REMOTE SENSING OF CYANOBACTERIA AND GREEN ALGAE IN THE BALTIC SEA

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ABSTRACT

Eutrophication and the subsequent effects are one of the major ecological and economical problems in the Baltic Sea region. Two seasonal blooms, one dominated by green algae in spring and one dominated by blue-green algae in summer, form the phytoplankton cycle in the biggest brackish sea in the world. Anthropogenic nutrient input amplifies the phytoplankton growth. Cyanobacteria cultures dominating the summer blooms are not only capable of fixing atmospheric nitrogen and thereby play an important role in the nitrogen cycle, but are also potentially toxic. Dependent on a high water temperature, cyanobacteria also have a potential use as bio-indicator for climate change. Therefor, monitoring the occurrence and extent of different phytoplankton species is of high importance for understanding the ecosystem and human influence on it, as well as to examine possibilities of early warning systems. With its high CDOM concentrations, the Baltic Sea is a region with very specific optical properties, which demand for special regional algorithms, that take these properties into account. The German Aerospace Center (DLR) in Berlin has developed a new model-based inversion algorithm using neural network technique to derive four important water constituent parameters from MERIS satellite scenes over the Baltic Sea. Chlorophyll concentration as a proxy for green algae, phycocyanin absorption as a proxy for cyanobacteria, CDOM absorption and sediment scattering as further important parameters for the assessment of water quality. The algorithm shows good compliance with in-situ measured data from ships-of-opportunity, monitoring network data and a field campaign. Using atmospherically corrected MERIS reduced or full resolution scenes, an immediate calculation of analysis maps is possible by the implementation in an existing software environment.

KEYWORDS: remote sensing, phytoplankton, cyanobacteria, eutrophication, Baltic Sea

INTRODUCTION

The Baltic Sea is of high importance to the 85 million people inhabiting its drainage basin and has a great influence on cycle systems. Eutrophication is the major problem in this biggest brackish water of the earth, where the inflow of oxygen-rich water from the north sea is strongly limited and the freshwater budget is strongly positive (Leppäranta, 2009). Following the annual cycle of light and nutrient availability, there are two seasonal phytoplankton blooms in the Baltic Sea. Besides the green-algae dominated spring blooms, huge blooms of phytoplankton, dominated by cyanobacteria ('blue-green algae') species, may appear in the summer months and have been observed to increase over the past years (Kahru et al., 1994). Some cyanobacteria species are potentially toxic and thereby pose a threat to other life forms directly or indirectly through the food chain. Furthermore, their ability to fix atmospheric nitrogen adds to the problem of eutrophication and thereby the extension of dead zones on the seafloor. The monitoring of these algal blooms hence is of vital interest for fishing and tourism industry as well as the research of material cycles and for a general improvement of the ecological status of the ecosystem.

Only satellite remote sensing enables efficient monitoring of the water quality throughout the Baltic Sea area. To improve satellite monitoring procedures, a new inversion algorithm was developed, that accounts for a new water constituent parameter phycocyanin absorption as a proxy for cyanobacterial biomass, besides the established parameters for chlorophyll-a (CHL), suspended matter (SPM) and colored dissolved organic matter (CDOM). Examples for inversion algorithms accounting for these standard-parameters are the Principle Component Inversion (PCI) by Krawczyk et al. (2004) and the Case-2-Regional algorithm by Doerffer (2007).

For the development, a model based approach with the use of an artificial neural network (ANN) was chosen. The work can be structured in the analysis of optical properties of the water constituents, the forward modeling based on a four-component Baltic Sea model to simulate optical properties for different water conditions, the inverse modeling with an artificial neural network to derive water parameters from reflectance data and the validation of satellite data using in-situ-data.

