Chapter 19
Multitemporal Remote Sensing of Coastal Waters

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Abstract In this chapter we address some of the recent developments in marine coastal remote sensing with regards to the evaluation of water quality from space using multi-temporal data. Most chapters in this book are devoted to terrestrial applications, whereas aquatic remote sensing requires a completely different approach in terms of mission and sensor design as well as data analysis and processing. Therefore, the first section is a general introduction to marine remote sensing. Then we report recent results from remote sensing of the Baltic Sea, which is optically dominated by the absorption of light by coloured dissolved organic matter (CDOM), and during summer months, by high standing stocks of filamentous cyanobacteria. Results both from basin-wide as well as coastal applications in the north-western Baltic Sea are presented. In next section we report results from the Bay of Biscay in the north-eastern Atlantic Ocean west of France, which is an area highly influenced by river discharge and dinoflagellate blooms, and the subsequent section is about a coastal area in the eastern Beaufort Sea in the Arctic that’s influenced by a pool
of CDOM. In all sections we discuss the relevance of regional remote sensing for ecological analysis and coastal management. The chapter concludes with a synthesis on merging of satellite data from different ocean colour missions and the limitations for coastal applications are discussed.

### Abbreviations

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<tr>
<th>Acronym</th>
<th>Explanation</th>
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<tr>
<td>AVHRR:</td>
<td>Advanced Very High Resolution Radiometer (NOAA)</td>
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<tr>
<td>Case-1 waters</td>
<td>Waters that are optically dominated by water itself and by Chl-a (and correlated CDOM)</td>
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<tr>
<td>Case-2 waters</td>
<td>Waters that are also optically significantly influenced by SPM and/or CDOM (besides water and Chl-a)</td>
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<tr>
<td>Chl-a</td>
<td>Chlorophyll-a</td>
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<td>Chl-b</td>
<td>Chlorophyll-b</td>
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<tr>
<td>CDOM</td>
<td>Chromophoric or Coloured Dissolved Organic Matter</td>
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<td>CZCS</td>
<td>Coastal Zone Colour Scanner (NASA)</td>
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<tr>
<td>DIN</td>
<td>Dissolved Inorganic Nitrogen</td>
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<td>DIP</td>
<td>Dissolved Inorganic Phosphorus</td>
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<tr>
<td>EC</td>
<td>European Commission</td>
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<td>ENVISAT</td>
<td>European ENVironmental SATellite (ESA)</td>
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<td>ESA</td>
<td>European Space Agency</td>
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<td>EU</td>
<td>European Union</td>
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<tr>
<td>FR</td>
<td>Full resolution</td>
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<tr>
<td>FUB</td>
<td>Freie Universität Berlin</td>
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<tr>
<td>GMES</td>
<td>Global Monitoring of Environment and Security</td>
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<td>GSM</td>
<td>Global System for Mobile communications</td>
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<tr>
<td>HELCOM</td>
<td>HELsinki COMmission</td>
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<tr>
<td>ICOL</td>
<td>Improved Contrast between Ocean and Land processor</td>
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<td>IOPs</td>
<td>Inherent Optical Properties</td>
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<td>MCI</td>
<td>Maximum Chlorophyll Index</td>
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<td>MERIS</td>
<td>MEedium Resolution Imaging Spectrometer (ESA)</td>
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<td>MLAC</td>
<td>Merged Local Area Coverage</td>
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<td>MODIS</td>
<td>MODerate Imaging Spectroradiometer (NASA)</td>
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<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
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<td>NIR</td>
<td>Near-InfraRed</td>
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<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
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<td>NPP</td>
<td>Net Primary Production</td>
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<tr>
<td>NSIDC</td>
<td>National Snow and Ice Data Center</td>
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<tr>
<td>OC</td>
<td>Ocean Colour</td>
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<td>OLCI</td>
<td>Ocean and Land Colour Instrument (ESA)</td>
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<tr>
<td>RGB</td>
<td>Red Green Blue</td>
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<tr>
<td>RR</td>
<td>Reduced resolution</td>
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SeaDAS  SeaWiFS Data Analysis Software
SeaWiFS  Sea-viewing Wide Field-of-view Sensor (NASA)
SPM     Suspended Particulate Matter
SST     Sea Surface Temperature
TOA     Top-of-Atmosphere
TSM     Total Suspended Matter
VIS     Visible
WFD     Water Framework Directive 2000/60/EC

**Optical coefficients**

- a: Absorption coefficient
- b: Scattering coefficient
- b_b: Backward scattering coefficient
- b_f: Forward scattering coefficient
- G_440: Absorption coefficient of CDOM
- I: Radiance
- E: Irradiance
- E_d: Downwelling Irradiance
- K_d: Diffuse attenuation coefficient of downwelling irradiance
- Rrs: Remote Sensing Reflectance

### 19.1 Introduction

Before satellite ocean colour remote sensing techniques were available, measurements of water quality parameters derived from seawater optical properties were spatially isolated and infrequent, being available primarily from ships and moorings, with a few airborne campaigns. With the new space imagery the full dynamics of algal blooms and river plumes were suddenly revealed, and a new understanding of ocean currents and dynamics was fostered in an unprecedented way (Whitehouse and Hutt 2006). The first ocean colour (OC) sensor launched was the Coastal Zone Color Sensor (CZCS) developed by NASA. It was launched on the Nimbus-7 satellite and operational from 1978 to 1986 (McClain 2009). CZCS was very speculative and a proof-of-concept mission for studying phytoplankton from space, but worked well for open ocean applications and provided the first estimates of global ocean productivity (Behrenfeld and Falkowski 1997). However, it did not have the required spectral and spatial resolution to deal with the complexity of coastal waters, nor could it sufficiently correct for atmospheric effects. The main operational OC missions to date have been NASA’s ‘Sea-viewing Wide Field-of-view Sensor ‘SeaWiFS (1997–2010), and the ‘MODErate Imaging Spectroradiometer’ MODIS (since 1999) and ESA’s ‘Medium Resolution Imaging Spectrometer’ MERIS (2002–2012). MERIS deserves a special mention as it was the first sensor especially designed for coastal applications (Doerffer et al. 1999). It
ceased working in March 2012 and has been replaced by the Ocean and Land Colour Instrument (OLCI) on Sentinel-3 on 16 February 2016 as part of the Copernicus mission (Donlon et al. 2012).

**Difference Between Terrestrial and Ocean Colour Remote Sensing**  Before discussing the optical properties of marine waters, we will first have a closer look at the difference between terrestrial and OC remote sensing data in terms of spatial, spectral and temporal resolution. The main difference between the terrestrial and marine biota is that the sea is highly dynamic as marine algae are suspended in the water and so move with the currents (advection), whereas plants do not change location and so their growth and decay can be monitored by examining the temporal variability of each individual pixel. Vegetation growth and the change in tree and leaf cover happen generally over a span of weeks or months (10-100 d) rather than within a few days (IOC CG 2000). The life cycle of algal blooms is much shorter than that of typical terrestrial plants, and requires suitable hydrodynamic conditions to deliver the nutrients and solar radiation needed for phytoplankton growth. An algal bloom, can develop within a few days, and disappear again within a week (Sect. 19.2.4). This is important in terms of the required temporal resolution (frequency) of remote sensing data: in terrestrial remote sensing the development can focus on attaining the best possible spatial resolution. Nowadays, the spatial resolution of terrestrial remote sensing data is in the range of about 2–30 m, whereas in OC remote sensing one needs to focus on developing satellite systems with a good temporal resolution as phytoplankton dynamics in the coastal zone can change on a daily or even diurnal basis. Some dinoflagellates, for example, are known to migrate up and down the water column dependent on the light and food availability which may have a drastic effect on the chlorophyll-a (Chl-a) concentration in the upper water layers that are sensed by OC remote sensing. Phytoplankton are also known to exhibit a diurnal change in photosynthetic production, dependent on the change in solar radiation during the day which is at its maximum values during mid-day. In areas of high tidal influence, the physical dynamics in bays and estuaries can also change drastically within 4–6 h.

