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Department of Remote Sensing Tartu Observatory, Faculty of Science and Technology, University of Tartu, Estonia

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TABLE OF CONTENTS

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Author's Contribution

I. Conducted statistical analyses on the data used and created four of the figures used in the article. Also, participated in reviewing, commenting on, and editing the manuscript.

II. Co-conceptualised the framework of the study. Contributed to data curation and participated in the collection of radiometric field data from the Baltic Sea. Contributed to the formal analysis, investigation, implementation of the methodology, and figure creation. Led the preparation of the original draft and contributed to manuscript review and editing.

III. Co-conceptualised the study. Contributed to the validation of satellite data, as well as to formal analysis, investigation, and data curation. Led the writing of the original draft and contributed to manuscript review and editing.

ABBREVIATIONS AND ACRONYMS

a_{CDOM}	–	Absorption of Coloured Dissolved Organic Matter
C2RCC	–	Case 2 Regional CoastColour
CCI	–	Climate Change Initiative
CDOM	–	Coloured Dissolved Organic Matter
CHIME	–	Copernicus Hyperspectral Imaging Mission for the Environment
Chl-a	–	Chlorophyll-a
Chl-b	–	Chlorophyll-b
Chl-c	–	Chlorophyll-c
CSA	–	Cyanobacteria Surface Accumulation
CyaBI	–	Cyanobacteria Bloom Indicator
CZCS	–	Coastal Zone Colour Scanner
D5	–	Descriptor 5
ECDF	–	Empirical Cumulative Distribution Function
EnMAP	–	Environmental Mapping and Analysis Program
ENVISAT	–	Environmental Satellite
EOF	–	Empirical Orthogonal Function
ES	–	Environmental Status
ESA	–	European Space Agency
GES	–	Good Environmental Status
HELCOM	–	Baltic Marine Environment Protection Commission
IOP	–	Inherent Optical Property
L1	–	Level-1
LSWT	–	Lake Surface Water Temperature
LWL	–	Lake Water Level
MAPD	–	Median Absolute Percentage Difference
MERIS	–	Medium Resolution Imaging Spectrometer
MCI	–	Maximum Chlorophyll Index
MODIS	–	Moderate Resolution Imaging Spectroradiometer
MSFD	–	Marine Strategy Framework Directive
NASA	–	National Aeronautics and Space Administration
NIR	–	Near-Infrared
OLCI	–	Ocean and Land Colour Instrument
P	–	Biomass
PACE	–	Plankton, Aerosol, Climate, Ocean Ecosystem
Peipsi *s.s.*	–	Peipsi *sensu stricto*
PCA	–	Principal Component Analysis

PII	–	Phytoplankton Intensity Index
PLS	–	Partial Least Squares
POLYMER	–	POLYnomial-based approach established for the atmospheric correction of MERIS data
PPC	–	Photoprotective Carotenoids
PSC	–	Photosynthetic Carotenoids
PSP	–	Photosynthetic Pigments
PRISMA	–	Precursore IperSpettrale della Missione Applicativa
RMSE	–	Root Mean Square Error
R_{rs}	–	Remote sensing reflectance
S3	–	Sentinel-3
S3VT	–	Sentinel-3 Scientific Validation Team
SD	–	Standard Deviation
SPM	–	Solid Particulate Matter
TSM	–	Total Suspended Matter
WFD	–	Water Framework Directive
WHO	–	World Health Organisation

1. INTRODUCTION

1.1. Background

Phytoplankton are microscopic organisms residing in aquatic environments. They are fundamental to these ecosystems, acting as the primary producers, forming the base of food webs, and supporting organisms from microscopic zooplankton to large fish, seabirds, and marine mammals (Chassot *et al.*, 2010). It is generally estimated that phytoplankton are responsible for ~49% of global primary production, whilst making up less than 1% of global biomass (Basu & Mackey, 2018; Field *et al.*, 1998; Naselli-Flores & Padisák, 2023; Tilstone *et al.*, 2023). Phytoplankton are also at the centre of biogeochemical cycling, rapidly transforming and recycling key nutrients such as nitrogen, phosphorus, and silica within aquatic systems. Additionally, through the biological carbon pump, phytoplankton regulate the climatic balance of the planet. They assimilate atmospheric carbon, transferring and storing it in the deeper layers of the oceans for centuries to millennia (Basu & Mackey, 2018; Hülse *et al.*, 2017). Phytoplankton provide numerous other functions, from regulating and supporting to provisioning services. The first two include primary production and carbon sequestration, whereas the latter can include the use of phytoplankton as a food supplement, in the medical field, and as a source of fuel (Falkowski, 1994; Naselli-Flores & Padisák, 2023; Wanek *et al.*, 2025). The cultural impact of phytoplankton has also been discussed in the literature. One interesting example of this is the naming of the Red Sea after a cyanobacterial bloom (*Trichodesmium erythraeum*) (Naselli-Flores & Padisák, 2023). Changes in the phytoplankton community, therefore, have far-reaching ecological and climatic consequences, with particularly severe ones on the global carbon balance.

Although phytoplankton play an important role in the ecosystem, they can also have negative impacts on their surroundings. These can include degraded water quality, reduced biodiversity, and some phytoplankton species producing toxins that directly affect the health of other organisms. The impacts on water quality and the aquatic ecosystem are most negative when phytoplankton biomass increases rapidly, triggering a phytoplankton bloom (Feng *et al.*, 2024). As a result, phytoplankton are a key parameter in the environmental assessment of both marine and freshwater systems. The increase in bloom events in inland waters (Brooks *et al.*, 2017; Malthus *et al.*, 2019) is of great importance, as the World Health Organisation (WHO) reports that the scarcity of clean freshwater is increasing globally (WHO *et al.*, 2022). In many cases, lakes and reservoirs are used for drinking water, recreation, tourism, and irrigation (Backer, 2002; Chorus & Welker, 2021). At the same time, the frequency and intensity of blooms are increasing globally due to climate change, as highlighted in previous work by Dai *et al.* (2023), Ho *et al.* (2019), and Huisman *et al.* (2018). Understanding bloom dynamics is crucial because, as mentioned, some groups of phytoplankton, namely diatoms, dinoflagellates, and cyanobacteria, pose ecological, economic, and public health risks through toxin production, surface scum formation, and habitat degradation. Determining which phytoplankton are present, or even predicting where and when a bloom might occur, is of utmost importance. These trends highlight that phytoplankton blooms are dynamic processes that evolve over space and time in response to multiple interacting environmental drivers. Consequently, assessing bloom risk requires not only identifying the harmful phytoplankton taxa but also understanding how bloom characteristics can change.

Accurate monitoring of bloom dynamics is essential in water bodies, where physical forcing and nutrient dynamics can rapidly alter bloom development. Long-running, water-body-specific observations therefore provide information not only for contemporary bloom events but also for broader ecosystem changes. Observations from large, shallow systems such as Lake Erie show that phytoplankton dynamics have also changed over a relatively short time frame, as a Microcystis bloom has developed and now occurs annually during the summer months (Moore *et al.*, 2017). In Lake Taihu, mitigation efforts, a community shift, and other factors have led to a decrease in *Microcystis* populations (Song *et al.*, 2024). To study the long-term dynamics of phytoplankton, consistent data over a long period are required, given the sporadic nature of the phytoplankton community. Another important aspect is the inherent spatial heterogeneity of phytoplankton. They are largely influenced by water and wind movements, making it difficult to determine the extent of blooms or even their location (Kutser, 2004). Such patterns underscore the need for monitoring systems that capture both the spatial heterogeneity and temporal variability of phytoplankton blooms.

Globally, phytoplankton comprises diverse taxonomic groups, including diatoms, cyanobacteria, dinoflagellates, chlorophytes, and cryptophytes, all of which can play different functions in their environment. In the Baltic Sea, the dominant groups are diatoms, dinoflagellates and cyanobacteria. Diatoms and dinoflagellates commonly bloom in the spring, followed by cyanobacteria blooms in the summer (Brando *et al.*, 2021; Thamm *et al.*, 2004; Wasmund & Uhlig, 2003). These blooms are largely controlled by nutrient inputs and light availability in spring (Brando *et al.*, 2021; HELCOM, 2018; Kahru *et al.*, 2025; Karlson *et al.*, 2015; Löptien & Dietze, 2022; Meier *et al.*, 2022). In Estonian lakes, phytoplankton communities vary significantly depending on factors such as nutrient levels, water temperature, and light availability. Seasonal changes and human activities, such as agriculture and urbanisation, also influence phytoplankton composition and abundance (Nõges *et al.*, 2020; Yang *et al.*, 2022). All photosynthesising phytoplankton contain chlorophyll-a (Chl-a), the primary photosynthetic pigment. Because of this, it is widely used as a proxy for total phytoplankton biomass. The optical signature of Chl-a is characterised by an absorption peak at 440 nm and another at 675 nm (Nguy-Robertson *et al.*, 2013). Phytoplankton also contain many other auxiliary pigments. These range from other chlorophylls (e.g. chlorophyll-b, chlorophyll-c) to carotenoids (e.g. fucoxanthin, alloxanthin, peridinin, zeaxanthin) and phycobiliproteins (e.g. phycocyanin, phycoerythrin). The accessory pigments vary systematically across phytoplankton groups and can serve as markers of taxonomic, functional, and physiological differences. For example, zeaxanthin has been proposed as a marker pigment for some cyanobacteria (e.g., *Synechococcus*, *Limnothrix planktonica*), and fucoxanthin can indicate the presence of diatoms, whereas peridinin is typically found in dinoflagellates (Barlow *et al.*, 2002; Kramer & Siegel, 2019; Schagerl & Müller, 2006; Sun *et al.*, 2021, 2022; Tamm *et al.*, 2015). Depending on the pigment, it can enable phytoplankton to be more adaptable to varying light conditions, depths, and optical environments.