THE SITUATION IN THE BALTIC SEA

The Baltic Sea is situated in the northeastern part of Europe and classified as an optically complex (Case2) water that comes with unique optical conditions. A high inflow of colored dissolved organic matter from the catchment area leads to high absorption, especially in the lower wavelengths, that dominates the reflected signal. The CDOM concentration follows a positive gradient from south-west to north accompanied by a salinity gradient in the opposite direction. Given the high absorption by CDOM in the lower wavelength, the Baltic Sea is a relatively dark water, especially in the higher latitude. Cyanobacteria growth is stronger in the southern and central parts of the Baltic Sea, where light availability and salinity are higher. Another important factor for cyanobacteria growth is the water temperature and stable weather conditions. For that reason, an increase in cyanobacteria growth could indicate a warming of the sea temperature. As a result of the special optical conditions in the Baltic Sea, most global algorithms fail to produce good results, as they were mostly trained for optical simpler (Case1) waters or for lower CDOM concentrations.

OPTICAL PROPERTIES OF PHYTOPLANKTON AND THE BALTIC SEA

Since optical remote sensing sensors measure physical values like the reflected radiance from the surface of the earth and the values of interest are of biologic origin like biomass or the amount of cells or pigments, a connection between the biological parameters and the physical parameters has to be found. Phytoplankton biomass is usually represented by the chlorophyll-a concentration, that can be derived by its absorption features in the blue and red domain of the spectrum. For the distinction of different phytoplankton groups like in this case between green algae and blue-green-algae, specific optical differences have to be determined. Cyanobacteria uses so called accessory pigments to harvest light in the green gap of the spectrum, between the two absorption peaks of chlorophyll-a. In cyanobacteria species occurring in the Baltic Sea, two accessory pigments are of relevance. Phycoerythrin with an absorption maximum near 570 nm and phycocyanin with an absorption maximum near 620 nm. In laboratory measurements, different phytoplankton-cultures were grown under different light- and nutrient-conditions and analyzed with the use of an UV/VIS Spectrophotometer. The measurements lead to the conclusion, that the presence of accessory pigments is limited to cyanobacteria species which can be further divided into picocyanobacteria, showing features of phycocyanin as well as phycoerythrin and filamentous species, showing only features of phycocyanin. The latter are also the main bloomforming species: Nodularia spumigena and Aphanizomenon flos-aquae. Similar results are stated in the comprehensive study by Seppällä (2009). For the use in remote sensing, the derivation of phycocyanin dependent features is more important, since this pigment occurs in all of the Baltic Sea cyanobacteria species and furthermore, picocyanobacteria rather grows in deeper water layers, which usually cannot be recognized by satellite remote sensing due to the low transparency of Baltic Sea water. Nevertheless, the derivation of a specific phycocyanin absorption (per pigment or mg/l) could not be measured in the absence of an effective method for the extraction and quantification of the accessory pigments (Simis et al., 2005). Therefore the phycocyanin absorption at 620 nm was chosen as a suitable parameter for the detection and quantification of cyanobacteria. Additionally, the pigment configuration of cyanobacterial cells can vary, depending on the light availability in the relevant water layer. By taking different nutrient- and light-conditions into account, these variations are represented in the derived optical properties of cyanobacteria. The optical properties of pure water, chlorophyll-a, suspended matter and colored dissolved organic matter were taken from an existing Baltic Sea model, based on data from Leibniz Institute for Baltic Sea Research in Warnemünde (IOW) that was used for the DLR PCI Processor (Krawczyk et al., 2004).

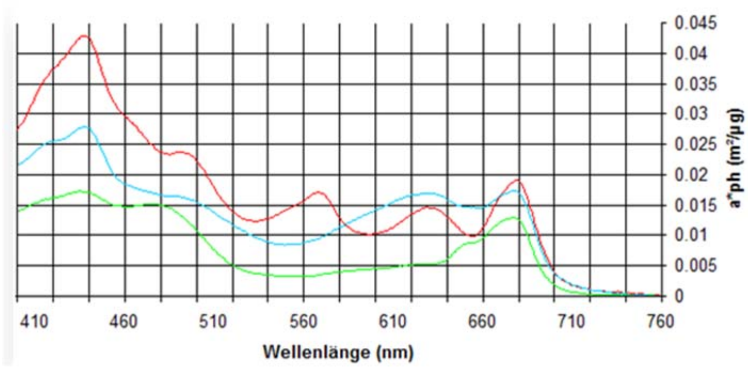

Figure 1. Absorption spectra of green algae Brachiomonas submarina (green), picocyanobacteria Synechococcus sp. (red) and filamentous cyanobacteria Nodularia spumigena (blue).