**Trade-Off Between Spatial and Temporal Resolution**  In order to get a good spatial resolution, and hence retrieve pixels of a smaller size, higher resolution sensors have a narrower swath width, which means they can only cover a smaller area of the Earth when revolving around the Earth. It therefore requires the accumulation of many more orbits, over subsequent days, to build up a complete global picture, leading to revisit intervals of many days and thus to a lower temporal resolution. The revisit time of Landsat (30 m spatial resolution) is about 16 days for Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper (ETM+), whereas OC sensors are designed and launched in such a way that they have a better temporal resolution i.e. the repeat time is optimised with a wider swath so that they cover a given location on the Earth over 1–3 days in order to capture the dynamics of phytoplankton production, coastal currents and river plumes, but this in turn increases the pixel size, leading to a lower spatial resolution. For OC missions the
standard pixel size is about 1000 m for open ocean applications (e.g. SeaWiFS and most MODIS channels), whereas in coastal water applications 250–300 m has been the highest spatial resolution. MODIS generally has 1 km resolution for its ocean colour bands and several terrestrial channels, plus a 250 m panchromatic channel, and it is also possible to retrieve 250 m resolution for the OC bands with a statistical method called ‘pan sharpening’. MERIS data has 300 m resolution, the so-called full resolution (FR), in all 15 programmable bands, but over the open ocean the full resolution was reduced in order to provide 1.2 km Reduced Resolution (RR) data. The Korean Geostationary Ocean Color Imager (GOCI), the first of its kind, has a spatial resolution of about 500 m over the Korean Sea.

Figure 19.1 shows RGB composites of a MERIS RR image (Fig. 19.1a) and a MERIS FR image (Fig. 19.1b) compared to a Landsat 5 TM image (Fig. 19.1c). One can clearly see that the 30 m resolution of Landsat is much more appropriate to resolve coastal morphology and to visualize coastal dynamics; the coastline is much clearer and the sediment plumes are much more detailed. However, the spectral

![Comparison of top-of-atmosphere (a) MERIS Reduced Resolution Image, (b) MERIS Full Resolution Image and (c) Landsat 5 TM image all acquired at the start of July 2006 over the Zeeland area of the Netherlands coast; images are in their provided projections, which is the satellite projection for the MERIS data and UTM for the Landsat data, with the geographical area shown being around 250 km in width. (d) is the MERIS Data corrected to bottom-of-atmosphere remote sensing reflectance using the NASA SeaDAS processor. Courtesy of ESA and the U.S. Geological Survey](image-url)
bands for the Landsat missions were chosen with land rather than OC applications in mind, so above the sea it is primarily used to derive information on Suspended Particulate Matter (SPM) as it does not have the required spectral resolution of OC sensors (meaning that the bands in the visible are too broad and too few in numbers); however, Chl-a has been mapped with Landsat when present in high concentrations (e.g. Nazeer and Nichol 2015). Figure 19.1d shows atmospherically corrected MERIS FR data, which is the first step in deriving quantitative information as described later in this section.

In addition to Landsat, sensors such as the Compact High Resolution Imaging Spectrometer (CHRIS/PROBA) have also been used for coastal OC remote sensing (spatial resolution of approximately 18 m) although they were primarily designed for terrestrial applications. In summary, it may be stated that in terrestrial remote sensing it is possible to concentrate effort and technical development on achieving a better spatial resolution, whereas in OC remote sensing a good temporal resolution is mandatory.

**Spectral Resolution** Besides the difference in requirements for spatial and temporal resolution, there is also a difference in the requirements for spectral resolution and signal-to-noise ratio (SNR) within these bands. In terrestrial remote sensing the bands of multi-spectral sensors tend to be rather broad (30–70 nm), whereas the bands in OC remote sensing should not be broader than 10 nm and tend to be much greater in numbers to capture subtle spectral features (IOCCG 2000). The number of bands is important for the number of water quality parameters that can be retrieved from the reflectance signature e.g. when developing band ratio algorithms to derive various geophysical products. It must be stated, however, that there is a trend towards hyperspectral remote sensing (e.g. Hyperion and the underlying instrument for MERIS and CHRIS/PROBA), although capturing and downloading hyperspectral data is an operational constraint in terms of the mission cost-efficiency.

**Difference in Data Analysis and Processing** As well as differences in sensor and mission design, there is also a major difference in how the data is processed (Sathyendranath 2000). In terrestrial remote sensing, clustering and classification are some of the methods used to derive information about different vegetation and land use types as well as soil cover. In OC remote sensing the main methods used to derive information about water quality are regression type empirical and semi-empirical algorithms plus inversion techniques such as neural networks (NN) that are more popular in coastal waters because of their optical complexity. These techniques are used to derive the main bio-geophysical products: Chl-a, SPM and CDOM that is sometimes also referred to as yellow substance (YS). This is possible because of the specific scattering and absorption properties of each optical constituent, with the reflectance of the sea (the colour of the sea) determined by a ratio between spectral absorption and backscatter.

In OC remote sensing, classification is mostly used to develop flags for those pixels that clearly differ from the spectral signature of a water pixel, so that
these pixels can be masked out (or flagged), and subsequently are not used in the processing of water pixels. Examples include the high reflectances from ice and clouds as well as land. It must be stated, however, that information about coastal soil and vegetation type is still interesting for coastal zone management and for coastal water optics, e.g. large expanses of bare soil lead to higher erosion, which may cause an increase in the run-off and therefore SPM. Wetlands, marshland and bog areas tend to be high in humic substance, and so the run-off may cause an increase in CDOM. Forests may act as a buffer area and reduce coastal run-off, and also have a lower impact on the land adjacency effect. ‘Adjacency effects’ can be described as blurring that occurs in pixels in close proximity to the coast. Land is usually more reflective than water, and an imager that measures above water close to the coastline may also receive scattered light that originated from the nearby land pixels.

**Dynamic Range** Another important requirement for OC sensors in coastal waters is that they must have a wide dynamic range to sense both the low reflectance from relatively dark water bodies as well as the high reflectance from waters that are laden with high concentrations of inorganic SPM. This means that they must achieve a high SNR even where the reflectance from water bodies is low i.e. 5–10 %, while not saturating at very high reflectances. Most of the top-of-the-atmosphere (TOA) signal over water surfaces originates from atmospheric processes such as gas and aerosol scattering. Atmospheric correction is therefore a critical step in the processing of OC data.

**Optical in-Water Constituents** As previously mentioned, the reason why we can sense optical water constituents is because of their specific absorption and scattering properties. Pure water absorbs at long wavelengths, in the red part of the electromagnetic spectrum, and the backscatter of water increases towards the blue wavelengths. Therefore, water with little or no other constituents appears blue. As the Chl-α concentration increases the water becomes greener and SPM often causes red/brown water. These constituents play a substantial role in the biogeochemistry of natural waters and are important for their optical properties. They all have specific spectral absorption properties, which have an effect on the reflectance signature, i.e. on the colour of the sea. The derived OC data products are called Level 2 (L2) products whereas the directly measured TOA signal is a Level 1 (L1) product. The key product for oceanographic studies and coastal management is Chl-α as it can give a good indication of changes in phytoplankton biomass and eutrophication (Sects. 19.2.4 and 19.3). Besides Chl-α one can also derive the Maximum Chlorophyll Index (MCI) (Sect. 19.2.1) the SPM concentration, which is a measure of the turbidity of the water, as well as the absorption coefficient of CDOM, ε₄₄₀ (Kirk 2011). Further important remote sensing products for management are Sea Surface Temperature (SST); (Sect. 19.2.1), the spectral diffuse attenuation coefficient, K₄₉₀ (Sects. 19.2.2 and 19.2.4), Secchi depth (Sect. 19.2.4), and the distribution of harmful algal blooms (Sects. 19.2.3, 19.3, 19.4), all of which give important information about water quality.
**Limitations** Besides the limitation in spatial resolution there are several other restrictions for OC remote sensing. One is the above-mentioned blurring of pixels due to the adjacency effect. Adjacency has been quite a problem for coastal and inland water remote sensing, but in recent years significant progress has been made in correcting such effects. For example, the Improved Contrast between Ocean and Land (ICOL) processor (Santer and Schmechtig 2010) has been shown to correct for adjacency effects both in lake waters (Guanter et al. 2010) and the Baltic Sea (Kratzer and Vinterhav 2010). Another way to correct for adjacency is the SIMilarity Environment Correction (SIMEC), an algorithm first proposed by Sterckx et al. (2011, 2015) for the correction of high resolution airborne remote sensing data in the North Sea. SIMEC estimates the contribution of the background radiance in correspondence with the Near-InfraRed (NIR) similarity spectrum (Ruddick et al. 2006) and has also been shown to correct well for adjacency effects in coastal and in-land waters. Another limitation worth mentioning is the effect of cloud cover as visible and NIR light is not able to penetrate through clouds. Although operational OC imagers usually have a temporal resolution of about 1–3 days, about 50% of the scenes in the Baltic Sea region will be covered by cloud during May-July (Isemmer and Rozwadowska 1999), and in the Northern Atlantic it may even be up to 70% during summer. Additionally, the registration of images at high latitudes is limited to March-October for the Baltic Sea, and only from April-September in the Arctic Ocean; in winter months the solar radiation at low sun angles is too low for passive remote sensing, and understandably the ice cover is also an obstacle to OC remote sensing. Despite the high cloud cover over the Baltic Sea, Harvey et al. (2015) could show that MERIS data still has a better temporal resolution than the data measured in situ by the coastal monitoring program in the Himmerfjärden area; one of the most monitored areas in the world. Combined with the good spatial resolution this makes MERIS data a very powerful and cost-effective tool for monitoring of algal blooms.