However, there are shortcomings to deriving phytoplankton group biomass from pigment data. Namely, individual species in a given phytoplankton group can range in size, but are described by the same marker pigment. Beyond their relevance to organisms, pigments play a crucial role in water remote sensing, as their distinct absorption features shape phytoplankton absorption spectra and, in turn, the water-leaving reflectance signal (Kramer *et al.*, 2022; Morel & Prieur, 1977; Wang *et al.*, 2016). Additionally, some marker pigments can be present in many phytoplankton taxa. Nevertheless, extracting pigment information from spectral data is a step towards using optical measurements to derive ecological insights. Consequently, the composition of a pigment ensemble has been widely used to infer phytoplankton community structure in the research (Cetinić *et al.*, 2024). Numerous approaches have been proposed to derive pigment concentration from spectral data (e.g. empirical orthogonal functions by Bracher *et al.*, 2015; Xi *et al.*, 2017; Gaussian decomposition by Chase *et al.*, 2013; Hoepffner & Sathyendranath, 1991; derivative analysis by Lavigne *et al.*, 2022; Organelli *et al.*, 2013). While these approaches work in optically simple oceanic (so-called Case-1) waters, their application in optically complex inland and coastal (Case-2) waters remains challenging due to the influence of coloured dissolved organic matter (CDOM), solid particulate matter (SPM), and highly variable pigment assemblages.

Traditional approaches such as microscopy and pigment analysis (HPLC) offer taxonomic detail and ground truth. Still, they are limited by sparse spatial coverage, high labour demands, and inconsistencies due to the patchiness of surface blooms. Satellite remote sensing can fulfil the temporal and spatial requirements to overcome some of these shortcomings (Li *et al.*, 2021; Mouw *et al.*, 2017; Zeng & Binding, 2021). The first satellite launched to monitor oceans was the Coastal Zone Colour Scanner (CZCS) in 1978 by the National Aeronautics and Space Administration (NASA). This marked the first time that satellite ocean-colour measurements could be quantitatively linked to phytoplankton biomass (Gordon *et al.*, 1983). Recent advances in remote sensing, however, have expanded the capacity to monitor bloom parameters at ecologically relevant scales. Satellite sensors developed for water remote sensing, such as the Sentinel-3 Ocean and Land Colour Instrument (OLCI) and the earlier Medium Resolution Imaging Spectrometer (MERIS) and Moderate Resolution Imaging Spectroradiometer (MODIS), have proven valuable for observing large water bodies, enabling the derivation of phytoplankton bloom indicators, water temperature, and other hydrological metrics. Yet, remote sensing in Case-2 waters remains challenging due to atmospheric correction issues, interference by other optically active components in the aquatic environment, and shallow bathymetry (O'Kane *et al.*, 2024; Mignot *et al.*, 2014). Several newer satellites with hyperspectral sensors have been launched in the last decade to help with deciphering the spectral signal into components. These include the Italian Precursore IperSpettrale della Missione Applicativa (PRISMA), the German Environmental Mapping and Analysis Program (EnMAP), as well as NASA's Plankton, Aerosol, Climate, Ocean Ecosystem (PACE). In the near future, the European Space Agency will launch the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME). Because these satellites are hyperspectral, they have been touted as the next step in satellite remote sensing for aquatic environments across all types of water. The higher spectral resolution enables the development of new algorithms to detect and quantify the spectral signatures of various substances in water, such as CDOM and SPM, and to differentiate various types of phytoplankton from space. To improve phytoplankton group identification in these complex environments, research has increasingly explored spectral-based approaches that leverage the optical signatures of pigments. Techniques such as those mentioned in the previous paragraph can isolate pigment-specific absorption features (Aguirre-Gomez *et al.*, 2001; Chase *et al.*, 2013; – 2017; Hoepffner & Sathyendranath, 1991; Ye *et al.*, 2019; Zhang *et al.*, 2021). Comparisons across Estonian lakes and the Baltic Sea reveal that although model performance varies with water optical complexity, the relationships between hyperspectral absorption data and pigment concentrations hold promise for differentiating phytoplankton (Grunert *et al.*, 2025; Teng *et al.*, 2022; Canuti & Penna, 2025).

Together, these studies illustrate a growing convergence between ecological understanding, spectral characterisation, and satellite-based operational monitoring. Long-term *in situ* datasets remain indispensable for ecological interpretation and algorithm validation, while remote sensing provides the spatial and temporal resolution necessary for comprehensive water-quality assessment. Integrating these approaches is crucial for improving bloom detection, characterising phytoplankton community dynamics, and supporting adaptive management in the face of accelerating environmental change.

1.2. Estimating the ecological status of the aquatic environment

Phytoplankton are recognised under the European Union's Water Framework Directive (WFD; Directive 2000/60/EC) and the Marine Strategy Framework Directive (MSFD; Directive 2008/56/EC) as a key biological quality element and an indicator of eutrophication and environmental shift, respectively. Within the WFD, phytoplankton are used to assess ecological status in rivers, lakes, transitional and coastal waters. Phytoplankton biomass, abundance, and taxonomic composition are used to detect eutrophication and to classify water bodies into high, good, moderate, poor and bad ecological status. The MSFD extends the eutrophication assessment beyond the coastal areas to all European marine waters. Under the MSFD, member states are encouraged to focus their monitoring activities on variables with direct effects, such as Chl-a concentration, phytoplankton abundance and composition, and water transparency, as well as on indirect effects, such as oxygen concentration and composition and abundance of macrophytes (Zampoukas *et al.*, 2014). Within the MSFD, the concept of good environmental status (GES) serves as the central management objective and is defined through 11 descriptors that describe acceptable conditions for marine ecosystems. Phytoplankton are mainly included under Descriptor 5 (D5). D5 requires that human-induced eutrophication be minimised, with special emphasis on excessive phytoplankton growth, harmful algal blooms, and oxygen deficiency in bottom waters. Achieving GES does not imply the absence of phytoplankton blooms, rather their magnitude, frequency, duration, and species composition are within limits consistent with natural variability (Zampoukas *et al.*, 2014). Importantly, the MSFD highlights the possibility of using remote sensing as a data source for monitoring. This is mainly due to the spatial and temporal coverage that remote sensing can provide (Zampoukas *et al.*, 2014). Although the WFD does not explicitly use the term GES, its objective is the same. It is intended as a guide for monitoring phytoplankton in rivers, lakes, transitional, and coastal waters, providing essential upstream support for meeting MSFD GES offshore. The two frameworks are thus complementary in managing the dynamics of phytoplankton blooms, in the framework of reducing eutrophication, and improving ecological status across the land-to-sea continuum.

1.3. Objectives of this work

The overarching objective of this research is to advance the monitoring and understanding of phytoplankton blooms in optically complex waters by integrating multi-sensor remote sensing, spectral modelling approaches, and traditional *in situ* methods. This includes evaluating the performance and applicability of satellite-derived indices and input parameters (e.g., Chl-a, turbidity, biomass), analysing bloom dynamics using spectral observations across multiple satellite missions, and assessing model-based approaches for identifying phytoplankton groups from absorption spectra. **By combining multiple data sources and analyses, this thesis aims to improve the reliability and regional relevance of phytoplankton bloom detection and classification to support ecosystem status assessment and aquatic research.** Three objectives describe the aims of the thesis:

- To study cyanobacterial bloom dynamics via a combination of remote sensing and traditional methods in a large transboundary lake **(I)**. The dynamics of the blooms are characterised using optical remote sensing and biomass data from traditional light microscopy. The impact of water level and temperature on blooms was studied using microwave remote sensing.

- To measure the effectiveness of using absorption spectra analysis in conjunction with phytoplankton pigment concentrations to decipher phytoplankton groups. To evaluate the strengths, weaknesses, and applicability of different models used for absorption data analysis in optically complex waters of the Baltic region **(II)**.
- To test the various indices used to monitor the environmental status of Estonian coastal areas in accordance with the MSFD (Directive 2008/56/EC) in regard to cyanobacteria biomass and to assess the applicability of input parameters such as the chlorophyll-a, turbidity, and biomass, derived from Sentinel-3 OLCI data products **(III)**.

2. MATERIALS AND METHODS

2.1. Study areas

The study areas for this thesis include the Baltic Sea and the Estonian Lakes (Figure 1). The data included both *in situ* and satellite data.

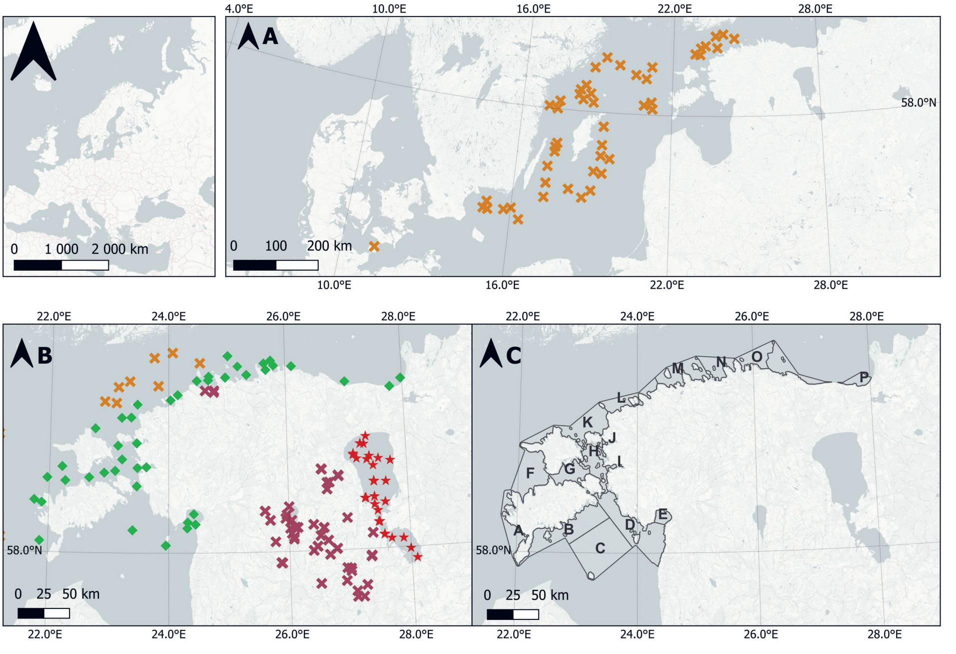

Figure 1. Map of sampling locations. The Baltic Sea locations are shown as orange crosses (**II**); in coastal areas, locations are shown as green diamonds (**III**); the Estonian lake dataset locations are shown as purple crosses (**II**); and shared locations between **I** and **II** in Lake Peipsi are shown as red stars. Labelled coastal areas used in **III** A) *Kihelkonna Bay*, B) *Gulf of Riga (NW)*, C) *Gulf of Riga (central)*, D) *Gulf of Riga (NE)*, E) *Pärnu Bay*, F) *Soela Strait*, G) *Kassari-Õunaku Bay*, H) *Moonsund Sea*, I) *Matsalu Bay*, J) *Haapsalu Bay*, K) *Hiiu Shallow*, L) *Pakri bays*, M) *Muuga-Tallinna-Kakumäe Bay*, N) *Hara and Kolga bays*, O) *Eru-Käsmu Bay*, P) *Narva-Kunda Bay*.