FORWARD MODELING

In order to simulate a sufficiently dimensioned dataset for the development of an inversion algorithm that is valid for a wide range of situations of possible input parameters in the area of interest, it is important to cover all possible water constituent combinations as well as geometric constellations for the remote sensing of the Baltic Sea with a certain sensor instrument. For this reason, a four component Baltic Sea model was set up with the absorption and scattering of pure Baltic Sea water, as well as chlorophyll-a, suspended matter, colored dissolved organic matter and phycocyanin in the spectral channels of the MERIS instrument. Furthermore, the geometric parameters sun zenith angle, sensor zenith angle and the difference between sun and view azimuth angle were varied over the expected range of values for the Baltic Sea area and the MERIS instrument aboard the ESA ENVISAT satellite.

The simulation of the radiative transfer was carried out for the value ranges shown in Table 1 of water constituent and geometry parameters, resulting in a dataset including a total amount of more than 300.000 different constitutions with corresponding reflectance values (R_{RS}) for the MERIS instrument. Following the natural conditions, smaller values are better represented in the training dataset than bigger values by using a quasi logarithmic distribution of the parameter values. Calculations were carried out using FEMWAT (Bulgarelli et al., 1999) a tool for calculating the radiative transfer in a plane-parallel stratified coupled atmosphere-ocean-system through the finite element method. The simulation of the reflectance values was carried out without atmospheric influence, which hence represent the values expected directly above the sea level, the so called bottom of atmosphere (BOA) reflectances.

Table 1. Parameter values for forward modeling

Parameter	Values
Chlorophyll-concentration [mg/m³]	0,001; 0,01; 0,1; 1; 5; 10; 30, 60
Sediment-scattering [bs(550)] [m^{-1}]	0,001; 0,01; 0,1; 0,5; 1, 10
CDOM-absorption [ay(440)] [m^{-1}]	0,001; 0,01; 0,1; 0,5; 1, 2
Phycocyanin-absorption [m^{-1}]	0,001; 0,01; 0,05, 0,1, 0,5; 1; 1,5; 5
Sun-zenith-angle [°]	20; 30; 40; 50; 60; 70; 80
View-zenith-angle [°]	0; 10; 20; 30; 40
Azimuthal-difference [°]	0; 30; 60; 90; 120; 150; 180

INVERSE MODELLING

In order to enable a fast analysis of satellite data, the computation of actual scenes shall be processed in a short amount of time. Therefor inversion techniques that enable fast processing are needed like artificial neural networks. The time consuming multivariate statistical analysis is being carried out during the training of a neural network, whereas the actual processing of satellite scenes takes only several seconds to meet the requirements of a near real-time monitoring system.

Different network topologies were tested, until the suitable network was found to be consisting of three layers as shown in Figure 2. An input layer with twelve neurons representing the nine MERIS channels in the visible and near-infrared wavelength and the geometry parameters zenith angles and azimuthal difference. A bias neuron. One hidden layer with 24 hidden neurons. And an output layer with four neurons representing the four water constituent parameters. After the construction of a network that is adequately shaped to meet the complexity of the inversion problem, the simulated dataset from the forward modeling was used to train the network for the inversion of the reflectance spectra. Therefore, each set of reflectance values and geometries is processed with the neural network and the output is compared to the expected values from the training data and the network parameters are adjusted to reduce the error between calculated and expected output until the error is low enough.

