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Supporting Environmental Management and Climate Change Governance with Satellite Chlorophyll-a Estimation from Space

“Documento Definitivo"

Doutoramento em Alterações Climáticas e Políticas de Desenvolvimento Sustentável
Especialidade em Ciências do Ambiente

Filipe Bernardo da Costa Agostinho Rodrigues Lisboa

Tese orientada por:
Profª. Doutora Vanda Brotas e pelo Prof. Doutor Filipe Duarte Santos

Documento especialmente elaborado para a obtenção do grau de doutor

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2025

To my mother, with infinite gratitude, who thought me to love life in all its forms.

To my family and friends, the giants who lend me their shoulders.

Making these people proud is part of my quest for meaning.

You can’t protect what you don’t love, you can’t love what you don’t know. To understand how improbable life is, you must venture out to space. To love life in all its forms, go to the oceans and venture out far past the shore.

Declaration

According to Chapter V, article 40, paragraph 1 of the Regulation concerning Post-Graduate Studies at the University of Lisbon, which was published in the Portuguese Republic's Official Journal (Series II, no153, of 5 July 2003), the PhD candidate hereby declares that he participated in the designing and carrying out the field work, as well as in interpreting the results, and drafting the manuscripts to be submitted for publication. This study was funded at its early stages by the Portuguese Science Foundation PhD grant PD/BD/113932/2015.

While drafting most of the thesis, the author also worked for the European Maritime Safety Agency (EMSA), an agency of the European Commission. As a project officer for Earth Observation Services, the work entails the provision of satellite-based data for a variety of users within the Copernicus Maritime Surveillance Service and CleanSeaNet. Under the Security component of Copernicus, data should only be available to authorised users and is request driven. In the other cases, data is either protected or confidential and/or protected by copyright. The author declares that no data used in his tasks at EMSA, exchanged between the different authorities, or even used for test beds, were used in the drafting of this thesis. The author also declares no conflicts of interest. The content of this research does not necessarily reflect the official opinion of the European Maritime Safety Agency. Responsibility for the information and views expressed in this study lies entirely with the author.

Most figures, plots and maps are original and have been drawn or created by the author, except for the ones explicitly cited and marked "adapted for the purpose of the thesis".

Filipe Agostinho Lisboa
Angra do Heroísmo, Azores, Portugal,
August 27th, 2025
(first observance of United Nations World Lake Day)

Parts of the work and dataset presented in this thesis have been considered and included in the following international publications, corresponding to chapters 4, 3 and 2, respectively:

1. Eduardo Eiji Maeda, **Filipe Lisboa**, Laura Kaikkonen, Kari Kallio, Sampsa Koponen, Vanda Brotas, and Sakari Kuikka *"Temporal patterns of phytoplankton phenology across high latitude lakes unveiled by long-term time series of satellite data*" - Remote Sensing of Environment, 2019 https://doi.org/10.1016/j.rse.2018.12.006
2. **Filipe Lisboa**, Vanda Brotas, Filipe Duarte Santos, Sakari Kuikka, Laura Kaikkonen, and Eduardo Eiji Maeda *"Spatial Variability and Detection Levels for Chlorophyll-a Estimates in High Latitude Lakes Using Landsat Imagery" - Remote Sensing, 2020* *https://doi.org/10.3390/rs12182898*
3. **Filipe Lisboa**, Vanda Brotas, Filipe Duarte Santos, *"Earth Observation—An Essential Tool towards Effective Aquatic Ecosystems' Management under a Climate in Change" - Remote Sensing, 2024* *https://doi.org/10.3390/rs16142597*

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Abbreviations and acronyms

Acronym	Meaning
AMT	Atlantic Meridional Transect
AP	Accessory Pigments
APD	Absolute Percentage Difference
ATBD	Algorithm Theoretical Baseline Documents
ATLP	ATLantic off Portugal
AOP	Apparent Optical Properties
BiOMAP	Bio-Optical Mapping of Marine Properties
CC_NN	CoastColour Neural Network
CC_QAA	CoastColour Quasi-Analytical Algorithm
CDOM	Coloured Dissolved Organic Matter
Chl-a	Chlorophyll a
Chlide-a	Chlorophyllide a
CoASTS	Coastal Atmosphere and Sea Time Series
CZCS	Coastal Zone Colour Scanner
DCM	Deep Chlorophyll Maximum
DHI	Danish Hydraulic Institute
DMS	Dimethyl Sulfide
EEZ	Exclusive Economic Zone
EM	Electromagnetic Spectrum
EMSA	European Maritime Safety Agency
ESA	European Space Agency
EU	European Union
EVC	Essential Climate Variable
FR	Full Resolution
GMES	Global Monitoring for Environment and Security
HPLC	High-Performance Liquid Chromatography
IOP	Inherent Optical Properties
EO	Earth Observation
IOCCG	International Ocean Colour Coordinating Group
MODIS	Moderate Resolution Imaging Spectroradiometer
MERIS	Medium Resolution Imaging Spectrometer
NDCI	Normalized Difference Chlorophyll Index
BRG	Blue-Red-Green index
SDG	Sustainable Development Goal
SDGs	Sustainable Development Goals
MPAs	Marine Protected Areas

ODS	Objetivos de Desenvolvimento Sustentável (English: Sustainable Development Goals)
GT	Gigatonnes
VHR	Very High Resolution
RMSE	Root Mean Square Error
BIC	Bayesian Information Criterion
LEAPS	Regression subset selection method (leaps and bound)
GLDAS	Global Land Data Assimilation System
NASA	National Aeronautics and Space Administration
UN	United Nations
FCT	Fundação para a Ciência e a Tecnologia
PhD	Doctor of Philosophy
ADEOS	Advanced Earth Observing Satellite
ADEOS-II	Advanced Earth Observing Satellite-II (*Midori-2*)
ALOS	Advanced Land Observing Satellite (*Daichi*)

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Resumo

O fitoplâncton desempenha um papel fundamental na regulação do clima global e na manutenção da vida nos ecossistemas aquáticos. Estes organismos microscópicos, que realizam fotossíntese, são responsáveis por cerca de metade da produção de oxigénio do planeta e pela absorção significativa de dióxido de carbono atmosférico. No entanto, as alterações climáticas têm vindo a modificar profundamente as condições dos ecossistemas aquáticos, afetando a composição, distribuição e fenologia das comunidades fitoplanctónicas. Este trabalho de investigação centra-se na monitorização do fitoplâncton como indicador de variabilidade climática, com especial enfoque na concentração de Clorofila-a (Chl-a), um pigmento fotossintético amplamente utilizado como proxy da biomassa fitoplanctónica.

A tese propõe o reforço da monitorização do fitoplâncton em regiões particularmente sensíveis às alterações climáticas, como os lagos boreais, onde o degelo sazonal e outras variações geofísicas têm impacto direto na produtividade primária. Através da análise de séries temporais de dados de satélite e de amostragens in situ, foi possível modelar padrões de floração e identificar alterações na fenologia do fitoplâncton ao longo de mais de três décadas. A tese demonstra que é possível utilizar imagens de satélites de alta resolução espacial que não foram concebidas inicialmente com o propósito de detetar Clorofila-a. O caso apresentado refere-se à utilização dos satélites da família Landsat (Landsat 5 e 7), com resolução espacial de 30 metros, onde foi possível estimar padrões sazonais de clorofila em pequenos lagos – porém, com limitações bem definidas devidas, sobretudo, à baixa resolução espectral destes satélites. O primeiro artigo da tese é então um estudo inovador que permitiu superar limitações associadas à baixa resolução de sensores tradicionais de cor do oceano, como o MODIS ou o MERIS, especialmente em corpos de água de pequena dimensão. Os resultados demonstram que é possível estimar com precisão a concentração média de Chl-a em lagos de diferentes estados tróficos, com coeficientes de determinação (R^2) superiores a 0.5 em lagos eutróficos. A metodologia adotada envolveu a calibração de modelos empíricos e semi-empíricos de regressão linear multivariada, utilizando bandas espectrais visíveis e infravermelhas dos sensores Landsat, bem como índices espectrais conhecidos como o NDCI

(Normalized Difference Chlorophyll Index) e o BRG (Blue-Red-Green index). Estes modelos foram validados com dados de campo recolhidos em lagos da Finlândia, abrangendo diferentes estados tróficos, condições óticas e geofísicas. Os resultados demonstraram que os modelos baseados em dados Landsat conseguem estimar a concentração média de Chl-a com elevada precisão, especialmente em lagos eutróficos, onde a biomassa fitoplanctónica é mais elevada e, consequentemente, o sinal espectral é mais pronunciado.

Partindo desta base, o segundo artigo associado à tese consiste numa análise fenológica de longo-termo. Esta análise revelou tendências significativas no prolongamento da estação de crescimento do fitoplâncton, com início mais precoce das florações em vários lagos estudados. Estas alterações foram correlacionadas com padrões climáticos, nomeadamente o aumento da precipitação sob a forma de chuva em detrimento da neve, o que pode antecipar o escoamento superficial e a disponibilidade de nutrientes no início da primavera. Ou seja, o segundo artigo da tese revelou um aumento significativo na duração da estação de crescimento do fitoplâncton em três dos quatro lagos estudados, com destaque para o lago Köyliönjärvi, onde se verificou um aumento de 28 dias na duração da estação entre 1984 e 2017. Este prolongamento deve-se, sobretudo, a um início mais precoce das florações, associado a alterações nos padrões de precipitação e à diminuição da queda de neve, que afeta o escoamento e a disponibilidade de nutrientes no início da primavera. Curiosamente, não foram observadas tendências significativas na temperatura superficial da água, sugerindo que outros fatores, como o regime hidrológico e o uso do solo nas bacias hidrográficas, desempenham um papel crucial na dinâmica fitoplanctónica.

Para além da componente científica, a tese explora, no seu terceiro artigo, o papel das tecnologias de Observação da Terra na gestão ambiental e suas implicações políticas visto que a monitorização remota de ecossistemas aquáticos pode responder a pacotes legislativos de grande importância. Através da análise de políticas europeias, como o programa Copernicus e a iniciativa das Variáveis Climáticas Essenciais (ECVs), argumenta-se que a cor da água dos lagos deveria ser considerada uma variável climática operacional, à semelhança da cor do oceano. A inclusão de dados de satélites de alta e muito alta resolução, incluindo missões comerciais, é apontada como essencial para colmatar lacunas na monitorização de pequenos lagos e Áreas Marinhas Protegidas (AMPs), que são frequentemente ignoradas devido à sua dimensão reduzida. Estes dados sinóticos e de longo prazo são essenciais para a deteção de tendências e anomalias em ecossistemas aquáticos. A tese demonstra a crescente importância da Observação da Terra na formulação de estratégias de gestão ambiental e na avaliação do cumprimento de metas globais, como os Objetivos de Desenvolvimento Sustentável (ODS) e o Quadro Global de Biodiversidade de Kunming-Montreal. A tese também aborda os desafios associados ao acesso a dados de satélite de alta resolução, muitas vezes restringidos por questões de segurança ou direitos de propriedade. Propõe-se a criação de séries temporais derivadas de imagens de satélite privadas, com base em produtos derivados e não nas imagens originais, como forma de contornar estas limitações e promover a ciência aberta. Esta abordagem permitiria a criação de indicadores ambientais de alta resolução espacial, fundamentais para a gestão adaptativa de ecossistemas vulneráveis. A tese sublinha ainda a importância de uma abordagem interdisciplinar na gestão de ecossistemas aquáticos, integrando dados de EO, modelos ecológicos, variáveis climáticas e informações socioeconómicas. Esta integração é essencial para compreender a complexidade dos processos ecológicos e para apoiar decisões de gestão baseadas em evidência científica.

No contexto das AMPs, destaca-se a importância da monitorização da qualidade da água, da deteção de florações algais nocivas e da avaliação da saúde dos habitats bentónicos, como pradarias marinhas e recifes de coral. Embora a maioria dos estudos sobre AMPs com dados de satélite se concentre na deteção de embarcações e na fiscalização de atividades ilegais, a tese argumenta que a monitorização ambiental deve ser igualmente priorizada. A utilização de sensores óticos de alta resolução pode fornecer informações valiosas sobre a distribuição de clorofila, turbidez e matéria orgânica dissolvida, contribuindo para uma gestão mais eficaz e baseada em ecossistemas.

Outro contributo relevante desta investigação é a proposta de algoritmos regionais para a estimativa de Chl-a em lagos de altas latitudes, tendo em conta as características óticas específicas destas águas, como a elevada concentração de matéria orgânica dissolvida (CDOM) e a variabilidade na turbidez. A análise da importância relativa das bandas espectrais e de índices como o NDCI e o BRG permitiu otimizar os modelos e identificar as combinações mais eficazes para diferentes condições tróficas.

A tese traz à luz outros fatores metodológicos como a viabilidade de utilizar plataformas de computação em nuvem, como o Google Earth Engine, para processar grandes volumes de dados de satélite e gerar produtos ambientais de forma eficiente. Esta abordagem permitiu ultrapassar limitações computacionais e facilita a replicação dos métodos por outros investigadores e instituições como foi feito na pareceria com a Universidade de Helsínquia. A integração de dados de satélite com modelos estatísticos e dados climáticos auxiliares, como temperatura da superfície da água e precipitação, permitiu uma análise abrangente dos fatores que influenciam a fenologia do fitoplâncton.

Em termos de contributo científico, a tese fornece uma base sólida para o desenvolvimento de algoritmos regionais e locais de estimativa de Chl-a em lagos de altas latitudes, adaptados às condições óticas específicas destes ambientes. Os resultados obtidos podem ser utilizados para calibrar e validar produtos operacionais de satélite, bem como para informar políticas de gestão da água e conservação da biodiversidade. A abordagem proposta é escalável e pode ser aplicada a outras regiões do globo, contribuindo para uma monitorização global mais profunda e que incluiu habitats fulcrais para perceber como diferentes fatores antrópicos podem afetar estes importantes habitats marinhos.

Por fim, a tese sublinha a importância de considerar os lagos e as AMPs como sentinelas das alterações climáticas, dada a sua sensibilidade a mudanças na temperatura, precipitação e uso do solo. A monitorização contínua e de alta resolução destes ecossistemas é essencial para detetar alterações precoces, avaliar a eficácia de medidas de mitigação e adaptação, e garantir a sustentabilidade dos serviços ecossistémicos que prestam. A integração da Observação da Terra na gestão ambiental representa uma oportunidade única para alinhar a ciência, a política e a ação em prol da resiliência dos ecossistemas aquáticos num clima em mudança.

Em termos de implicações políticas, os resultados desta investigação reforçam a necessidade de políticas de acesso aberto a dados de satélite de alta resolução, especialmente para fins científicos e de monitorização ambiental. A proposta de criação de séries temporais derivadas de imagens de satélite comerciais, com salvaguardas de segurança e direitos de propriedade intelectual, é apresentada como uma solução viável para melhorar a cobertura e a frequência de observações em habitats sensíveis.

Conclui-se que a monitorização do fitoplâncton através de EO é uma ferramenta essencial para a gestão sustentável dos ecossistemas aquáticos num clima em mudança. A capacidade de detetar alterações na fenologia, na composição e na produtividade do fitoplâncton permite antecipar impactos ecológicos, orientar medidas de mitigação e adaptação, e contribuir para a conservação da biodiversidade aquática. A abordagem metodológica desenvolvida nesta tese pode ser replicada noutras regiões e adaptada a diferentes contextos ecológicos, contribuindo para o avanço do conhecimento científico e para a implementação de políticas ambientais mais eficazes.

Palavras-chave: Clorofila, Alterações Climáticas, Fenologia, Monitorização Ambiental, Deteção Remota

Summary

Phytoplankton play a fundamental role in regulating the global climate and sustaining life in aquatic ecosystems. These microscopic, photosynthetic organisms are responsible for approximately half of the planet's oxygen production and for the significant absorption of atmospheric carbon dioxide. However, climate change has profoundly altered the conditions of aquatic ecosystems, affecting the composition, distribution, and phenology of phytoplankton communities. This research focuses on monitoring phytoplankton as an indicator of climate variability, with a special emphasis on the concentration of Chlorophyll-a (Chl-a), a photosynthetic pigment widely used as a proxy for phytoplankton biomass.

The thesis proposes enhancing phytoplankton monitoring in regions particularly sensitive to climate change, such as boreal lakes, where seasonal thawing and other geophysical variations have a direct impact on primary productivity. Through the analysis of time series from satellite data and *in situ* samples, it was possible to model bloom patterns and identify changes in phytoplankton phenology over more than three decades. The thesis demonstrates that it's possible to use high-spatial-resolution satellite images that were not initially designed to detect Chlorophyll-a. The presented case refers to the use of satellites from the Landsat family (Landsat 5 and 7), with a spatial resolution of 30 meters, which allowed for the estimation of seasonal chlorophyll patterns in small lakes. However, this method has well-defined limitations due mainly to the low spectral resolution of these satellites. The first article in the thesis is an innovative study that overcame the limitations associated with the low resolution of traditional ocean color sensors, such as MODIS or MERIS, especially in small bodies of water. The results show that it is possible to accurately estimate the mean Chl-a concentration in lakes of different trophic states, with coefficients of determination (R^2) greater than 0.5 in eutrophic lakes. The adopted methodology involved the calibration of empirical and semi-empirical multivariate linear regression models using visible and infrared spectral bands from Landsat sensors, as well as spectral indices known as the NDCI (Normalized Difference Chlorophyll Index) and the BRG (Blue-Red-Green index). These models were validated with field data collected from lakes in Finland, covering different

trophic states, optical conditions, and geophysical characteristics. The results demonstrated that Landsat-based models can estimate the mean Chl-a concentration with high precision, especially in eutrophic lakes, where phytoplankton biomass is higher and, consequently, the spectral signal is more pronounced.

Building on this foundation, the second article associated with the thesis consists of a long-term phenological analysis. This analysis revealed significant trends in the lengthening of the phytoplankton growing season, with an earlier start to blooms in several of the studied lakes. These changes were correlated with climate patterns, specifically the increase in precipitation in the form of rain over snow, which can lead to an earlier surface runoff and nutrient availability in the early spring. In other words, the second article of the thesis revealed a significant increase in the duration of the phytoplankton growing season in three of the four lakes studied, with a notable increase of 28 days in Lake Köyliönjärvi between 1984 and 2017. This extension is primarily due to an earlier start of blooms, associated with changes in precipitation patterns and a decrease in snowfall, which affects runoff and nutrient availability in early spring. Interestingly, no significant trends were observed in water surface temperature, suggesting that other factors, such as the hydrological regime and land use in the watersheds, play a crucial role in phytoplankton dynamics.

In addition to the scientific component, the thesis's third article explores the role of Earth Observation technologies in environmental management and its political implications, as remote monitoring of aquatic ecosystems can help enforce important legislative packages. Through an analysis of European policies, such as the Copernicus program and the Essential Climate Variables (ECVs) initiative, it is argued that lake water color should be considered an operational climate variable, similar to ocean color. The inclusion of data from high and very high-resolution satellites, including commercial missions, is highlighted as essential for filling gaps in the monitoring of small lakes and Marine Protected Areas (MPAs), which are often overlooked due to their small size. This synoptic and long-term data is essential for detecting trends and anomalies in aquatic ecosystems. The thesis demonstrates the growing importance of Earth Observation in formulating environmental management strategies and assessing compliance with global goals, such as the Sustainable Development Goals (SDGs) and the Kunming-Montreal Global Biodiversity Framework. The thesis also addresses the challenges associated with accessing high-resolution satellite data, which is often restricted by security concerns or property rights. It proposes the creation of time series derived from private satellite images, based on derived products rather than original images, as a way to circumvent these limitations and promote open science. This approach would allow for the creation of high-spatial-resolution environmental indicators, which are fundamental for the adaptive management of vulnerable ecosystems. The thesis also underscores the importance of an interdisciplinary approach to aquatic ecosystem management, integrating EO data, ecological models, climate variables, and socioeconomic information. This integration is essential for understanding the complexity of ecological processes and supporting management decisions based on scientific evidence.

Within the context of MPAs, the importance of monitoring water quality, detecting harmful algal blooms, and assessing the health of benthic habitats, such as seagrass meadows and coral reefs, is highlighted. Although most studies on MPAs using satellite data focus on detecting vessels and enforcing against illegal activities, the thesis argues that environmental monitoring should be equally prioritized. The use of high-resolution optical sensors can provide valuable information on the distribution of chlorophyll, turbidity, and dissolved organic matter, contributing to more effective and ecosystem-based management. Another relevant contribution of this research is the proposal of regional algorithms for estimating Chl-a in high-latitude lakes, considering the specific optical characteristics of these waters, such as the high concentration of dissolved organic matter (CDOM) and the variability in turbidity. The analysis of the relative importance of spectral bands and indices like NDCI and BRG allowed for the optimization of the models and the identification of the most effective combinations for different trophic conditions.

The thesis also sheds light on other methodological factors, such as the feasibility of using cloud computing platforms, like Google Earth Engine, to efficiently process large volumes of satellite data and generate environmental products. This approach overcame computational limitations and facilitated the replication of the methods by other researchers and institutions, as was done in the partnership with the University of Helsinki. The integration of satellite data with statistical models and auxiliary climate data, such as water surface temperature and precipitation, allowed for a comprehensive analysis of the factors influencing phytoplankton phenology.

In terms of scientific contribution, the thesis provides a solid basis for the development of regional and local algorithms for estimating Chl-a in high-latitude lakes, adapted to the specific optical conditions of these environments. The results obtained can be used to calibrate and validate operational satellite products, as well as to inform water management and biodiversity conservation policies. The proposed approach is scalable and can be applied to other regions of the globe, contributing to more in-depth global monitoring that includes key habitats for understanding how different anthropogenic factors can affect these important marine habitats.

Finally, the thesis emphasizes the importance of considering lakes and MPAs as sentinels of climate change, given their sensitivity to changes in temperature, precipitation, and land use. Continuous, high-resolution monitoring of these ecosystems is essential for detecting early changes, assessing the effectiveness of mitigation and adaptation measures, and ensuring the sustainability of the ecosystem services they provide. The integration of Earth Observation into environmental management represents a unique opportunity to align science, policy, and action to promote the resilience of aquatic ecosystems in a changing climate. In terms of political implications, the results of this research reinforce the need for open-access policies for high-resolution satellite data, especially for scientific and environmental monitoring purposes. The proposal to create time series derived from commercial satellite images, with safeguards for security and intellectual property rights, is presented as a viable solution to improve the coverage and frequency of observations in sensitive habitats.