Lake Peipsi is the fifth-largest lake in Europe, which is shared by Estonia and Russia. It is divided into three optically diverse parts: Lake Pihkva, Lake Lämmijärv, and Peipsi *sensu stricto* (*s.s.*). Lake Pihkva is the southernmost and the second-largest, with an area of 708 km^2 and an average depth of 3.8 m. Lake Lämmijärv connects the other two parts and has an area of 236 km^2 average depth of 2.5 m. Peipsi *s.s.* is the northernmost and largest, with an area of 2611 km^2, and an average depth of 8.3 m (Keskkonnaseire infosüsteem, 2023). The Chl-a in Peipsi *s.s.* was 17.1 mg m^{-3}, 34.0 mg m^{-3} in Lake Lämmijärv, and 44.4 mg m^{-3} in Lake Pihkva (June-September median value 1989–2019). The dataset used in

I consisted of 19 *in situ* sampling locations (four in Lake Pihkva, three in Lake Lämmijärv, and 12 in Peipsi *s.s.*) (Figure 1B).

The Estonian lakes are optically diverse. Chl-a for the lake dataset used in **II** ranged from 0.01 to 109.6 mg m^{-3}, Secchi depth was in the range 0.1–5.5 m, CDOM absorption at 443 nm ($a_{CDOM}(443)$) was in the range 0.7–41.4 m^{-1}, and the amount of total suspended matter (TSM) was in the range 0.8–143.3 g m^{-3}. Altogether, data from 46 sampling locations in Estonian lakes were used in **II** (Figure 1B). The phytoplankton community in the lake samples included mainly bacillariophytes, chlorophytes, chrysophytes, cryptophytes, cyanobacteria, and dinoflagellates. Information on the community was gathered using inverted light microscopy.

The Baltic Sea is a semi-enclosed brackish sea located in northern Europe. It is bordered by 9 countries and connected to the North Sea via the Danish straits. The dataset used in **II** was collected during the Alkor (AL597) research cruise from 6 to 23 July 2023. During the cruise, the Secchi depth measurements ranged from 3.5 to 9.5 m, and $a_{CDOM}(443)$ ranged from 0.2 to 0.6 m^{-1}, and Chl-a ranged from 0.68 to 8.5 mg m^{-3}. TSM was not measured during the cruise. The water samples from the cruise revealed that the phytoplankton community consisted mainly of cyanobacteria, cryptophytes, chrysophytes, and dinoflagellates. In total, 47 samples were analysed in the Baltic Sea for **II** (Figure 1A).

The *in situ* sampling points in **III** of the Baltic Sea comprised 42 locations along the Estonian coastline (Figure 1B). The data consisted of measurements from 2016 to 2022. The coastal areas are influenced by varying environmental conditions, which affect their optical characteristics. Specific characterisation of the 16 coastal areas is given in **III** (Figure 1C).

2.2. *In situ* data

In the three articles, several different types of *in situ* data were used in the analyses. These ranged from absorption and reflectance measurements and ancillary data (e.g., air and water temperatures) to the collection of water samples for further analysis of components in the laboratory. A description of the sampling is given below.

- In **I**, the sampling took place on the Estonian side of Lake Peipsi monthly at seven locations per vegetation period. Additionally, bi-monthly sampling data were used at three other Estonian locations. Data from the nine sampling points on the Russian side were collected only in August of each year. The Chl-a concentration and phytoplankton biomass were measured from an integrated water sample, depending on the sampling depth: 0.5 m, then every metre to 1 m from the bottom, pooled, and sampled according to EVS-EN 16698 (2015). Samples for Chl-a were filtered through GF/F filters, stored at –16 °C until analysis, extracted for up to 24 h with 96% ethanol, measured spectrophotometrically (Hitachi U-3010), and calculated according to the method of

Jeffrey and Humphrey (1975). The Utermöhl (1958) method and inverted light microscopes Nikon Eclipse and Olympos CK 40 were used to count phytoplankton cells. The mean volume of each species was estimated in all samples by approximating its shape with the closest geometric form (Wetzel & Likens 1991). The length of at least 50 cyanobacterial filaments on fixed-width transects over the phytoplankton settling chamber was recorded for each species, and the wet weight of cyanobacterial genera was determined according to EVS-EN 16695 (2015).

- In **II**, *in situ* data consisted of pigment concentration and absorption data from various lakes in Estonia and the Baltic Sea. HPLC was used to obtain the pigment concentrations. The HPLC analysis of the lake data was conducted by the Centre for Limnology at the University of Life Sciences (Alikas *et al.*, 2023; Tamm *et al.*, 2015). The water samples used were first vacuum-filtered through Whatman glass-fibre filters GF/F (25 mm, 0.7 µm pore size). The filters were placed in plastic vials, frozen immediately, and stored at –70 °C until analysis. The pigments used here were extracted with a mixture of 100% acetone/internal standard (2 mL) and sonicated (Branson 1210) for 5 min. The extracts were kept in the dark at −20 °C for 24 h and then filtered through 0.45 µm syringe filters (Millex LCR, Millipore) before HPLC analysis (Tamm *et al.*, 2015). The HPLC analysis of the Baltic Sea samples was conducted at Helmholtz-Zentrum Hereon. The samples were prepared according to the methods of Garrido *et al.* (2011) and modified in accordance with the standards. The samples were first filtered on glass fibre filters (GF/F). The pigments were extracted in 2 mL acetic acid (AcOH) (100%) for 24 h at –20 °C. The DHI Lab Products pigment standards were used. The HPLC used was the LC-2030 RF-20AXS LabSolutions, V5.96. A total of eight pigments were analysed in the lake dataset, and 12 in the sea dataset. Due to the lack of measured pigment group data for photoprotective and photosynthetic pigments in the lake dataset, these consisted of fucoxanthin and peridinin for photosynthetically active carotenoids (PSC), and alloxanthin and zeaxanthin for photoprotective carotenoids (PPC).

  The phytoplankton absorption data from lakes were measured using a dual-beam spectrophotometer (Hitachi U-3010), equipped with an integrating sphere (50 mm diameter). The lake data were analysed using a filter pad technique with NaClO as the bleacher, according to Tassan and Ferrari (1995). The absorption data were recorded at 1 nm intervals. The spectra were limited to 400–700 nm for analysis to compare with the Baltic Sea dataset. The Baltic Sea samples were analysed using a PSICAM (Point-Source Integrating Cavity Absorption Meter) developed by Röttgers *et al.* (2005) at Helmholtz-Zentrum Hereon. The absorption spectra ranged from 400 to 700 nm at 2 nm intervals.

- In **III**, the samples were collected by the Estonian Marine Institute within the national monitoring program. Measurements of Chl-a and cyanobacterial biomass were performed according to the HELCOM (2018) guidelines (phytoplankton and Chl-a) for the period 2016–2022. Chl-a was measured spectrophotometrically after extraction with 96% ethanol and calculated according to Arvola (1981). The depth of the measurements ranged from 0 m to 10 m. The temperature measurements were obtained from the Estonian Environment Agency and were taken at various ports (19 locations) along the coastline (Keskkonnaagentuur, 2023).

2.3. Satellite data

- In **I**, MERIS (ENVISAT) and OLCI (Sentinel-3A) level 1 full-resolution images were used. OLCI data were obtained from the Copernicus Open Access Hub website. MERIS data were obtained from the ESA Envisat MERIS Online Dissemination Service. Image processing was performed in SNAP 8.0, where 14-day average composite images for June–September were created for the periods 2003–2011 and 2016–2022. A buffer zone of 1000 m from the coastline was used to decrease the effects of adjacency (brighter land influences the satellite signal), bottom effects, and vegetation in the shallow shoreline waters. Data from the Lakes Climate Change Initiative (CCI) v.2.0.2 (Carrea *et al.*, 2022) on Lake Surface Water Temperature (LSWT), derived from optical and thermal satellite observations, and Lake Water Level (LWL), derived from altimetry data from various satellites, were used.
- In **III**, Sentinel-3A/B OLCI Level-1 full-resolution data were used. To validate Chl-a from the two processors, Case-2 Regional CoastColour (C2RCC) and POLYnomial-based algorithm applied to MERIS (POLYMER), satellite data were collected from April to September from 2016 to 2022. C2RCC is a neural-network-based atmospheric correction processor which provides the results of water-leaving reflectance (ρ_w), inherent optical properties (IOPs), Chl-a, and TSM (Brockmann *et al.*, 2016; Schiller & Doerffer, 1999). The Chl-a output (chl_conc product) of C2RCC was used. POLYMER is an atmospheric correction model based on spectral matching. It uses a polynomial to model the atmosphere's spectral reflectance, a water reflectance model, and all available spectral bands in the visible region (Steinmetz *et al.*, 2011). Monthly average temperatures and a salinity of 5 PSU were used as inputs to the C2RCC v1.9. Validation of the satellite data was performed in accordance with most Sentinel-3 validation recommendations (EUMETSAT, 2022). The suggested flags were used and are given in detail in **III**. The pixel outliers were removed based on the mean and standard deviation (SD) of the results, following the filtration methods in the recommendations, and values within a 20% coefficient of variation were retained. A minimum of 50% of the pixels in each 3×3 window had to be valid. Although not recommended by the Sentinel-3 Scientific Validation Team (S3VT), to consider more data points, a maximum time difference of 12h was chosen.

2.4. Methodology

An overview of the methodological approaches used in each of the three articles is given below. The statistical analyses used are also described.

In **I**, the cyanobacterial bloom dynamics were studied using *in situ* and satellite data. To determine Chl-a from satellite imagery, the region-specific empirically derived coefficients of Alikas *et al.* (2010) were used. Similarly to the approach used in **III**, the bloom parameters of maximal areal coverage and duration were calculated based on the Chl-a derived from the Maximum Chlorophyll Index (MCI). The long-term median values of *in situ* Chl-a measurements from June–September 1989 to 2019 were calculated to determine the Chl-a thresholds corresponding to cyanobacteria blooms. Pixels were categorised as "bloom" when the Chl-a concentration exceeded the median value of that period by at least 5%. The thresholds were calculated separately for Peipsi *s.s.*, Lake Lämmijärv and Lake Pihkva. Chl-a concentration was assumed to correspond to a blooming period if it exceeded 18.0 mg m^{-3} in Peipsi *s.s.*, 35.7 mg m^{-3} in Lake Lämmijärv, or 46.6 mg m^{-3} in Lake Pihkva.