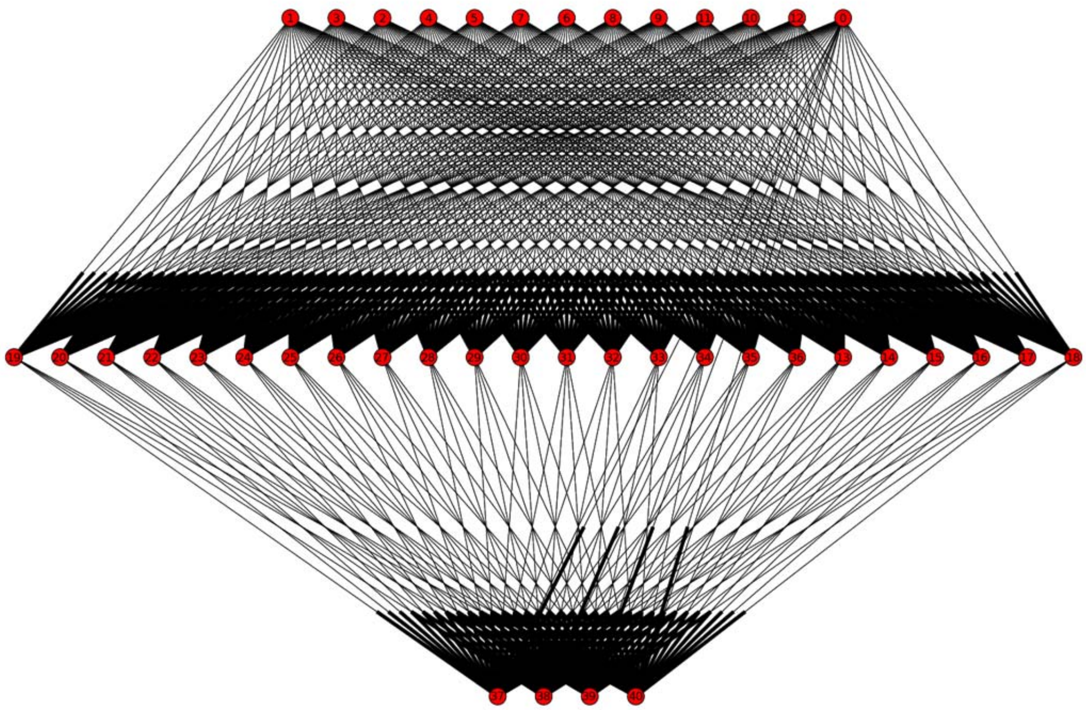

Figure 2. CyanoANN Neural Network topology.

After the successful training process, the neural network is capable of abstracting the problem from the training dataset, deriving the four water constituent parameters within the range of the simulation. Whereas values beyond these limits are likely to produce high errors due to the weak extrapolation possibilities of a neural network. The quality of the neural network is strongly dependent on the training data, since this is the basis for the learning and generalization.

To test the quality of the neural network, a comprehensive set of test cases, other than the training dataset but within its range, was simulated with the Baltic Sea model, the same way as the training dataset. The test dataset was then processed with the trained neural network. Good results are achieved for chlorophyll-a, phycocyanin and yellow substance, whereas the suspended matter values show a bit more uncertainties. The results are shown in

Figure 3.