We conlude that monitoring phytoplankton through EO is an essential tool for the sustainable management of aquatic ecosystems in a changing climate. The ability to detect changes in

the phenology, composition, and productivity of phytoplankton allows for the anticipation of ecological impacts, guides mitigation and adaptation measures, and contributes to the conservation of aquatic biodiversity. The methodological approach developed in this thesis can be replicated in other regions and adapted to different ecological contexts, contributing to the advancement of scientific knowledge and the implementation of more effective environmental policies.

Keywords: Chlorophyll, Climate Change, Phenology, Environmental Monitoring, Remote Sensing

Yhteenveto

Kasviplanktonilla on keskeinen rooli globaalin ilmaston säätelyssä ja vesiekosysteemien elämän ylläpitämisessä. Nämä mikroskooppiset, fotosynteesiä harjoittavat organismit vastaavat noin puolesta maapallon hapentuotannosta ja merkittävästä osasta ilmakehän hiilidioksidin sitomisesta. Ilmastonmuutos on kuitenkin muuttanut syvällisesti vesiekosysteemien olosuhteita, vaikuttaen kasviplanktonyhteisöjen koostumukseen, jakautumiseen ja fenologiaan. Tämä tutkimustyö keskittyy kasviplanktonin seurantaan ilmastonmuutoksen indikaattorina, erityisesti keskittyen klorofylli-a (Chl-a) -pitoisuuteen, fotosynteettiseen pigmenttiin, jota käytetään laajalti kasviplanktonin biomassan välittäjänä.

Väitöskirjassa ehdotetaan kasviplanktonin seurannan tehostamista alueilla, jotka ovat erityisen herkkiä ilmastonmuutokselle, kuten boreaalisilla järvillä, joissa vuodenaikojen sulaminen ja muut geofysikaaliset vaihtelut vaikuttavat suoraan perustuotantoon. Satelliittitietojen aikasarjojen ja in situ -näytteenoton analyysin avulla oli mahdollista mallintaa kukintojen malleja ja tunnistaa muutoksia kasviplanktonin fenologiassa yli kolmen vuosikymmenen ajan. Väitöskirjassa osoitetaan, että on mahdollista käyttää korkean spatiaalisen resoluution satelliittikuvia, joita ei alun perin suunniteltu klorofylli-a:n havaitsemiseen. Esitetty tapaus viittaa Landsat-perheen satelliittien (Landsat 5 ja 7) käyttöön, joiden spatiaalinen resoluutio on 30 metriä. Niillä oli mahdollista arvioida klorofyllin vuodenaikaisvaihteluita pienissä järvissä – kuitenkin selkeillä rajoituksilla, jotka johtuivat pääasiassa näiden satelliittien matalasta spektraalireesoluutiosta. Väitöskirjan ensimmäinen artikkeli on siten innovatiivinen tutkimus, joka onnistui ylittämään perinteisten valtameren värisensorien, kuten MODISin tai MERISin, matalaan resoluutioon liittyvät rajoitukset erityisesti pienissä vesistöissä. Tulokset osoittavat, että Chl-a:n keskipitoisuus voidaan arvioida tarkasti eri trofisten tilojen järvissä, ja määrityskertoimet (R^2) ovat yli 0,5 rehevöityneissä järvissä. Käytetty metodologia sisälsi empiiristen ja puoli-empiiristen monimuuttuja-lineaariregressiomallien kalibroinnin käyttäen Landsat-sensorien näkyviä ja infrapunaspektrin kaistoja sekä tunnettuja spektri-indeksejä, kuten NDCI (Normalized Difference Chlorophyll Index) ja BRG (Blue-Red-Green index). Nämä mallit validoitiin

kenttätiedoilla, jotka kerättiin Suomen järvistä ja jotka kattoivat eri trofisia tiloja, optisia ja geofysikaalisia olosuhteita. Tulokset osoittivat, että Landsat-tietoihin perustuvat mallit voivat arvioida Chl-a:n keskipitoisuuden erittäin tarkasti, erityisesti rehevöityneissä järvissä, joissa kasviplanktonin biomassa on korkeampi ja siten spektri-signaali on voimakkaampi.

Tämän pohjalta väitöskirjan toinen artikkeli koostuu pitkäaikaisesta fenologisesta analyysistä. Tämä analyysi paljasti merkittäviä suuntauksia kasviplanktonin kasvukauden pidentymisessä, ja kukinnat alkoivat aikaisemmin useissa tutkituissa järvissä. Nämä muutokset korreloivat ilmasto-olojen kanssa, erityisesti sateen lisääntymisen kanssa lumen sijaan, mikä voi aikaistaa pintavaluntaa ja ravinteiden saatavuutta alkukeväästä. Toisin sanoen väitöskirjan toinen artikkeli paljasti kasviplanktonin kasvukauden merkittävän pidentymisen kolmessa neljästä tutkitusta järvestä, erityisesti Köyliönjärvessä, jossa kauden kesto piteni 28 päivällä vuosina 1984–2017. Tämä pidentyminen johtuu pääasiassa kukintojen aikaisemmasta alkamisesta, mikä liittyy sateen muutoksiin ja lumisateen vähenemiseen, joka vaikuttaa valuntaan ja ravinteiden saatavuuteen alkukeväästä. Mielenkiintoista on, ettei merkittäviä suuntauksia veden pintalämpötilassa havaittu, mikä viittaa siihen, että muut tekijät, kuten hydrologinen järjestelmä ja valuma-alueiden maankäyttö, ovat ratkaisevassa roolissa kasviplanktonin dynamiikassa.

Tieteellisen osuuden lisäksi väitöskirja tarkastelee kolmannessa artikkelissaan kaukokartoitusteknologioiden roolia ympäristöhallinnossa ja niiden poliittisia vaikutuksia, sillä vesiekosysteemien etäseuranta voi vastata erittäin tärkeisiin lainsäädäntöpaketteihin. Eurooppalaisten politiikkojen, kuten Copernicus-ohjelman ja Essential Climate Variables (ECVs) -aloitteen, analyysin kautta väitetään, että järvien veden väri tulisi ottaa huomioon operatiivisena ilmastomuuttujana, samaan tapaan kuin valtameren väri. Korkea- ja erittäin korkean resoluution satelliittitietojen, mukaan lukien kaupallisten missioiden, sisällyttäminen mainitaan olennaisena pienten järvien ja merellisten suojelualueiden (MPA) seurannan puutteiden korjaamiseksi, jotka usein jätetään huomiotta niiden pienen koon vuoksi. Nämä synoptiset ja pitkäaikaiset tiedot ovat välttämättömiä trendien ja poikkeamien havaitsemiseksi vesiekosysteemeissä. Väitöskirja osoittaa kaukokartoituksen kasvavan merkityksen ympäristöhallintastrategioiden laatimisessa ja globaalien tavoitteiden, kuten kestävän kehityksen tavoitteiden (SDG) ja Kunming-Montrealin globaalin biodiversiteettikehyksen, noudattamisen arvioinnissa. Väitöskirja käsittelee myös korkearesoluutioisten satelliittitietojen saatavuuteen liittyviä haasteita, joita usein rajoittavat turvallisuuskysymykset tai omistusoikeudet. Ehdotetaan yksityisistä satelliittikuvista johdettujen aikasarjojen luomista, jotka perustuvat johdettuihin tuotteisiin eikä alkuperäisiin kuviin, tapana kiertää nämä rajoitukset ja edistää avointa tiedettä. Tämä lähestymistapa mahdollistaisi korkean spatiaalisen resoluution ympäristöindikaattoreiden luomisen, jotka ovat olennaisia haavoittuvien ekosysteemien adaptiiviseen hallintaan. Väitöskirja korostaa myös monitieteisen lähestymistavan merkitystä vesiekosysteemien hallinnassa, integroimalla kaukokartoitustietoja, ekologisia malleja, ilmastomuuttujia ja sosioekonomisia tietoja. Tämä integrointi on välttämätöntä ekologisten prosessien monimutkaisuuden ymmärtämiseksi ja tieteelliseen näyttöön perustuvien hallintapäätösten tukemiseksi.

Merellisillä suojelualueilla korostetaan vedenlaadun seurannan, haitallisten leväkukintojen havaitsemisen ja pohjaeloisympäristöjen, kuten meriruohoniittyjen ja koralliriuttojen, terveyden arvioinnin tärkeyttä. Vaikka useimmat merellisten suojelualueiden satelliittitietoja koskevat tutkimukset keskittyvät alusten havaitsemiseen ja laittoman toiminnan valvontaan, väitöskirjassa väitetään, että ympäristöseurantaan tulisi kiinnittää yhtä paljon huomiota. Korkearesoluutioisten optisten anturien käyttö voi tarjota arvokasta tietoa klorofyllin, sameuden ja liuenneen orgaanisen aineksen jakautumisesta, mikä edistää tehokkaampaa ja ekosysteemipohjaisempaa hallintaa.

Toinen tämän tutkimuksen olennainen panos on alueellisten algoritmien ehdotus Chl-a:n arvioimiseksi korkeilla leveysasteilla sijaitsevissa järvissä, ottaen huomioon näiden vesien erityiset optiset ominaisuudet, kuten korkea liuenneen orgaanisen aineksen (CDOM) pitoisuus ja sameuden vaihtelu. Spektrikaistojen ja indeksien, kuten NDCI:n ja BRG:n, suhteellisen merkityksen analyysi mahdollisti mallien optimoinnin ja tehokkaimpien yhdistelmien tunnistamisen eri trofisissa olosuhteissa.

Väitöskirja tuo esiin muita metodologisia tekijöitä, kuten pilvilaskentaympäristöjen, kuten Google Earth Enginen, käytettävyyden suurten satelliittitietomäärien käsittelyyn ja ympäristötuotteiden tehokkaaseen luomiseen. Tämä lähestymistapa on mahdollistanut laskennallisten rajoitusten ylittämisen ja helpottaa menetelmien toistettavuutta muiden tutkijoiden ja instituutioiden, kuten Helsingin yliopiston kanssa tehdyn kumppanuuden, toimesta. Satelliittitietojen integrointi tilastollisten mallien ja muiden ilmastotietojen, kuten veden pintalämpötilan ja sademäärän, kanssa on mahdollistanut kattavan analyysin kasviplanktonin fenologiaan vaikuttavista tekijöistä.

Tieteellisen panoksen osalta väitöskirja tarjoaa vankan perustan alueellisten ja paikallisten Chl-a-estimointialgoritmien kehittämiselle korkeiden leveysasteiden järvissä, mukautettuna näiden ympäristöjen erityisiin optisiin olosuhteisiin. Saadut tulokset voidaan hyödyntää operatiivisten satelliittituotteiden kalibroinnissa ja validoinnissa sekä vesihuoltopolitiikan ja biologisen monimuotoisuuden suojelun tiedottamisessa. Ehdotettu lähestymistapa on skaalautuva ja sitä voidaan soveltaa muille globaaleille alueille, mikä edistää syvempää maailmanlaajuista seurantaa, joka sisältää kriittisiä elinympäristöjä, jotta voidaan ymmärtää, miten erilaiset antropogeeniset tekijät voivat vaikuttaa näihin tärkeisiin merellisiin elinympäristöihin.

Lopuksi väitöskirjassa korostetaan järvien ja merellisten suojelualueiden merkitystä ilmastonmuutoksen ilmaisijoina, koska ne ovat herkkiä lämpötilan, sademäärän ja maankäytön muutoksille. Näiden ekosysteemien jatkuva ja korkearesoluutioinen seuranta on välttämätöntä varhaisten muutosten havaitsemiseksi, lieventämis- ja sopeutumistoimenpiteiden tehokkuuden arvioimiseksi ja niiden tarjoamien ekosysteemipalvelujen kestävyyden varmistamiseksi. Kaukokartoituksen integrointi ympäristöhallintaan tarjoaa ainutlaatuisen mahdollisuuden yhdistää tiede, politiikka ja toiminta vesiekosysteemien kestävyyden puolesta muuttuvassa ilmastossa.

Poliittisten vaikutusten osalta tämän tutkimuksen tulokset vahvistavat korkearesoluutioisten satelliittitietojen avoimen pääsyn politiikkojen tarvetta, erityisesti tieteellisiin ja ympäristönseurantatarkoituksiin. Ehdotus kaupallisten satelliittikuvien johdannaisten

aikasarjojen luomisesta, turvallisuus- ja immateriaalioikeussuojausten kera, esitetään elinkelpoisena ratkaisuna herkkien elinympäristöjen havaintojen kattavuuden ja tiheyden parantamiseksi.

Yhteenvetona voidaan todeta, että kasviplanktonin seuranta kaukokartoituksen avulla on olennainen työkalu vesiekosysteemien kestävään hallintaan muuttuvassa ilmastossa. Kyky havaita muutoksia kasviplanktonin fenologiassa, koostumuksessa ja tuottavuudessa mahdollistaa ekologisten vaikutusten ennakoinnin, lieventämis- ja sopeutumistoimenpiteiden ohjaamisen ja vesistöjen biologisen monimuotoisuuden suojelun edistämisen. Tässä väitöskirjassa kehitetty metodologinen lähestymistapa voidaan toistaa muilla alueilla ja mukauttaa erilaisiin ekologisiin konteksteihin, mikä edistää tieteellisen tiedon kehittymistä ja tehokkaampien ympäristöpolitiikkojen toteuttamista.

Avainsanat: Klorofylli, Ilmastonmuutos, Fenologia, Ympäristön seuranta, Kaukokartoitus

Thesis motivation, objectives, and outline

- The satellite approach to Earth science is promising, full of applications and new capabilities.
- Observations from satellite data on climate change vary on topics ranging from the agreement between satellite missions on sea level rise to changes in ice covers and different biogeochemical variables.
- Lakes are sentinels of a climate in change. Changing small lakes across different scenarios is fundamental to better understand how climate change and other stressors are impacting these habitats and, in turn how these habitats respond to these changes.
- There is a data gap in terms of satellite imagery that currently does not allow for synoptic estimation of Chl-a in small lakes.
- Data retrieval and synergetic analysis between different earth observation datasets is fundamental for better use of ocean and lake colour data.
- Results show how these variations can bring light to quantify phenology changes.

This thesis was motivated by the need to better understand the performance of standard Chl-a satellite products. Phytoplankton represents the basis of aquatic food webs. Their dynamics may have significant implications in terms of fisheries, and they can be considered as indicators of ecosystem quality. Therefore, they are key elements to evaluate and monitor, both in short and long-term perspectives. The aim of this thesis was to evaluate the bottlenecks of satellite-based Chl-a estimation in the context of small water bodies, such as lakes. The work presented here, includes the conception of algorithms for Chl-a estimations in lakes and to apply those algorithms to spatial and temporal variability of phytoplankton across different lakes. The main objective was pursued by focusing on the following specific tasks:

①. Revise the portfolio of available missions to study small lakes.

②. Assess the role of Earth observation data in effective environmental monitoring and on the creation of environmental variables.
③. Use a specific region to test a new approach on the estimation of Chl-a in high-latitude lakes
④. Conceive regional algorithms for the estimation of Chl-a
⑤. Evaluate temporal shifts of phytoplankton phenology in the selected regions, based on satellite-derived Chl-a estimations.
⑥. Evaluate spatial patterns and shifts in phytoplankton phenology, assessed by satellite-based Chl-a estimations.

A schematic representation of the thesis organization is presented in Figure 1. The thesis is organized in 6 Chapters. Chapter 1 includes a general introduction to provide the reader the background and necessary context to understand the work described in the following chapters. Basis of ocean-colour and phytoplankton knowledge are provided and its relationship with climate change. We also provide a characterization of the study areas. In Chapter 2 we review the currently available satellite data to study aquatic scenarios that are currently uncovered by systematic monitoring from space. Chapter 3 uses the case of high latitude lakes unveil detection levels of phytoplankton monitoring with satellites the Landsat satellites, a family of satellites that was not originally suited to estimate water quality parameters. In this chapter we also assess the spatial variability across many different lakes over a vast region. Chapter 4 uses the methods developed in chapter 3 to unveil the first temporal patterns of phytoplankton phenology over such a wide study area. An overall discussion on the role of Earth observation for monitoring specific habitat is given in chapter 5. Concluding remarks, as well as future perspectives are addressed in Chapter 6.

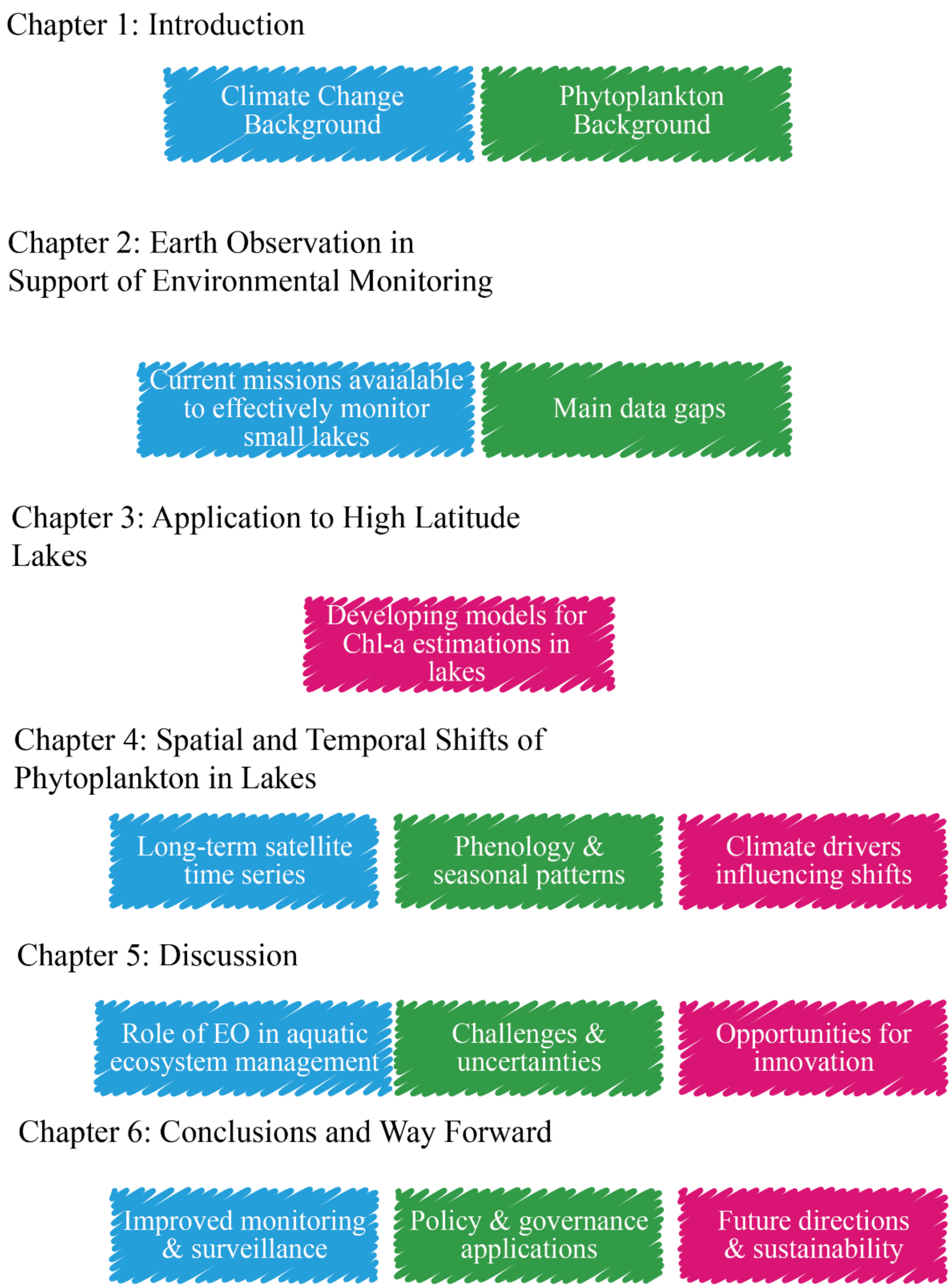


Figure 1 Schematics of thesis organization and investigated topics.

Chapter 1. Introduction

1.1. The History of Life on Earth: The Role of Phytoplankton

The history of life on Earth is a story of intricate interdependencies and evolutionary milestones, spanning over 4.5 billion years. Among the myriads of life forms that have shaped our planet's biosphere, phytoplankton—tiny photosynthetic organisms inhabiting the ocean—hold a particularly crucial role. These microscopic marvels have not only driven key processes that sustain marine ecosystems but have also significantly influenced Earth's atmosphere, climate, and the evolutionary trajectory of other life forms.

1.1.1. The Emergence of Life and Early Photosynthesis

Life is believed to have originated around 3.5 to 4 billion years ago in Earth's primordial oceans (Bada, 2004). The earliest life forms were likely simple, anaerobic microorganisms. Among these, cyanobacteria (formerly known as blue-green algae) stand out due to their revolutionary capability of oxygenic photosynthesis. By harnessing sunlight to convert carbon dioxide and water into organic matter and oxygen, cyanobacteria began a process that would alter the planet's atmosphere and biosphere fundamentally (Figure 2).

Phytoplankton, including cyanobacteria, are the descendants of these early photosynthetic pioneers. Their existence dates to these ancient times, contributing to what is known as the Great Oxygenation Event (GOE) around 2.4 billion years ago (Margulis and Sagan, 2023). Although the exact mechanisms that triggered this event are still being unveiled (Sessions et al., 2009; Olejarz et al., 2021), the proliferation of photosynthetic organisms led to a dramatic increase in atmospheric oxygen levels, setting the stage for the evolution of aerobic (oxygen-dependent) life forms.

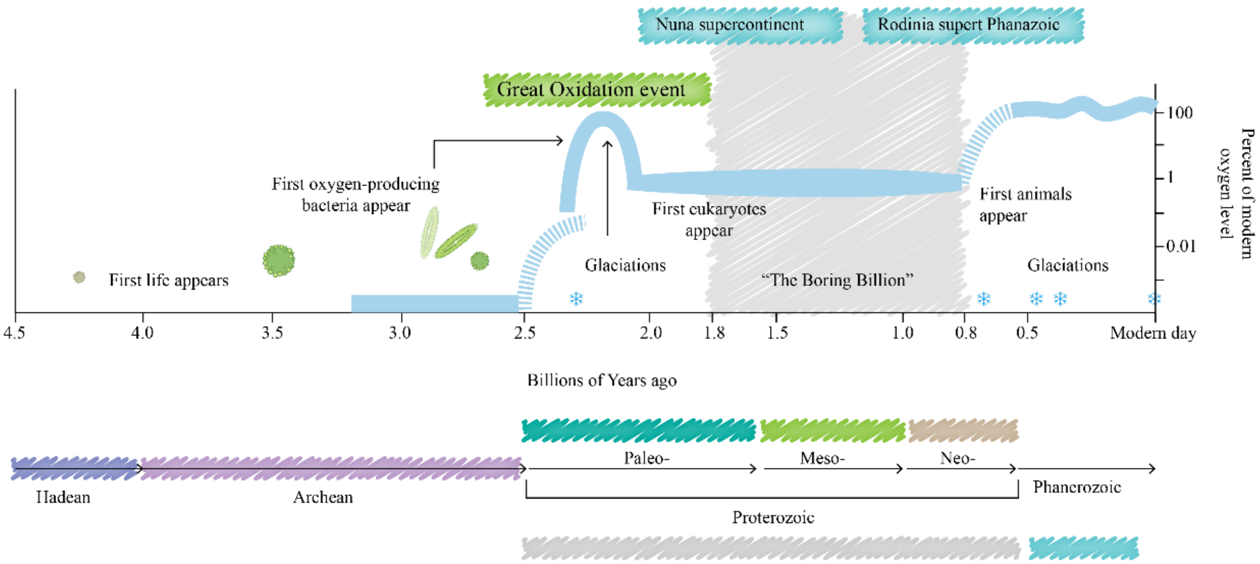


Figure 2 Emergence of life and early photosynthesis. The first oxygen-producing bacteria, known as blue-green algae, were responsible for the so-called Great Oxygenation Event.