To determine the influence of temperature and water level on the cyanobacterial bloom, the long-term averages of LSWT and water level LWL were calculated from 1995 to 2020. The daily differences from the long-term average were then calculated for the period 2004 to 2020. Linear regression was used to compare the average temperature and average water level, a month before the maximal cyanobacterial bloom coverage. The relationship between the wet weight of *Microcystis* and the number of days during which the LSWT was over 20 °C was also evaluated based on the coefficient of determination R^2.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(C_{\mathrm{oi}} - C_{\mathrm{pi}}\right)^2}{\sum_{i=1}^{N}\left(C_{\mathrm{oi}} - \overline{C}_{\mathrm{oi}}\right)^2} \qquad \text{(Eq. 1)}$$

Where C_{oi} is the observed value and C_{pi} is the predicted value of a variable (**I**).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_{\mathrm{oi}} - C_{\mathrm{pi}}\right)^2} \qquad \text{(Eq. 2)}$$

Where C_{oi} is the observed value and C_{pi} is the predicted value of the variable (**I**).

In **II**, three approaches for decoding the spectral data to obtain information on the phytoplankton community were analysed. This study assumes that specific groups of phytoplankton have unique 'marker' pigments, the signal from which could be determined from absorption data. The study analysed data from both the Baltic Sea and Estonian lakes. The datasets were split into training (75%) and test (25%) sets for all three approaches. The first approach is based on the relationship between Chl-a concentration and each marker pigment concentration ('Chl-a model'). The second approach relies on decomposing the phytoplankton absorption spectra into 10 Gaussian peaks ('Gaussian model'). The Gaussian's location and peak height should correspond to the concentration of a marker pigment. A power function was then calculated, with the independent variable being phytoplankton absorption at a specific wavelength and the dependent variable being the concentration of the specific pigment. The third approach used Principal Component Analysis (PCA) weights, calculated from phytoplankton absorption spectra, and the corresponding pigment concentrations as inputs to a Partial Least Squares model ('PLS-model'). The PLS-model was further divided into three based on the processing of phytoplankton absorption data. The second and fourth derivatives of phytoplankton absorption were also used as separate inputs to the PLS model.

Statistical analyses conducted in the article, in addition to R^2 (Eq. 1) are the following:

$$RMSE_{ln} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(ln(C_{oi}) - ln(C_{pi})\right)^2} \quad \text{(Eq. 3)}$$

$$MAPD = Median\left(\frac{|C_{oi}-C_{pi}|}{C_{oi}} \times 100\right) \quad \text{(Eq. 4)}$$

$$\text{bias} = \frac{1}{N}\sum_{i=1}^{N}\left(ln(C_{oi}) - ln(C_{pi})\right) \quad \text{(Eq. 5)}$$

Where C_{oi} is the observed pigment concentration and C_{pi} is the predicted pigment concentration (**II**).

Article III compared four different cyanobacterial bloom indices in Estonian coastal areas. These included both satellite and *in situ* data, depending on the index used. A thorough description of each index is found in **III**. The 'Phytoplankton Intensity Index' (PII) was initially developed by Fleming and Kaitala (2006). This index is based on the time-intensity integral over a time period during which a threshold Chl-a concentration of 5 mg m^{-3} was exceeded. The 'Cyanobacterial Surface Accumulation' (CSA) index was developed by Anttila *et al.* in 2015 (Martin *et al.*, 2015). CSA uses the weighted sum of the proportions of positive algal bloom estimates for a pixel belonging to 1 of 4 groups (0 – no algae, 1 – some algae, 2 – abundant algae, and 3 – very abundant algae). The groups are based on Chl-a (mg m^{-3}) and turbidity (FNU) values. An empirical cumulative distribution function (ECDF) was calculated for each algal group, yielding seasonal bloom volumes, intensities, and durations. Based on these bloom parameters, the CSA index could be calculated. The 'Cyanobacterial Bloom Indicator' (CyaBI) was similarly developed by Anttila *et al.* (2018). The CyaBI is an extension of the CSA that includes cyanobacterial biomass. The cyanobacterial biomass used comprised the total biomass of *Aphanizomenon*, *Nodularia*, and *Dolichospermum*, determined from *in situ* samples. The CyaBI was also calculated from satellite-derived cyanobacterial biomass using the MCI applied to OLCI data following Eq. 6. The two CyaBI values come from averaging the normalised CSA and the *in situ* cyanobacterial biomass or the satellite-derived biomass.

To determine cyanobacteria biomass (P) from satellite data, a polynomial algorithm was developed based on the MCI:

$$P = 346.33 * \mathrm{MCI}^2 + 1043.2 * \mathrm{MCI} + 1089.1 \qquad \text{(Eq. 6)}$$

The environmental status of each of the 16 coastal areas was also determined in **III**. For this, it was assumed, based on prior work by others, that the 75th percentile of the time-series values is an indicator of good environmental status (GES) (Boyer *et al.*, 2009; Mischke *et al.*, 2009; Nõges *et al.*, 2020). For each coastal area, the threshold for the year 2022 was set to the 75th percentile of the 2016–2021 values for each index and coastal area.

3. RESULTS AND DISCUSSION

3.1. Phytoplankton dynamics in a freshwater lake based on a combination of data (I)

3.1.1. Bloom dynamics in Lake Peipsi (I)

The dynamics of Chl-a in Lake Peipsi were analysed from 2003 to 2020. The annual average Chl-a was the lowest in Peipsi *s.s.* during the entire study period. In Lake Lämmijärv and especially in Lake Pihkva, the interannual variability in Chl-a concentrations was apparent (**I**).

Analysis of nearly two decades of satellite and *in situ* observations revealed that cyanobacterial blooms in Lake Peipsi are extensive and persistent, and are strongly influenced by hydrological and climatic variability (**I**). Blooms frequently covered the majority of the lake surface area, with the average coverage during blooms reaching 96.5% in Lake Lämmijärv, 85.0% in Peipsi *s.s.*, and 84.5% in Lake Pihkva. At their maximum extent, the blooms occasionally covered the entire surface. To highlight the dynamics of the blooms, a comparison between 2018 and 2019 is shown in Figure 2. These years correspond to a relatively modest bloom year (2018) and a heavy bloom year (2019). In 2018, a bloom could be observed in Peipsi *s.s.* in June-July. Another bloom event covering some parts of Lake Lämmijärv and Lake Pihkva in addition to Peipsi *s.s.* occurred at the end of August and lasted into October 2018. Overall, however, 2018 can be considered a low-bloom year for Lake Lämmijärv and Lake Pihkva. In contrast, in 2019, the entire Lake Lämmijärv and Lake Pihkva were covered with blooms at two different periods. The first total bloom coverage took place at the end of June and the beginning of July. The second, from the 7th of August until the middle of September (**I**).

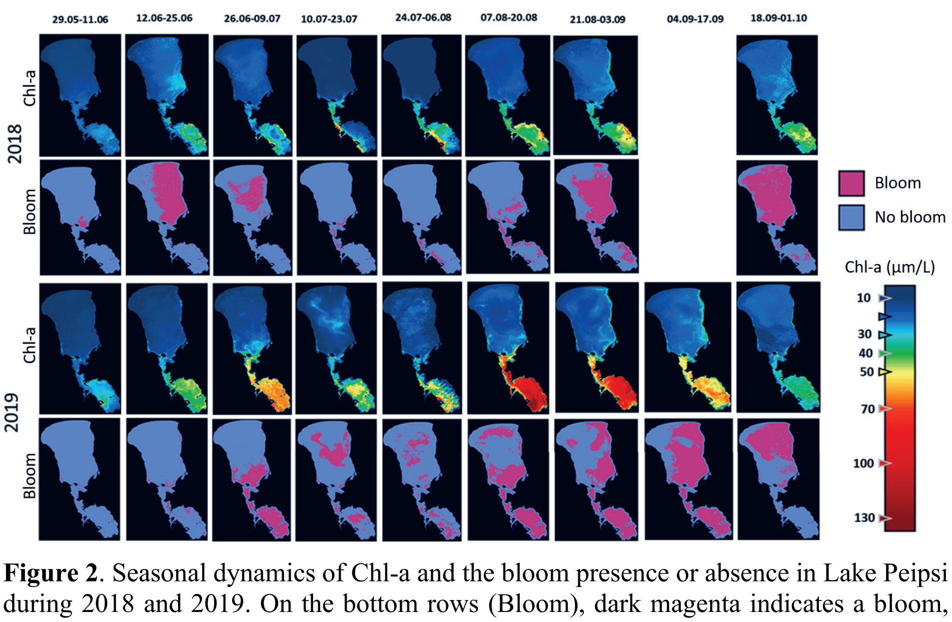

Figure 2. Seasonal dynamics of Chl-a and the bloom presence or absence in Lake Peipsi during 2018 and 2019. On the bottom rows (Bloom), dark magenta indicates a bloom, and periwinkle-blue indicates a no-bloom condition.

Bloom duration varied between the three parts, averaging 101 days in Peipsi *s.s.*, 89 days in Lake Lämmijärv, and 69 days in Lake Pihkva. Comparing the periods 2003–2011 and 2016–2022, the average bloom duration in Peipsi *s.s.* stayed consistent, whereas the blooming period was 11 days longer on average in Lake Lämmijärv and 16 days longer in Lake Pihkva during 2016–2022 (**I**).

3.1.2. Factors influencing cyanobacterial bloom dynamics (I)

The environmental conditions associated with cyanobacterial bloom development in Lake Peipsi were analysed. The focus was on two physical drivers of water level and temperature. However, it must be noted that bloom formation is governed by a combination of interacting biological, chemical, and physical processes. The availability of nutrients such as nitrogen and phosphorus is another critical variable regulating cyanobacterial dynamics.