**Sea Surface Temperature** Very often analysis of spatial and temporal variations of OC variables/products is facilitated by availability of other oceanographic data. Algorithms for determination of such a key parameter as SST are worth mentioning. Satellite-derived SST products are based on measurements of the infrared radiance emitted from the sea surface which in turn depends on the water surface temperature and emissivity. To avoid the interference of the atmosphere, the NOAA and NASA SST retrieval algorithms (the so-called split-window algorithms) sense the brightness temperature at the two wavelengths with different sensitivity to water vapour: 11 μm (T11) and 12 μm (T12). This allows to retrieve SST accurately in different atmospheric conditions. The most general expression for such algorithm may be formulated as: SST = f (T11, T11-T12); (Robinson 2004). In the following sections we show examples of how time series data derived from satellite can improve our understanding of phytoplankton bloom development and ecology in coastal waters. The areas of investigation are the Himmerfjärden bay in the Baltic Sea, the Bay of Biscay and the Beaufort Sea, all shown in Fig. 19.2.
19.2 Remote Sensing of the Baltic Sea

The Baltic Sea, a semi-enclosed brackish sea, is situated in the north-eastern part of Europe, and is surrounded by Scandinavia in the north, the Baltic countries in the east and by the Polish and German coast in the south (Fig. 19.2). The Baltic Sea has a salinity gradient ranging from 0 to 3 in the north to about 18–26 in the southwest, with a mean salinity of around 7. The low salinity is caused by: the topography with sills separating shallow basins and the narrow Danish Straits, which leads to a restricted water exchange with the North Sea and a low water turnover rate; and a high freshwater input from large rivers (Leppärantta and Myrberg 2009). The drainage basin is about four times larger than the Baltic Sea itself, and the catchment area covers 14 countries, nine of which border the sea. About 85 million people live in the drainage basin and 40 million of these inhabit the coastal areas and big cities along the coast, which leads to high anthropogenic stress for the marine ecosystem and environmental problems, like eutrophication (HELCOM 2007; Leppärantta and Myrberg 2009). The main optical constituent in the Baltic Sea is CDOM (Ferrari and Dowell 1998). The high CDOM content (like the salinity) is linked to the restricted water exchange, the freshwater input and land use with large forested and peat land areas.
19.2.1 Mapping Cyanobacteria Blooms in the Baltic Sea Using the Maximum Chlorophyll Index (MCI)

The main bloom-forming filamentous cyanobacteria are the toxic *Nodularia spumigena* and non-toxic *Aphanizomenon* sp in the open areas of Baltic Sea, and potentially toxic *Anabaena* spp in coastal areas. The development of blooms is favoured by Phosphorus (P)-rich water and, especially for *N. Spumigena*, by calm and warm weather. Filamentous cyanobacteria blooms can occur from July to September, and have a patchy spatial and temporal distribution.

**Data and Methods** Mapping extreme conditions, such as intense cyanobacteria surface blooms, by OC remote sensing data requires alternative approaches to the standard neural network approaches that have been used for atmospheric correction and bio-optical models. Especially towards the end of a surface accumulation, the cyanobacteria tend to break the water surface and therefore change the surface optical properties to appear more like those of vegetation on land, which can be identified using a red-edge ratio. During such events (Chl-α > 30 μg L⁻¹), the combination of Chl-α absorption and scatter can be clearly detected in the radiance spectrum (Gower et al. 2008) and algorithms can be applied to extract the parameters directly from L1 TOA data. The MCI has been developed by Gower et al. (2008), which considers a peak at 709 nm in the radiance spectrum that has been associated with high levels of Chl-α (above 30 μg L⁻¹). It has been shown that parameters like Chl-α, phytoplankton biomass and cyanobacteria biomass could be extracted via MCI during cyanobacteria blooms (Binding et al. 2011, Alikas et al. 2010). As the MCI spectral index is applicable both to L1 and L2 data, atmospheric correction is not required.

**Spatial Distributions of Phytoplankton Blooms in the Baltic Sea** The MCI equation was applied to MERIS RR L1 images to estimate the intensity and frequency of surface accumulations in the Baltic Sea during the period 2002–2009 (Fig. 19.3). The monthly composites for July and August were calculated based on the maximum value of MCI for each pixel. MCI composites reveal high variability in surface accumulations between years. The most intense blooms usually develop in the central part of the Baltic Sea in July, and were most pronounced in 2003 and 2005 when high SST in July initiated intense, large surface accumulations in the central Baltic Sea. However, the locations and intensity of blooms can vary from year to year. For example, in 2006, July was the warmest month (similar to 2005) in the southern and western Baltic Sea (max values 23–25 °C, Fig. 19.4) where the most intense blooms developed. However in August, the most intense bloom was located in the Gulf of Bothnia where monthly mean SST reached the maximum values of that year. Note that cyanobacteria blooms are rather rare in the Gulf of Bothnia as these waters are P limited. The mean temperature in the central Baltic Sea for July 2006 was lower than the average for that month from 2002–2009 (Fig. 19.4). The patterns of SST (Siegel and Gerth 2013 and references therein) in 2006 correlate well with the bloom locations depicted by MCI; the
surface blooms were dominating in the central and southern part in July and in the northern part in August. SST was below the long-term mean in 2004 and 2007 and therefore the conditions were not suitable for intense bloom development. The surface accumulations of cyanobacteria blooms in the Baltic Sea, as derived by MCI, were compared with a method developed by Kahru et al. (2007) that was applied to MODIS L2 data by SMHI (Öberg 2013). Both methods give similar bloom patterns for the surface accumulations, demonstrating the capability of OC remote sensing methods to monitor the development and the spatial distribution of the blooms.