1.1.2. Phytoplankton and the Marine Ecosystem

Phytoplankton are the foundation of the marine food web. These tiny, photosynthetic organisms include various taxa such as diatoms, dinoflagellates, and coccolithophores. They float near the ocean surface, where sunlight penetrates, and perform photosynthesis, producing organic compounds from carbon dioxide and sunlight. This process not only fuels their own growth but also sustains a vast array of marine life (Figure 3).

As primary producers, phytoplankton form the base of the food chain, supporting organisms ranging from microscopic zooplankton to large fish and whales. Zooplankton graze directly on phytoplankton, small fish consume zooplankton, and larger predators feed on those fish, creating a complex, interconnected trophic network (Falkowski, 2012; Behrenfeld and Boss, 2014a).

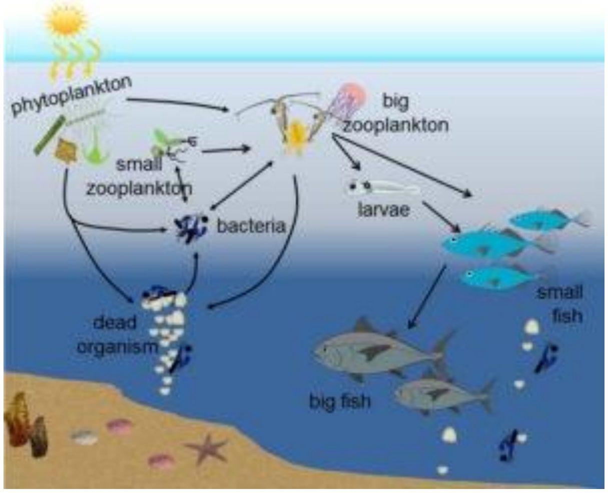


Figure 3 Simplified diagram of the role of phytoplankton in marine ecology.

Beyond their ecological role, phytoplankton are central to biogeochemical cycling. When phytoplankton die, many cells sink to the seafloor, contributing to the marine sediment. This process, known as the biological pump, helps sequester carbon dioxide from the atmosphere, thereby mitigating climate change (Reichle, 2023). Their decomposition also regenerates nutrients, sustaining further primary production and maintaining the balance of marine ecosystems (Turekian and Holland, 2014).

1.1.3. Phytoplankton and Climate Regulation

Phytoplankton play a significant role in regulating Earth's climate. Through photosynthesis, they absorb carbon dioxide, a greenhouse gas, from the atmosphere. This not only reduces the amount of carbon dioxide but also generates oxygen, which is essential for most life forms on Earth. It is estimated that phytoplankton are responsible for producing about 50% of the world's oxygen, a testament to their importance in maintaining atmospheric balance (Field et al., 1998a).

Moreover, phytoplankton influence cloud formation. Some species produce dimethyl sulphide (DMS), a compound that, when released into the atmosphere, can lead to the formation of sulphate aerosols. These aerosols act as cloud condensation nuclei, promoting cloud formation and increasing cloud albedo (Mayer et al., 2020). Enhanced cloud cover can reflect more sunlight back into space, cooling the Earth's surface and potentially offsetting some warming caused by greenhouse gases.

1.1.4. Evolutionary Impact

The evolutionary significance of phytoplankton extends beyond their ecological and climatic roles. The oxygenation of Earth's atmosphere, driven by ancient photosynthetic organisms, enabled the evolution of complex aerobic life. The rise in oxygen levels allowed for the development of larger and more energy-demanding organisms, leading to the Cambrian Explosion approximately 541 million years ago, when most major animal phyla appeared (Conway Morris, 2006;Briggs, 2015;Darroch et al., 2018).

Phytoplankton themselves have evolved and diversified over millions of years, adapting to changes in the environment. Their ability to photosynthesize, fix carbon, and influence nutrient cycles has been a cornerstone of marine evolution. The evolution of different phytoplankton groups, such as diatoms with their silica cell walls, has further diversified marine life by providing various niches and food sources.

1.1.5. Phytoplankton in Freshwater Ecosystems

While much attention is given to marine phytoplankton, their freshwater counterparts play equally crucial roles in lake ecosystems. Phytoplankton in lakes, which includes in abundance green algae, cyanobacteria, and diatoms, perform similar functions as their marine relatives (Borics et al., 2021). They are the primary producers in these ecosystems, forming the base of the food web and supporting a range of aquatic organisms, from microscopic zooplankton to fish (Williams et al., 2003;Striebel et al., 2009). In lakes, phytoplankton contribute to nutrient cycling by absorbing nutrients like nitrogen and phosphorus from the water. Their growth is influenced by nutrient availability, light conditions, and temperature. The death and decomposition of phytoplankton in lakes also contribute to the nutrient dynamics and may lead to phenomena such as seasonal algal blooms (Rolland et al., 2009).

In sum, phytoplankton, though microscopic, have played and continue to play a fundamental role in shaping the history of life on Earth. From their ancient beginnings as some of the earliest life forms, they have driven oxygenation, supported aquatic food webs, and regulated the climate. Their influence on both the evolution of life and the maintenance of Earth's biosphere underscores their importance. As we face unprecedented environmental changes within a very short time scale (Lenton et al., 2019), protecting and understanding phytoplankton become ever more critical to ensure the health and stability of our planet. These tiny but mighty organisms play crucial roles in sustaining life on Earth, in both marine and freshwater ecosystems, hence it is important to understand their role in Effective climate change mitigation as well as their adaptation strategies to a rapid changing environment (Acevedo-Trejos et al., 2014;.Deppeler and Davidson, 2017;Henson et al., 2021)

1.2. A Climate in Change: The Role of Phytoplankton

Today, phytoplankton continue to be vital for the health of our planet, but their biomass and taxonomic composition may be increasingly threatened by the impacts of climate change. Rising global temperatures, ocean and freshwater acidification, and pollution pose significant challenges to the equilibrium of present-day phytoplankton communities and their ability to perform critical ecological functions.

1.2.1. Temperature and Stratification

Climate change is causing sea and freshwater temperatures to rise, which can disrupt the delicate balance of phytoplankton growth. Warmer waters can lead to increased stratification of the ocean and lakes, where the water layers do not mix well. This stratification is known to limit the availability of nutrients from deeper waters, which are essential for phytoplankton growth, potentially leading to reduced primary productivity in some regions (Doney, 2006).

1.2.2. Ocean and Freshwater Acidification

As atmospheric carbon dioxide levels rise, more CO2 is absorbed by the oceans and freshwater bodies, leading to acidification. This change in pH can affect the ability of certain phytoplankton, particularly those with calcium carbonate shells like coccolithophores, to maintain their structures. Acidification can impair these organisms' growth and survival, altering the composition of phytoplankton communities and the broader aquatic food web.

1.2.3. Shifts in Distribution and Blooms

Changes in temperature and chemistry can cause shifts in the relative distribution of phytoplankton species. Some species may thrive and expand their range, while others may decline or be displaced. Additionally, harmful algal blooms (HABs), which are often toxic, may become more frequent and widespread due to warmer temperatures and nutrient runoff from agriculture and urbanization. These blooms can have devastating effects on marine and freshwater life, human health, and local economies.

1.2.4. The Future of Phytoplankton and Climate Mitigation

Phytoplankton's role in carbon sequestration and oxygen production makes studying and monitoring it crucial in combating climate change. Protecting phytoplankton requires a multi-faceted approach that includes:

1. Reducing Carbon Emissions: Phytoplankton are crucial to aquatic food webs and global ecosystems. Their populations fluctuate with temperature, water mixing, resources, and grazing. Climate change alters these factors, impacting phytoplankton structure, seasonality, and composition. Climate directly affects phytoplankton physiology and indirectly changes water stratification, resource availability (nutrients and light), and grazing. These changes affect phytoplankton processes, leading to observed shifts in bloom timing and magnitude. Climate warming also alters phytoplankton species composition and size, favouring adaptable species. These phytoplankton shifts have significant ecosystem-wide consequences. Understanding the mechanisms linking climate and phytoplankton is vital for predicting climate change impacts on aquatic ecosystems (Winder and Sommer, 2012) Mitigating climate change by reducing greenhouse gas emissions is fundamental.

2. Monitoring and Research: Continuous monitoring of phytoplankton populations and health is essential. Advances in satellite technology and oceanographic and limnological research allow scientists to track changes in phytoplankton abundance and distribution, helping predict and mitigate the impacts of climate change (IOCCG, 2018).

3. Nutrient Management: Implementing better land-use practices to manage agricultural runoff and reduce nutrient pollution can prevent harmful algal blooms and maintain healthier marine and freshwater ecosystems. For example, eutrophication in the Baltic Sea is a complex issue with varying drivers depending on location. Coastal waters, especially those less connected to the open sea, are primarily driven by nutrient pollution (nitrogen or phosphorus depending on isolation). These ecosystems' health is tied to climatic factors like wind and salinity, and it is influenced by a mix of local runoff, sea ice, and even conditions in the open sea itself. This interconnectedness means that managing eutrophication requires a holistic approach, combining local land management with broader, whole-sea strategies, rather than just focusing on local pollution sources (Vigouroux et al., 2021).

4. Marine and Freshwater Protected Areas: Establishing and enforcing protected areas can safeguard critical habitats and promote biodiversity, which includes diverse and resilient phytoplankton communities. Furthermore, these areas are essential to understanding the natural equilibrium between the different trophic layers in contrasting geographical regions (Lisboa et al., 2024).

Phytoplankton in the World Ocean is responsible for cycling around 50GT of carbon per year, on a global scale (Longhurst, 1995) roughly half of the atmospheric carbon dioxide uptake (Field et al., 1998a). In the present scenario of atmospheric CO_2 increase, virtually all phytoplankton cells are subject to warmer and more acidic waters. Studying phytoplankton ecology and phenology is therefore of the utmost importance for the understanding of future climate variations. We propose strengthening phytoplankton monitoring in the perspective of a climate variability indicator, with a focus on freshwaters. Such datasets will be focused on regions where changes are occurring faster, mostly related with ice-melting and other geophysical seasonal variations. The creation of a platform of match-ups will allow us to study blooms anomalies and associated changes better. We will start by focusing on boreal lakes and seas using covariate analysis of historical data, based on *in situ* sampling and satellite estimates of Chl-a concentrations. This will allow us to model and observe shifting patterns of water systems primary production. Additionally, a tool for marine environmental management will result from the methodological approach of this research project.

1.2.5. The biogeochemical role of phytoplankton

Like much of climate change impacted environments, the oceans ought to be studied in a much valuable interdisciplinary way. Their threats vary from sea level rise, ocean warming, and ocean acidification. From the three, ocean acidification is one of the most warming effects as about one-third of atmospheric carbon dioxide dissolves straight into the sea — "the prospect of ocean acidification is potentially the most serious of all predicted outcomes of anthropogenic carbon dioxide increase" (Veron, 2008).

Phytoplankton provides the basis for oceanic food webs. Phytoplankton is responsible for fixing some 50 GT of carbon per annum globally (Longhurst, 1995; Field et al., 1998a). The process is supported by photosynthesis and known as primary production. The magnitude of ocean primary pro duction is comparable to the net production by terrestrial plants at the global scale (Longhurst et al., 1995). As emissions from fossil fuels are estimated to be 9.4 GT globally per annum (Le Quéré et al., 2018a), it is therefore very important to understand to which changes is phytoplankton subject to and how can these be impactful for the global carbon cycle.

But phytoplankton's role in the food web and biogeochemistry of the oceans vary as phytoplankton community composition is greatly dependent on environmental conditions. Many organisms like corals, shellfish, and crabs, are dependent on important calcium carbonate ($CaCO_3$), for example. Phytoplankton calcifiers (Coccolithophores) provide the necessary compound:

$Ca^{2+} + 2HCO_3 \longrightarrow CaCO_3 + H_2O + CO_2$

Nevertheless, as oceans become more acidic — more accurately less alkaline — free H+ ions compete with this reaction to form bicarbonate (HCO3-) making this the main mechanism for coral reef death around the globe. Furthermore, different types of phytoplankton impact differently on the fish species abundances. As an example, in the Benguela ecosystem, flagellates might favour the growth of sardines and diatoms might allow for the growth of anchovy (Cury et al., 2008) – the differences are supported by small or large copepods.

Other types of phytoplankton have important roles on the climate. Some phytoplankton types produce dimethylsulfoniopropionate (DMSP), a volatile organic compound precursor of dimethyl sulphide. The CLAW hypothesis (named after their authors – Robert J. Charlston, James E. Lovelock, Meinrat O. Andreae and Stephen G. Warren) proposes that the phytoplankton release DMSP is responsible for forming aerosols that seed clouds, increasing their reflectivity (Charlson et al., 1987). This increased cloud albedo then reflects more sunlight, potentially creating a negative feedback loop that cools the Earth. While some aspects are supported, the hypothesis remains subject to ongoing research and debate regarding its overall impact. According to the CLAW hypothesis, the major source of cloud condensation nuclei (CCN) is dimethyl sulphide which oxidises in the atmosphere to form a sulphate aerosol. Because the albedo of clouds (and thus the Earth's radiation budget) is sensitive to CCN density, biological regulation of the climate is possible through the effects of temperature and sunlight on phytoplankton population and dimethyl sulphide production (Charlson et al., 1987). According to the CLAW hypothesis, to counteract the warming due to a doubling of atmospheric CO_2, an approximate doubling of CCN would be needed.

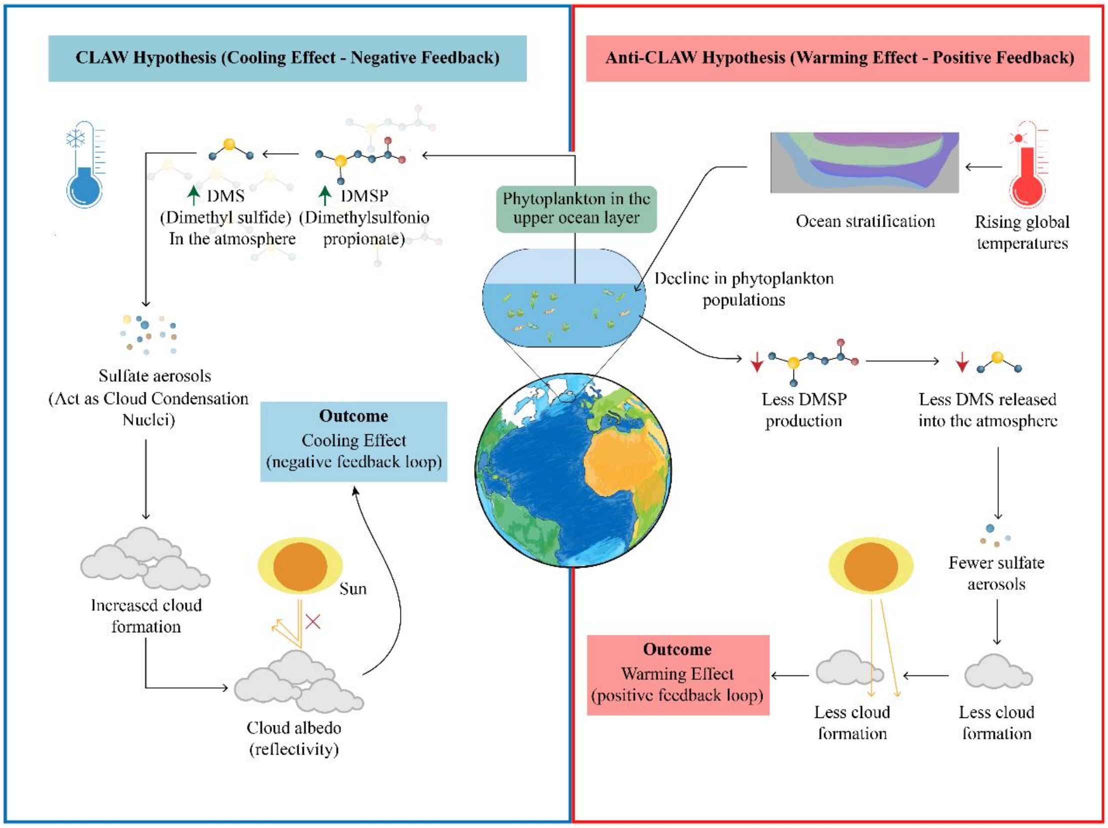


Figure 4 A diagram of the CLAW and anti-CLAW hypotheses and the central role of phytoplankton in both climate mechanisms.

In contrast with the CLAW hypothesis from the late 80s, James E. Lovelock (Lovelock, 2006) proposed a positive feedback hypothesis in which increased temperature increases stratification, diminishing the supply of nutrients to the surface waters and hence primary production and DMS production. Via this process, CCN concentration is lessened, and the climate would become warmer (Figure 4).

As briefly outlined, different phytoplankton taxonomic classes have many impactful factors on current concerns about the climate. In fact, they are a central piece of current concerns and discussions about Earth’s changing climate. But monitoring these small aquatic unicellular organisms is complicated. Most methodologies were purely biological but now, with the advantage of Earth-looking satellites, with better spectral and spatial resolution, studying phytoplankton can be done from space.

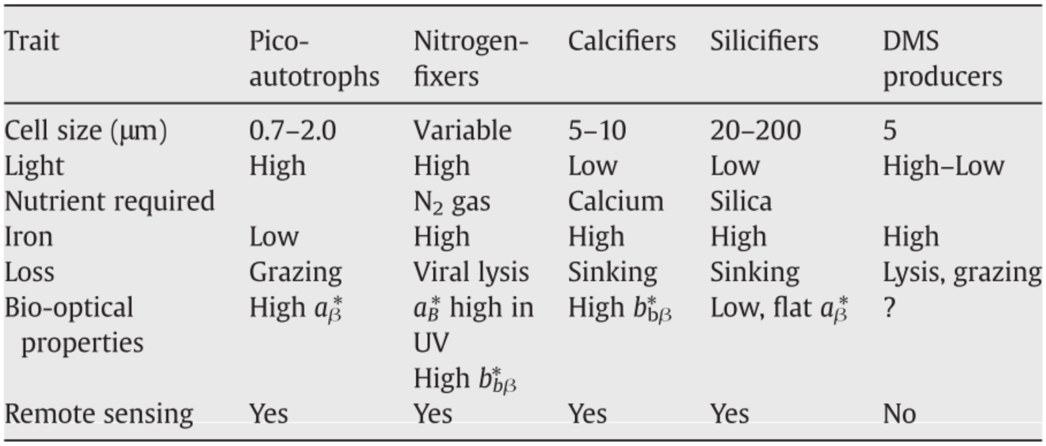
1.2.6. Different types of Phytoplankton

Most of the carbon dioxide released from fossil fuel combustion is either absorbed by terrestrial systems, sunk into the oceans or remain in the atmosphere as one of the most important anthropogenic greenhouse gases. According to estimates, 2.4 GT of CO_2 are absorbed by the oceans every year whereas 3.0 GT by land (Le Quéré et al., 2018) , and 4.45 GT stay in the atmosphere. In the evidence of a changing climate and due to the extreme urgency in the understanding of the carbon cycles — especially in such a large component as the oceans — oceanographers are growingly concerned about its importance for Earth's future energetic balance.

As stated before, space-borne sensors accurately detect phytoplankton biomass by means of the reflectance of cell pigments. The new challenge is to better detect which phytoplankton groups are present once a bloom is detected. The techniques have been initiated by functional type and size-class characterisation and partitioning. Examples were given before as the main function partitions are related to how these cells contribute to the biogeochemistry of the oceans — calcifiers, silicifiers, DMS production or nitrogen fixation. For the marine environment, the concept of Phytoplankton Functional Types is still under discussion, in fact, the definition and the number of functional types is adaptable to oceanic regions and aquatic systems. Nonetheless, this categorization by the geochemical process and cycles has proved of great value (Hood et al., 2006), especially when it comes useful to explore the potential for monitoring of PFT distribution globally using remote sensing of visible spectral radiometry (Nair et al., 2008).

Partitioning of phytoplankton size classes dates back to 1978 (Sieburth et al., 1978). The approach is to separate phytoplankton into the following size classes: picophytoplankton (0.2-2 µm), nanophytoplankton (2-20 µm), and micro phytoplankton (> 20 µm). The influence of size on phytoplankton physiology is well established (Platt and Jassby, 1976; Chisholm, 1992;Raven, 1998) and this approach can come of use in the assessment of some biogeochemical functions. For example, picophytoplankton can thrive in nutrient-limited conditions, the dominate oligotrophic waters and sink slowly. Micro phytoplankton is represented by diatoms and dinoflagellates; they dominate nutrient rich waters and are the main contributors to the sinking of carbon into deep waters. But dimethyl sulphide producers and calcifiers are together amongst nanophytoplankton size class (*vd.* Table 1). Furthermore, the two have a different effect regarding atmospheric carbon dioxide. While DMS producers can cause a negative feedback effect on temperature with carbon dioxide increase (as given by the CLAW hypothesis), change in alkalinity due to calcification enhances the increase of carbon dioxide release to the atmosphere.

Table 1 Proprieties of phytoplankton functional groups — from Le Quéré et al., 2005.

