OLCI performances in Danish waters. For Sentinel-3, the issues with the vicarious calibration will be solved in the near future and the data should be more or less ready for implementation within NOVANA (although the MERIS data need a Danish tuning to provide optimal results (Poser et al. 2015), once the best algorithms have been decided upon. Regarding the Sentinel-2 MSI sensors, a more comprehensive test of the best retrieval procedure of Chl-a and corrections for the adjacency effects needs to be evaluated. It is also important to assess how close to land the data can be retrieved, without having a major influence from bottom reflectance, depending on the light attenuation in the area.

Submerged aquatic vegetation mapping in Denmark based on RS-technology still require further development both regarding the use of drones, aerial orthophotos and satellite data and their combined use. In order to optimize the use of airplane-derived summer orthophotos available biennially, it is necessary to ensure a better coverage and color normalization over sea areas as well as to explore their potential to distinguish different vegetation types. Also techniques need to be developed to further develop the currently available methods for use at the national scale. There is also a need to test the potential strengths and limitations of satellite data for assessing vegetation cover.

The major advantages of RS-data are the increased spatial resolution and the increased temporal coverage. However, all methods have drawbacks. One of the limitations for commercial RS is that the data are collected within short periods. Using aerial RS make you very dependent on weather conditions and only cloudless days are usable for measurements. If the hired airplane or drone is equipped with specially mounted cameras for the purpose, the drones and their pilots need to be standing by, which usually includes a cost. The costs associated with this is of course lower for using drones than aircraft. Regarding vegetation mapping, there is a depth limit depending on the water clarity to which the signal is being absorbed to such a high degree that the features at the bottom no longer are detected. Hence, the details gained from *in situ* data are needed both for development and validation of RS-algorithms and in other ways to supplement the RS-generated data, e.g. by providing information on depth limits. The same can be said about Chl-a, as the results

are an integrated value over the depth penetration of the water-leaving reflectance. If the water body is vertically well mixed, the RS-value corresponds to the *in situ* surface value. Problems in mismatch usually occur in stratified areas or where the Chl-a maximum is very deep. Field sampling can provide detailed information about e.g. depth profiles on small spatial scales and detailed phytoplankton identification. However, there is an emerging field of identifying phytoplankton functional groups also by means of hyperspectral RS-data. Limitations for the retrieval of satellite data are cloud cover and low azimuth angle of the sun during the winter months in high latitudes, as in the Nordic countries (IOCCG 2000).

The use of RS-data at different levels within the monitoring and environmental assessment cycle is presented in *figure 10*. The concept is that RS-data add an additional cost-effective data source together with *in situ* data; the combined data sources are used within data analyses for assessment of e.g. seasonal changes, bloom events, spatial changes, changes in vegetation areal distribution, Good Ecological Status (GES) assessment for water bodies within both the WFD and the MSFD. The RS-data can be used as either an input to environmental models or for validation of them. The RS-techniques thus add data to the official databases supporting the planning of the programmes by identifying the most suitable spots to sample or identify needs for reallocation of monitoring efforts. RS-data can also be used to identify natural borders within the water bodies, often based on physical characteristics such as resuspension, run-off or upwelling. As an example, a massive phytoplankton bloom was observed in extreme close proximity to and along the Belgian coast by S2 MSI data. This is an area which never has been included in the monitoring programme (the depth is too shallow for the ships) and the phenomena would not have been known if not for the spatial RS-data.