19.2.2  Mapping Changes in Water Transparency in the Central Baltic Sea

Remote sensing estimates of transparency plays an important role in describing the spatial and temporal variation of under-water light conditions that have a direct effect on water quality and on primary production. In optical oceanography the attenuation of light in the water column is commonly described by the diffuse
attenuation coefficient of downwelling irradiance, $K_d(\lambda)$. Austin and Petzold (1981) first developed an empirical band ratio algorithm, which used the blue-to-green ratio of water-leaving radiances to derive $K_d(490)$ over optical Case-1 waters. Over optically-complex waters, a shift towards longer wavelengths is required since the ratio $R_{\text{rs}}(490)/R_{\text{rs}}(555)$ reaches an asymptotic value with increasing absorption and loses its sensitivity at high $K_d(490)$ values, resulting in an underestimation of $K_d(490)$ over turbid inland and coastal waters (Wang et al. 2009). It has been demonstrated (Alikas et al. 2015), that the combined algorithm based on $R_{\text{rs}}(490)/R_{\text{rs}}(709)$ and $R_{\text{rs}}(560)/R_{\text{rs}}(709)$ is very robust for retrieving $K_d(490)$ values over a wide range of all three main optical in-water constituents: Chl-α, Total Suspended Matter (TSM) and CDOM. The $K_d(490)$ algorithm was applied to the monthly means from May until September, and to MERIS FR data for 2005 (Fig. 19.5). The spatial distribution of $K_d(490)$ in the Baltic Sea was well described - indicating lowest transparency in the open Baltic Sea in July during the occurrence of cyanobacteria blooms, and also a decreased transparency in coastal areas, presumably due to an increase in both CDOM and TSM (Kratter and Tett 2009). Therefore, this study demonstrates that $K_d(490)$ is a reliable measure of water transparency from space.
### Fig. 19.5 MERIS-derived monthly means (from May to September) of $K_d(490)$ in Nordic lakes and the Baltic Sea in 2005

and using the combined algorithm it is possible to derive more reliable and basin-wide products from satellite data over coastal and open sea waters as well as inland waters.

### 19.2.3 Remote Sensing of Algal Blooms in Himmerfjärden Bay, North-Western Baltic Proper, Sweden

In this section we report results from a remote sensing study of Himmerfjärden bay which is situated about 60 km south of Stockholm at 58.42–59.20 N 16.22–8.70 E in the north-western part of the Baltic proper (Fig. 19.2). The bay and surrounding area have been investigated intensely since the 1970s; the ship-based monitoring program in this area is unique with an unusually high sampling frequency. A MERIS time series was used to visualize the natural spatial and temporal dynamics of
algal blooms, river outflows and seasonal variations in the region (Harvey et al. 2015). The Chl-a retrieval was based on a neural network (NN) approach adapted to coastal waters and developed by the Free University Berlin, FUB (Schroeder et al. 2007a, b). Before deriving the Chl-a concentrations, the data was corrected for adjacency using ICOL (Santer and Schmehltig 2010) and applied to the MERIS TOA radiances (Kratzer and Vinterhav 2010). The MERIS images were mostly cloud-free and had been geometrically corrected, and screened for low sun angle, failed atmospheric corrections as well as high sun glint (Harvey et al. 2015). The in situ Chl-a data were all sampled and analysed spectrophotometrically by the monitoring group at the Department of Ecology, Environment and Plant Sciences, Stockholm University. For the comparison between satellite retrieved and in situ measured Chl-a concentrations, an average of a 3 × 3 pixel-matrix around each in situ monitoring station in the MERIS scene was used for every station and date.

Figure 19.6 shows a time series of MERIS-derived Chl-a images from April to September 2010. The spatial patterns and terrestrial influence close to land can easily be followed on all images due to the observed changes in Chl-a concentration as a response to nutrient input, e.g. in the Nyköping coastal bay area marked as “Ny” on the image from 19 April 2010. Furthermore, the synoptic view makes it possible to follow the spring bloom that occurs during April and May, as well as the development and retreat of several summer blooms during July, August and September. The spatial patterns and the extent of the blooms are clearly visible. Figure 19.7 displays a synoptic view of the development of a cyanobacteria bloom with surface accumulations during July 2008. Remote sensing makes it possible to capture and study the change over time, the spatial coverage and the variable distribution of the Chl-a concentrations within the bloom (Kahru et al. 2007; Ruddick et al. 2008; Harvey et al. 2015). In Harvey et al. (2015) it was also demonstrated that OC time series data have a good agreement with in situ measurements and that both the temporal and spatial resolutions increase when adding satellite measurements; more data leads to an improved assessment of algal blooms i.e. both the timing of the blooms as well as extent (e.g. Kahru et al. 2007). Ship sampling is time consuming and expensive, thus restricting the possible number of stations and samples collected. In one example, the satellite data revealed blooms that the conventional monitoring obviously missed out (Harvey et al. 2015). Figure 19.8 shows a time series of MERIS and in situ Chl-a concentrations for the productive season (April-Sep) in 2010 from two monitoring stations in the Himmerfjärden bay. The spring bloom in April, typically for the area, is well described by both methods. Both the concentrations and the variability are higher at station H4. Harvey et al. (2015) also showed no difference between monthly means of Chl-a concentrations between the methods. The two sets of MERIS image time series data illustrate the increased information gained from remote sensing, thus demonstrating the effectiveness of using of OC data together with conventional methods when monitoring coastal zones; it is possible to follow the spatial and temporal changes in a more comprehensive way.
The benefits of the improved amounts of data and spatial coverage as well as its cost effectiveness is important both for monitoring and management (e.g. Kahru et al. 2007; Kratzer et al. 2014). Satellite data can substantially increase the amount of data available for water quality classifications within the water quality directives and legislations, e.g. European Union’s (EU) Water Framework Directive 2000/60/EC (WFD) and Marine Strategy Framework Directive 2008/56/EC (MSFD) from the European Commission (EC), the OSPAR Convention and the HELCOM’s (HElsinki COMmission) Baltic Sea Action Plan (CEC 2000, 2008; OSPAR Commission 1992; HELCOM 2007).
Fig. 19.7  Time series over Himmerfjärden bay (Hf) (Sweden) and adjacent areas derived from MERIS data (300 m resolution) during the summer of 2008. The images show the concentrations of chlorophyll-a (μg l⁻¹) on the 23rd, 24th, 28th, 30th and 31st of July 2008. This time series illustrates the dynamics and development of a cyanobacteria bloom, and how important it is to get a spatial coverage to capture the development and the spatial extent of the blooms. Map © Lantmäteriet, Gävle 2010, permission I 2010/0053. MERIS data with courtesy from the European Space Agency (ESA), Harvey et al. (2015)

Fig. 19.8  Time series of chlorophyll-a (μg l⁻¹) from April to September 2010 for 2 monitoring stations, H4 (head of HF bay) and B1 (situated just outside the bay). The solid line is MERIS derived data and the dashed line represents in situ data. Adapted from Harvey et al. (2015)
19.2.4 Mapping the Spatial-Temporal Distribution of Secchi Depth and the Diffuse Attenuation Coefficient $K_d$(PAR) in Himmerfjärden Bay

19.2.4.1 Background

The euphotic depth, $Z_{eu}$, is the upper, illuminated part of the water column. It is the layer in which photosynthesis can take place, and where photosynthesis exceeds heterotrophic consumption (Tett 1990). Physically, it is defined as the depth at which the irradiance has reached 1% of its surface value. Assuming the diffuse attenuation of light, $K_d(z)$, to be approximately constant with depth, the euphotic zone can thus be derived by the following equation:

$$Z_{eu} = 4.6 \times K_d(PAR)^{-1}$$  \hspace{1cm} (19.1)

(Kirk 2011), where $PAR$ stands for photosynthetically active radiation, which is the visible part of the spectrum that can be used for photosynthesis. An easy method to measure how light penetrates with depth in the water column is by using a Secchi disk. Usually, a white disk of 30 cm diameter is lowered into the water column. The depth at which the Secchi disk disappears from the viewer’s vision, is known as Secchi depth. Although it is a rather common measurement of water clarity (transparency), Secchi depth is qualitative in nature rather than quantitative (Preisendorfer 1986). Secchi depth is inversely correlated to the diffuse attenuation coefficient of light, $K_d(PAR)$ depth (Kirk 2011). $K_d(PAR)$ can also be related to the spectral diffused attenuation coefficient, $K_d(490)$, e.g. via a regression analysis. Kratzer et al. (2003) found that the relationship between the two parameters in the NW Baltic Sea can be described as:

$$K_d(PAR) = K_d(490) \times 1.48^{-1}$$  \hspace{1cm} (19.2)

This relationship was based on a rather restricted number of data points ($n = 17$). Pierson et al. 2008 showed that the relationship can also be described as a logarithmic function:

$$K_d(PAR) = 0.668 \times K_d(490)^{0.676}$$  \hspace{1cm} (19.3)

The regression model in Eq. 19.3 was based on a semi-empirical Baltic Sea model that simulated 500 matching data points for both variables. Kratzer et al. (2008), showed how to derive Secchi depth and the spectral diffuse attenuation coefficient, $K_d(490)$, from MERIS data using empirical regression models based on Secchi depth and $K_d(490)$ data, respectively, and the matching reflectance ratio of MERIS band 3 (490 nm) and band 6 (620 nm) derived from in-water radiometric measurements. For the present study we derived local algorithms for Secchi depth and for $K_d(PAR)$ from a much larger optical data base measured in
the Himmerfjärden area during 2000–2012 (n = 97). These local algorithms were then applied to the whole MERIS archive (2002–2012), covering Himmerfjärden and adjacent areas (Fig. 19.9) in order to map the temporal and spatial variability in water quality.