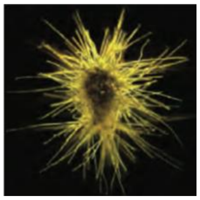
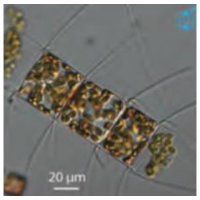
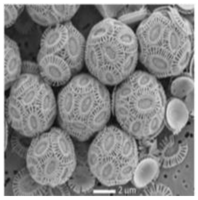


Trait	Pico-autotrophs	Nitrogen-fixers	Calcifiers	Silicifiers	DMS producers
Cell size (μm)	0.7–2.0	Variable	5–10	20–200	5
Light	High	High	Low	Low	High–Low
Nutrient required		N_2 gas	Calcium	Silica	
Iron	Low	High	High	High	High
Loss	Grazing	Viral lysis	Sinking	Sinking	Lysis, grazing
Bio-optical properties	High a_β^*	a_B^* high in UV High $b_{b\beta}^*$	High $b_{b\beta}^*$	Low, flat a_β^*	?
Remote sensing	Yes	Yes	Yes	Yes	No

For these and other reasons, the size-based approach is not always satisfactory as representative of the biogeochemical function. On the other hand, size does have an important role in the food webs. Pico- and nanoplankton increased growth led to greater gelatinous zooplankton like jellyfish (Parsons and Lalli, 2002). The links between size, weight, abundance, growth and metabolic rate, long recognised as the basis for the size spectra of pelagic organisms (Platt and Denman, 1977;Platt, 1978), are now known as the metabolic theory of ecology. A summary view of the phytoplankton functional types could be given here. The literature has been vast in identifying their roles in the biogeochemical process, in the food webs and specifically in the cycles that regulate Earth's climate — Nitrogen, Carbon, DMS.

Table 2 summarises the state-of-the-art for these many species of cells with the most important references so far.

Table 2 Table of Phytoplankton Functional Types

Functional Type	**Taxonomic group**	**Notes**
Nitrogen-fixers (eg. Trichodesmium) 	• diazotrophs	• *Trichodesmium* is the dominant nitrogen-fixer • Katagnymene sp. Occurs in open water oceans Zehr et al., 2000 • Cyanobacterial symbionts of certain open-ocean diatoms such as *Chaetoceros*, *Bacteriastrum*, and *Rhizosolenia* are capable of nitrogen fixation • Hemiaulus sp. contributes to 15% of the total nitrogen fixed in the Pacific ocean Fuhrman et al., 2001.
Silicifiers (e.g. Diatom Chaetocero)  	• Chrysophyta; • Silicoflagellates • Xanthophyta • Bacillariophyta Brownlee et al., 2002	• Diatoms (Bacillariophyta) are the dominant silicifiers in the marine ecosystem as they contribute to 40% of the total marine primary production (Sarthou et al., 2005) • Major organisms in spring blooms • Found in nutrient-rich waters • Diatoms sink fast due to silica-rich cell walls. The dense walls also protect them against zooplankton Smetacek, 2001
Calcifiers (eg. Emmiliania huxleyi) 	• Coccolithophores	• coccoliths external plates made of calcium carbonate; • calcium carbonate formation lowers the surface ocean carbonate concentration, reduces seawater alkalinity and produces carbon dioxide; • Can act like as a potential source of carbon dioxide Robertson et al., 1994; Rost et al., 2004

DMS producers (e.g. Neoceratium pentagonum) 	• Dinoflagellates • Haptophytes	• Contribute to $15x10^{12}$ to $33x10^{12}$ g per year of total atmospheric sulphur (Simó 2001) • They can impact climate regulation through the formation of cloud condensation nuclei • Acidic rain from DMS Liss et al., 1997 • Haptophytes such as *Emiliania huxleyi* and *Phaeocystis* sp. are known to form extensive blooms in several coastal and oceanic waters Tyrrell et al., 2004 • Since *E. huxleyi* is a coccolithophore as well, it is both a calcifier and a DMS producer. Phaeocystis blooms may represent extremely high values of carbon biomass: up to 10 mg C L^{-1} Schoemann et al., 2005.

Nonetheless, the aim of this doctoral thesis project is not to go into further details of the taxonomic identification of phytoplankton function types and their characterization but on new techniques for monitoring them from space, validating them with field measurements and correlate them with impacts to and from the environment on the food webs. For remote sensing, *in situ* observation must be “the truth” against which any algorithm is validated (IOCCG, 2014).

It is in this context that the scope of this research project is very up to date in terms of innovative research. Much is still to know on the contribution of each Phytoplankton Functional Type for carbon fluxes. By better identifying Functional Types from space, one will get further knowledge on how the oceans react to and respond from anthropogenic carbon emissions.

1.3. Seeing it all from Space

The first photo of Earth from space predates the Sputnik era by over a decade, captured in 1946 by a 35-mm camera aboard an American V-2 rocket that reached an altitude of 105 km, surpassing the Kármán line (White, 1952). This moment is arguably the inception of Earth

Observation, a field that gained prominence with the advent of the space race during the Cold War. The space race officially began with the launch of Sputnik in 1957, a seminal event that, despite its rudimentary payload, marked the dawn of Earth observation satellite technology and sparked the "Sputnik crisis," intensifying the military exploration of space in the United States (Wang, 2009)

Earth observation satellites provide critical data that help decision-makers manage the environment, understand and mitigate climate change impacts, and ensure civil security. This technology has evolved to support a range of applications, from environmental monitoring to the enforcement of human rights.

Satellites offer more than just scientific data for policymakers; they can also enhance governance by increasing transparency. The widespread availability of satellite imagery and the diffusion of remote sensing expertise contribute to global transparency, allowing the public to access and utilize satellite data (Baker and Williamson, 2006).

In the realm of human rights, satellites can offer visual evidence of violations, although challenges remain in ensuring accountability. In the Amazon, satellite imagery has been integrated into both governmental policies and civil society activism, becoming a vital part of the "knowledge infrastructure" essential for environmental protection (Oliveira and Siqueira, 2022) However, shifts towards restricted access to satellite data can hinder transparency and promote counter-activism. The effectiveness of governance related to climate issues significantly depends on the interplay between different institutions, all of which benefit from Earth observation data (Onoda and Young, 2017).

1.3.1. Earth observation and its impact on society

Earth observation provides a wealth of data that allows decision-makers to have access to reliable, timely and accurate information services to manage the environment, understand and mitigate the effects of climate change and ensure civil security.

The rapid advancement of Earth Observation technologies provides great value to human activities and decision making. Most global changes witnessed since the last centuries – like loss of biodiversity, increased pollution, and forest loss, among others – have three main characteristics: they are anthropic, they have an exponential nature and, thirdly, they are global. Because most of these changes are global it is paramount to have synoptic views of the Earth and that the systems involved can be quantitatively assessed. The knowledge involved in studying our planet from this perspective must be multidisciplinary and have a long-term perspective. Numerous efforts have been made for studying the Earth as an integrated ecosystem, with special focus on the Oceans (Schlesinger, 2006).

In fact, we currently face a new area of scientific development which, according to some authors, is akin to a second Copernican revolution. The Copernican revolution fundamentally changed our understanding of the cosmos by dethroning Earth from its central place in the Universe. Similarly, today's scientific and technological advances, particularly around climate and Earth system science, are revolutionizing how we view and manage our planet. Schellnhuber's idea emphasizes that in the face of global environmental crises, we need a new way of thinking and understanding Earth's complex systems, which he sees as akin to another Copernican-level transformation (Schellnhuber, 1999).

The creation of digital twins—virtual, high-resolution replicas of Earth's systems that also rely on Earth observation—represents a crucial part of this shift. These digital twins are expected to provide advanced modelling and predictive capabilities, allowing scientists to simulate various environmental scenarios and their impacts, offering deeper insights into climate change and its management. This new cognitive basis could indeed serve as the foundation for global sustainability efforts, much like the telescope did for the Copernican revolution in terms of astronomy.

In this view, the goal is not only to study Earth's processes but also to actively manage them in light of the Anthropocene, where human activity increasingly influences planetary systems. The analogy captures the profound transformation in both thought and practical approach needed to address our climate crisis. However, satellites are not only an instrument of delivering valuable science for policy makers. They can be valuable, for example, to pressure governance. The public now has more access than ever to satellite imagery and there is a global diffusion of remote sensing expertise. Those two factors create improved conditions for global transparency (Baker and Williamson, 2006).

In terms of human rights watching, the value of remote sensing in general and of Earth Observation in particular has been debated in the scientific literature. Satellites are amongst the information technologies that can provide visual evidence on the implementation of human rights, but they lack attention and capacity to ensure accountability. In the Amazon Forest, satellite imagery and derived deforestation data were incorporated in both governmental policies and civil society activism (Oliveira and Siqueira, 2022) making satellites an important part of “knowledge infrastructure”. Nevertheless, a different truth regime was documented in which a change in transparency, a shift from public data to restricted access, and the change from broad civil society usage of satellite information to a restricted access can promote counter-activism and tolerance towards deforestation (Oliveira and Siqueira, 2022).

Earth Observation data benefits from high societal standards of prestige and impartiality and often support a “knowledge regime” that is paramount for worldwide environment monitoring (Oliveira and Siqueira, 2022), with the Brazil’s example we encounter the same limitation as we will see throughout this thesis: the need of very high-resolution to monitor remote regions in the Amazon inevitably leads to the contracting of privately-owned data – see news report (Prizibisczki, 2020).

The usage of satellite data as an instrument of delivering valuable science to support policy making is not uncommon and it has been used at various levels. The Intergovernmental Panel on Climate Change uses a variety of satellite data in their assessment reports, the European Union relies on Copernicus data to monitor different environment, municipalities use satellite data to monitor and manage environmental resources. However, satellite data can also be valuable to pressure governance. The public now has more access than ever to satellite imagery, and there is a global diffusion of remote sensing expertise. Those two factors create improved conditions for global transparency (Baker and Williamson, 2006).

1.3.2. Earth observation data policies

Now-a-days Earth observation data is a paramount example of dual benefit for military and civil applications. Currently, most data policies related to Earth observation data entail some degrees of full, open and free access.

Some definitions should be clarified in this context:

- By “full” we mean the release of all data is available and not just part of it (although subject to some exceptions may apply regarding security or technical concerns)(Von der Dunk, 2021).
- “open” that it can be freely used, reused, linked and redistributed for commercial and non-commercial users
- “free” is specific to data being free of charge.

A previous study identified 21 policy statements for Earth observation data, identifying that most of the current policies abide for some type of free and open data access. Nonetheless, when all the exceptions are outlined across all these policy statements, the situations are extensive and potentially very restrictive. But, in most cases, the application of these restrictions is too broad to be applied (Baker and Williamson, 2006).

1.4. Ocean Colour

Ocean-colour research focuses on the study of a Chl-a as a biomass proxy for phytoplankton. It has begun with the proof-of-concept Coastal Zone Colour Scanner [CZCS] satellite mission. Since then, satellite data proved to be an indispensable way to provide synoptic views of the upper ocean optical proprieties with ever increasing spatial and temporal resolution. Although total biomass is soundly given by these satellite data, the new endeavour is to accurately identify phytoplankton functional types from space.

Given the fact that this work presents a methodological approach and accurate studies from the basis of ocean life dynamics, it represents an important advantage for future monitoring of the natural environment and its health assessment. Furthermore, changes in phytoplankton concentration and types are subject to anthropogenic pressures and their consequences are impactful on economic activities like fisheries and tourism.

As the primary pigment in phytoplankton, Chl-a has historically been regarded as a proxy for biomass in the water column or living terrestrial plants. Ocean colour has long been an invaluable tool for scientists to understand global and regional oceanographic events. In the 19th and early 20th centuries oceanographers were already using ocean colour as an indicator of water masses and, indirectly, ocean currents (Robinson, 2004). This was conducted through qualitative methods such as the Forel Scale (Forel, 1890), used to determine the colour of seawater, and the Secchi disk used to quantify the transparency of seawater (Secchi, 1866). In the 1960s and 1970s, the technological basis for marine applications of ocean-colour remote sensing began to emerge with airborne studies aimed at Chl-a detection (Clarke et al., 1970). During that period the fundamental theoretical basis for marine radiative transfer (Preisendorfer, 1961) and the relationship between spectral radiance or reflectance at the sea surface and phytoplankton pigments (Morel and Prieur, 1977) also emerged, and the first satellite sensor to monitor ocean colour was launched in 1978, by the American space agency (National Aeronautics and Space Admnistration - NASA). The Coastal Zone Colour Scanner (CZCS) was a proof-of-concept mission which flew aboard the Nimbus-7 satellite for the period 1978-86. During this period, the feasibility of ocean-colour satellite remote sensing was finally established (*e.g. Smith et al., 1982; Gordon et al., 1983)*. It had been proven that the radiance leaving a water body could be detected and quantified by a sensor put into orbit, and further quantitatively related to its Chl-a content. The main concepts and processes involved in the quantification of substances present in a water body through ocean-colour will be introduced in the following sections.

1.4.1. Electromagnetic radiation and optical properties

Electromagnetic radiation is made up of a continuum of wavelengths ranging from very short (gamma rays, typically 0.1 nanometres) to very long (radio waves, typically in the order of meters). The sun emits all forms of radiation within the electromagnetic spectrum (EM), but the Earth's atmosphere blocks part of the radiation and passive remote sensing (RS) from space is only possible due to atmospheric windows in different parts of the EM (Figure 5). Atmospheric windows are parts of the EM where the atmosphere has a small influence on the transmission of light and determine which wavebands are available for oceanography. For instance, in the visible region (400-700 nm), atmospheric opacity is low allowing for the analysis of the "colour" of the targets observed. In fact, the visible portion of the EM accounts for approximately 45 % of total solar energy (Kirk, 1983) and, as a consequence, evolution has resulted in many organisms utilising the visible portion of the EM whether for sight, as with the case of humans, or for energy, as in the case of photosynthetic organisms (Raven, 1998; Falkowski and Raven, 2013). Photosynthetically Active Radiation (PAR) is the specific range of electromagnetic solar radiation (400–700 nm) that plants and photosynthetic organisms use for photosynthesis.

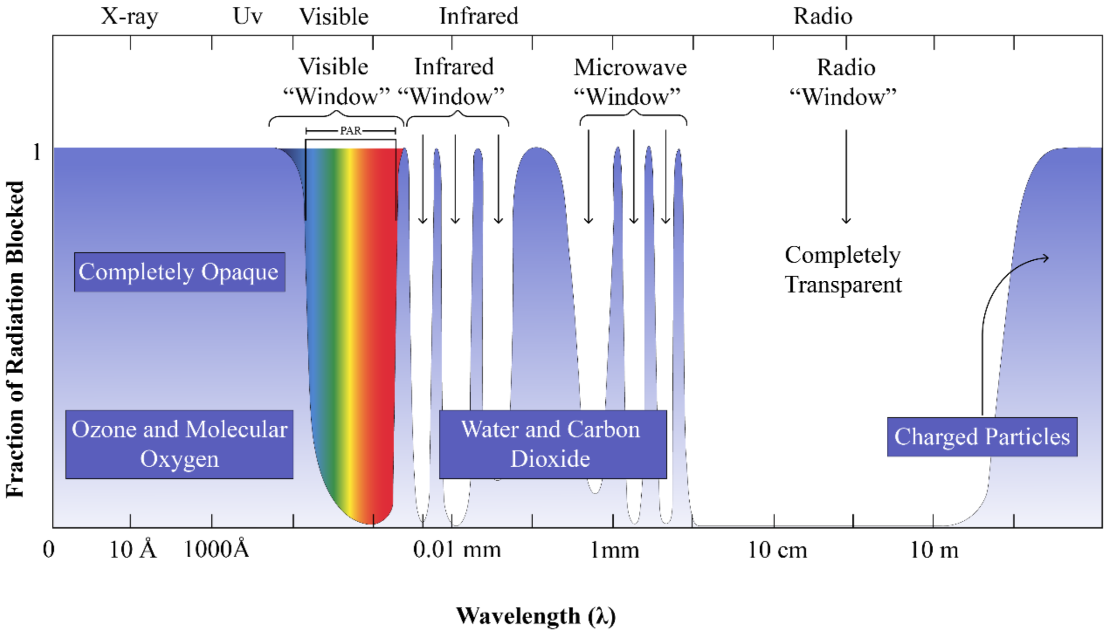


Figure 5 Electromagnetic radiation spectrum and its interaction with the Earth's atmosphere

1.4.2. Apparent and inherent optical properties

Apparent Optical Properties (AOPs) and Inherent Optical Properties (IOPs) are optical properties that describe the interaction between light and water and its components, such as phytoplankton, suspended matter, and dissolved organic material.

Apparent Optical Properties (AOPs)

AOPs are characteristics that depend on the ambient light field and observation geometry. They are influenced by both the inherent properties of the water and the external light environment. AOPs normally vary with the angle of viewing, angle, and incident light intensity. Some common AOPs include:

1. Diffuse Attenuation Coefficient (K_d): This Coefficient is the ratio of light reduction with depth in the water column. It is wavelength-dependent and influenced by absorption and the scattering process.

Typically used to estimate the depth of the euphotic zone (the depth to which light is sufficient to support photosynthesis).

2. Remote Sensing Reflectance (R_rs): Water-leaving radiance (light reflected out of the water) divided by downwelling irradiance (light from the sun or sky). Used in satellite and aerial remote sensing to estimate concentrations of water constituents such as chlorophyll, dissolved organic matter, and suspended sediments.

3. Upwelling Radiance (L_u): The light intensity (radiance) just below or above the water surface traveling upwards. It depends upon both the inherent characteristics of the water and the conditions of incident light.

4. Downwelling Irradiance (E_d): The total quantity of light from above that is incident at a certain depth within the water. Affected by both direct sun and diffuse skylight.

Inherent Optical Properties (IOPs)

IOPs are those properties that are a function of the water and its contents alone, irrespective of the surrounding light field. These are inherent properties of the medium and are a function of the absorption and scattering properties of the water and its contents. Among the most important IOPs are:

1. Absorption Coefficient (a): Quantifies the intensity of light absorbed by the water and its constituents (*e.g.*, phytoplankton, dissolved organic matter, particulate matter). Wavelength dependent and assists in measuring the water content.

2. Scattering Coefficient (b): Measures the rate with which water particles scatter light. Scattering scatters light in other directions without absorption.

3.Backscattering Coefficient (b_b): Scattering coefficient that measures the rate at which the light becomes backscattered to the surface. Important in remote sensing as it affects the water-leaving radiance.

4.Attenuation Coefficient of the beam (c): Total of the absorption and the scattering coefficients ($c = a + b$). Is responsible for the total loss of the transmitted light intensity through the water.

5. Volume Scattering Function (VSF): The scattering of light in the water by angle. Gives detailed information about the redirection of light by particles at various angles.

Quantification and identification of AOPs and IOPs are of key importance in many applications, such as environmental monitoring, oceanography, and remote sensing. They enable description of water quality, estimation of phytoplankton biomass, and identification of aquatic ecosystem changes.

1.4.3. Water types

The distribution, abundance, and diversity of phytoplankton are strongly correlated with the properties of the aquatic ecosystems in which they live (summarised in Table 3). To understand these communities clearly, scientists often divide water bodies into their optical, geographical, and biogeochemical classes. This subsection describes one of the most popularly used systems of classification developed from the International Ocean Colour Coordinating Group (IOCCG) (IOCCG, 2018) and based on seminal work like Moore et al. (2001).

1.4.3.1. Case 1 Waters

Case 1 waters are those open oceanic areas in which the intrinsic optical properties of water are dominated by phytoplankton and its by-products, such as detritus. They are usually far from the terrestrial influence, and their optical properties—absorption and scattering—can be accurately estimated with chlorophyll-a concentration as a proxy. Consequently, the bio-optical relationships in Case 1 waters are fairly uncomplicated. Phytoplankton in such areas are mostly responding to light penetration and nutrient availability, and the waters themselves vary from oligotrophic (low) to eutrophic (high) conditions. Case 1 waters have traditionally been used as the foundation for the majority of satellite ocean colour algorithms because of their stability and predictability.

1.4.3.2. Case 2 Waters

Case 2 waters are optically complicated environments, often in coastal areas, estuaries, and inland water bodies like lakes and reservoirs. In these waters, optical properties are not only controlled by phytoplankton but are greatly affected by other constituents including suspended inorganic particles, coloured dissolved organic material (CDOM), and riverine and terrestrial inputs. These materials introduce high variability in attenuation and scattering of light and make it difficult to interpret satellite information as well as bio-optical models. These environments tend to have variable nutrient concentration, turbidity, and salinity, resulting in dynamic and heterogeneous phytoplankton communities that necessitate context-dependent sampling and analytical approaches.

1.4.3.3. Brackish and Specialized Waters

Brackish water, such as estuaries and coastal lagoons, are mixed water zones where seawater and river or stream water mix. These areas are characterized by highly variable salinity and nutrient conditions that host phytoplankton communities that thrive in variable conditions. Estuaries, specifically, are under both tidal and freshwater control and are therefore productive but turbid. Lagoons, being shallow and naturally more or less closed, likewise provide a diverse assemblage of phytoplankton species by virtue of the retention of nutrients and relatively constant hydrology.

Extreme physical and chemical conditions are found in specialized aquatic habitats, such as hypersaline lakes and polar waters. Hypersaline lakes possess salinity that is far greater than seawater and limits biodiversity but supports highly tolerant phytoplankton species with abilities to cope with osmotic stress. Polar waters in the Arctic and Antarctic oceans are occupied by uniformly low temperatures and atypical light regimes with cycles of continuous sunlight or darkness. These conditions lead to the predominance of cold-tolerant phytoplankton with specialized metabolic tactics that allow for survival and growth under suboptimal temperature and light conditions.

Every water body type mentioned above poses different ecological and methodological challenges for the analysis of phytoplankton. Knowledge of the classification and nature of these environments is key to choosing suitable sampling methods, interpreting ecological processes, and using remote sensing technology. Researchers need to adjust their methodologies to the exact environmental and optical characteristics of the water body under investigation in order to gain trustworthy and meaningful results.