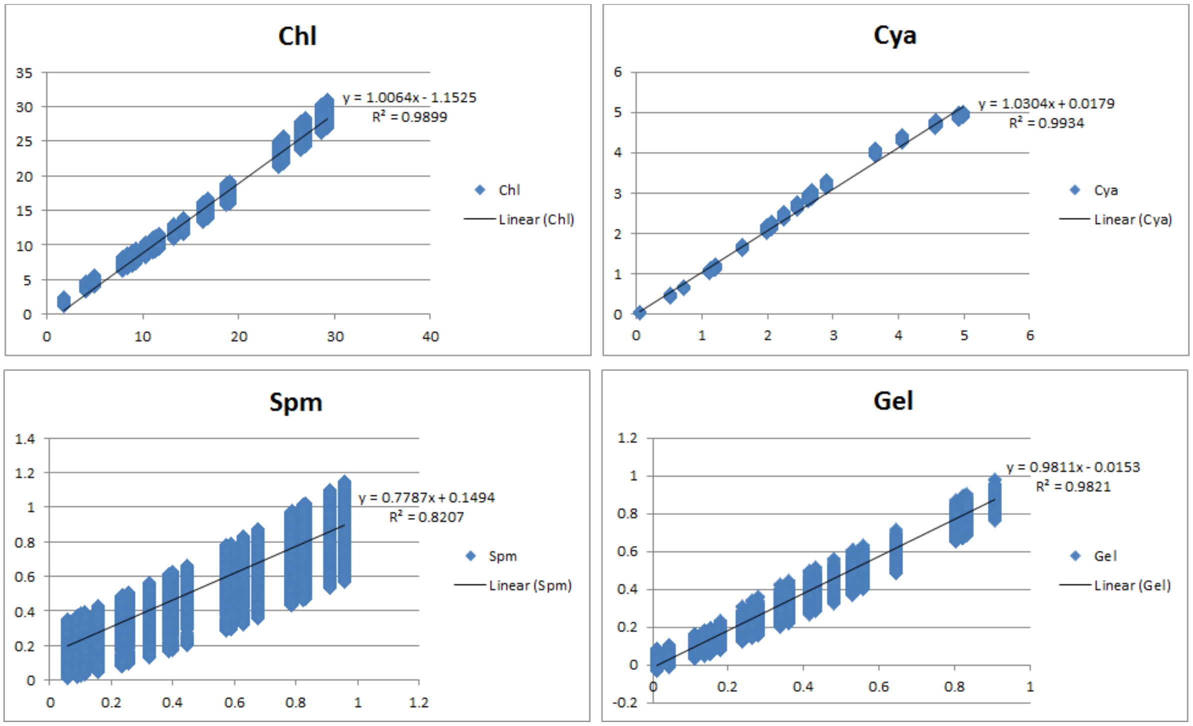

Figure 3. Comparison of calculated and estimated values for every water parameter of a test-dataset.

Afterwards, the developed and tested inversion algorithm was implemented as a plugin for the open source remote sensing toolbox BEAM VISAT (Fomferra and Brockmann, 2005). When called, each valid water-pixel is processed with the neural network, producing values for each water constituent parameter, resulting in four analysis maps that are written to the output product. Since the forward modeling was carried out for BOA reflectances, whereas the satellite-measured signal twice passed the atmosphere, the atmospheric part of the measured signal has to be removed prior to the application of the water constituent inversion. The atmospheric correction used in the Case2Regional processor is also based on radiative transfer simulations and shows good overall results for the MERIS instrument. To derive the water constituents with the CyanoANN-algorithm, the atmospheric correction from Case2Regional-processor has to be applied.

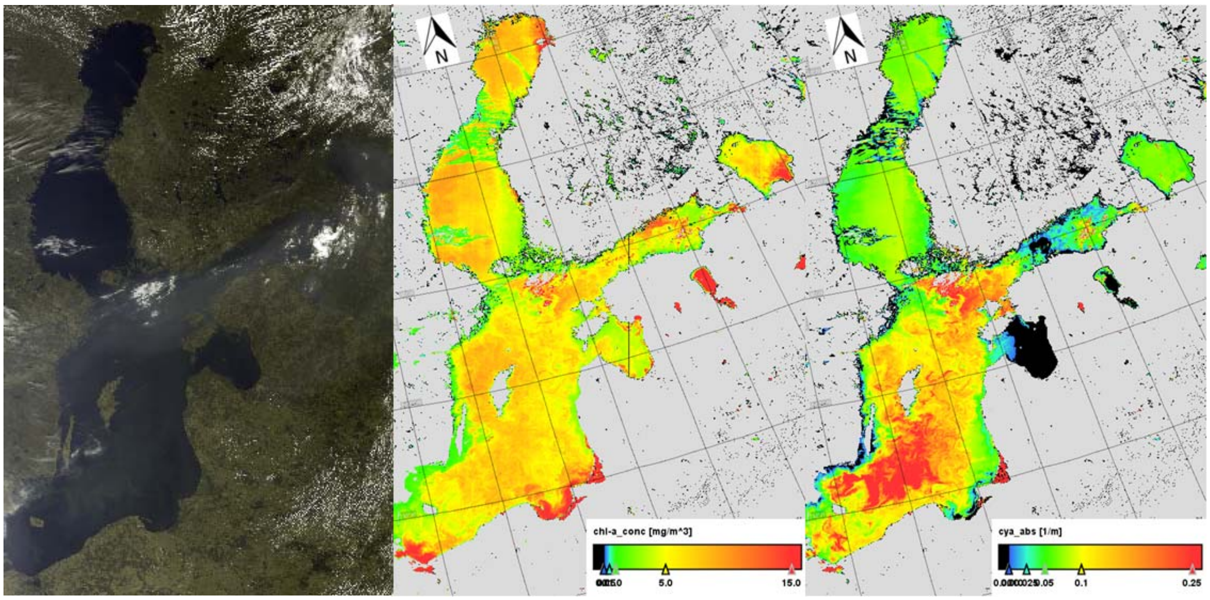

Figure 4. Analysis maps for Chlorophyll-a-concentration (left) and phycocyanin-absorption (right) on 2010-07-11 in the Baltic Sea.