The average long-term water level in Lake Peipsi has a pronounced seasonal pattern. The level is highest in the spring-summer months. The highest fluctuations in water levels were –0.8 m to +0.8 m compared with the long-term average. It was found that the water level a month before a bloom also significantly influenced the duration of the bloom in Lake Lämmijärv (R^2 = 0.59). This relationship was weaker in Lake Pihkva (R^2 = 0.29) and insignificant in Peipsi *s.s.* (**I**). This emphasises the spatial variability in the response of bloom dynamics to hydrological conditions within the lake system.

As is common in the area, the annual lake surface temperature follows a bell curve, with the highest temperatures in July. Warmer summer conditions supported higher *Microcystis* biomass, especially when temperatures exceeded 20 °C, but other genera showed weaker responses. However, a triggering effect could not be observed from this study, as no clear relationship between bloom duration and lake surface temperature a month prior to bloom initiation was found (**I**). This suggests that temperature alone is not a primary trigger of bloom initiation in this system.

3.1.3. Phytoplankton community composition in Lake Peipsi (I)

Long-term species composition analyses indicated notable ecological change, including a decline in *Gloeotrichia echinulata* dominance, increased biomass peaks of *Aphanizomenon*, and an earlier seasonal onset of *Microcystis* growth. Throughout the years, in June-July, *Aphanizomenon* were absent in Peipsi *s.s.* However, they were more numerous in August and September. In Lake Lämmijärv, *Aphanizomenon* were present in July and again peaked in August. *Dolichospermum* could be observed from July to September in Peipsi *s.s.* However, *Dolichospermum* had lower biomass than *Aphanizomenon*. A similar dynamic was present in Lake Lämmijärv, where *Dolichospermum* were mainly present in July–August and only occasionally in September. In Lake Pihkva during August, the community was mainly composed of *Aphanizomenon* and *Microcystis*, with *Dolichospermum* accounting for a minor share (**I**).

Satellite remote sensing (ENVISAT MERIS, Sentinel-3 OLCI) effectively captured bloom extent and frequency despite challenges such as cloud cover and aerosol interference. Overall, the study demonstrated that combining satellite data with microscopy provides a robust understanding of bloom evolution, identifying multi-year shifts linked to climate warming, water-level and community compositional changes. Optical satellite data are especially beneficial for early detection of surface bloom events due to their rapid and widespread coverage (Malthus *et al.*, 2019), whereas microwave remote sensing and altimetry provide information on factors that affect bloom presence. The use of Chl-a as a proxy for bloom events has been established previously (Behrenfeld & Falkowski, 1997). Additionally, when relying on a regional-specific algorithm for satellite-derived Chl-a, it can be successfully applied to optically complex lake data. However, this approach is not applicable if the goal is to provide information on phytoplankton community composition, as Chl-a does not give taxonomic information (Chase *et al.*, 2013). For this, a promising method is to convolve hyperspectral reflectance data to enhance the signatures of different phytoplankton groups. Several methods have been proposed in the literature, such as Gaussian decomposition (Chase *et al.*, 2013; Ficek *et al.*, 2004; Hoepffner & Sathyendranath, 1991; Ye *et al.*, 2019; Zhang *et al.*, 2021), PCA/Empirical Orthogonal Functions (EOF)(Bracher *et al.*, 2015; Xi *et al.*, 2017), and differentiation (Liu *et al.*, 2019; Xi *et al.*, 2015; Zhang *et al.*, 2021).

3.2. Pigments in the Baltic Sea and Estonian lakes and their corresponding phytoplankton absorption spectra (II)

3.2.1. The role of pigments and their detection in the Baltic Sea and Estonian lakes (II)

The role of pigments is twofold: photoprotective, promoting the dissipation of excess excitation energy as heat, and light-harvesting, using visible light for photosynthesis (Jeffrey *et al.*, 2011). Spectral analyses of phytoplankton absorption revealed substantial differences in pigment composition across Estonian lakes and the Baltic Sea, illustrating the complexity of pigment-based classification in optically challenging waters. Table 1 presents the pigments analysed in Estonian lakes and the Baltic Sea **(II)**.

Table 1. Pigment concentrations (mg m^{-3}) in the Baltic Sea and in Estonian lakes. Chlorophyll-a (Chl-a), chlorophyll-c (Chl-c), chlorophyll-b (Chl-b), photoprotective carotenoids (PPC), photosynthetic carotenoids (PSC), photosynthetic pigments (PSP).

Pigments	**Lakes**		**Baltic Sea**	
	Range	Standard deviation	Range	Standard deviation
Alloxanthin	0.01–3.3	0.31	0–0.37	0.07
Chl-a	0.01–109.6	10.4	0.68–8.5	1.86
Echinenone	0–5.98	0.57	0–0.41	0.08
Fucoxanthin	0.00–1.78	0.31	0.07–0.67	0.13
Lutein	0.01–0.95	0.13	0–0.06	0.01
Peridinin	0–1.67	0.17	0–0.65	0.14
Zeaxanthin	0–6.51	0.78	0.05–0.66	0.15
Chl-b	0–1.16	0.16	0.00–0.07	0.01
Chl-c			0.00–0.53	0.11
PPC			0.23–1.88	0.40
PSC			0.07–1.39	0.29
PSP			0.77–10.4	2.22

Fucoxanthin is a marker for diatoms, whereas alloxanthin signals the presence of cryptophytes (Sun *et al.*, 2021, 2022). Peridinin is typically found in dino-flagellates (Sun *et al.*, 2021, 2022). Chl-b is associated with chlorophytes or green algae (Sun *et al.*, 2021, 2022), whereas zeaxanthin has been proposed as a marker pigment for cyanobacteria (Schagerl & Müller, 2006; Sun *et al.*, 2022; Tamm *et al.*, 2015). However, others have found that some of the more common cyano-bacterial species in the Baltic Sea, such as *Dolichospermum* (formerly *Anabaena*) and *Nodularia spumigena*, lack the pigment zeaxanthin (Wojtasiewicz & Stoń-Egiert, 2016). This makes it difficult to rely on zeaxanthin characteristics to determine the presence, quantify concentration, and monitor these cyanobacterial species from their absorption data. An alternative would be phycocyanin, which is found in all cyanobacteria. Although phycocyanin (PC) is typically considered a marker for cyanobacteria, obtaining PC *in situ* is difficult because of its complex extraction. This further complicates the validation of spectral algorithms (Yan *et al.*, 2018). The presence or absence of the pigments should be detectable from remote sensing reflectance (R_{rs}) or, more directly, from absorption spectra (Sun *et al.*, 2021). Regarding the results from **II**, in both analysed datasets, especially in Estonian lakes, there were large differences in the phytoplankton absorption spectra (**II**, Figure 3). A difference in the extent of phytoplankton absorption between the two datasets is also evident. The measured absorption in the Baltic Sea is 10 times lower than in most lakes (**II**, Figure 3).

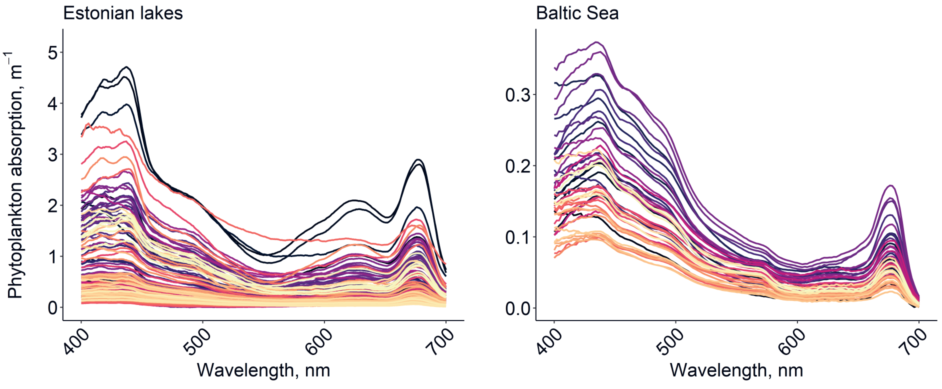

Figure 3. Phytoplankton absorption spectra (m^{-1}) collected from the Estonian lakes and the Baltic Sea. Colours represent different sampling points.

To further dissect the absorption signal, three models were set up using the two datasets (**II**).

3.2.2. Comparison of three modelling approaches—Chl-a ratio models, Gaussian decomposition, and Partial Least Squares (PLS) (II)

The Chl-a model relies on the covariance of each marker pigment concentration with the concentration of Chl-a. Overall, the model performed better when trained on the Baltic Sea dataset. This is probably due to the relatively uniform pigment concentrations measured in the samples. Regarding the Baltic Sea data, the Chl-a model provided satisfactory results for alloxanthin, echinenone, and peridinin (R^2 = 0.86–0.99, *MAPD* < 28.6%) (**II**). For the lake dataset, the model performed best at differentiating echinenone (R^2 = 0.78, *RMSE* = 1.25 mg m^{-3}, *MAPD* = 82.7%, bias = 0.26 mg m^{-3}) (**II**). The low accuracy of the Chl-a model in Case-2 waters could be attributed to the complex optical nature of the study area. In comparison, Zhang *et al.* (2021) found much more promising results in oceanic waters. Their Chl-a-based model reliably identified various pigments, including Chl-c, diadinoxanthin, fucoxanthin, PSC, and PPC. However, the concentration of all pigments, including Chl-a, was many times higher in our dataset than theirs, with more variability. This suggests that the model may not perform as well at very high pigment concentrations or when the pigment concentrations vary. Additionally, their model was trained on Case-1 oceanic waters, where the reflectance in the blue region of the spectrum is relatively high. In contrast, the green-dominated waters of the Baltic Sea exhibit strongly reduced reflectance in the blue. This influences which spectral regions become relevant for pigment retrievals, with a greater focus on higher-wavelength regions of the spectra (Kratzer & Moore, 2018). Overall, the Chl-a model, while being the simplest to implement, showed little promise for most pigments, especially when trained on a complex lake dataset.