Table 3 Water types, subtypes, characteristics and examples

Water Type	Subtype	Characteristics	Examples
Oceanic Waters	Oligotrophic	Low nutrient concentrations, clear water, low phytoplankton biomass	Central gyres of oceans
	Mesotrophic	Moderate nutrient concentrations, moderate water clarity, intermediate phytoplankton biomass	Marginal seas and transition zones
	Eutrophic	High nutrient concentrations, less clear water, high phytoplankton biomass	Coastal upwelling regions

Coastal Waters	Estuarine	Brackish water, varying salinity, high nutrient input from rivers, high phytoplankton biomass	Chesapeake Bay, San Francisco Bay
	Shelf Seas	Shallow waters over continental shelves, moderate to high nutrient levels, significant phytoplankton biomass	North Sea, South China Sea
Inland Waters	Lakes	Clear, deep lakes with low nutrient levels, low phytoplankton biomass	Lake Tahoe, Lake Baikal
		Lakes with intermediate nutrient levels and phytoplankton biomass	Lake Michigan
		Shallow, nutrient-rich lakes with high phytoplankton biomass	Lake Erie
		Extremely nutrient-rich lakes with excessive phytoplankton biomass, often leading to algal blooms	Lake Okeechobee
	Rivers	Flowing freshwater bodies, nutrient levels and phytoplankton biomass vary based on surrounding land use and season	Mississippi River, Amazon River
	Wetlands	Saturated land areas, high nutrient levels, significant phytoplankton and other biomass	Florida Everglades, Pantanal
Polar Waters	Arctic Waters	Cold, nutrient-rich waters, seasonal phytoplankton blooms	Arctic Ocean
	Antarctic Waters	Cold, nutrient-rich waters, seasonal phytoplankton blooms	Southern Ocean
Special Water Types	Upwelling Zones	Areas where deep, nutrient-rich waters rise to the surface, leading to high phytoplankton biomass	Peruvian Upwelling, Benguela Upwelling
	Hypersaline Waters	Extremely salty waters, low to moderate nutrient levels, specialized phytoplankton communities	Great Salt Lake, Dead Sea
	Freshwater Springs	Sources of freshwater, low to moderate nutrient levels, varying phytoplankton biomass	Florida Springs, Banff Hot Springs

1.4.4. Ocean colour algorithms

Ocean colour algorithms are simple instruments for satellite or aerial remote sensing reflectance analysis, enabling the estimation of significant seawater properties like chlorophyll-a concentration, coloured dissolved organic matter (CDOM), and suspended sediments. Such algorithms are usually classified into three broad categories:

Empirical Algorithms: Statistical correlations between measured reflectance and *in situ* data form the basis of these algorithms. Efficient and simple, they are region dependent. The OC3 and OC4 algorithms, for example, calculate chlorophyll-a concentration from blue-to-green wavelength ratios.

- OC3M is specifically designed for MODIS data (Campbell and Feng, 2005)
- OC4v6 is used extensively with SeaWiFS data (Tilstone et al., 2011; Hu et al., 2012a)

Semi-analytical Algorithms combine theory with empirical correlations for light absorption and scattering in aquatic systems, with results that are more general and more flexible. Some examples are:

- GSM (Garver-Siegel-Maritorena), which offers chlorophyll absorption, CDOM, and particulate backscattering (Siegel et al., 2002).
- QAA (Quasi-Analytical Algorithm), which decouples absorption and backscattering to better approximate water constituents (Carder et al., 2002; Joshi and D’Sa, 2018).

Analytical (Inversion) Algorithms: According to radiative transfer theory principles, two algorithms derive inherent optical properties (IOPs) directly from reflectance measurements. GIOP (Generalized Inherent Optical Properties) supports flexible solutions for a range of satellite sensors (Brando et al., 2012; Werdell et al., 2013). Hydrolight is a sophisticated radiative transfer model used to model light propagation in water and to create or test ocean colour algorithms (Mobley, 1989, 1999; Mobley et al., 2011).

In addition, machine learning and neural network-based algorithms have been found to be useful tools for the processing of ocean colour data (Fasnacht et al., 2022). The models are able to portray complex, non-linear relationships and are able to handle optically complex waters (Hadjal et al., 2023; Zhang et al., 2025). For example, the C2RCC (Case 2 Regional/Coastal Chlorophyll) algorithm is used for coastal waters with optically highly variable properties, and the ESA OC-CCI (Ocean Colour Climate Change Initiative) uses neural networks in order to merge data from a series of sensors into a single global product for 14 distinct types of waters. Generally, ocean colour algorithms vary from simplicity of use to complexity of application. From local empirical models to globally applicable analytical and machine learning approaches, they form the backbone of the monitoring of marine ecosystems and the assessment of water quality from space-based observations.

1.4.5. Ocean colour sensors and satellites

Various satellites and sensors have been developed to monitor ocean colour in different bodies of water, and the information they yield are necessary to study marine biology, water quality, and climate change. The most prominent ocean colour satellites and their corresponding sensors are shown in Table 4. However, as will be illustrated in the following chapters, the estimation of Chl-a and other optical properties of water are not necessarily ocean colour based, and other satellites can be employed.

Table 4 List of ocean colour sensors as an update from IOCCG, 2012

Sensor	Satellite	Mission Developer	Launch Year	Operational Period	Spatial Resolution (m)	Notes
CZCS	NIMBUS-7	NASA (USA)	1978	1978 – 1986	825	The first dedicated ocean colour sensor, providing essential data on coastal and oceanic phytoplankton.
POLDER	ADEOS	CNES (FRANCE)	1996	1996 – 1997	6000	Used for observing the polarization and directionality of Earth's reflectances.
OCTS	ADEOS	JAXA (JAPAN)	1996	1996 – 1997	700	Provided valuable data on ocean colour and phytoplankton concentration.
SeaWiFS	SeaStar	NASA (USA)	1997	1997 – 2010	1100	Known for its high-quality global ocean colour data, essential for

						climate and marine studies.
OCI	ROCSAT	NSPO (TAIWAN)	1999	1999 – 2004	800	Provided data specific to the region, focusing on ocean colour and coastal monitoring.
OCM	IRS-P4	ISRO (INDIA)	1999	1999 – 2014	350	Used for monitoring ocean colour and coastal zones, providing high-resolution data.
MODIS	Terra/Aqua	NASA (USA)	1999	Terra (1999 - Present), Aqua (2002 - Present)	1000	Provides comprehensive data on ocean colour, land, and atmospheric conditions with global coverage.
MERIS	ENVISAT	ESA (EU)	2002	2002 – 2012	300 & 1200	High spectral resolution sensor used for ocean colour and coastal monitoring.
GLI	ADEOS-II	JAXA (JAPAN)	2002	2002 – 2003	1000	Provided data on ocean colour and other environmental parameters.
COCTS	HY-1B	CAST (CHINA)	2007	2007 – 2011	1100	Used for monitoring ocean colour and coastal environments.
GOCI-I	COMS	KIOST (KOREA)	2010	2010 - Present	500	The first geostationary ocean colour sensor, providing high-frequency observations.
VIIRS	Suomi NPP	NOAA (USA)	2011	2011 - Present	750	Continues the legacy of MODIS with improved spatial resolution and additional spectral bands.

OLCI	SENTINEL 3	ESA (EU)	2014	2016 - Present	300	Offers high spectral and spatial resolution, focusing on ocean colour, land, and atmospheric applications.
SGLI	GCOM-C1	JAXA (JAPAN)	2015	2015 - Present	250 & 1000	Provides high-resolution data for ocean colour and other environmental observations.
GOCI-II	GeoKOMPSAT-2B	KIOST (KOREA)	2021	2021 - Present	250 & 1000	An advanced geostationary sensor that provides detailed and frequent observations of ocean colour.
HICO	ISS	DOD/NASA (USA)	2009	2009 – 2014	~100	Hyperspectral imager designed for coastal and inland water studies.
MSI	Sentinel-2	ESA (EU)	2015	2015 - Present	10, 20, 60	MultiSpectral Instrument providing high-resolution imagery for coastal and inland water monitoring.
MSI	Sentinel-2B	ESA (EU)	2017	2017 - Present	10, 20, 60	Continuation of Sentinel-2A, enhancing global coverage and revisitation times.
VIIRS	NOAA-20	NOAA (USA)	2017	2017 - Present	750	Continuation of VIIRS on Suomi NPP, providing high-quality ocean colour data.
OCM-2	Oceansat-2	ISRO (INDIA)	2009	2009 - Present	360	Successor to OCM, providing improved data for ocean and

						coastal monitoring.
OCM-3	Oceansat-3	ISRO (INDIA)	Expected 2024	TBD	360	Next-generation Ocean colour monitor, expected to enhance data quality and coverage.

1.5. Lakes as Sentinels of Climate Change

Furthermore, even with the time spans of remotely sensed data from 1997 it is possible to study some phenology shifts in phytoplankton (Figure 6). The earth’s primary production, in the ocean as well as on land, displays characteristic seasonality, and generally, the higher the latitude, the more pulsed the production (Ji et al., 2013a). Changes in the initiation and duration of the growth season can impact the biogeography of those copepod species in the Arctic Ocean. In some areas annual phytoplankton bloom maximum has advanced by up to 50 days which may have consequences for the Arctic food chain and carbon cycling (Kahru et al., 2011).

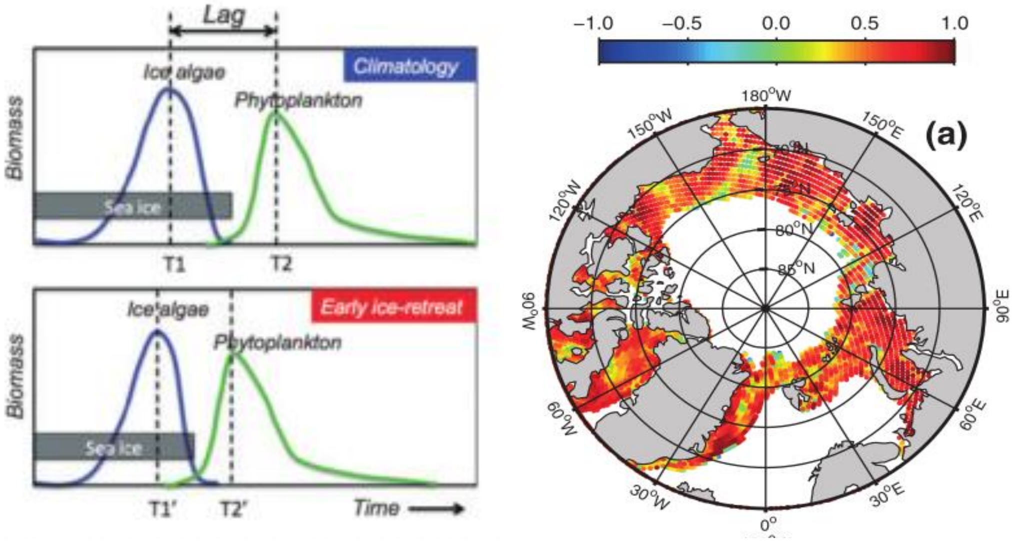


Figure 6 Phytoplankton blooms timing in different environmental conditions (left) and correlation between earlier ice melt and earlier blooms Ji, 2013.

1.5.1. Polar Amplification

Due to the phenomenon of Arctic amplification, climate change is happening faster at high latitudes (Yamanouchi, 2011; Cohen et al., 2014) – see Figure 7. Studies indicate that the Arctic region has warmed more than twice as fast as the global average (Screen and Simmonds, 2010). High latitude lakes are thus particularly interesting for studying environmental changes in aquatic ecosystems. Furthermore, in northern countries, such as Finland, we can observe lakes with vast range of trophic states and distributed along a large latitudinal gradient.

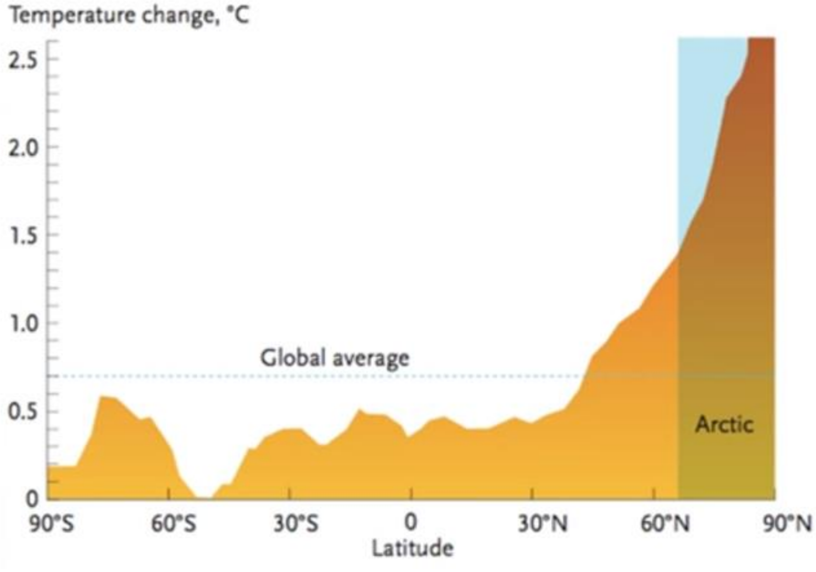
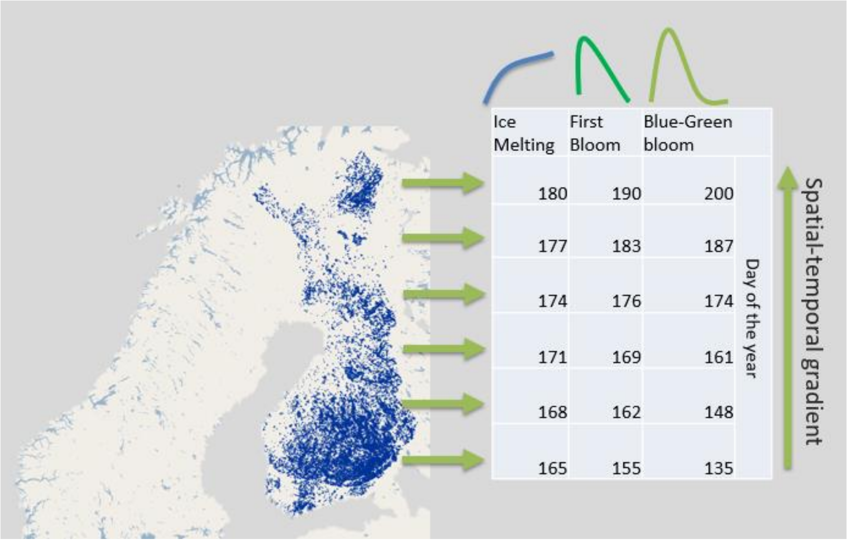


Figure 7 The average increase in surface temperature since the 1951 – 1980 reference period is greatest in the Arctic (figure adapted from the book "A Farewell to Ice" by Peter Wadhams, authorised by the author for this text).

1.5.2. Moving Beyond

The northernmost areas have seen greater effects from climate change. Warming in Finland, for example, is expected to be roughly 50 % higher than the global average, that is 0.15-0.20 °C/decade (Mikkonen et al., 2015). High latitude lakes are considered sentinels for a climate in change, due to both to the effects of polar amplification and the high sensitivity of photosynthetic organisms to the changing temperature patterns (Kraemer et al., 2017). Given Finland's geographical location, the country is largely subjected to polar amplification from climate change-induced warming. With hundreds of thousand lakes spread across the country and a vast history of water quality monitoring, Finland consists of the best starting point to observe changes in phytoplankton communities linked to climate change. The different lakes are also distributed across a latitude gradient which is advantageous to study the phenology shifts (Figure 8).



Ice Melting	First Bloom	Blue-Green bloom
180	190	200
177	183	187
174	176	174
171	169	161
168	162	148
165	155	135

Figure 8 Distribution of lakes in Finland (blue) and schematics (with hypothetical numbers) of phenology metrics to be studied.

A variety of studies showed the importance of studying lakes as sentinels for climate change, including variables such as water level, ice phenology, chemical variables, dissolved organic carbon and oxygen (Adrian et al., 2009). Additionally, biota's growth rates, abundance, and species composition can be considered an indicator of climate change (Rühland et al., 2008; Adrian et al., 2009).

Many remote-sensing algorithms provide estimates of different phytoplankton types as an absolute or relative contribution to pigment biomass, but intrinsically there is still a difficulty in merging two sets of methods for observation: the ones associated to *in situ* measurements and those related to remote sensing techniques. It is not straightforward to use microscope counts (Brotas et al., 2013), cytometry, and/or HPLC to evaluate algorithms; some assumptions must be made regarding Chl-a content per cell or other conversion factors.

Satellite observations provide information resolved to surface areas of hundreds of square meters, whereas microscopic counts are carried out on extremely small volumes of just a few millilitres. This incompatibility of space scales makes it difficult to compare satellite observations and microscope counts directly, though the mismatch of space scales is not unique to microscopy and plagues all comparisons of *in situ* observations with satellite estimates.

The extent of this work is to provide innovative methods and an enhanced mechanism to monitor phytoplankton from space and further understand their roles in the carbon cycle in challenging scenarios such as small Marine Protected Areas and small lakes. However, there is room to further understand bloom mechanisms and their role as a basis for oceanic and freshwater food webs specific bloom variabilities were studied for small boreal lakes, but we did not assess variations in the phytoplankton communities.

Understanding the temporal patterns of phytoplankton blooms is particularly interesting for assessing the ecological status of aquatic ecosystems. Information on phytoplankton phenology can foster policies related to water resources management and environmental impacts mitigation (Anderson, 2009; Mitrovic et al., 2011). Furthermore, understanding the phytoplankton seasonal patterns can help identifying drivers of environmental changes in aquatic ecosystems. The timing of the onset of phytoplankton blooms is mainly driven by the physicochemical conditions of the water column, such as thermal stratification and water column mixing conditions, variation in solar radiation and the extent of the possible ice cover (Bleiker and Schanz, 1989; Adrian et al., 1999; Vehmaa and Salonen, 2009). The increase in phytoplankton blooms have been shown to be closely associated with climatic variables, the surrounding land use and nutrients flow (Gittings et al., 2018). Nonetheless, currently the temporal and spatial dynamics of phytoplankton blooms across inland waters have not yet been comprehensively studied.

Chapter 2. Earth Observation – an essential tool towards effective aquatic ecosystems' management under a climate in change

Abstract. Numerous policies have been proposed by international and supranational institutions, such as the European Union, to survey Earth from space and furnish indicators of environmental conditions across diverse scenarios. In tandem with these policies, different initiatives, particularly on both sides of the Atlantic, have emerged to provide valuable data for environmental management such as the concept of essential climate variables. However, a key question arises: do the available data align with the monitoring requirements outlined in these policies? In this paper, we concentrate on Earth Observation (EO) optical data applications for environmental monitoring, with a specific emphasis on ocean colour. In a rapidly changing climate, it becomes imperative to consider data requirements for upcoming space missions. We place particular significance on the application of these data when monitoring lakes and marine protected areas (MPAs). These two use cases, albeit very different in nature, underscore the necessity for higher-spatial-resolution imagery to effectively study these vital habitats. Limnological ecosystems, sensitive to ice melting and temperature fluctuations, serve as crucial indicators of a climate in change. Simultaneously, MPAs, although generally small in size, play a crucial role in safeguarding marine biodiversity and supporting sustainable marine resource management. They are increasingly acknowledged as a critical component of global efforts to conserve and manage marine ecosystems, as exemplified by Target 3 of the Kunming–Montreal Global Biodiversity Framework (GBF), which aims to effectively conserve 30% of terrestrial, inland water, coastal, and marine areas by 2030 through protected areas and other conservation measures. In this paper, we analysed different policies concerning EO data and their application to environmental-based monitoring. We also reviewed and analysed the existing relevant literature in order to find gaps that need to be bridged to effectively monitor these habitats in an ecosystem-based approach, making data more accessible, leading to the generation of water quality indicators derived from new high- and very high-resolution satellite monitoring focusing especially on Chlorophyll-a concentrations. Such data are pivotal for comprehending, at small and local scales, how these habitats are responding to climate change and various stressors.

2.1. Introduction

Monitoring Earth: From Oceans to Lakes and MAPs

Our understanding of the Earth's environmental systems has undergone a transformative shift, akin to a second Copernican revolution, emphasising the paramount importance of comprehending the global environment for the effective implementation of policies (Schellnhuber, 1999). A remarkable revolution in understanding the Earth's system as a whole has been made possible through the continuous advancements in technology and the launch of Earth-observing satellites, marking a significant milestone in planetary monitoring. Among the various components of the Earth system, the watery expanse stands out as the one benefiting most profoundly from space-derived data. Oceanography, traditionally a resource-intensive science, has seen a revolutionary shift, with satellites providing synoptic views and enabling the continuous monitoring of critical oceanic variables. Consequently, a comprehensive grasp of EO's role in shaping policy, as well as identifying existing gaps, is imperative for both current policies and future governance. While satellite data have long been acknowledged as an essential governance tool, we must now explore the new demands and opportunities to bridge the gap between policies and effective monitoring. Previous research has outlined that EO data are only present in 9% of lake shift studies, but its use is increasing over the last few years (Calamita et al., 2024). In this paper, we identify possible reasons on why Earth observation data is not widely used to study Marine Protected Areas and could be improved in limnological scenarios. Other environments such as rivers or lagoons are not part of this study since studying shifts over these areas is more challenging from a standpoint of satellite data alone.

The oceans play a vital role in Earth's climate due to their capacity to redistribute heat across the globe and to absorb and store greenhouse gases, primary productivity of the ocean accounts for 48.5 Pentagrams of carbon per year (0.65 Pg C y−1), which corresponds to almost half of total Earth primary production (Field et al., 1998). In particular, the mixed layer of the oceans has an effective heat capacity 20 times that of the effective heat capacity of the entire atmosphere (Soldatenko and Yusupov, 2017; Dias et al., 2022). The oceans have taken up more than 90% of the excess heat in the climate system that results from the anthropogenic greenhouse gases (GhG) emissions (H.-O. Pörtner et al., 2022), making them a critical regulator of our climate's thermal balance. They also play a vital role in the thermal memory of the climate system since deep currents govern climate change in a millennia timescale and the surface currents do the same in the short term (years) (Schiermeier, 2006). Satellites have been crucial in estimating not only primary production at sea (Westberry et al., 2023) but also on deriving EO data on oceanic heat content (Jayne et al., 2003; Smale and Wernberg, 2009; Irrgang et al., 2019; Maturi et al., 2024). However, as we will see, the resolutions used are not sufficient to study smaller regions that must be incorporated in environmental variables.

Lakes, although not matching the oceans in heat storage capacity, are vital in terms of primary production, with a substantial global impact. Global gross primary production (GPP) in lakes is estimated to be 0.65 Pg C y^{-1} (Pace and Prairie, 2005). The rate of organic carbon burial in inland water sediments exceeds that of organic carbon sequestration on the ocean floor (Tranvik et al., 2009). Additionally, lakes serve as sensitive indicators of climate change through shifts in phytoplankton phenology, ice melting patterns, and temperature variations (Maeda et al., 2019). They also play a significant role in regulating greenhouse gases, and the shrinking of lakes – combined with surface runoff, atmospheric deposition, and biogeochemical transformation – amplifies greenhouse gas re-emission, particularly in smaller (less than 1 km^2) lakes (Pi et al., 2022).