RESULTS

The data availability for in-situ measurements aiming on cyanobacteria is very rare. Standard measurements mostly only cover chlorophyll-a for biomass measurements, caused also by the lack of standardized pigment extraction methods and difficulties in quantification of cyanobacterial biomass. Good coverage is achieved by ships-of-opportunity measuring with ferrybox-systems. The Finnish Algaline-project (Seppälä, 2007, Lips et al., 2007) operates several of these systems taking measurements in a high temporal frequency aboard ferries, merchant ships as well as research and coastguard vessels. The measurements of phycocyanin fluorescence can as well as the phycocyanin absorption be seen as a proxy for the amount of cyanobacteria, but for comparison of remotely-sensed phycocyanin absorption and ferrybox-measured phycocyanin fluorescence some sources of errors shall be named. The satellite scene covers the whole area at the time of the sensor overpass while the ship-track covers a time span of several hours to days. The information of satellite data is limited to the upper water layers, depending on the water transparency, which is rather low in the Baltic Sea, while the input hole for flow-through systems is situated in the ships hull five meters below the waterline. Figure 5 shows the result of a comparisons of a two hour time span of Algaline in-situ-data and satellite results for phycocyanin on 2010-07-19. Despite all the factors and the different methods of sampling and measuring, there is a good comparison of the peaks in absorption respectively fluorescence and two false peaks in the satellite data appearing to be cloud affected. Reducing the timespan to 15 minutes, the actual time for the satellite scene is plotted in Figure 6 from the Algaline transect of the same day and compares the chlorophyll-fluorescence to the satellite derived chlorophyll-concentration. In several other comparisons, the algorithm shows a good agreement with in-situ-measurements also from a ship measurement campaign with limitations due to weather conditions and data from a station based coastal monitoring network by the State Agency for the Environment, Nature Conservation and Geology of Mecklenburg - Western Pomerania.