The study's results showed that Gaussian decomposition provided the most reliable estimation of Chl-a, with Baltic Sea results achieving R^2 values up to 0.98 and relatively low error metrics (*RMSE* < 0.24 mg m^{-3}, *MAPD* < 12.8%, and bias < 0.09 mg m^{-3}) (**II**). The model performed well across all pigments and datasets, demonstrating a promising approach for spectral analysis in an optically complex environment (**II**). There have been several prior studies that also decomposed phytoplankton-specific absorption spectra to determine optical components, e.g., by Hoepffner and Sathyendranath (1991), Chase *et al.* (2013), Ye *et al.* (2019), and Zhang *et al.* (2021). In their work, all identified 12–13 Gaussian bands corresponding to specific pigments. In contrast, our study relied on eight Gaussian peaks for the lake and ten for the Baltic Sea dataset, reflecting the limited number of pigments available for validation. Ye *et al.* (2019) demonstrated that Gaussian decomposition, based on the Gaussian peaks provided by Hoepffner and Sathyendranath (1991) and Chase *et al.* (2013), could be effectively applied to waters bearing similarities to the Baltic Sea with satisfactory results. They could successfully identify Chl-a, Chl-c, PSC, and carotenoids using this approach. Thrane *et al.* (2015) also used Gaussian decomposition to determine pigment concentrations. Their work, conducted on Norwegian lakes, provided good results for identifying the total pigment group concentrations (e.g., total chlorophyll and total carotenoids; R^2 = 0.94 and 0.84, respectively), but performed worse for individual marker pigments. Conversely, Canuti and Penna (2025) found that their Empirical Orthogonal Function (EOF) model, a tuned version of Bracher *et al.* (2015), outperformed the Gaussian decomposition approach in the Baltic Sea.

The PLS model performed strongly in the Baltic Sea for pigments such as Chl-a, PSP, PPC, and particularly zeaxanthin (R^2 > 0.95, $RMSE_{ln}$ < 0.27 mg m^{-3}, *MAPD* < 11%), but it performed poorly in Estonian lakes, likely due to greater variability in pigment ratios. The PLS-model's ability to quantify zeaxanthin from absorption spectra highlights its potential for monitoring cyanobacteria. The same model established by Zhang *et al.* (2021) showed similarly strong results, but for a broader range of pigments, including Chl-a, Chl-b, and Chl-c, diadinoxanthin, fucoxanthin, 19′-hexanoyloxyfucoxanthin, PSC, and PPC. They attributed its success to the use of hyperspectral data and a well-calibrated dataset from oceanic waters, which typically exhibit simpler and more uniform optical properties than inland Case-2 waters. Supporting these findings, Xi *et al.* (2017) demonstrated that hyperspectral R_{rs} data could be used to identify dominant phytoplankton groups across a wide range of optical conditions. This included highly turbid Case-2 waters. The model by Xi *et al.* (2017), which incorporated simulated and *in situ* data, successfully identified cyanobacteria during a bloom in Lake Taihu, China, using spectral features associated with pigments such as zeaxanthin. These findings suggest that with appropriate pre-processing of the absorption spectra and further parameterisation of the model, the PLS-model can be a powerful tool for pigment-based phytoplankton monitoring in optically complex waters.

The aim of taking a second derivative of a phytoplankton absorption spectrum is to amplify the signal where the change in slope is fastest. It further increases the signal-to-noise ratio of pigment peaks. This should allow for distinguishing overlapping absorption curves from different pigments, which is especially useful when pigments such as Chl-a, Chl-b, and various carotenoids have closely spaced absorption characteristics (Astoreca *et al.*, 2009; Bidigare *et al.*, 1989; Ruddick *et al.*, 2023). Additionally, this approach reduces baseline effects, making it particularly effective in optically complex Case-2 waters (Astoreca *et al.*, 2009; Bidigare *et al.*, 1989; Ruddick *et al.*, 2023). Taking the fourth derivative provides similar benefits to taking the second derivative. These include the ability to discriminate fine absorption peaks, thus improving the detection of even minor pigments (Bidigare *et al.*, 1989; Roelke *et al.*, 1999). Derivative processing (2^{nd} and 4^{th} derivatives) enhanced the detection of fine absorption features, moderately improving pigment discrimination, especially in the Baltic Sea samples. To note, however, is the relatively poor ability to determine zeaxanthin concentrations using differentiation (values correspond to 2^{nd} and 4^{th}, respectively; $R^2 = -0.15$, 0.32; $RMSE_{ln} = 0.62$, 0.38 mg m^{-3}, $MAPD = 42.64$, 32.85%). The results of the two derivatives for the Estonian lakes showed moderate to good fit and accuracy (average $R^2 = 0.26$, 0.90; $RMSE_{ln} = 0.57$, 2.03 mg m^{-3}), although with significant underestimation of most pigments (mean bias = −0.35 mg m^{-3}). Overall, however, the derivative analysis only slightly improved the identification capabilities of the PLS-model. Despite challenges, the results demonstrate the feasibility of developing regional spectral–pigment models for differentiating phytoplankton functional groups, with future opportunities to link absorption-based approaches to satellite-derived reflectance for operational remote sensing applications. Given the ever-increasing interest in satellite-based water-quality monitoring, refining models to accurately retrieve pigment concentrations from spectral data is crucial. Our work here provides new insights and highlights some of the obstacles that must be overcome to establish a more comprehensive and user-friendly method for assessing phytoplankton community composition. The next step in the workflow would be connecting these absorption-based (Gaussian and PLS-models) or the Chl-a model to satellite R_{rs} data. Establishing a robust relationship between absorption and R_{rs} is essential for developing algorithms that can retrieve taxonomic information about the phytoplankton community from satellite imagery and for studying phytoplankton dynamics from space.

3.3. Cyanobacteria dynamics in the Baltic Sea using satellite and *in situ* data (III)

3.3.1. *In situ* and satellite data in the Estonian coastal areas (III)

Chl-a and turbidity consisted of national monitoring data from 2016 to 2022 across 16 coastal areas of Estonia (Figure 1C). Chl-a in the coastal areas ranged from 3.0 to 7.3 mg m^{-3} (*in situ*) and satellite-derived Chl-a from 2.9 to 15.6 mg m^{-3}. The highest Chl-a was observed at Haapsalu, Matsalu and Pärnu bays (Figure 1C). The highest turbidity was also observed in these three coastal areas. The satellite-derived turbidity ranged from 0.3 to 5.4 FNU, whereas *in situ* turbidity was not measured (**III**).

To determine the two parameters, satellite data can be useful for covering large areas and providing a time series. However, the Baltic Sea is an optically complex water body, where atmospheric correction and bio-optical modelling are difficult, as evidenced by previous work by Toming *et al.* (2017) and Kratzer and Plowey (2021) and especially in coastal areas of the Baltic Sea, where Chl-a is typically lower and where influence by CDOM and TSM is strong (Kutser *et al.*, 2009; Kyryliuk & Kratzer, 2019). In **III**, the satellite-derived parameters were based on the C2RCC and POLYMER atmospheric correction algorithms. Validation of C2RCC relied on 135 valid Chl-a match-ups, whereas validation of POLYMER relied on only 46. Both processors showed a weak relationship: C2RCC $R^2 = 0.2$ ($p < 0.05$), and POLYMER $R^2 = 0.39$ ($p < 0.05$). One reason for the poor validation is the difference inherent in the collection methodology. The satellite data consist of pixels covering a 300 m × 300 m area, whereas the *in situ* data consist of depth-integrated point measurements from a specific location. It must also be noted that the current sampling methodology is not set up with satellite validation in mind. Because of this, the *in situ* data used in **III** lacked the precise time of sampling in addition to the date. Importantly, the exact coordinates of the samples are not required to be recorded under current sampling practices and are therefore usually logged to the nearest station coordinates. Furthermore, the current way of collecting *in situ* samples aboard ships mixes the water column and disrupts the surface bloom, yielding results that do not reflect the actual conditions (Kutser, 2004). Although POLYMER provided better results, there were significantly fewer match-ups than in C2RCC (N = 46 vs N = 135, respectively). Previous work has also suggested that for the Baltic Sea region, C2RCC is the best available processor for Chl-a estimates (Soomets *et al.*, 2022; O'Kane *et al.*, 2024). Owing to previous reports of its serviceability and the relatively minor performance difference between the atmospheric corrections in our analysis, it was decided to proceed with the C2RCC products regardless (**III**).

The relationship between *in situ* biomass and MCI was relatively weak ($R^2 = 0.39$, $p < 0.05$). An important aspect is that the MCI method for estimating cyanobacteria biomass is only useful at high Chl-a concentrations (10–300 mg m^{-3}), as reported by Binding *et al.* (2013). The MCI uses red and near-infrared (NIR) wavelengths, which are also significantly influenced by turbidity, making it difficult to estimate at low Chl-a levels in coastal areas. Difficulties in assessing cyanobacteria biomass using satellite data, especially in areas with low biomass, are not unique, but are known issues with current remote monitoring techniques, as evidenced in Binding *et al.* (2013), Konik *et al.* (2023), Clark *et al.* (2017), and Mishra *et al.* (2019). The poor relationship here can partly be explained by the relatively low Chl-a concentrations and high turbidity in coastal areas compared to inland lakes, where the application of MCI has been successful (Alikas *et al.*, 2010) (**III**). The average *in situ* cyanobacteria biomass was highest in the Hara and Kolga bays (731.4 mg m^{-3}) and lowest in the Gulf of Riga (NW)

(1.0 mg m^{-3}). *In situ* measurements were sparse both in time and spatially. Only in four coastal areas were data available for the entire time series.

3.3.2. Cyanobacterial bloom dynamics based on indices in the Baltic Sea (III)

Satellite-derived bloom indices revealed strong spatial variability in cyanobacterial bloom intensity and environmental status across Estonia's 16 coastal water bodies (Figure 1C). Using Sentinel-3 OLCI data processed with C2RCC, the study evaluated three indices, PII, CSA, and CyaBI using *in situ*, and CyaBI using satellite biomass, to assess ecological condition under the MSFD. PII is a non-normalised index based solely on Chl-a concentration, where higher values correspond to more extensive cyanobacteria biomass. In several coastal areas, the index value was 0, and there was considerable variation in index values across years. Because the index relies solely on Chl-a concentrations, it is impossible to accurately determine whether a cyanobacterial bloom is present, even in coastal areas with high index values (**III**). As discussed in the previous sections, relying on a simple relationship with Chl-a does not provide taxonomic information.