There are more than 117 million lakes in the world (Verpoorter et al., 2014). Moreover, very small ponds, of less than 0.001 km^2, comprise 8.6% of lakes and ponds by area globally, but account for 15.1% of CO_2 emissions and 40.6% of diffusive CH_4 emissions (Holgerson and Raymond, 2016). Furthermore, lakes influence regional climate, acting as local coolants (Rouse et al., 2003) and by dampening the variability in near-surface temperature such as in the Great Lakes area, affecting the living of millions of people (Notaro et al., 2013). Finally, saline lakes contribute two times more to the emission of CO_2 than freshwater lakes (Duarte et al., 2008). The importance of satellites for the monitoring of lakes has been stated by previous research (Calamita et al., 2024), we review the bottlenecks on the use of EO for lake monitoring and assess if monitoring of lakes health and water quality parameters is already possible on a global scale so as to include lake colour as an essential climate parameter.

Despite their importance, most lakes are small and shallow. It is estimated (Downing et al., 2006) that 304 million lakes exist globally out of which 91% are of the smallest size (0.001 - 0.01 km^2), and the average lake is 0.012 km^2. Most lakes, therefore, are typically shallow with plenty of light and nutrients but they emit similar amounts of carbon to the atmosphere as the global terrestrial net ecosystem production (Tranvik et al., 2009). Studying very small lakes or water bodies over extensive areas and different habitats can be of great value to better understand climate change. For further reference, we define “very small lakes” in this paper as less than 0.4 km^2; such a value is important since the resolution of Sentinel-3 is 300 m which is not suitable to study water bodies less than 600 m in extension or 0.36 km^2. The resolution of Sentinel-2 is 20 meters (HR2) and of Landsat-8 is 40 meters (MR1). Whilst some studies have delved into the use of these satellites for Chlorophyll-a estimations, their low spectral resolutions suggested that these satellites can still be used but are sub-optimal to effectively assess these ecosystems since Chlorophyll-a detection is only possible under very specific conditions (Beck et al., 2016; Boucher et al., 2018; Lisboa et al., 2020).

Marine Protected Areas (MPAs) exhibit similarities with lakes in terms of ecological significance, social benefits, and economic value. They also play a role in biodiversity conservation, fisheries management, and carbon capture. MPAs, especially those preserving specific ecosystems like seagrass beds and mangroves, have the potential to store significant amounts of carbon, contributing to climate change mitigation. It has been assumed that ocean habitats such as seagrasses and mangroves (and associated food webs) can sequester carbon dioxide from the atmosphere at rates up to four times higher than terrestrial forests can (Searles Jones, 2019). However, estimations of this “blue carbon” sequestration rates can be two orders of magnitudes higher when considered on a “per area” basis (McLeod et al., 2011). Mangroves and other coastal habitats are some of the most carbon-rich ecosystems

(Donato et al., 2011) although discussions about the precise contributions and menaces of blue carbon sequestrations are still elusive and new advances are dependable on EO data (Pham et al., 2023).

Because of the natural habitats they encompass, MPAs are very sensitive to climate change and other environmental impacts. The definition of MPAs objectives should also be enlarged as in many cases they are restricted to non-take areas and should comply to a more effective ecosystem-based management approach (Halpern et al., 2010). High resolution satellites, already used to survey fishing activities in sensitive areas (Hamel and Andréfouët, 2010), are critical to address other aspects of MPAs ensuring ocean health and better marine conservation.

The role of higher-resolution satellites in addressing diverse aspects of MPAs and lakes, and their sensitivity to climate change and environmental threats cannot be overstated. From such methods, we can derive indicators that to meet important environmental targets, such as the Kunming-Montreal Global Biodiversity Framework. Nevertheless, the challenge lies in developing methods for consistent and synoptic monitoring, particularly in areas that are often isolated or too small for satellite observation, limited not by technology but by policies and restrictions on the collection, use and exploitation of VHR data.

This article will analyse the EO-based environmental surveillance assets at the European level. Since Copernicus is currently seen as the largest EO programme in the world in terms of budget, scope, and applications, we want to analyse what are the current scientific applications of EO data in small water bodies such as lakes and MPAs. Then, we move to the prospectives on the feasibility of high- and very high-resolution satellites for lake and ocean colour by revising many studies that have considered and tested the feasibility of data outside of the Copernicus programme to monitor water quality. Finally, we discuss the application to governance of this ecosystem-based monitoring and conclude on the needs for future data.

2.2. Materials and Methods

In this paper, we analysed the role of EO policies and initiatives that provide monitoring on ecosystem-based management and support decision making, framing these initiatives considering the EU Space Regulation and the Essential Climate Variables initiative. However, this analysis should be accompanied with research on current needs and bottlenecks of the scientific community, given that space EO missions not only serve scientific purposes but also societal ones like surveillance. In performing this literature search, we have used Web of Science and the VOSviewer for visualisation. The VOSviewer is a computer program developed by van Eck and Waltman (2010). (Beck et al., 2016) for creating, visualising, and exploring bibliometric maps of science. This program, was used to analyse co-occurrence relations between scientific terms and how these occurrences appeared in different periods. The specific queries in Web of Science are outlined in the results. Additionally, we also reviewed the current available EO data providers not limited to public initiatives such as Copernicus. We reviewed the current available technology from both public and privately owned satellites and what studies have used these data to retrieve water colour parameters.

Then, we derive conclusions on the applications of these data to governance and ecosystem-based monitoring.

2.3. Results on EO Policies and Decision-Making Structures

2.3.1. The EU Space Programme and Copernicus

Copernicus is the EO component of the EU Space Programme, established in 2014 by the European Union through EU Regulation 377/2014 and coordinated by the European Commission. This EU's flagship initiative for EO is backed by a substantial budget of nearly 6 billion EUR for the period 2021–2027. The program's primary aim is to enhance the European Union's capacity in EO, enabling it to address global challenges such as emergency response, global food security, climate change mitigation, and national security. Copernicus is divided into three main components: the space segment, in situ data, and various public services. The programme is implemented in partnership with ESA, entrusted with the space component, and benefits from contributions from partner agencies and organisations (see https://www.copernicus.eu/en/about-copernicus, accessed on 17 May 2024).

The space component of the Copernicus includes the Sentinel family of missions, which are Sentinel-1 (providing all-weather radar imagery), Sentinel-2 (providing high-resolution optical imagery), and Sentinel-3 (providing optical data for marine and land services). Additionally, Sentinel-4 and Sentinel-5 offer atmospheric composition monitoring from geostationary and polar orbits, respectively. Sentinel-5 Precursor bridges the gap between Envisat and Sentinel-5 (for sciamachy data), while Sentinel-6 provides radar altimetry data for oceanography and climate studies (see https://sentiwiki.copernicus.eu/web/sentiwiki, accessed on 16 May 2024).

Copernicus (Figure 9) also comprises six service components, which includes Atmosphere, Marine Environment, Land, Climate Change, Emergency, and Security services. These services are provided free of charge to users, but data collected and processed via the Security component are request driven and might be subject to restricted access, an example of the restrictions identified by (Harris and Baumann, 2015).

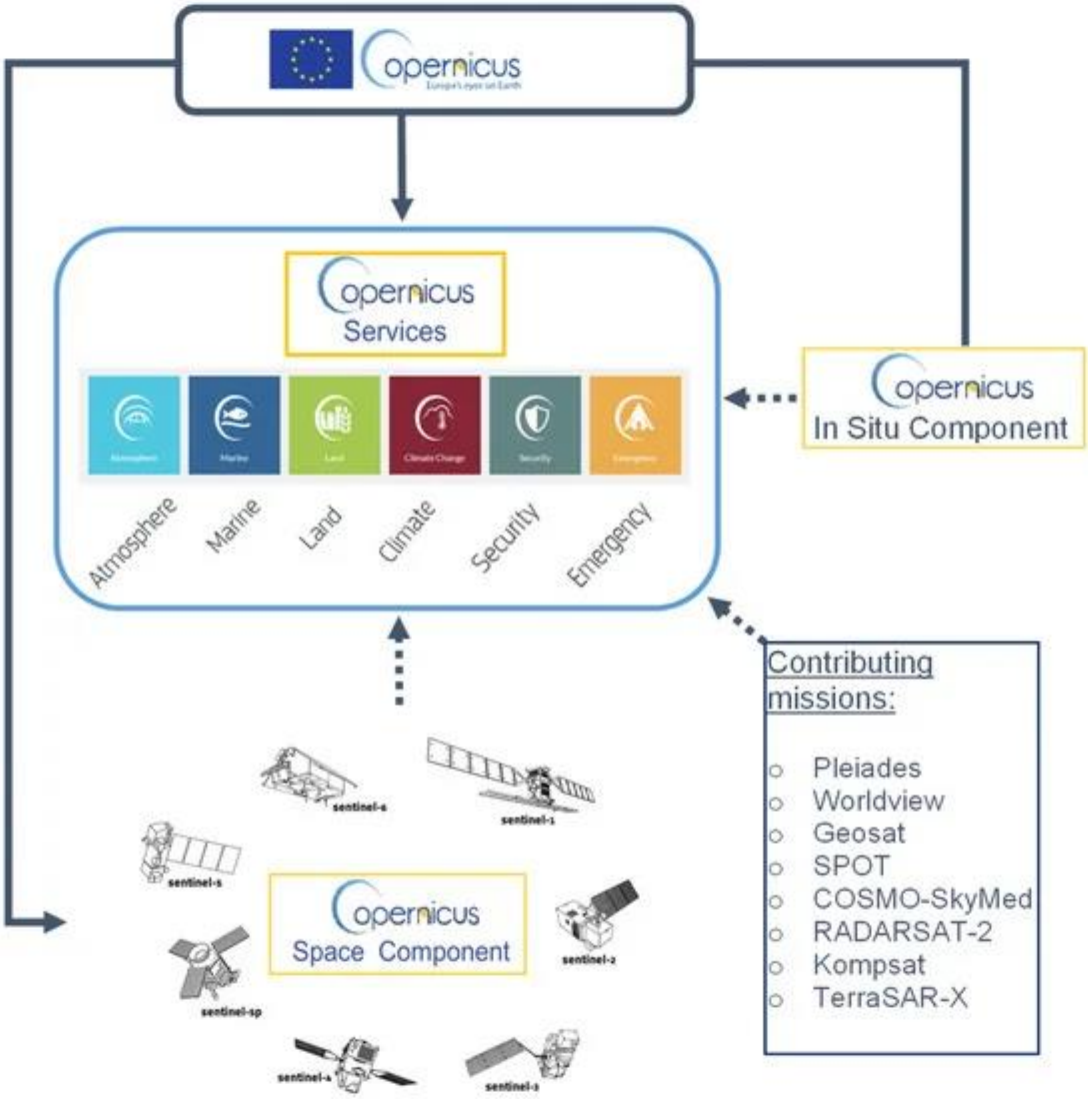


Figure 9 Overview of the three Copernicus components: space, in situ and services. Contribution missions are not part of the space component. They can be included directly in the provision of Copernicus services.

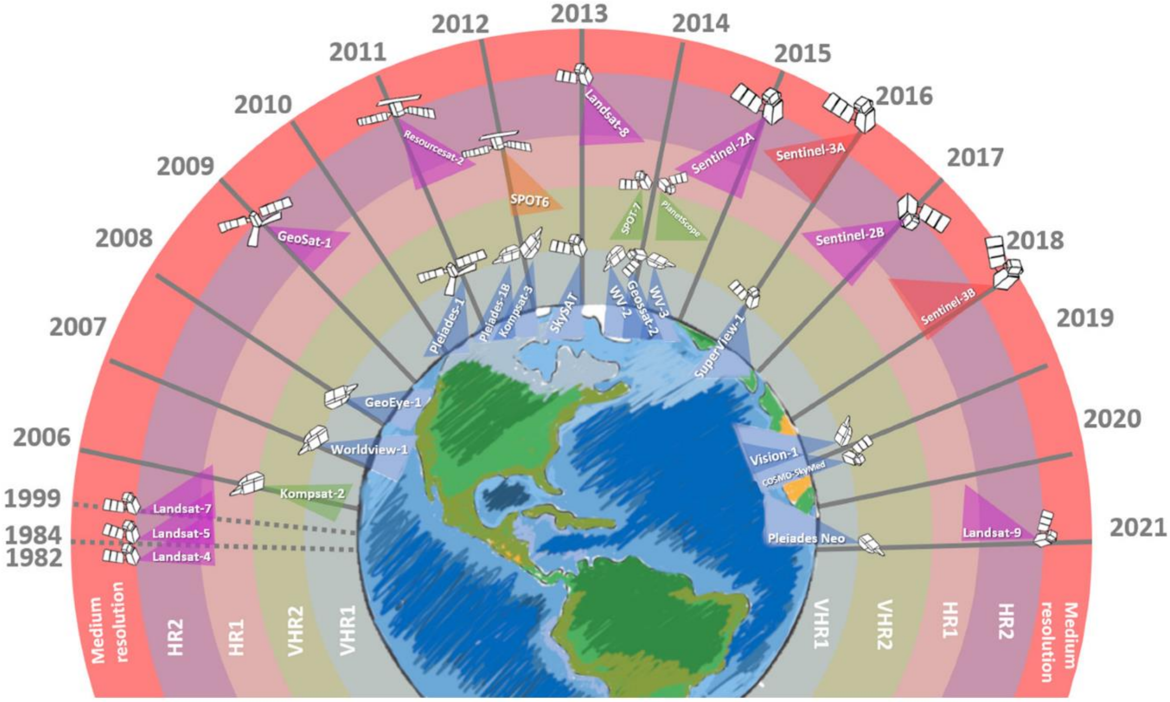


Figure 10 Overview of the resolutions available for Copernicus Space segment and contributing missions. VHR resolutions, needed for the monitoring of very small lakes and MPAs are only available through contributing missions. All satellites in blue, green and orange are privately owned.

Figure 10 provides an overview of the available resolutions outlining the fact that satellites in VHR are commercially owned. Cortosat-3 is the only public optical satellite in VHR, owned by the government of India (Cubaynes and Fretwell, 2022). The privately owned satellites shown in Figure 10 provide additional data to Copernicus through an activity entrusted to ESA under Copernicus Contributing Missions, CCM. As some of these services are heavily reliant on high- and very high-resolution missions, the new EU Space Regulation (EU) 2021/696 foresees a cautionary use of such data due to security factors but simultaneously supporting third-party engagement to facilitate the integration of VHR data across the Copernicus Service Components:

“(Article 38) The Commission should work with data providers to agree licensing conditions for third-party data to facilitate their use within Copernicus, in compliance with this Regulation and applicable third-party rights. As some Copernicus data and Copernicus information, including high-resolution images, may have an impact on the security of the

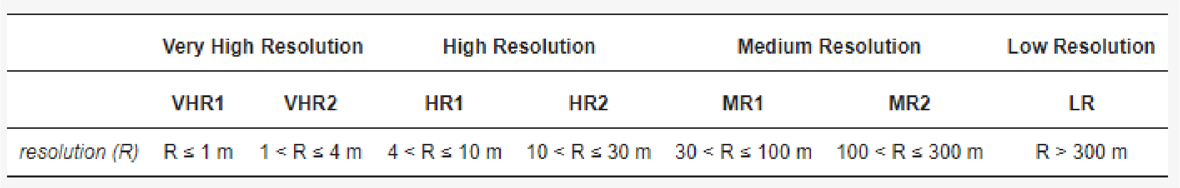
Union or Member States, in duly justified cases, measures in order to deal with risks and threats to the security of the Union or Member States may be adopted.”

From EU Space Regulation (EU) 2021/696

Although understanding the security risks imposed by such type of high-resolution imagery, this paper reflects on how specific environments—such as very small lakes and marine protected areas—could benefit from lifting restrictions for the creation of high-resolution variables such as ocean colour and water reflectance. Ocean colour should be read in its wider term as the retrieval of water quality parameters in different scenarios not restricted to the oceans.

We have organised available missions along a clear definition of resolution categories:

Table 5 Resolution classes definition.



	Very High Resolution		High Resolution		Medium Resolution		Low Resolution
	VHR1	**VHR2**	**HR1**	**HR2**	**MR1**	**MR2**	**LR**
resolution (R)	R ≤ 1 m	1 < R ≤ 4 m	4 < R ≤ 10 m	10 < R ≤ 30 m	30 < R ≤ 100 m	100 < R ≤ 300 m	R > 300 m

A benchmark of resolution classes is not yet practiced in the literature. We believe that the definition proposed in this paper, summarised in Table 5, could be used to organise and clarify the potential use of private and publicly owned data when applied to specific scenarios.

2.3.2. Essential Climate Variables

In accordance with the requirements of the United Nations Framework Convention on Climate Change (UNFCCC), outlined in the Second GCOS Adequacy Report (WMO et al., 2003), a set of Essential Climate Variables (ECVs) have been defined by the Global Climate Observing System (GCOS). Figure 11 provides a representation of the whole set of variables, their related geophysical areas and concerned organisations. GCOS is a program that systematically evaluates the status of global climate observations and offers guidance for their enhancement. Additionally, GCOS facilitates and encourages the accessibility of climate observations for both national and international organisations. At present, there are 54 variables that comprehensively represent the observations needed to consistently monitor Earth’s climate and other physical and biological changes. Experts regularly develop plans to maintain, coordinate and improve these physical, chemical, and biological observations.

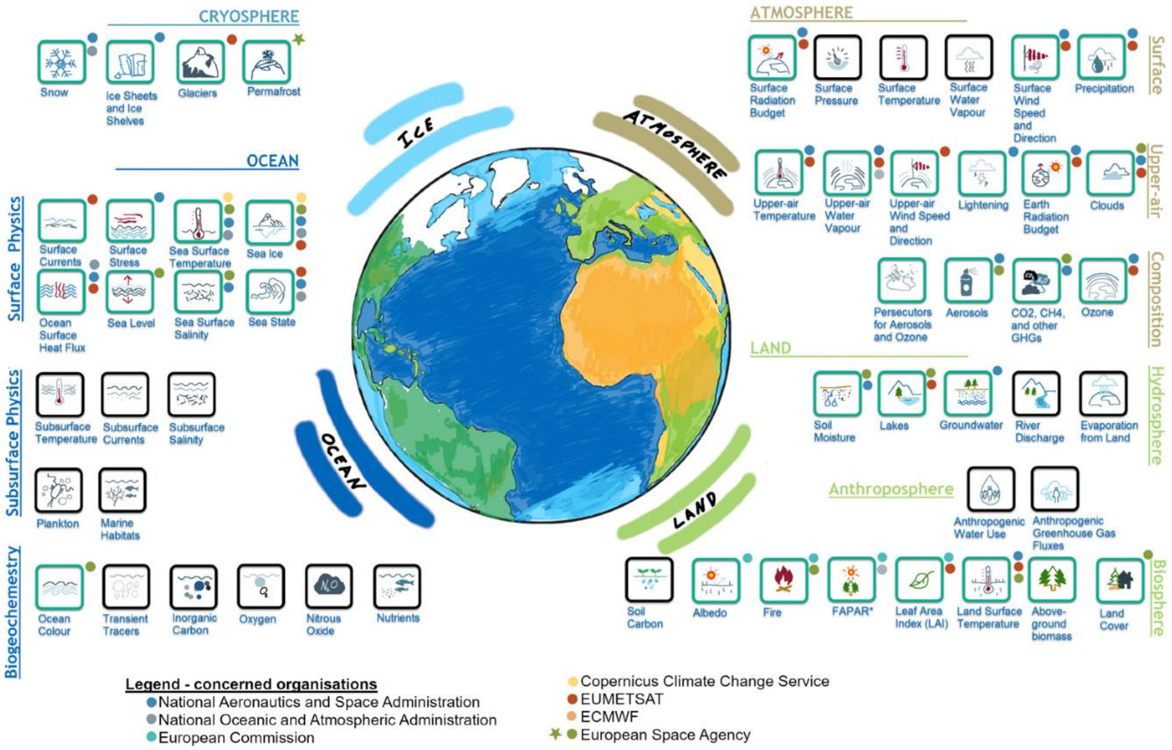


Figure 11 From the 56 ECVs, 36 (highlighted in green) rely on EO data. Some of the concerned organisations are depicted on the top right of each ECV. The concerned organisations are given as examples since many more are involved in providing products for each ECV. The concerned organisations are given as examples since many more are involved in providing products for each ECV. For example, nine organisations are involved in providing data for the Precipitation ECV. Only NASA manages the Lightening ECV and only ESA is responsible for the Ocean Colour ECV. The star represents a future engagement of ESA in the Permafrost ECV.

ECVs hold paramount importance in our comprehension and prediction of the Earth’s climate system. The variables encompass critical parameters such as temperature, precipitation, atmospheric and oceanic circulation, and greenhouse gas concentrations, among others. The significance of ECVs arises from their fundamental role as key indicators of climate change. By consistently monitoring these variables, scientists can detect trends, patterns, and anomalies within the climate system, providing essential insights into its state, behaviour, and potential impacts on ecosystems, society, and the economy.

Furthermore, ECVs serve as the foundation for climate modelling and forecasting, facilitating the projection of future climate scenarios. This, in turn, empowers policy makers to make informed decisions on climate change mitigation and adaptation strategies. Moreover, ECVs play a pivotal role in international climate agreements, providing standardised parameters for assessing global climate change. The availability of consistent ECV data supports evidence-based decision making, allowing policy makers to formulate effective climate policies and strategies (Bojinski et al., 2014).

Next, we identify four ECVs that currently benefit from satellite medium resolutions but for which spatial resolution could eventually be increased due to allow for the monitoring of the two specific habitats addressed in this paper.

Sea Surface Temperature (SST) is vital for the climate system as it influences energy, momentum, and gas exchanges between the ocean and atmosphere. SST largely controls the ocean-atmosphere interaction at both weather and climate time scales. Daily SST variations exceed 3 degrees Celsius, impacting the surface energy budget by over 10 Wm-2 in the tropics and subtropics. SST and its gradients are crucial for atmospheric–ocean coupling, particularly in sub-seasonal to seasonal predictions. SST patterns reveal ocean dynamics, including fronts, eddies, coastal upwelling, and exchanges between coastal and open ocean regions. Sea Surface Temperature is studied at resolutions between 1 and 100 km (Beggs et al., 2023).

Ocean colour is the radiance from the ocean normalised by the illuminating irradiance. It provides information on ocean albedo, seawater constituents like Chlorophyll-a, and phytoplankton pigments. Ocean colour remote sensing (OCRS) products assess ecosystem health, productivity, marine resource management, the global carbon cycle, and quantify climate impacts. Currently, the resolutions for Ocean colour have been defined at 4 km for both water leaving radiance and Chlorophyll-a concentrations (GCOS, 2016; Groom et al., 2019). However, ocean colour provision as an ECV is provided under ESA's Climate Change Initiative through the Sentinel-3 OCLI sensor at a resolution of 300 m. As discussed in the literature reviewed, there is a consistent gap in resolutions < 10 m, which is useful for inland water detection of Chlorophyll-a and other water quality parameters (Field et al., 1998; Boucher et al., 2018; Maeda et al., 2019; Sayers et al., 2019; Lisboa et al., 2020; Veerman et al., 2022; Calamita et al., 2024). This need gives rise to the term "lake colour", which is not consistently used in the literature and as seen below could provide more maturity (in terms of definition of measurable parameters) to the "Lakes" ECV.