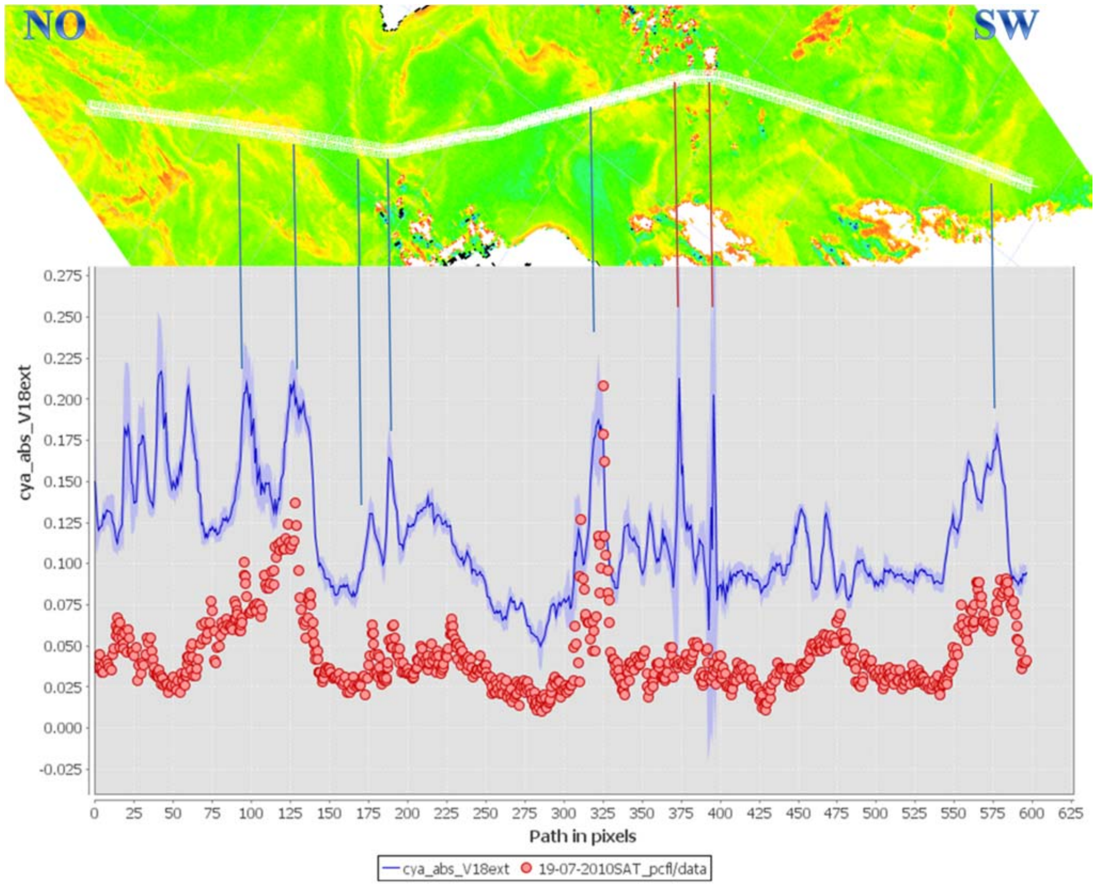

Figure 5. Comparison of satellite derived phycocyanin absorption (blue) and ship-of-opportunity measured phycocyanin fluorescence (red).

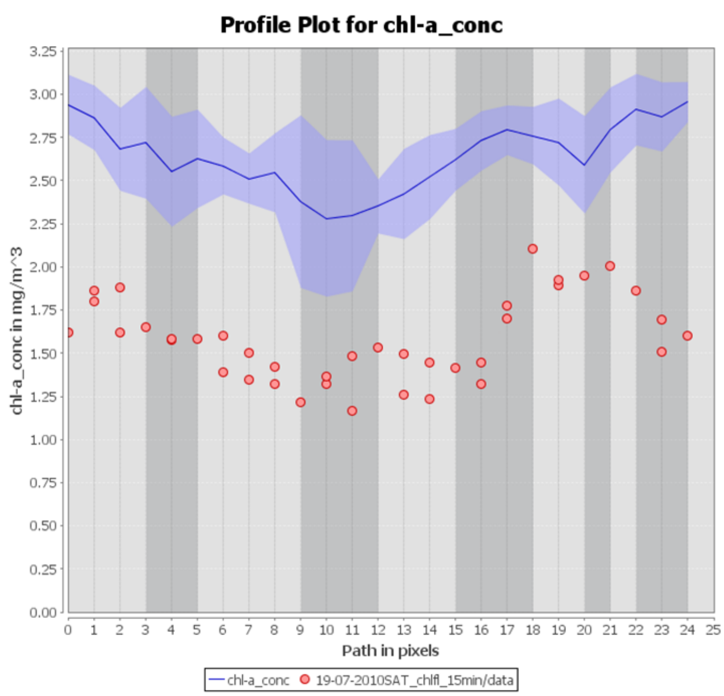

Figure 6. Comparison of satellite derived phycocyanin absorption (blue) and ship-of-opportunity measured phycocyanin fluorescence (red) on 2010-07-19.

DISCUSSION

Regarding the sparse availability of in-situ data for validation of cyanobacteria algorithms and the difficulties in quantification, there is a need for further comparison between ground data and satellite data. Because of the sensor parameters and the high temporal coverage, the MERIS sensor was chosen to enable a regular monitoring. After the end of the ENVISAT mission, there is currently no new sensor to fill the gap until the start of the OLCI instrument aboard Sentinel 3. Operational sensors like MODIS or SeaWIFS do not provide the spectral information in the absorption region of phycocyanin (620 nm) but as a follow up mission to MERIS, OLCI is very likely to need only minor adaptions to the inversion algorithm to be applicable and until then, the MERIS archive offers ten years of data for research on phytoplankton in the Baltic Sea.

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