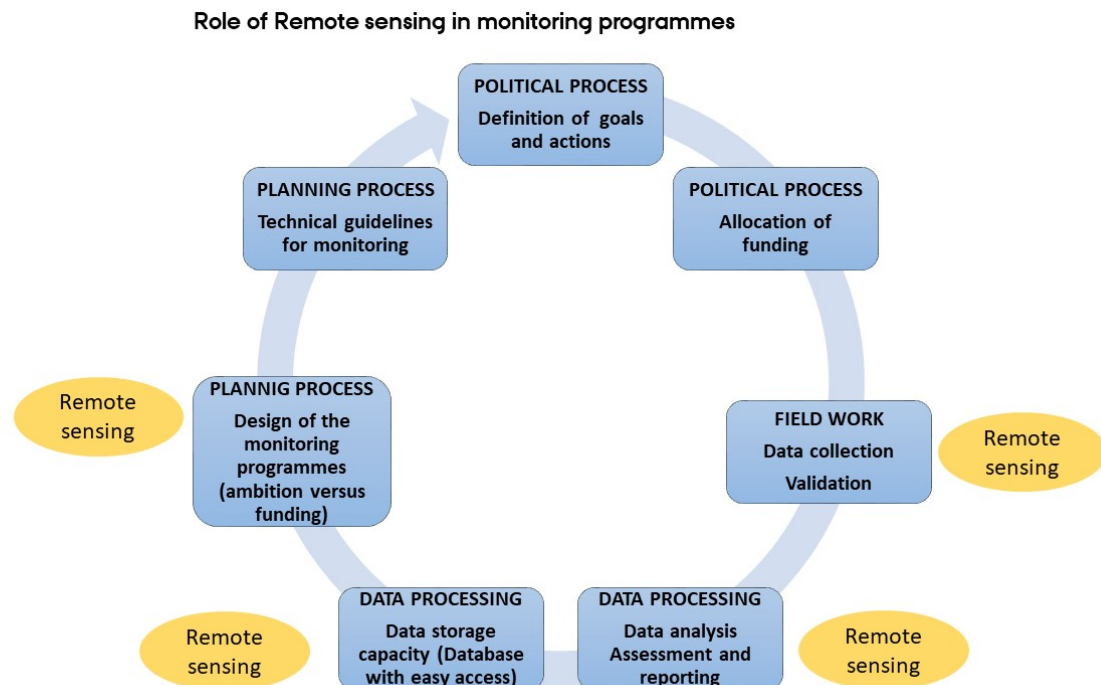


Figure 10. Conceptual model describing the cycle of monitoring programmes in which steps remote sensing data will contribute.

The assessment of GES within the EU directives based on RS-data is illustrated for Chl-a in figure 11. Step 1 includes daily single images from any type of RS-sensor. Step 2 is merged products for every week, month, year or assessment period (3-years). Step 3 is the final GES assessment per water body. The information is used as it is, or fed into a total GES assessment for the areas. The assessment or data input can of course also be included with *in situ* or modelled data to give an integrated value. The RS-assessments are extra valuable for areas less monitored by ships.