Sea ice is a key climate indicator in polar regions, impacting albedo, energy budget, and air–sea exchanges. Parameters like concentration, area, extent, motion, and thickness define its state, influencing water masses and freezing/melting processes. The decreasing sea ice surface extension in the Arctic has a significant impact on the Earth's albedo and contributes to the Arctic amplification of temperature (Osman et al., 2021). Furthermore, the weaker surface temperature gradient between the Arctic and regions to the south affect the polar jet stream patterns and the weather in mid-latitudes (Ballari et al., 2023).

Lakes variable provides information on changes at the lake level and area, required monthly for climate assessment purposes. Approximately 95% of the volume of water held globally in approximately 4,000,000 lakes is contained in the world's 80 largest lakes. Lakes ECV includes the following: Lake Water Level, Lake Water Extent, Lake Surface Water temperature, Lake Ice Cover and Thickness, and Lake Surface Reflectance. Although lake colour, i.e., the estimation of Chlorophyll-a in lakes, is foreseen as part of this ECV there is currently no operational worldwide product providing these data. Nevertheless, there have been efforts to provide such estimates in local scenarios based on high-resolution data, such as from the Landsat family (Lisboa et al., 2020). We make the case in this paper that privately owned satellite data could be used to feed this ECV, providing a clearer definition of variables such as Chlorophyll-a estimations and other water quality parameters monitoring, which is not currently done.

EO data, when combined with the definition of these ECV variables, are extremely valuable to support the sustainable development goals (SDGs). For lakes, SDGs 3, 6, 11, 14 and 16 are applicable and dependent on EO data (Ballari et al., 2023). The production of satellite-based timeseries of some of these ECVs has been crucial in many environmental studies and the discussion of higher temporal and spatial resolution, a constant subject in specialised scientific meetings (Choi, 2018) the following pages, we will analyse the resolution bottlenecks that, if surmounted, could provide higher resolution data to finally implement operational products such as the lake colour.

2.4. Results and Analysis on the Current Scientific Demand of Satellite Data to MPAs and Lake Research

Based on Web of Science, we have performed a literature search focusing on the application of satellite data usage for gathering knowledge on MPAs and lakes. We have devised three groups of queries:

- *Query A: Research on MPAs or marine reserves: ALL = (“marine protected area” OR “marine reserve”).*
- *Query B: The former applied to satellite data: ALL = ((“marine protected area” OR “marine reserve”) AND (“satellite data” OR “satellite” OR “Earth Observation”)).*
- *Query C: Lake research that already focused on the use of satellite data: ALL = (“lake” AND (“satellite data” OR “satellite” OR “Earth Observation”)).*

Our results (Figure 12) show that the number of results for query A is 41%, 2% for query B and for 57% for query C. Additionally, there is a well-established relationship between the use of satellite data and the study of lakes, equivalent to the general literature on MPAs or marine reserves (not considering the inclusion of satellite data).

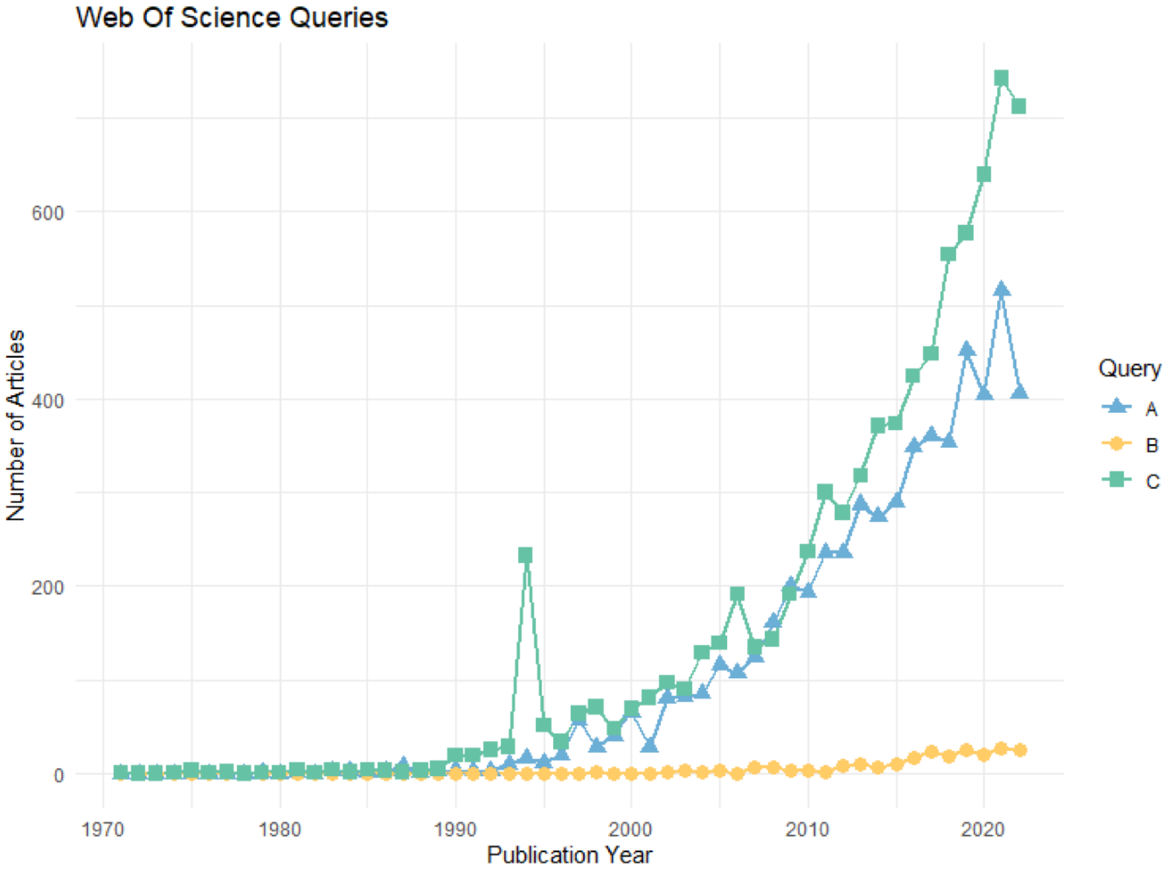


Figure 12 Results from the Web of Science query.

Gathering the results from queries B and C, we exported the full abstract and titles of each output article and preformed a text mining on the corpus of these texts.

For query B, we have defined a minimum threshold of 50 co-occurrences to create a map, we have also deleted terms specific to countries and regions since our study attempts to review the literature independently of geographical boundaries.

The created map (Figure 13) clearly shows how lake research is closely tied with remote sensing. Furthermore, more recent publications are including terms such as “algal blooms”, “eutrophication”, “water quality” and “machine learning” proving that this area of research is in the forefront of satellite technology. The most relevant satellites presented in this map are exactly the optical ones publicly available in resolutions much higher (HR1 and HR2) than the only satellite (Sentinel-1, OLCI sensor, MR2) devoted to ocean colour estimations: the Landsat family, being used before 2018 and Sentinel-2 being used more recently, after 2018. It should also be noted that Sentinel-2, being launched in mid-2015, can only now start to have sufficient data for timeline creation and analyses. Out of the 8054 articles analysed, 2640 mentioned the use of HR or VHR satellite data [(“lake” AND (“satellite data” OR “satellite” OR “Earth Observation”) AND (“high resolution” OR “WorldView” OR “Geoeye” OR “SPOT” OR “Landsat” OR “Hyperion” OR “RapidEyE”))].

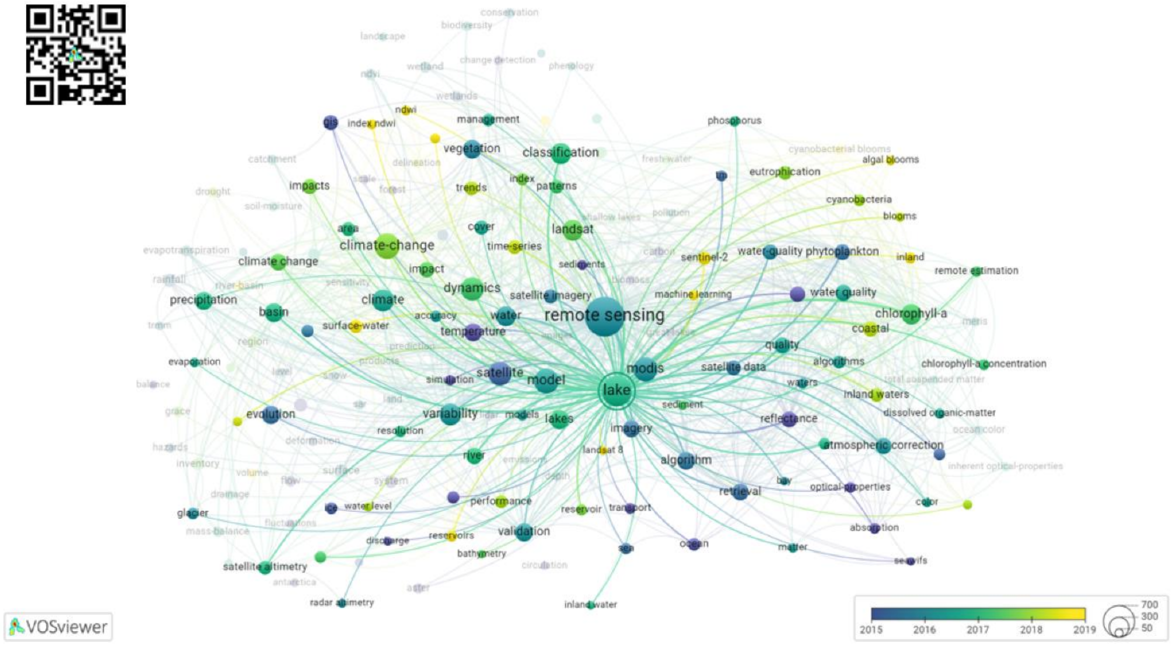


Figure 13 VOSviewer map of co-occurrences in the 8054 abstracts analysed, showing how lake research and satellite remote sensing are close subjects.

Studies that use satellite data on MPAs are still rare. We have considered both terms “MPAs” and “marine reserves” since it has been clear in previous research that most MPAs do not address ecosystem base management and lack other objectives aside from conservation and limitation on fisheries (Halpern et al., 2010). For example, marine protected areas usually do not consider eutrophication from land-sourced nutrients which can be an important indicator of how healthy an ecosystem is in an MPA. Access to high-resolution data would be of the utmost importance to generate further knowledge on these topics. Furthermore, several MPAs include shallow waters, where seagrasses prairies, macroalgae or other benthic substrates could be assessed by remote sensing, depending on their dimensions.

Our second map (Figure 14) shows how terms such as “remote sensing” and “satellite” are part of the papers on MPA research; however, they still do not have the same weight as in the case of lakes. The results also show how “satellite tracking” is also part of the text on MPAs, which is a field not related to EO. In fact, based on our results, satellites can be used to monitor MPAs for a variety of needs from tracking species (Catry et al., 2023), monitoring corals (Eakin et al., 2010) or maritime surveillance (Rowlands et al., 2019). A common application of satellite images in MPAs is the support to law enforcement in the detection of vessels not transmitting positioning information. Such vessels are often involved in illegal, unreported or unregulated fishing activities in restricted areas (Rowlands et al., 2019; Toonen and Bush, 2020; Appleby et al., 2021). These satellite data, although not directly related to environmental assessment of the MPAs, is being used in remote locations such as the Ascension Island Exclusive Economic Zone for surveillance and law enforcement purposes (Appleby et al., 2021).

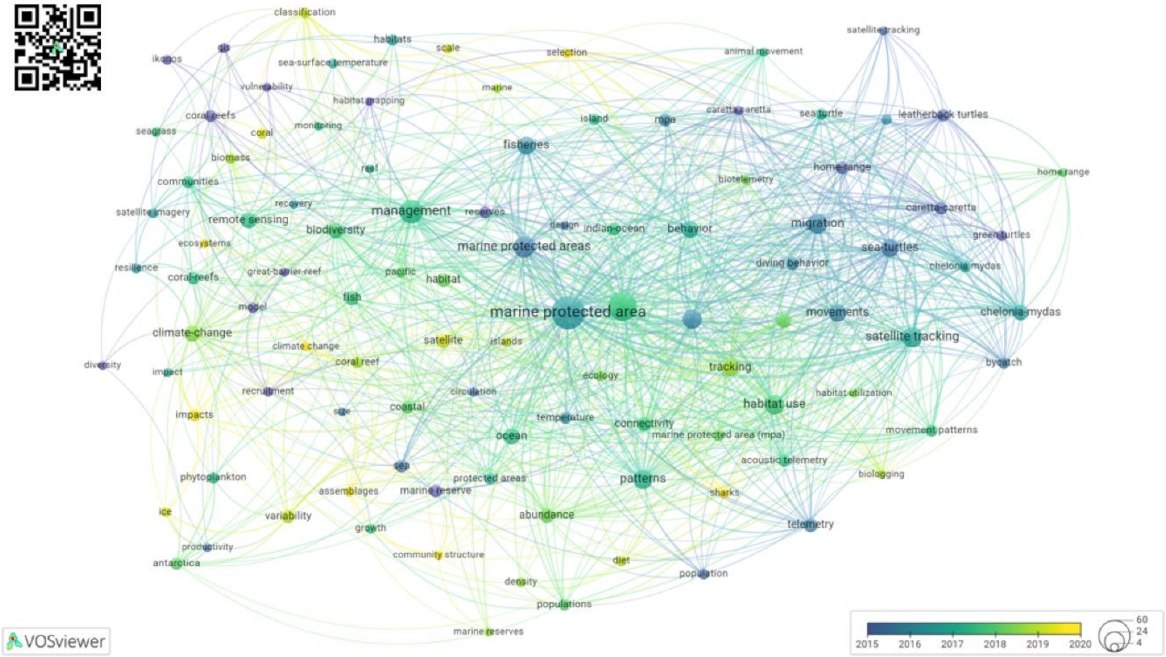


Figure 14 VOSviewer map of co-occurrences in the 231 abstracts analysed, showing how marine protected areas and satellite remote sensing are not co-occurring in the scientific literature. The map can be accessed through the QR code with the possibility to explore the clusters.

Figure 14 also shows that terms like “climate change“ and “satellite” have only been used in the more recent literature about MPAs, not presenting the kind of maturity seen for lakes. The occurrence of high-resolution satellite data in MPA-related data are 11.2%. However, amongst these, the number of articles using satellites for tracking of species in MPA contexts is 30.5%, and the rest on the surveillance of such areas for the detection of vessels involved in illegal activities such as fisheries.

2.5. Discussing Prospectives on the Feasibility of High- and Very High-Resolution Optical Satellites for Ocean and Lake Colour

There is already a clear scientific consensus on the need for better spatial resolution to respond to some environmental monitoring. A resolution gap in high-resolution (<10 m) and very high-resolution (submeter) observations of ocean (and lake colour) has been identified (Groom et al., 2019). It should be noted that at resolutions between 10 and 100 m, Sentinel-2 MSI and Landsat 8 have proved useful to provide data on sediment plumes, floating vegetation and phytoplankton (Bailey and Werdell, 2006; Groom et al., 2019; Pahlevan et al., 2019; Lisboa et al., 2020); however, these satellites cannot provide the type of data needed for an effective and constant monitoring of small water surfaces.

A new policy can be put forward to facilitate access to long-term data without compromising, and even boosting the activity of the private sector. According to article 38 above, this is in line with the new EU Space Regulation (EU) 2021/696. Privately owned satellite data responds to a need on time criticality which, in the context of long-term datasets, is no longer the case. It is strongly suggested to put forward a roadmap for public access of high-resolution data in non-politically sensitive areas. Such data entails the application of averaging and mosaicking of different singular data products and therefore individual images do not need to be facilitated, thus avoiding security threats.

In Table 6, we have included a summary of potential high- and very high-resolution private and public satellites that could be used to respond to the demands of such higher resolution monitoring for both lakes and small MPAs. The available options are many and some of these missions are already part of the Copernicus Contributing Missions. A recent study has showed the usefulness of privately owned satellites such as PlanetScope to monitor small water reservoirs and an advantage to estimate Chlorophyll-a in cases where the water bodies are too small to be monitored by coarser resolution satellites like Landsat-8 and Sentinel-2 (Pahlevan et al., 2019). The PlanetScope satellites have a resolution of 3 m, which fall within the very high-resolution definition of this paper (VHR1) (Mansaray et al., 2021). Furthermore, Formosat-2, a satellite owned and operated by the National Space Organisation (NSPO) of Taiwan, was the first mission in very HR1 capable of estimating Chlorophyll-a in small reservoirs (Chang et al., 2009; Liu et al., 2011). One study provided a good model (R2 = 0.78) between surface reflectance retrieve from Formosat-2 and Chlorophyll-a with data match-ups from 2005 and 2006 (Chang et al., 2009). Proving that a public-private initiative to monitor small lakes and MPAs in HR and VHR will make the construction of long data series possible. In sum, as outlined in Table 2, Chlorophyll-a detection is possible in all resolution classes defined in our paper. However, there is a gap in publicly available data of with resolution below 10 m (HR1 or better).

Table 6 Resolution class of each satellite mission, spatial and temporal resolution, launch dates and water quality parameters viability. This table was inspired by the often-cited 17th report from the IOCCG, 2018 but updated with recent research and more comprehensive list of satellite missions. Characteristics of KOMPSAT were assumed since the bands for this satellite are like those of Landsat-5. Symbols: ✅ "highly suitable", ✔ "suitable" and ❓ "potential". The symbol refers to variables that in the original table were regarded has "potential" but some research made efforts that Chlorophyll-a can be inferred from Landsat systems (Lisboa et al., 2020).

Resolution Class	Sensor/Satellite	Resolution (Pixel Size)	Number of Bands	Revisit Time	Data Cost	Launch Date	Water Quality Variables						Part of CCM?	References
							Chlorophyll-a	Cynobacterial Pigments	Total Suspended Matter	CDOM	Kd	Turbidity		
MR2	Sentinel-3 OLCI	300 m	21	daily	Free	2016	✔	✔	✔	✔	✔	✔	Copernicus Space Segment	(IOCCG, 2018b; Groom et al., 2019)
HR2	Landsat 1–7	30 m	4	16 days	Free	Early July 1972	★	❓	✔	❓	✔	✔	No	(IOCCG, 2018; Groom et al., 2019)
HR2	Hyperion	30 m	60	60 days	Free	2000 to 2017	✔	✔	✔	✔	✔	✔	No	(IOCCG, 2018b; Groom et al., 2019a)
HR2	Landsat 8	30 m	5	16 days	Free	September 2013	★	✔	✔	❓	✔	✔	No	Potential by (IOCCG, 2018; Groom et al., 2019) feasible by (Lisboa et al., 2020b; Veerman et al., 2022b)
HR2 and MR1 (depending on the bands selected)	Sentinel-2 MSI	10 m to 60 m bands	10	5 days	Free	June 2015	✔	✔	✔	✔	✔	✔	Copernicus Space Segment	(IOCCG, 2018; Groom et al., 2019; Mansaray et al., 2021)
HR2	KOMPSAT-2	1 m panchromatic 4 m multispectral	4	5.5 days per satellite 1 day per constellation	Paid	July 2006	✔	❓	✔	❓	✔	✔	Yes	No models assessed, feasibility assessed by comparison with Landsat-5
VHR1 and VHR2	QuickBird, SPOT 6 and GeoEYE	2–4 m	3–4	Programmable 60 days to 1 day	Paid	After 1999	❓	✔	✔	❓	✔	✔	No	Potential by (Groom et al., 2019)

HR1	RapidEye	6.5 m	5	Daily	Paid	August 2008	?	✓	✓	?	✓	✓	No	(IOCCG, 2018; Groom et al., 2019)
VHR2	WordView-2	2 m spectral, 0.5 m panchromatic	8	Programmable 60 days to 1 day	Paid	October 2009	✓	✓	✓	✓	✅	✓	Yes	(IOCCG, 2018; Groom et al., 2019)
VHR1	WorldView-3	0.5 m spectral	8	Programmable 60 days to 1 day	Paid	2016	✓	✓	✓	✓	✅	✓	Yes	(IOCCG, 2018; Groom et al., 2019)
VHR2	PlanetScope	3 m	8	Daily	Paid	2016	✓	?	?	?	?	✓	No	(Mansaray et al., 2021)
HR1	Formosat-2	8 m multispectral, 2 m panchromatic	4	Daily	Paid	May 2004	✓	?	✅	?	?	?	No	(Chang et al., 2009; IOCCG, 2018)
HR1	ALOS/AVNIR-2	10 m	4	Daily	Free	April 2006 to April 2011	✓	?	✓	?	?	?	No, but available through ESA	(Murakami and Dupouy, 2013; Aoyama, 2010; (Sakuno et al., 2014)

2.6. Applications to Governance and Ecosystem-Based Management of the Cases Studied

2.6.1. Lakes and Inland Water Systems—A Much-Needed Variable for Ecosystem-Based Management

ECVs play a critical role in ocean governance by providing the necessary data to understand and predict the changes in the ocean's climate, identify the impacts of climate change in the ocean domain and its resources, and inform decision making on how to adapt and manage these changes. Essential Climate Variables related to the aquatic ecosystems biological carbon pump have reached high levels of maturity (IOCCG, 2018); however, we see that the same is not true for the corresponding variables of the lakes. Additionally, other variables such as the lake level and water temperature, are reaching high levels of maturity. As an example, not only it is possible to map lakes worldwide (Verpoorter et al., 2014) but also water occurrence is now available in high resolution (Pekel et al., 2016) and available online (https://global-surface-water.appspot.com/map, accessed on 17 May 2024) to create temporal profiles of water occurrence, change and seasonality worldwide. This tool provides worldwide maps that are essential for local and worldwide governance.

Other ECVs related to lakes are still at a relatively low level of maturity. For example, measurements of ice cover, evaporation, or solar radiation have not been widely used or have not been consistently measured over a long period of time. Additionally, some ECVs such as water quality, have a moderate level of maturity, and there is a good understanding of the methods and techniques used to measure them, but data availability and consistency may be limited.