The Cyanobacteria Surface Accumulation (CSA) index, based on satellite-derived Chl-a concentration and turbidity, is a normalised index with values ranging from 1 (no accumulations) to 0 (extensive algal growth). According to the CSA, in three coastal areas, there were years without blooms. These were Eru-Käsmu Bay, Kassari-Õunaku Bay, and Matsalu Bay. Similarly to PII, the CSA values also varied considerably across years. An index value of 0 was also observed in three areas, corresponding to extensive surface accumulation – Hara and Kolga bays, Kihelkonna Bay, and Moonsund Sea (**III**). In calculating the CSA, turbidity serves as a proxy for dead phytoplankton cells. But in the case of Estonian coastal areas, turbidity is not only caused by organic material, but it is also most likely dominated by mineral particles, especially in shallow areas, river inflows, and during strong wind events (Uudeberg *et al.*, 2020). Therefore, the relationship between Chl-a concentration and turbidity is not linear in most coastal areas. Additionally, according to the cluster analysis, a Chl-a peak is not followed by a turbidity peak, as would be expected if dead cyanobacteria cells were present in the area (**III**).

The CyaBI indicator functions similarly to the CSA in its outputs, but it also includes an additional input parameter for cyanobacteria biomass. Where *in situ* biomass was used, CyaBI reported the heaviest blooms in Hara and Kolga bays, Kihelkonna Bay, and the Moonsund Sea. However, it must be noted that for Hara and Kolga bays and the Moonsund Sea, the additional *in situ* biomass data were unavailable. Effectively, this means that the CyaBI (*in situ*) value is equivalent to CSA at Hara and Kolga bays and the Moonsund Sea. The cyanobacteria biomass parameter indicates the actual biomass in the water column and thus complements surface measurements in remote sensing data, yielding more reliable results for phytoplankton group specification. The lowest CyaBI values were in Liivi Bay

(NW), Eru-Käsmu Bay, and Narva-Kunda Bay (**III**). Different results across the three bays, where the indices predicting the highest surface blooms differ between CSA and the CyaBI, indicate a benefit of adding a biomass parameter to the status assessments. When satellite-derived cyanobacteria biomass was used, the results slightly differed. The highest indicator values were reported in Hara and Kolga bays, Pärnu Bay and the NW Gulf of Riga. Relying on satellite-derived biomass, the CyaBI indicator showed the greatest variation among the indices. In one example, neighbouring coastal areas of Soela Strait and Kihelkonna Bay, which are experiencing similar conditions, exhibited the highest CyaBI values of 0.67 and the lowest of 0.47, respectively (**III**). It is generally advisable to supplement satellite-derived Chl-a and turbidity estimates with *in situ* measurements of cyanobacterial biomass. But in areas where turbidity is less of a factor (turbidity < 1 FNU), satellite-derived biomass could provide better temporal coverage within a specific area (**III**).

3.4. Environmental status in the coastal areas of the Estonian Baltic Sea (III)

Monitoring and managing aquatic resources is essential to safeguard these environments. The MSFD sets out rules for all European member states to organise efforts to monitor and improve their coastal areas. Under the MSFD, Estonian coastal waters must be monitored, and GES must be achieved and maintained (European Union, 2008). The formation of harmful cyanobacterial blooms is a key indicator of the environmental status (ES) of a coastal area. The purpose of the assessment in **III** was to obtain the ES of the Estonian coastal areas. This could then be used as input to improve their conditions and to focus on adaptation and remediation efforts. Another goal was to develop a methodology for using satellite data to estimate phytoplankton blooms as input for the ES assessment of the Estonian Environment Agency.

In 2022, only the NW Gulf of Riga achieved GES across all indices, whereas several enclosed bays, including Haapsalu, Matsalu, and Pärnu, failed to meet GES under any indicator due to persistently high turbidity, strong river inputs, and hydrodynamic isolation. The reliability of determining the "good-bad" threshold value and environmental status depends primarily on the representativeness of the data, as the inclusion of anomalous data can skew the threshold and, in turn, the ES assessment. Because variability between years can be quite pronounced, it would be beneficial to assess the environmental status of an area over a longer time frame than presented here. On the other hand, the data series analysed in **III** cannot be extended back to the very distant past due to differences in Earth Observation instruments and their limitations. In general, however, the results indicating poor ES in Estonian coastal areas are consistent with other studies. Previous HELCOM assessments also found poor ES based on the CyaBI in the Gulf of Finland, the Gulf of Riga, the Eastern Gotland Basin, and the Northern Baltic Proper (Estonian coastal areas are a sub-area of these larger waterbodies) (HELCOM, 2018). Interestingly, under HELCOM's methodology, a sampling station was not established in the NW part of the Gulf of Riga before 2022, which, according to analysis in **III**, achieved GES.

Overall, the results highlight the value of satellite-based monitoring for broad-scale assessment whilst emphasising the need for improved atmospheric correction, more robust biomass algorithms, and the incorporation of additional cyanobacterial pigments, such as phycocyanin.

CONCLUSIONS

This thesis aimed to advance the monitoring of phytoplankton dynamics in optically complex waters by integrating satellite remote sensing, spectral modelling, and *in situ* data. The overarching results indicate that no single method is sufficient for enhancing phytoplankton monitoring in optically complex waters. Rather, for a robust analysis of phytoplankton dynamics, the integration of multiple complementary data sources is required. *In situ* data provide information on community composition, whereas satellite data can provide the spatial and higher temporal coverage needed to map the extent, intensity, and frequency of blooms for local, regional, and global applications. By addressing the challenges faced with Case-2 waters, this work contributes conceptually and methodologically to improving the detection, characterisation, and assessment of phytoplankton blooms in inland and coastal environments.

The first objective of the thesis was to investigate cyanobacterial bloom dynamics using a combination of remote sensing and *in situ* methods. The microwave-derived temperature and altimetry-derived water level helped explain the cyanobacterial bloom parameters in Lake Peipsi. It was found that **higher water levels lead to a significantly shorter bloom with lower coverage**. Whereas **lower water levels were consistently associated with longer bloom durations**, particularly in Lake Lämmijärv.

Phytoplankton community analysis revealed several compositional changes over the last 20 years in Lake Peipsi. **The importance of *Gloeotrichia echinulata* as a bloom-former has declined during the last 10 years** in Peipsi *s.s.* At the same time, **the biomass peaks of *Aphanizomenon* have increased**. The onset of the *Microcystis* growth period has shifted earlier to June. Additionally, it was noted that **the longer the period with daily temperatures >20 °C, the higher the *Microcystis* biomass**.

The second objective focused on evaluating spectral approaches for identifying phytoplankton groups based on the relationship between pigments and the absorption signal. It was demonstrated that solely using Chl-a is insufficient for determining phytoplankton composition in Case-2 waters, confirming a key limitation. Accessory pigments such as fucoxanthin, peridinin, alloxanthin, and zeaxanthin can provide valuable information on community composition, differentiating between diatoms, dinoflagellates, cryptophytes, and cyanobacteria. Leveraging the full phytoplankton absorption spectrum for pigment retrieval and group identification showed strong potential. **The decomposition of phytoplankton absorption into pigment-specific Gaussians could successfully reveal and quantify chlorophylls and other pigment groups**. Also, **modelling pigment concentrations using partial least squares with phytoplankton absorption performed well in the Baltic Sea** but struggled with optical variability in the lakes. Together, these findings highlight both the potential and the limitations of current spectral approaches. There is clearly a need for region-specific model development and for incorporating environmental co-variables.

The third objective addressed the applicability of indices derived from satellite data for assessing the environmental status of Estonian coastal waters in relation to the MSFD. Indices based on Chl-a or turbidity alone cannot reliably distinguish cyanobacterial blooms in coastal waters. Incorporating the cyanobacterial biomass improves the ecological relevance of the indices. However, accurately deriving the biomass from satellite data remains a challenge, particularly at low phytoplankton concentrations and turbid waters. These findings further demonstrated that **a multi-parameter approach is required, combining satellite and *in situ* data for a dependable environmental assessment**. **Assessing bloom parameters with satellite data successfully complements *in situ* monitoring practices by providing a more frequent and spatially expansive overview**.

Taken together, the central conclusion of this work is that the **optical complexity of inland and coastal waters fundamentally limits the transferability of standard remote sensing algorithms and requires region-specific approaches**. Varying levels of CDOM and TSM, along with the various phytoplankton assemblages, influence the optical signal, necessitating the adaptation of retrieval algorithms and analytical approaches to local conditions.

This thesis also contributes to the field by demonstrating the value of synergistic use of satellite remote sensing and *in situ* sampling. The integration of the two approaches improves the ability to monitor bloom extent, duration, and composition. It also improves confidence in satellite-derived products via validation. This is particularly important for supporting future environmental management and policy frameworks.

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SUMMARY IN ESTONIAN

Fütoplanktoni dünaamika järvedes ja Läänemeres: kombinatsioon *in situ* ja satelliidiandmetest

Doktoritöös on uuritud fütoplanktoni dünaamikat ja uute meetodite arendamist fütoplanktoni koosluse uurimiseks neeldumisandmetest optiliselt keerukates veekogudes, keskendudes Eesti järvedele ja Läänemerele. Fütoplankton on veekogudes toiduahelate aluslüli ning omab keskset rolli aineringes ja kliima reguleerimises. Kuigi fütoplankton on ökoloogiliselt väga tähtis, võivad nad liigse vohamise korral, eriti tsüanobakterite ehk sinivetikate domineerimisel, põhjustada nii mage- kui riimvees ökoloogilisi, majanduslikke kui terviseriske. Seetõttu on nende täpne ja usaldusväärne seire väga oluline nii teaduslikus kui ka keskkonna parema majandamise kontekstis.