19.2.4.2 Algorithm Development from Optical, in-Water Measurements

During the optical campaigns, Secchi depth, $K_d(490)$ and the main three optical components, Chl-α, SPM and CDOM were measured. The reflectance at different channels was derived from radiometric measurements (TACCS, Satlantic; Kratzer et al. 2008; Zibordi et al. 2012). Next, the optical data base from 2000 to 2012 was used to derive new local Secchi depth and $K_d(490)$ algorithms by regressing each parameter against various reflectance ratios measured by the TACCS. As in the previous study (Kratzer et al. 2008) it was found, that the MERIS reflectance band 3 (490 nm) and band 6 (620 nm) provided the best results for retrieving Secchi depth from in water reflectance data. The algorithms that explained most of the variance were:

$$\text{Secchi depth} = \exp \left(1.36 \times \ln \left(\frac{\rho_{490}}{\rho_{620}}\right) + 1.03\right) n = 97, \ r^2 = 0.75 \quad (19.4)$$

$$K_d(490) = \exp \left(-1.17 \times \ln \left(\frac{\rho_{490}}{\rho_{620}}\right) - 0.29\right) n = 97, \ r^2 = 0.80 \quad (19.5)$$
Where \( \rho_{490} \) and \( \rho_{620} \) are the MERIS band 3 and band 6, respectively. Equations 19.4 and 19.5 were then applied to MERIS data to derive Secchi depth and \( K_d(490) \), respectively. \( K_d(PAR) \) was then derived in a second step from MERIS \( K_d(490) \) data using Eq. 19.3.

19.2.4.3 Satellite Data Processing

The MERIS dataset was provided by the CoastColour project (http://www.coastcolour.org). This dataset is an enhanced Level 1B (L1B) dataset, so-called Level 1P products (CCL1P, version 1.6.3). The main differences of CCL1P compared to the standard MERIS L1B products (v.3) includes: an accurate geolocation information for each pixel, radiometric correction providing similar quality as the standard L1B products from the 3rd reprocessing, plus smile correction and equalization of coherent noise. The CCL1P datasets also includes an additional pixel classification step, generating a precise coastline and additional quality flags (Ruescas et al. 2014). The CCL1P datasets were pre-processed for corrections of land adjacency effects using the Improved Contrast between Ocean and Land (ICOL, Santer and Schmechtig 2010). The L2 products were derived by using the WeW Water Processor developed by the Free University of Berlin (FUB, Schroeder et al. 2007a, b). Quality datasets were produced by masking out pixels based on CoastColour flags (i.e. flags indicating land and coastline, cloud and potential cloud pixels, snow and ice, and risk of sun glint) and FUB processor specific quality flags (i.e. general mask and flags indicating in the input and output products were within the training range); see Beltrán-Abaunza et al. (2016) for full details on processing and quality control. Weekly composites of averaged values of the L2 products, were spatially aggregated by using water bodies polygons defined by the Swedish Meteorological and Hydrological Institute (SMHI) (Fig. 19.9). A requirement for spatial aggregation was that a minimum of 25 quality pixels should be included per water body to describe their weekly statistics. Here, Hovmöller diagrams of MERIS-derived Secchi depth and the diffuse attenuation coefficient showed how the temporal and spatial distributions of water transparency can be aggregated to analyse an optical gradient from the inner bay (water body 7), the outer bay (water body 9), and towards the open sea (water body 20).

The spatial and temporal resolution of the MERIS archive can be used to complement in situ data, and so improve our understanding of light availability in the water column. The satellite data has an improved temporal and spatial resolution when compared to in situ monitoring data (Harvey et al. 2015; Beltrán-Abaunza et al. 2016). The coastal monitoring in Himmerfjärden is usually undertaken 2-weekly, and in weekly cycles during phytoplankton blooms. The results shown in Figs. 19.10 and 19.11 represent the full MERIS datasets available for Himmerfjärden. It is notable from these figures that it is possible to produce quality datasets as early
Fig. 19.10 Hovmöller diagram of MERIS-derived Secchi depth. The squares in the Hovmöller diagrams contain the weekly mean-aggregated value of all the valid pixels within a given water body. Selected water bodies showed an optical gradient from the inner bay (water body 7), outer bay (water body 9) to the open sea adjacent to the bay (water body 20) see Fig. 19.9

Fig. 19.11 Hovmöller diagrams of MERIS-derived $K_d$(PAR). The squares in the Hovmöller diagrams contain the weekly mean-aggregated value of all the valid pixels within a given water body. Selected water bodies showed an optical gradient from the inner bay (water body 7), outer bay (water body 9) to the open sea adjacent to the bay (water body 20) see Fig. 19.9
as week 5 (i.e. the beginning of February) in the adjacent open sea. Beltrán-Abauenza et al. (2016) showed that through using Chl-a anomalies it is possible to detect early phytoplankton anomalies in Himmerfjärden during February; often related to the presence of *Mesodinium rubrum*, which occurs early in the year. The Hovmöller diagrams exemplify changes in coastal water transparency and show that light availability decreases towards the head of the bay; i.e. lower Secchi depths (Fig. 19.10) and higher diffuse attenuation coefficients (19.11) are found in the inner bay (water body 7). The increased light attenuation appears to trigger an increased frequency of quality flags for the radiometry over MERIS band 3 and 6, used to derive the algorithms, causing lower data quality when compared to the chlorophyll product (Beltrán-Abauenza et al. 2016). Quality flags are processor dependent, and the FUB processor used here has specialized flags for assessing the quality of reflectance products, and uses different flags for radiometry and water products (Schroeder et al. 2007a, b). However, the increased frequency of flagged radiometry products does not necessarily limit the successful retrieval of water quality-products, such as Chl-a or SPM. For example, in the study of Beltrán-Abauenza et al. (2016), where a similar methodology was applied using FUB-derived L2 water products, the retrieval of weekly Chl-a composites included enough information to complement in situ datasets from the Swedish national monitoring programme.

The higher $K_d$(PAR) values in the inner bay, are directly correlated with the phytoplankton dynamics in the bay. With increased $K_d$(PAR) values and low Secchi depths indicate also temporal changes during the spring and summer phytoplankton blooms. As more intensive blooms can be detected within the bay (Beltrán-Abauenza et al. 2016), higher Secchi depth values are more frequent in the more transparent, outer bay and towards the open sea. One can also assess inter-annual variability of light attenuation using Hovmöller diagrams (Figs. 19.10 and 19.11). As an example, during summer 2008, an unusual bloom of the phytoplankton species *Prymnesium polylepis* was observed (Hajdu et al. 2015). This bloom caused an anomaly of light attenuation as observed in water bodies 7 and 9 (inside Himmerfjärden bay), where the maximum values in light attenuation shifted by more than 10 weeks from their normal conditions, reaching their peak during June and July in 2008. Furthermore, in 2006, industrial toxins lead to an unexpected malfunctioning of the nitrogen treatment in the local sewage treatment plant at the head of the bay (discharging into water body 7), leading to an increase in phytoplankton abundance (Beltrán-Abauenza et al. 2016).