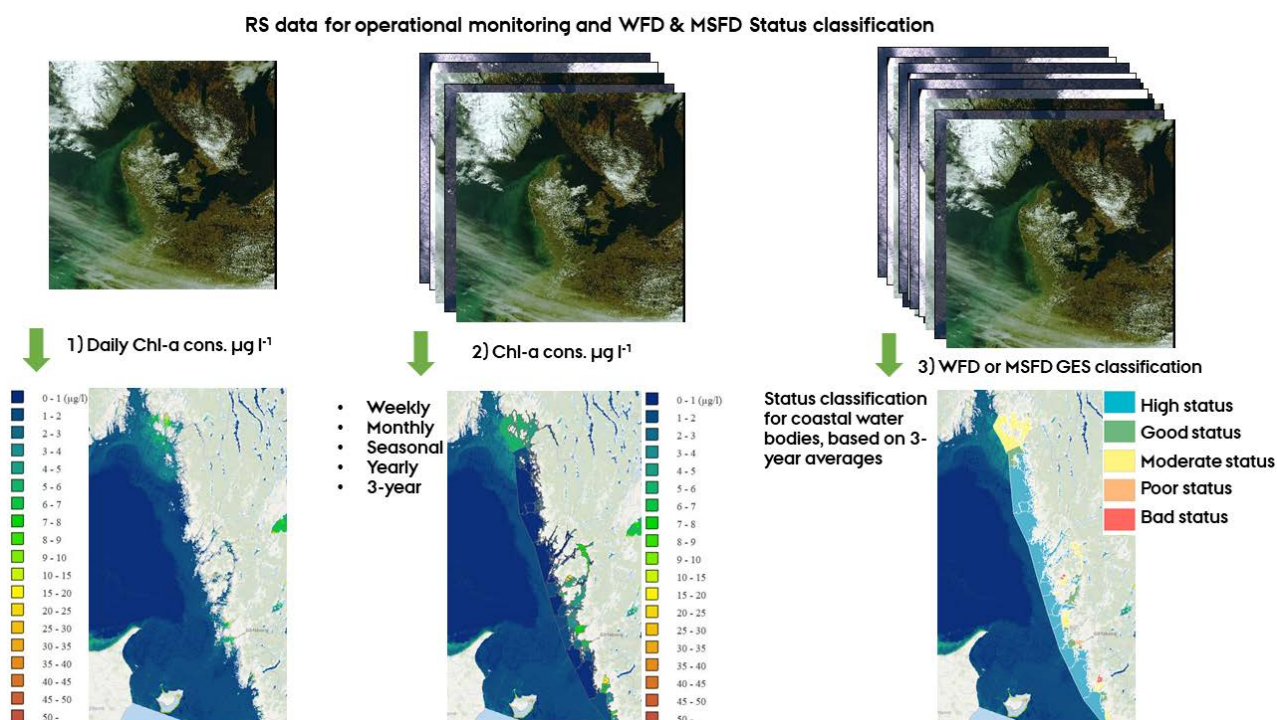


Figure 11. Maps showing processed scenes. Maps in the bottom row are processed by Petra Philipson at Brockmann Geomatics AB, MERIS 3rd reprocessing, ICOL & FUB.

5.1 General recommendations for RS-implementation

Based on the summarised literature review above, including previous results for Danish waters, some general conclusions and suggestions according to implementation and enhanced use of RS-data in NOVANA can be made.

- 1) Include coastal water areas in a structured way, when collecting the bi-annual collection of ortophotos for land use. By doing so, the shallow Danish coastal areas could be mapped in regard to eelgrass coverage.
- 2) Start using and evaluating drone and satellite data for vegetation mapping and water quality.
- 3) Allocate resources for analyses and method development of RS-algorithms and techniques.
- 4) Start building up and including a sampling procedure that is sufficient for RS water quality validation. This can be done by:
 - Mounting the monitoring ships with fixed radiometers to measure the remote sensing reflectance.

- Making sure that the data are sampled within the correct time frames for *in situ* validation, by having all ships scheduled to stop at any position on the corresponding time to an RS overpass given that the sky is clear enough.
 - Including the optical parameters listed in *table 3* within the NOVANA programme.
- 5) Evaluate the NOVANA monitoring programme for potential additional macro algae and eelgrass sampling in accordance with RS-validation, both aerial and by satellite.

The use of RS-data for water applications has been evaluated for many years. We are now in a situation where an implementation followed by consistent commitment for long-term use can be fruitful for the monitoring programme providing quality-assured RS-data for monitoring and assessment. Given that, EU's and ESA's Copernicus mission is the largest Earth observation investment in time with a long-term commitment, and this provides a unique opportunity for environmental applications. In particular, incorporation of RS-data in aquatic ecological studies is the way forward for improving monitoring and management of aquatic ecosystems. Using RS-data to a higher extent than today, will help in fulfilling the aims for ecosystem health within the UN Sustainable Development Goals, the Baltic Sea Action Plan as well as EU directives and the OSPAR Convention.

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LITERATURE REVIEW OF REMOTE SENSING TECHNOLOGIES FOR COASTAL CHLOROPHYLL-A OBSERVATIONS AND VEGETATION COVERAGE

Part of ReSTEK (Brug af Remote Sensing teknologier til opgørelse af klorofyl-koncentrationer og vegetationsudbredelse i danske kystvande) and DCE Remote sensing in coastal area projects

This report reviews the possibilities of using data from different remote sensing techniques to supplement the conventional national NOVANA programme for monitoring of water quality (chlorophyll-a) and submerged aquatic vegetation (seagrasses and macroalgae) in Danish coastal waters. Strengths, weaknesses and knowledge gaps are briefly discussed and recommendations on future steps for integration of RS techniques for monitoring in Danish coastal waters are provided.