Fütoplanktoni pinnaõitsengute seire arendamiseks optiliselt keerukates vetes tuleks kombineerida satelliitkaugseiret ja traditsioonilisi *in situ* mõõtmisi. Satelliidiandmed on eriti kasulikud, kuna võimaldavad koguda andmeid sagedamini ning kattes suurema ala võrreldes *in situ* andmetega. Samuti on satelliidiandmed tänu Copernicuse programmile tasuta kättesaadavad. Lisaks, on üha enam kasutuses hüperspektraalsed andmed, mis võimaldavad ekstraheerida rohkem informatsiooni kui seni laialdaselt kasutuses olnud multispektraalsetest satelliidiandmetest. Praegusel hetkel on vaja paremaid juhiseid, kuidas satelliidiandmeid rakendada koos *in situ* mõõtmistega ökoloogiste uuringute läbiviimiseks ning keskkonnaseisundi hindamiseks. Hetkel kasutuses olevad kaugseiremudelid töötavad edukalt ookeanivetes, kuid tihtipeale ebaõnnestuvad Eesti optiliselt keerukates vetes. Doktoritöö üldine eesmärk on hinnata kaugseire andmete sobilikkust fütoplanktoni dünaamika uurimisel Eesti (ja laiemalt Läänemeres) vetes. Satelliidiandmete ja *in situ* andmete sünergia saavutamiseks on doktoritöös analüüsitud kolme omavahel seotud artiklit. Esimeses artiklis käsitletakse tsüanobakterite õitsengute pikaajalist dünaamikat Peipsi järves, kasutades mikroskoopia-baasil biomassi ja satellidiandmete kooskõla. Teises artiklis hinnatakse erinevaid lähenemisi fütoplanktoni pigmentide ja nende alusel fütoplanktoni rühmade tuvastamiseks neeldumisspektrite alusel nii Eesti järvedes kui ka Läänemeres. Kolmandas artiklis analüüsitakse tsüanobakterite õitsenguid Eesti rannikumeres, rakendades erinevaid satelliidipõhiseid indekseid ning hinnates keskkonnaseisundit Merestrateegia Raamdirektiivi (MSFD) kontekstis.

Uurides Peipsi järve selgus, et tsüanobakterite õitsengud on järves ulatuslikud, pikaajalised ja samas tugevalt mõjutatud hüdroloogilistest ning kliimatingimustest. Satelliidilt tuletatud klorofüll-a aegridade (2003–2022) põhjal ilmnesid märkimisväärsed erinevused Peipsi järve eri osade vahel. Lämmijärves ja Pihkva järves oli nii õitsengute kestus kui ka ulatus suurem kui Peipsi *s.s.* Madalam veetase oli eriti Lämmijärves selgelt seotud pikemate ja ulatuslikumate õitsengutega. Samuti ilmnes, et mida kauem kestis periood, millal veetemperatuur ületas 20 °C, seda suurem oli potentsiaalselt mürgise perekonna *Microcystis* biomass. Ka koosluses täheldati pikaajalisi muutusi. Traditsioonilise õitsengu-

tekitaja *Gloeotrichia echinulata* osakaal on järves vähenenud, samas kui niitja tsüanobakteri perekonna *Aphanizomenon* biomass on kasvamas. *Microcystis* kasvuperioodi algus on nihkunud varasemaks. Artiklis on rõhutatud satelliitkaugseire võimaluste ja *in situ* andmete kombineerimise olulisust, kuna satelliidid võimaldavad tabada õitsengute ruumilist heterogeensust, mida ainult punktmõõtmistele toetudes ei oleks võimalik uurida.

Teises artiklis analüüsiti fütoplanktoni pigmentide seoseid neeldumisspektritega ning võrreldi kolme modelleerimisviisi: klorofüll-a-põhine lineaarne mudel, Gaussi kõverate-põhine mudel ja vähimruutude regressioonimudel (ingl. k. *Partial Least Squares* (PLS)). Klorofüll-a-põhine mudel ei ole Eesti järvedes ja Läänemeres piisavalt usaldusväärne pigmentide eristamiseks. Kõige täpsem on neeldumisspektri jaotamine Gaussi kõverateks, mis võimaldas kvantifitseerida mitmeid pigmente nii järve kui ka Läänemere andmetest. PLS-meetod töötas hästi Läänemere andmetel, kuid oli järvedes suure varieeruvuse tõttu vähem usaldusväärne. Kokkuvõttes võib järeldada, et regionaalsed spektraalsetel andmetel tuginevad pigmendimudelid on paljulubavad, kuid vajavad edasist kohandamist uute andmetega, ning üheks edasiseks uurimissuunaks oleks fütoplanktoni rühmade tuletamine peegeldustegurist, mis võimaldab laiendada tulemusi satelliidipiltidele.

Tsüanobakterite õitsengute hindamiseks Eesti rannikualadel Sentinel-3 OLCI andmetest võrreldi erinevaid indekseid, sh. fütoplanktoni intensiivsuse indeksit (PII), tsüanobakterite pinnakogunemise indeksit (CSA) ja tsüanobakterite õitsengu indikaatorit (CyaBI). Selgus, et toetudes ainult klorofüll-a või hägususel põhinevatele indeksitele, ei ole võimalik tuvastada, kas õitsengud on põhjustatud tsüanobakterite poolt. Kõige terviklikuma pildi andis CyaBI, eriti juhul, kui see oli täiendatud *in situ* tsüanobakterite biomassiga. Rannikualade keskkonnaseisundi hindamisel selgus, et 2022. aastal saavutas kõigi indeksite alusel hea keskkonnaseisundi vaid Loode-Liivi laht. Samas mitmed suletumad lahed (nt. Haapsalu, Matsalu ja Pärnu laht) ei vastanud ühelegi hea seisundi kriteeriumile.

Kokkuvõttes näitab doktoritöö, et satelliitkaugseire on kasulik vahend fütoplanktoni ja tsüanobakterite ulatuslikuks seireks, kuid selle usaldusväärsus sõltub tugevalt piirkonnaspetsiifilise algoritmi kasutamisest ning atmosfäärikorrektsioonist. Samuti on tähtis ka *in situ* andmete kogumine ja kättesaadavus, et kaugseireandmeid valideerida. Erinevate andmeallikate ja meetodite integreerimine parandab oluliselt õitsengute dünaamika mõistmist ning toetab nii teaduslikku analüüsi kui ka praktilist keskkonnajuhtimist Läänemerel ja Eesti siseveekogudes.

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Education:

MSc Environmental Geology and Contamination (*Cum laude*), 01/09/2019 – 01/10/2020 – Portsmouth

Thesis (*Cum laude*, 73%): titled “Modelled dose rates of reference animals and plants located in the Chornobyl Exclusion Zone with the RESRAD-BIOTA and ERICA tool”.

BSc Biology, 19/09/2016 – 16/07/2019 – York

Thesis: “Meta-analysis of the effectiveness of riparian buffer strips in maintaining species richness in tropical agricultural areas”.

Presentations:

Poster presentation at the Living Planet Symposium 2025, titled "Identifying phytoplankton groups from absorption spectra – a regional approach based on data from the Baltic Sea and Estonian lakes"

Oral presentation at the Tartu Observatory Science Conference 2025, titled "Identifying Phytoplankton Groups from Absorption Spectra – A Regional Approach Based on Data from the Baltic Sea and Estonian Lakes"

Poster presentation at the Trevor Platt Science Symposium 2023, titled "Application of Satellite-Derived Summer Bloom Indicators for Estonian Coastal Waters of the Baltic Sea"

Oral presentation at the ESTHub Vision Day 2023, titled "Support of remote sensing data in phytoplankton assessment to refine the assessments of the state of the Estonian coastal areas"

Eesti Kaugseirepäev 2022 and 2024 moderator

Supervising:

Max Sebastian Segerkrantz (BSc) – "Peipsi järve vetikaõitsenguid esilekutsuvate ja pärssivate parameetrite uuring kaugseire abil", Geology and Environmental Technology Department, 2024, supervisors: Krista Alikas, Erko Jakobson, Ian-Andreas Rahn

Teaching:

Conductor of the workshop "Veekogude kaugseire välitööd Tõravere tiigil" as part of the Tartu Observatory career day "Karjääriredel viib kosmosesse" in 2023–2025

Lecturer in Data Science in Remote Sensing (LTTO.00.027) – 2023–2025

Lecturer in Keskkonnakaugseire I (LTTO.00.002) – 2023–2026

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Keskkonnaanalüütik – Nomine Consult AS – 04/01/2021 – 13/09/2021

Veeanalüütik – Eesti Keskkonnaagentuur – 01/01/2020 – 01/03/2020

Publikatsioonid:

Rahn, I.-A.; Alikas, K.; Hieronymi, M.; Röttgers, R.; Freiberg, R.; Kangro, K. Identifying Phytoplankton Pigments from Absorption Spectra – A Regional Approach Based on Data from Case-2 waters. *Frontiers in Environmental Science, 14,* 1795916. https://doi: 10.3389/fenvs.2026.1795916

Kangro, K.; Pall, A.-M.; Laugaste, R.; Piirsoo, K.; Maileht, K.; **Rahn, I.-A.**; Alikas, K. Two decades of cyanobacterial bloom dynamics in a shallow eutrophic lake: remote sensing methods in combination with light microscopy. *Hydrobiologia, 852*, 425-442. https://doi.org/10.1007/s10750-024-05546-x

Rahn, I.-A.; Kangro, K.; Jaanus, A.; Alikas, K. Application of Satellite-Derived Summer Bloom Indicators for Estonian Coastal Waters of the Baltic Sea. *Applied Sciences, 13*(18)*,* 10211. https://doi.org/10.3390/app131810211

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Postriettekanne Living Planet Symposium 2025, pealkirjaga “Identifying phytoplankton groups from absorption spectra – a regional approach based on data from the Baltic Sea and Estonian lakes”

Suuline ettekanne Tartu Observatooriumi Teaduskonverentsil 2025, pealkirjaga “Identifying Phytoplankton Groups from Absorption Spectra – A Regional Approach Based on Data from the Baltic Sea and Estonian Lakes”

Postriettekanne Trevor Platt Science Symposium 2023, pealkirjaga “Application of Satellite-Derived Summer Bloom Indicators for Estonian Coastal Waters of the Baltic Sea”

Suuline ettekanne ESTHubi Visioonipäeval 2023, pealkirjaga „Support of remote sensing data in phytoplankton assessment to refine the assessments of the state of the Estonian coastal areas“

Eesti Kaugseirepäev 2022 ja 2024 moderaator

Juhendamine:

Max Sebastian Segerkrantz (BSc) – “Peipsi järve vetikaõitsenguid esilekutsuvate ja pärssivate parameetrite uuring kaugseire abil”, Geoloogia ja Keskkonnatehnoloogia osakond, 2024, juhendajad: Krista Alikas, Erko Jakobson, Ian-Andreas Rahn

Õppetegevus:

Töötoa “Veekogude kaugseire välitööd Tõravere tiigil” läbiviija Tartu Observatooriumi karjääripäeva raames “Karjääriredel viib kosmosesse” aastatel 2023–2025

Lektor Andmeteadus Kaugseires (LTTO.00.027) – 2023–2025

Lektor Keskkonnakaugseire I (LTTO.00.002) – 2023–2026

Auhinnad:

Juhan Rossi Stipendium Keskkonnafüüsikas laureaat

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