The spatial and temporal information provided here demonstrates the advantage of using the MERIS time series to assess light availability at a coastal site. It must be noted that this coastal site is optically-complex and highly dominated by CDOM and also influenced by land adjacency effects. It is very unlikely that such high quality data and information could be retrieved by using other available ocean colour sensors, such as MODIS.
19.3 Identification and Monitoring of Lepidodinium Chlorophorum Harmful Blooms in the Coastal Bay of Biscay

The Bay of Biscay is a gulf of the north-east Atlantic Ocean stretching from the western coast of France from Brest southwards to the Spanish border, and along the northern coast of Spain. The main anthropogenic activities in the region, among others, include tourism, fishing and aquaculture. Thus, the ecological state and its dynamics are of significant importance for the riparian countries. Satellite monitoring as a component of an integrated monitoring system can offer improved spatial and temporal coverage, as exemplified below. The gently sloping shelf zone is an area that is subject to seasonal variations in river run-off, determining the input of suspended minerals and nutrients as well as fresh water. The main rivers flowing into the Bay are the Vilaine, Loire, Charente, and Gironde, and Adour.

Two major phytoplankton blooms occur annually in spring and autumn (Lavender et al. 2008). In spring, diatoms are dominant in the phytoplankton community at the shelf zone. In addition the shelf zone also accommodates blooms of the harmful green dinoflagellate *Lepidodinium chlorophorum* (Elbraechter and Schnepf 1996). Unlike many other species of dinoflagellates, which generate toxic blooms, this alga releases polysaccharides in the form of transparent colloidal biopolymers. This enhances sedimentation, generation of colloidal mass and promotes the accumulation of bacteria and viruses within the bloom, which is located predominantly in coastal waters and bays. Although non-toxic, this alga still has a potentially harmful effect on the ecology as it may cause anoxic conditions, especially in shallow waters. This may cause the death of crustaceans, molluscs, and small fish (Claquin et al. 2008). Ecologists as well as fish and shellfish farmers are therefore interested in monitoring the outbursts and spatio-temporal dynamics of this phenomenon, and remote sensing is a cost-effective way to do this.

Data and Methods  Satellite OC and SST data for 2002–2009 were obtained from MODIS data. Up to date, *in situ* measurements of *L. chlorophorum* are very scarce, presumably because of the high cost of effective monitoring programs. The only available data were microscopic cell identification and counts by the ‘Institut Français de Recherche pour l’Exploitation de la Mer’, (IFREMER; http://www.ifremer.fr/) at two stations accounting for 47 measurements during different months from 2001 to 2008, and from cases of intensive *L. chlorophorum* blooms reported in the press. For detecting the extent of *L. chlorophorum* blooms, two conceptually different techniques were applied, namely a NN and the fuzzy c-means classification (Morozov et al. 2010, 2013). The input data needed for the network operation are $R_{rs} \lambda$ in the six MODIS visible bands, i.e. at 412, 443, 488, 531, 551, and 667 nm. Using the available *in situ* data the NN was trained to invert the input spectral sub-surface reflectance values, $R_{rsw} \lambda$, in the above six channels into a numerical output characterising whether the analysed pixel belongs to a *L. chlorophorum* bloom or not. Using the available *in situ* data the NN was trained to invert the input spectral
sub-surface reflectance values, $R_{rs} (\lambda)$, in the above six channels into a numerical output ranging from 0 to 1. The value 0 indicates the absence of the $L. chlorophorum$ bloom; 1 means that the pixel confidently belongs to the bloom. All results in between 0 and 1 can be considered as a transition from non-blooming to blooming areas.

The second algorithm is based on fuzzy c-means classification or clustering, i.e. sorting objects into groups based on the likelihood of features for the objects of one group and the divergence from other groups. An important advantage of such algorithms is that they do not require any training i.e. in situ data to be able to classify the pixels in the image. Fuzzy partitioning allows us to easily solve the problem related to objects located at the interface of two clusters by attributing each object its fractional degree of belonging (Zimmermann 2001).

In order to improve algorithm performance, an additional selection criterion was introduced in order to dismiss pixels erroneously attributed to $L. chlorophorum$. The cause of such an erroneous attribution resides in the inherent limitation of the NN interpolation/extrapolation ability (Haykin 1998) or, else, because of noise and errors in the training data set, and the presence of different types and numbers of other phytoplankton species, resulting in a transitional zone between bloom and non-bloom areas. The advantage of the unsupervised classification employing a fuzzy logic is that it does not require any a priori information and relies exclusively on the characteristics of the general inhomogeneity in the spatial distribution of input data (in this case, space-borne water surface reflective characteristics in pixels of the image). Also, the fuzzy c-means classification method easily deals with the transitional zones between $L. chlorophorum$ bloom and blooms of other algae. However, areas identified with the fuzzy c-means classification are a result of assigning all pixels in the image towards one of the two classes, and additional, independent information is required. The additional selection criterion that can provide this information resides in the fact that $L. chlorophorum$ signals must have a minimum at the 488 nm channel due to the presence of Chl-b and peridinin pigments present in this dinoflagellate species (Matsumoto et al. 2011) which result in increased absorption in the spectral range of 450–500 nm in comparison to other phytoplankton species in the Bay (see Fig. 19.12a). Subsequently, spectra with a maximum in this channel are ignored. The actual spectra obtained from remote sensing (see Fig. 19.12b as an example) fully confirmed this assumption.

Application of both algorithms to an independent data set (which was not used for algorithm development) shows their consistency. In order to increase the robustness of bloom identification it is possible to use both algorithms simultaneously, which may help to decrease incidents of false identification (Fig. 19.13).

Along with diatom-dominated phytoplankton blooms, outbursts of the harmful alga $L. chlorophorum$ are observed in the coastal zone of the Bay. The occurrence frequency of $L. chlorophorum$ blooms proves to be area-specific. As Fig. 19.14 illustrates, there are areas (river estuaries) where the blooms of this alga occur annually; whereas in the Iroise Sea and near the Bailiwick of Guernsey the temporal bloom pattern is remarkably different: in the latter areas, extensive blooms of
L. chlorophorum (covering 5% or more of the respective area) occurred only in 2003, 2006, 2007, and 2008 (Guernsey) and 2006, 2007, and 2008 (Iroise Sea). The reason for that may be the continuous supply of nutrients by rivers, and therefore, a reduced need for L. chlorophorum to compete for nutrients with other species.

Relatively little is known about the ecology of L. chlorophorum. However, it is not unreasonable to suppose that in conditions of restricted supply of nutrients (both areas are not recipients of riverine waters), these algal blooms occur when they are preceded by low-level blooms of indigenous diatoms (and hence the nutrient depletion is not significant). In addition, this alga is not only immune to photoinhibition but also prefers ample illumination by sunlight (Elbraechter and Schnepf 1996). Therefore, L. chlorophorum blooms can be spurred on by conditions of scarce cloudiness. As Fig. 19.14 illustrates for the Iroise Sea, it is indeed the
case: the peaks of L. chlorophorum emerge during September, August–September, and July of the above-mentioned years when the preceding diatom abundance and degree of cloudiness were low. However, the same Figure indicates that there are exceptions to this regularity. This implies that some other factors may control the growth of this phytoplankton species. SST is likely to be one of the controlling factors, and it can also be derived from space. This assumption seems to be also supported by Fig. 19.15. Thus, it appears that an concurrence of the above three factors - weak preceding diatom blooms, enhanced SST, and availability of sufficient incident light – may control the massive growth of L. chlorophorum. However, there might be some other conditions that need to be met, which cannot be detected from space. It must be noted that high concentrations of Chl-a concentrations in April-May, April, and May 2006, 2007, and 2008 respectively should be explained by spring diatom blooms, whereas autumn peaks are mostly due to L. chlorophorum blooms.
Fig. 19.15 A 10-day averaged time series of L. chlorophorum bloom relative area in % (black solid) and contemporaneous variations of possible influencing parameters in the Iroise Sea: diatom Chl-α concentration in μg l⁻¹ (grey dashed), cloudiness in % (grey solid), and MODIS-derived SST in °C (black dashed)


Introduction Global warming is known to mostly affect the Arctic Ocean where a rapid decrease in thickness and extent of sea-ice, and changes in the marine ecosystem have recently been observed. The transition from thick multi-year ice to a seascape increasingly dominated by thinner, first-year ice (Comiso 2011), has brought discernible modifications to the phenology of the Arctic Ocean region, such as earlier occurrences of the annual phytoplankton blooms (Kahru et al. 2011) and an overall increase in ocean net primary production (NPP) (Arrigo and van Dijlen 2011). The Eastern Beaufort Sea (BS) is characterized by the presence of Cape Bathurst and flaw lead polynyas that play a major role in high latitude ecological and biogeochemical processes. These areas are expected to have a higher biological production than offshore waters. In this study we assess the spatial and temporal variability of Chl-α in order to evaluate possible impacts of climate-change induced physical processes onto phytoplankton productivity. The aim of this study is to estimate phytoplankton biomass variability using time series of Chl-α and SST for a 7 year time series (1998–2004).

Ocean Colour Data SeaWiFS Level 1A (L1A) Merged Local Area Coverage (MLAC, 1.1 km resolution at nadir) data were downloaded from the NASA Ocean Color Web site (www.oceancolor.gsfc.nasa.gov). L1A MLAC data contains raw radiance values for each SeaWiFS band (412, 443, 490, 510, 555, 670, 765, and
865 nm). The images were processed to L2 using the SeaWiFS Data Analysis Software (SeaDAS version 5.2.0). We applied the NASA standard atmospheric correction algorithm, which includes a clear water scheme for open ocean pixels an iteration scheme for moderately turbid waters where the black pixel assumption is violated. The Chl-α values from SeaWiFS OC data were corrected by using a SeaWiFS-Adapted regional algorithm (Ben Mustapha et al. 2012). First, monthly composite images of the 5 sub-areas for the 1998–2004 study period were generated. Sub-areas (Fig. 19.2) of size 3 × 3 pixels (27 × 27 km) were then extracted to study the spatio-temporal variability at meso-scale.

**Sea Surface Temperature Data** Daily mean NOAA (National Oceanic and Atmospheric Administration) AVHRR (Advanced Very High Resolution Radiometer) SST (1.1 km) were used to generate monthly mean averages for the five sub-areas. Individual images (day and night overpasses) covering the Beaufort Sea from 145 W to 115 W and available from the Remote Sensing Laboratory, Department of Fisheries and Oceans Canada, Maurice-Lamontagne Institute were processed and analysed (Table 19.1). After cloud screening, SST data were computed from each overpass using the ‘split window’ Multi-Channel SST algorithm (McClain et al. 1985). After this initial process, image data were compared to ice cover maps generated by the National Snow and Ice Data Center (NSIDC) to eliminate false SST in spring time when the ice surface is melting.

**Results** Figure 19.16 shows the climatological average values of SST and Chl-α concentrations observed in spring (May–June) and summer (July–August–September) from 1980 to 2004. The highest temperatures are observed in the Mackenzie River mouth and on the Mackenzie Shelf both in spring and summer. The Amundsen Gulf is characterized by cold waters in both seasons while Chl-α concentration remains low, except along the south coast in summer. This region is characterized by the presence of a persistent thermal front associated with intermediate upwelling supporting increased phytoplankton biomass (Williams and Carmack 2008).

In order to assess the temporal variability, SST and Chl-α were extracted in the five sub-regions. It is noted that the availability of data is different for both parameters. This is the result of contamination of the OC radiometric signal by the adjacency of ice and free water mass. Therefore, there is not enough Chl-α data available from the offshore region of the Beaufort Sea to analyse the seasonal and inter-annual variability. Table 19.1 shows the seasonal evolution of SST where the peak is usually reached in August. The increase in temperature between June and July is higher than the decrease between August and September. This may be caused by the strong solar irradiance on this region during summer. The sun warms the surface layer faster than in autumn. The seasonal maximum of SST in August seems not to be related to the decrease of ice cover observed over the 7 years. The peak anomalies of this time series occurred in summer 1998, especially during July and August (in all regions). There is a good agreement between these observations and the air temperature measured at Sachs Harbour over the same period of time.
Table 19.1 Monthly mean of satellite chlorophyll concentration and SST time series for the 5 sub-areas in the Beaufort Sea. The numbers in the boxes are the monthly mean values. The numbers to the right are the 1998–2004 climatological means and standard deviations. The color coding highlights the corresponding standardized anomaly.

<table>
<thead>
<tr>
<th>Sub-Area</th>
<th>Chlorophyll (mg m(^{-3}))</th>
<th>SST (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amundsen Gulf</td>
<td>J 0.32, A 0.68, S 0.55</td>
<td>2.41°C ± 3.49</td>
</tr>
<tr>
<td></td>
<td>J 0.33, A 0.68, S 0.55</td>
<td>3.86°C ± 2.58</td>
</tr>
<tr>
<td></td>
<td>J 0.30, A 0.13, S 0.09</td>
<td>2.70°C ± 1.52</td>
</tr>
<tr>
<td></td>
<td>J 0.06, A 0.07, S 0.08</td>
<td>0.17 mg m(^{-3}) ± 0.12</td>
</tr>
<tr>
<td></td>
<td>J 0.08, A 0.10, S 0.09</td>
<td>0.08 mg m(^{-3}) ± 0.04</td>
</tr>
<tr>
<td></td>
<td>J 0.09, A 0.12, S 0.12</td>
<td>0.14 mg m(^{-3}) ± 0.03</td>
</tr>
<tr>
<td></td>
<td>J 0.09, A 0.12, S 0.12</td>
<td>0.21 mg m(^{-3}) ± 0.16</td>
</tr>
<tr>
<td></td>
<td>J 1.84, A 0.85, S 0.73</td>
<td>0.57°C ± 1.68</td>
</tr>
<tr>
<td></td>
<td>J 1.84, A 0.85, S 0.73</td>
<td>2.91°C ± 2.85</td>
</tr>
<tr>
<td></td>
<td>J 1.84, A 0.85, S 0.73</td>
<td>3.27°C ± 2.07</td>
</tr>
<tr>
<td></td>
<td>J 1.84, A 0.85, S 0.73</td>
<td>1.51°C ± 2.20</td>
</tr>
<tr>
<td></td>
<td>J 0.10, A 0.09, S 0.12</td>
<td>0.08 mg m(^{-3}) ± 0.02</td>
</tr>
<tr>
<td></td>
<td>J 0.11, A 0.09, S 0.12</td>
<td>0.11 mg m(^{-3}) ± 0.03</td>
</tr>
<tr>
<td></td>
<td>J 0.14, A 0.09, S 0.12</td>
<td>0.14 mg m(^{-3}) ± 0.08</td>
</tr>
<tr>
<td></td>
<td>J 3.31, A 2.04, S 1.40</td>
<td>2.37°C ± 2.36</td>
</tr>
<tr>
<td></td>
<td>J 3.31, A 2.04, S 1.40</td>
<td>5.20°C ± 2.70</td>
</tr>
<tr>
<td></td>
<td>J 3.31, A 2.04, S 1.40</td>
<td>5.29°C ± 2.04</td>
</tr>
<tr>
<td></td>
<td>J 3.31, A 2.04, S 1.40</td>
<td>2.94°C ± 2.60</td>
</tr>
<tr>
<td></td>
<td>J 1.90, A 0.95, S 0.95</td>
<td>1.10 mg m(^{-3}) ± 0.69</td>
</tr>
<tr>
<td></td>
<td>J 1.90, A 0.95, S 0.95</td>
<td>1.13 mg m(^{-3}) ± 0.52</td>
</tr>
<tr>
<td></td>
<td>J 1.90, A 0.95, S 0.95</td>
<td>1.15 mg m(^{-3}) ± 0.24</td>
</tr>
<tr>
<td></td>
<td>J 1.84, A 0.85, S 0.73</td>
<td>1.22 mg m(^{-3}) ± 0.46</td>
</tr>
</tbody>
</table>

[Diagram showing standardized anomaly values]
(Ben Mustapha 2013), indicating a strong coupling between the atmosphere and the ocean surface. The influence of El Niño and the Arctic Oscillation seem to have effects on the strong positive anomaly observed in 1998, by means of changing wind patterns in the regions (Maslanik et al. 1999).

Monthly Chl-\(a\) show relatively weak seasonal variability in all sub-regions except for the Amundsen Gulf where two phytoplankton biomass maxima are observed in June and September, indicating a phenology different from the other regions. The highest Chl-\(a\) concentrations were observed in the Mackenzie region (MK), the Cape Bathurst (CB) and Franklin Bay (FB). Sachs Harbour (SH) and the Amundsen Gulf (AG) have lower concentrations of Chl-\(a\). However, in the Mackenzie plume region, it is likely that the observed values are still overestimated because of CDOM
absorption associated with fluvial freshwater. The seasonal variability observed might therefore rather indicate the impact of river discharge than an increase in phytoplankton production.

The results also show a strong interannual variability of Chl-a concentrations. Positive anomalies of chlorophyll were observed in 2002 in the Amundsen Gulf, in Franklin Bay and Cape Bathurst. In the region of Sachs Harbour, positive anomalies of chlorophyll concentration are observed in some months of the years 2001, 2002 and 2003. It is possible that a change in the coupling between primary producers and higher trophic levels (Tremblay et al. 2006) may explain some of the observations during the time series.

Because of the strong stratification of the Beaufort Sea, there is only a limited nutrient replenishment during the winter period. This limits nutrient availability for the phytoplankton bloom. Mixing events are thus very important for the generation of surface phytoplankton blooms during the open water period. The most important mixing factor is the wind, used as a proxy, representative of the mixing (Ben Mustapha 2013). During the open water season (May–October), winds show a dominance of south-easterly winds that cause coastal upwelling along the southern AG coast as indicated by the higher Chl-a concentrations observed in FB and CB. The SH region always shows low Chl-a values because it is located in a downwelling-prone area. In the AG region, it appears that wind intensity is only rarely strong enough to generate vertical mixing. Winds in the coastal areas (SH) blew primarily along the East-West axis. Strong winds forced the MK plume to expand alongshore. The winds mix nutrients from deeper waters into the surface, resulting in increased Chl-a values.

In 1998 an exceptionally early retreat of the sea ice cover occurred, followed by an early phytoplankton bloom. 1998 was also a record year for warm air temperature in the Arctic. Positive anomaly as high as +7 °C in spring was observed. The period of breakup of the sea-ice cover was the longest observed (20 weeks) during the observation period. In 2004, the breakup of the sea ice cover occurred in the end of May in the AG, SH, FB and in early June for the CB and MK while a complete freeze-up occurred within 1 week in late October (Galley et al. 2008).

For all investigated areas the monthly mean Chl-a derived from remote sensing has a high interannual variability in the timing, strength and duration of phytoplankton blooms. Recent trends of earlier sea ice break-up and later sea ice formation in the Beaufort Sea have important implications for the biological productivity in the Cape Bathurst polynya at all trophic levels. This study provides mesoscale information about the spatial and temporal variability of phytoplankton in five investigated sub-areas of the Beaufort Sea. Good data coverage was during May to early September; during the other months there was hardly any data available due to ice cover, clouds and the low solar elevation. Monthly and seasonal average images of Chl-a were processed over the period 1998–2004, which is the period of availability of mesoscale resolution SeaWiFS data (1 km) over the studied area, while the SeaWiFS data at low spatial resolution (9 km) was available until 2011. For the study presented here, however, mesoscale resolution data was required as a
minimum. It must be noted, however, that the recent decade (2005–2014) has seen remarkable reduction of sea ice cover over the Arctic and might be expected to show even stronger anomalies of SST and Chl-a than are revealed here.

### 19.5 Merging and Fusion of Multi-satellite Datasets to Provide Improved Temporal Coverage

The previous regional examples showed how ocean colour remote sensing improves our understanding of coastal zone dynamics and bloom development. There are efforts to develop merged satellite products on a global scale. The impetus for the merging of global ocean colour data came from the proliferation of polar-orbiting missions and the knowledge that a single polar-orbiting mission does a rather poor job of sampling the ocean on short time scales (IOCCG 2007). The NASA Research, Education and Applications Solutions Network/Making Earth System Data Records for Use in Research Environments (MEaSUREs) (Maritorena et al. 2010) and ESA GlobColour (Pinnock et al. 2007; Fanton d’Andon et al. 2008) projects focused on combining multiple mission observations (MERIS, MODIS-Aqua and SeaWiFS) into a single data product with better spatial and temporal coverage than the individual missions, albeit with a lower spatial resolution. Both projects used the Maritorena & Siegel (2005) GSM bio-optical model to retrieve L2 products and the Level 3 (L3) products (time- or space-binned versions of the L2 products), and are then produced as global products of varying spatial and temporal resolutions. In MEaSUREs, e.g., L3 binned normalised water-leaving radiance data from MERIS and MODIS were converted to 9 km resolution to match the resolution of SeaWiFS before the merging was performed. For GlobColour, the L3 data were processed from L2 with an output resolution of 1/24 degree at the equator which is equivalent to 4.63 km. The ESA Ocean Colour Climate Change Initiative (OC-CCI) project has created 4 km resolution L3 products from L1 data processed using POLYMER (POLynomial based algorithm applied to MERIS; Steinmetz et al. 2011) for MERIS and the SeaDAS standard processing for SeaWiFS and MODIS, then the remote sensing reflectance is band shifted to fit the SeaWiFS bands before bio-optical products are derived using the algorithms in SeaDAS (OC-CCI 2015). Figure 19.17 shows the similarities in the general Chl-a patterns between GlobColour (CHL1 product) and OC-CCI (version 1 dataset release NASA OC4.V6 algorithm product); lower values in the North Eastern Atlantic Ocean and Mediterranean Sea with higher values over the continental shelf, and especially where there is river/estuarine outflows which could represent high Chl-a or inorganic SPM affecting the bio-optical models. The differences result from several sources including the atmospheric correction and bio-optical models used, and both products come with estimates of the uncertainties.

The OC-CCI product has a greater number of merged pixels, and hence lower number of missing pixels in the L3 products, as the POLYMER atmospheric correc-
Fig. 19.17 Merged monthly Chlorophyll-a products for April 2003 from (a) Globcolour using the GSM bio-optical model provided as a monthly product with (b) showing the Ocean Colour Climate Change Initiative (OC-CCI) project product where the daily products were provided and then merged using the BEAM Visat binning module by applying simple averaging.

tion can be applied within the MERIS sun glint influenced pixels. These efforts, to globally merge ocean colour products, tend to result in products that have a relatively coarse spatial resolution that is not adequate for coastal monitoring. Furthermore, the algorithms used have tended to be optimised for oceanic waters, which often lead to greater uncertainty in the coastal water quality evaluation. However, these issues are well understood and more recently the GlobColour and OC-CCI project activities have transitioned into the Copernicus Marine Environment Monitoring Service products, which have improved resolutions of 1 and 2 km for regional products. Also, OC-CCI is focusing on improving the algorithms for Case-2 waters; the version 3 dataset with optimised bio-optical algorithms is due for release in Spring 2016. The examples shown in Sects. 19.1 and 19.2.2, however, demonstrate that for coastal bays and estuaries, the 1 km resolution is still sub-optimal. But these areas are important for assessing production, as most of the production happens in coastal waters.

Whilst globally merged products remain sub-optimal for coastal waters, alternative regional approaches should also be considered. Kahru et al. (2012) combined over 10 000 Chl-a samples collected by various research programs in the California Current with daily L2 satellite data (OCTS, SeaWiFS, MODIS-Aqua and MERIS) at the highest routinely available resolution using a modification of the Gregg et al. (2009) Empirical Satellite Radiance-In situ Data (ESRID) method to create a 15-year locally optimised time series.

Kahru and Elmgren (2014) describe the compilation of a 35-year-long time series (1979–2013) of cyanobacteria surface accumulations in the Baltic Sea using merged
data from different satellite sensors. The results showed that during the 35 years the timing of the accumulations has been shifted by approximately 20 days earlier during the summer season.

Researchers are also combining ocean colour data with medium resolution sensors, such as the Landsat series, to provide higher resolution coastal products e.g. the Landsat 5 satellite acquired around 28 years of data with its TM instrument at a spatial resolution of 30 m. Approaches have focused on using ocean colour data to aid in the atmospheric correction of Landsat (e.g. Hu et al. 2001) or using the Landsat infrared bands themselves.

References


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