In general, the level of maturity for ECVs related to lakes is increasing as more research is conducted and new technologies are developed to monitor and measure these variables. However, there is still a need for more consistent and comprehensive monitoring, as well as for the development of new methods and techniques to improve the measurement and understanding of these variables.

Very High-Resolution satellite data could be highly beneficial for both the monitoring of very small lakes and small MPAs. Applications are many, for example Harmful Algal Blooms from cyanobacteria have been possible in a relatively small area of Lake Erie, even constructing a 20-year timeseries based on data from the SeaWiFS sensor (Sayers et al., 2019). This study showed that blooms from cyanobacteria became longer and longer lasting in recent years and accelerating after 2010 (it includes data until 2018). In another study, lakes across the US with frequent cyanobacterial algal blooms have been quantified based on satellite monitoring (Coffer et al., 2018). Another example is the Science and Policy Integration for Coastal Systems Assessment (SPICOSA) project, Kratzer et al. (2014) aimed at integrating data from ocean colour in coastal zones with the participation of different stakeholders. In the case of very small lakes, due to their value in different local communities, similar projects would be highly beneficial.

Although these are important examples, they do not apply to very small lakes and effective analysis of algae phenology is only possible when a long timeseries is freely available. Having long term analyses is paramount to better understand changing patterns in algal phenology due to climate variability (Maeda et al., 2019) or specific algal events. For example, in Botswana, a landscape-wide cyanobacteria bloom might have been the root cause of one of the most severe elephant population die-off (Veerman et al., 2022). The authors clearly state how current resolutions limit the satellites that can be used in these studies.

In summary, while some Essential Climate Variables related to lakes have a relatively high level of maturity, many of them are still at a relatively low level of maturity, and more research and development is needed to improve their measurement and understanding.

2.6.2. Marine Protected Areas

As of 2021, approximately 7.7% of the world’s oceans are designated as marine protected areas (MPAs). This includes different regimes of protection and treaties for their definition:

from fully protected areas, where all human activities are banned to partially protected areas, where some activities are allowed (Blasiak and Yagi, 2016).

This percentage has been increasing in recent years, as more countries and organisations have recognised the importance of protecting marine environments and have established new MPAs, albeit it has long been seen that established goals have not been reached and definition of MPAs, especially large ones, is not without criticism. One of the arguments for the establishment of MPAs in remote areas is the lack of surveillance methods essential for their enforcement (Delfour-Samama and Leboeuf, 2014). The goal set by the Convention on Biological Diversity (CBD), also known as the Aichi targets, was to protect at least 10% of coastal and marine areas by 2020 (Target 11, (Carr et al., 2020)). This goal has not been reached four years past, and the situation, especially in terms of the coverage of MPAs is far from being a success. A new goal, known as the 30 × 30 target, consists of protecting 30% of the World's oceans by 2030 and was first proposed by the United Nations Decade on Ocean Science for Sustainable Development. The 30 × 30 target has been endorsed by several other organisations, including the United Nations Framework Convention on Climate Change and the United Nations Convention to Combat Desertification. This new goal aims to conserve and protect marine biodiversity, habitats, and ecosystem services, and to enhance their resilience to the impacts of human activities and climate change. In addition, it also aims to support the achievement of other sustainable development goals, such as those related to food security, poverty reduction, and climate change mitigation and adaptation.

It is important to note that the coverage of MPAs alone does not guarantee the protection of marine biodiversity and ecosystems. The effectiveness of MPAs in conserving biodiversity and ecosystems depends on many factors, such as the size, location, and management of the MPA, as well as the level of enforcement of the regulations (Halpern et al., 2010).

In terms of their need for high temporal and spatial resolution, MPA monitoring lacks the same type of systematic monitoring as very small lakes. In fact, based on data from the Marine Protection Atlas (Marine Protection Atlas, n.d.) , 37% of MPAs are of very small size

(<10 km2), which renders current open and free EO technology inefficient in terms of observing such small areas.

Our literature search outlined in Figure 6 was refined to include benthos and seagrass (in Web of Science: (“seagrass” or “benthos”) and “satellite” and “marine protected area”). There were no results for benthos but 16 results for “seagrass” co-occurrence with “satellite” and “marine protected area”. These mostly reveal studies on the usage of high- and very high-resolution data for environmental management in specific scenarios. The ALOS AVNIR-2 and Landsat-2 satellites were used to assess the dynamics of seagrass beds in the Cu Lao Cham MPA, underlining a loss of seagrass area (Tin et al., 2020).

GeoEye-1 was used in Karimunjawa National Park for the assessment and distribution of seagrass (Prasetya and Purwanti, 2017).

In summary, the status of MPA conservation and environmental-based monitoring is not mature. The satellite resources to monitor MPAs have been mostly related to the use of satellite tracking for tracking species and detection of illegal activities, environmental monitoring of Chlorophyll a is practically non-existent.

2.7. **Conclusions: Changing Climate, Changing EO Needs**

ECVs are critical for understanding and monitoring the Earth’s climate system. These variables provide important information about the Earth’s biogeochemical processes and help to improve our understanding of the climate system and its response to natural and human-induced changes. In a changing climate, ECVs provide an important example on the possibility to create coherent timeseries of temperature, ocean colour and many other variables. But lake extent, lake colour, and ocean colour in small oceanic regions are still not possible. By monitoring these and other ECVs, scientists and policy makers can better understand the causes and consequences of climate change and develop strategies to mitigate its impacts. However, there is a spatial and radiometric resolution gap to monitor small yet very important habitats. Privately own satellites are integrated into services such as Copernicus but, currently, there is no public access to long-time series derived from such data. The same algorithms and processing methods used for ocean colour can be applied to data from other sensors to assess the water quality and phytoplankton abundance in lakes and other small water bodies (Lisboa et al., 2020). The lack of VHR1 and VHR2 resolution imagery provides a significant limitation not only on the science that can be done in the two use cases (lakes and MPAs) but also a potential operational water quality monitoring system in high resolution.

Effective ecosystem-based management (EBM) in MAPs offers a variety of factors not restricted to sustainable fisheries and conservation measures (Halpern et al., 2010). The capabilities of high-resolution data, specifically in terms of detection of Harmful Algal Blooms, euphotic depth, CDOM and organic matter might contribute to a more pressing view of MPA monitoring, but the literature is not yet mature in terms of use cases. However, the applications of EO data in the scope of MPAs are vast and due their remoteness, satellites are vital to monitor such zones.

A previous study identified 21 policy statements for EO data, identifying that most of the current policies abide for some type of free and open data access. Nonetheless, when all the exceptions are outlined across all these policy statements, the situations are extensive and potentially very restrictive. In most cases, the application of these restrictions is too broad to be applied (Harris and Baumann, 2015). As seen before, VHR is needed for effective environmental monitoring. There are three main arguments, protecting VHR satellite owners and concerns surrounding security threats, considering that the provision of the creation of a long time series from VHR imagery of the ocean is not time critical:

(1) The maritime picture, being highly dynamic and constantly changing, is not subject to the same risks and threats posed by land imagery.

(2) Creation of timeseries on water quality parameters could be specific to MPAs where military activities are in principle not foreseen.

(3) Although the images themselves could still be protected by user rights, their scientific derived products do not need to be, especially considering these data are not sensitive.

The usage of EO data for lakes and MPAs is currently only possible via some privately owned satellites especially considering the necessary EO data characteristics (higher spatial, spectral, and temporal resolutions). The EO methods necessary to perform analysis on an environmental basis (such as the retrieval of algorithms) are not suitable to produce long timeseries, with the biggest disadvantage being scientists needing to purchase an entire collection of privately owned data to study these small environments. However, the challenges are clear: studying small lakes and monitoring MPAs over long timespans is crucial.

Albeit not addressed in this article, LiDAR ("light detection and ranging") is capable of detecting Chlorophyll in water, though it is not as commonly used as an optical remote sensing method. Its high resolution and ability to provide subsurface information make it a valuable tool in certain applications, despite its higher cost and complexity (Zheng et al., 2022). For routine monitoring of Chlorophyll concentrations, traditional optical methods remain the preferred approach.

2.8. Monitoring the ocean and lakes with satellites

Planetary monitoring has been possible since the launch of the first space missions and the constantly evolving technologies on board of Earth observing satellites. Arguably the hydrosphere is the component of the 'Earth system' that benefits the most important from space-derived data. Oceanography has always been an expensive and difficult science, but the synoptic views provided by satellites allow for the continuous monitoring of important ocean variables. It is therefore paramount to fully understand Earth observation in the scope of policy and what gaps currently exist to support policy and decision-making. It has been long assumed that satellite data is an essential tool for governance but what new demands are there to bridge the gap between policies and effective monitoring?

The oceans play a vital role in Earth's climate due to their capacity to redistribute heat all over the planet and to absorb and store greenhouse gases. In particular, the mixed layer of the oceans has an effective heat capacity 20 times that of the effective heat capacity of the entire atmosphere (Soldatenko and Yusupov, 2017; Dias et al., 2022). The ocean has taken up more than 90% of the excess heat in the climate system that results from the anthropogenic emission of greenhouse gases (GhG) (Pörtner et al., 2019). The oceans also play a vital role in the thermal memory of the climate system since deep currents control climate change in a millennia timescale and the surface currents do the same in the short term (years) (Schiermeier, 2006).

Although lakes do not compare to the oceans in their capacity to store and redistribute thermal energy, they do have high rates of primary production. Global gross primary production (GPP) in lakes is estimated to be 0.65 Pg C y^{-1} (Pace and Prairie, 2005). The rate of organic carbon burial in inland water sediments exceeds that of organic carbon sequestration on the ocean floor (Tranvik et al., 2009). Therefore, many lakes' hydrological and biophysical variables are potential indicators of current climate change, and therefore, lakes present a high sensitivity to climatic patterns. Therefore, we can safely deem them as sentinels for world-wide shifts on phenology of the phytoplankton, ice melting and temperature patterns (Maeda et al., 2019). Lakes also regulate greenhouse gases (surface runoff, atmospheric deposition, and biogeochemical transformation) and the shrinkage of lakes amplifies GhG re-emission – shallow and small lakes are more active in GhG re-emission and research show emerging effects of small (<1 km^2) lakes (Pi et al., 2022).

Moreover, very small ponds, of less than 0.001 km^2, comprise 8.6% of lakes and ponds by area globally, but account for 15.1% of CO_2 emissions and 40.6% of diffusive CH_4 emissions (Holgerson and Raymond, 2016). Lakes also influence regional climate, not only as the local cooling effect (Rouse et al., 2003) but also by dampening the variability in near-surface temperature such as in the Great Lakes area, affecting the living of millions of people (Notaro et al., 2013). Finally, saline lakes contribute two times more to the emission of CO2 than freshwater lakes (Duarte et al., 2008).

Downing et al. (2006) estimated that 304 million lakes exist globally out of which 91% were of the smallest size (0.001 - 0.01 km^2), and the average lake is 0.012 km^2. Most lakes, therefore, are typically shallow with plenty of light and nutrients but they emit similar amounts of carbon to the atmosphere as the global terrestrial net ecosystem production (Tranvik et al., 2009).

Marine Protected Areas (MPAs) also present striking similarities with lakes. Not only because they provide a range of ecological, social, and economic benefits but also because of their role in biodiversity conservation, fishery management and their role in capturing CO2. Most MPAs, especially the smaller ones, correspond to specific ecosystems, such as seagrass beds, mangroves, and salt marshes. They can store large amounts of carbon, which can help to mitigate the impacts of climate change, but they are also sensitive to the effects of climate change and other environmental impacts. We do understand, however, that MPAs objectives can be enlarged in order to comply with effective ecosystem-based management in many areas of the World (Halpern et al., 2010). In addition, it has been stated that "ocean habitats such as seagrasses and mangroves, along with their associated food webs, can sequester carbon dioxide from the atmosphere at rates up to four times higher than terrestrial forests can." (Searles Jones, 2019) However, estimations of this "blue carbon" sequestration rates can be two orders of magnitudes higher when considered on a "per area" basis (Mcleod et al., 2011). This makes mangroves and other coastal habitats some of the most carbon-rich ecosystems (Donato et al., 2011) although discussions about the precise contributions and menaces of blue carbon sequestrations are still elusive and new advances are dependable on Earth observation data (Pham et al., 2023).

As we will see, higher resolution satellites, with enhanced coverage, are critical to address many aspects of MPAs not restricted to fisheries control but to ensure ocean health and better marine conservation.

Together, lakes and small MAPs are "canaries in the coal mine" because of their sensitivity to climate change effects and other menaces. Studying and continuously monitoring these areas is paramount for effective policies to fulfil the Kunming-Montreal Global Biodiversity Framework targets. Nevertheless, methods for synoptic and consistent monitoring are elusive since these areas are often isolated and/or too small for satellite monitoring.

2.9. The Marine Strategy Framework Directive

The challenges posed by Earth Observation, policy, and decision-making structures are substantial and have far-reaching consequences. In European waters, numerous marine species are experiencing population declines and habitat loss due to the impact of human pressures (European Environment Agency, 2015). Halpern et al. (2008) assert that no ocean area remains unaffected by human influence, with Europe being particularly susceptible to this issue. Furthermore, there is a considerable amount of uncertainty surrounding the conservation assessment status of many species (European Environment Agency, 2015). By 2012, the Natura 2000 network covered just over 4% of Europe's seas. While this may seem modest, it represents a significant milestone in addressing the complex challenges ahead.

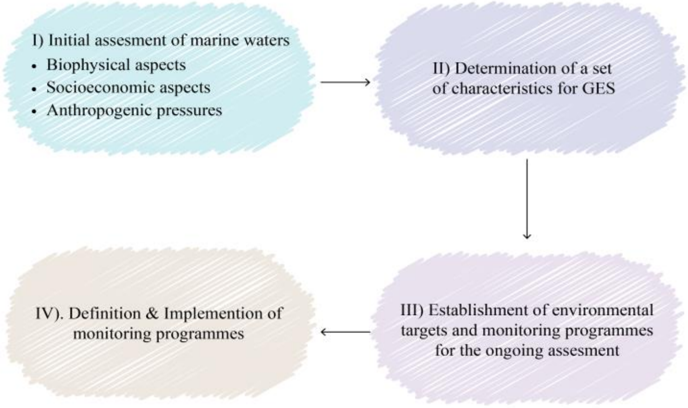


Figure 15 Steps towards the national strategies preparation, according to the required specifications in preambles 24 to 28 of MSFD.

The Marine Strategy Framework Directive (MSFD) represents a critical step in addressing these challenges, aiming to establish healthy, productive, and sustainable seas in Europe. One key question in implementing the MSFD's measures is how to apply an ecosystem approach to resource management and spatial planning, particularly in the context of Coastal and Maritime Spatial Planning (MSP).

The MSFD, Directive 2008/56/EC of the European Parliament and the Council, provides a framework within which all member states must achieve or maintain good environmental status (GES) throughout their marine environments, encompassing the water column, seabed, and subsoil, from coastal waters to exclusive economic zones. While the MSFD is a binding document, each member country is responsible for developing its own marine strategies and implementing the necessary measures – see Article 5 paragraph 1 of the MSFD (The European Parliament and the Council of the European Union, 2008).

The mandatory steps toward developing individual national strategies to comply with the MSFD ensure a coordinated approach across the European Union and commitment at the global level. As a starting point (Figure 15), "member-states may use assessments already conducted in the context of regional sea conventions (RSC) as a basis for their analyses." It is worth noting that international regional agreements were already established, such as OSPAR and HELCOM, before the establishment of the MSFD.

In this context, a new multi-disciplinary paradigm for ocean management is urgently needed: Ecosystem-based Marine Spatial Management (EB-MSM). This integrated approach, not restricted to fisheries no-take, aims to consider all potential factors for growth, including resources, job creation, international competitiveness, and innovation, while also prioritizing biodiversity protection and marine ecosystem preservation (Halpern et al., 2010). In 2012, the "blue economy" in the European Union was estimated to provide 5.4 million jobs and contribute a gross added value of 500 billion euros annually (European Commission, 2012). One of the descriptors of the MSFD is eutrophication, which integrates data such as turbidity, chlorophyll and suspended particulate matter. Sentinel-2 provides ocean colour data for the eutrophication descriptor at a resolution of 10 m, although restricted at coastal areas up to 20 km from the coast. The descriptor can also be monitored with lower resolution sensors (Cristina et al., 2015) but would certainly benefit from higher resolution data.

Chapter 3. Spatial Variability and Detection Levels for Chlorophyll-a Estimates in High Latitude Lakes Using Landsat Imagery

Abstract. Monitoring lakes in high-latitude areas can provide a better understanding of freshwater systems sensitivity and accrete knowledge on climate change impacts. Phytoplankton are sensitive to various conditions: warmer temperatures, earlier ice-melt and changing nutrient sources. While satellite imagery can monitor phytoplankton biomass using Chl-a as a proxy over large areas, detection of Chl-a in small lakes is hindered by the low spatial resolution of conventional ocean colour satellites. The short time-series of the newest generation of space-borne sensors (*e.g.* Sentinel-2) is a bottleneck for assessing long-term trends. Although previous studies have evaluated the use of high-resolution sensors for assessing lakes' Chl-a, it is still unclear how the spatial and temporal variability of Chl-a concentration affect the performance of satellite estimates. We discuss the suitability of Landsat (LT) 30-m resolution imagery to assess lakes' Chl-a concentrations under varying trophic conditions, across extensive high-latitude areas in Finland. We use in situ data obtained from field campaigns in 19 lakes and generate remote sensing estimates of Chl, taking advantage of the long-time span of the LT 5 and 7 archives, from 1984 to 2017. Our results show that linear models based on LT data can explain approximately 50 % of the Chl-a interannual variability. However, we demonstrate that the accuracy of the estimates is dependent on the lake's trophic state, with models performing in average twice as better in lakes with higher Chl-a concentration (> 20 µg/l) in comparison with less eutrophic lakes. Finally, we demonstrate that linear models based on LT data can achieve high accuracy ($R2 = 0.9$; $p\text{-value} < 0.05$) in determining lakes' mean Chl-a concentration, allowing the mapping of the trophic state of lakes across large regions. Given the long time-series and high spatial resolution, LT-based estimates of Chl-a provide a tool for assessing the impacts of environmental change.

3.1. Introduction

High latitude lakes are considered sentinels for a climate in change, due to their coupling with ice phenology, response to changes in humidity and precipitation patterns, and the high sensitivity of photosynthetic organisms to changing temperatures (Adrian et al., 2009; Kraemer et al., 2017). In particular, the growth rates, abundance, and species composition of phytoplankton are an indicator of changing environmental conditions (Rühland et al., 2008; Winder and Sommer, 2012; Kraemer et al., 2017). Nevertheless, monitoring water bodies has been difficult because *in situ* methods are very localised and cannot always be performed routinely. *In situ* datasets might also contain data gaps and data gathering is not coherent across different regions and field sampling is deemed expensive.

Given Finland’s geographical location, the country can experience a faster warming with respect to the global average. Warming in Finland is estimated to be roughly 50 % higher than the global average, which corresponds to a 0.15-0.20 °C increase per decade (Adrian et al., 1999). Most Finnish lakes are from glacial origin and during most winters the lakes in Finland have ice cover, resulting in an annual cycle of water quality parameters that also affect primary production dynamics (Ilmavirta, 1982).

Phytoplankton phenologies vary within the lake's trophic state and climate induced changes in the environmental conditions affect both the species composition and dynamics of the phytoplankton community (Peltomaa et al., 2013). In many lakes the effects of eutrophication are common with algal blooms being exacerbated by climate change (Rühland et al., 2008), it is therefore critical to have extensive temporal and spatial information on Boreal lakes (Sass et al., 2007).

A powerful way to have synoptic views of changes in water bodies is to monitor them from space. Phytoplankton biomass, which can be proxied from the Chl-a concentration, can be used to estimate primary production in aquatic environments (Kallio, 2012). Satellites have now been collecting decades of remotely sensed optical imagery over large areas. Due to the characteristic reflectance of Chl-a pigments, we can estimate concentrations from such images. Earth Observation satellites have been designed and launched with the specific purpose of studying phytoplankton from space with sensors specifically suited to the assessment of aquatic ecosystems. For example, NASA's Sea-viewing Wide Field-of-View Sensor (SeaWiFS) launched in August 1997 onboard the SeaStar satellite, collected data until 2010 at a resolution of 1.1 km. The Terra and Aqua Satellites both collect data through the 36-band MODIS sensor at wavelengths between 0.41 and 14.24 µm applicable to extensive ocean colour algorithms (Gregg et al., 2017). Additionally, the MERIS sensor was an imaging spectrometer at fifteen spectral bands and a spatial resolution of 300 m over land. Its visible to near-infrared sensitivity ranged from 390 nm to 1400 nm at programmable bandwidths between 2.5 and 30 nm. Following the loss of the Envisat-1 payload in 2012, the MERIS data spans until April 2012 having started in May 2002. Recently, the European Space Agency (ESA) has launched the Sentinel 3 constellation as part of the Copernicus Programme. Onboard the two sentinels, the Ocean and Land Colour Instruments (OCLI) are collecting data at wavelengths from 0.4 µm to 1.02 µm at 21 spectral bands, allowing for algal pigment discrimination and the further development of phytoplankton functional types characterisation from space (IOCCG, 2014). The resolution of the new OCLI sensor is 300 m, which is not suitable for studying lakes smaller than 30ha.

The use of the above-mentioned satellites hampers the study of small lakes due to their coarse resolution in relation to the size of the lakes. In fact, 95% of the roughly 56 000 Finnish lakes have an area < 1 km^2 (Kallio et al., 2005). Additionally, consistent data from the Ocean Colour missions' dates to 1997, which provides a relatively short time series. Given these limitations, the high-resolution Landsat satellites (LT) can be advantageous to use on small water bodies. LT satellites have collected one of the most comprehensive datasets, with almost 40 years of observations. LT 5 was launched in March 1984 providing data for the following 28 years. LT 5 carried the 7-band Thematic Mapper (TM) multispectral sensor. LT 7, launched in April 1999, is still in operation and carries the 8-band Enhanced Thematic Mapper Plus (ETM+). Exploring this archive for assessing Chl-a concentrations offers an excellent opportunity to evaluate how changes in phenology (i.e. timing of the blooms and their duration) have occurred in previous decades, due to both climate change and eutrophication. Furthermore, the high spatial resolution of LT data (30 m) allows the assessment of smaller lakes or lakes with complex shapes, minimizing the influence of surrounding land vegetation.

The LT data has been used for the assessment of regional lake water clarity with reliable empirical relationships between satellite data and ground observations in the north American glaciated lakes (Kloiber et al., 2002) and in Europe (Östlund et al., 2001). Similarly, the interest on studying Finnish lakes through LT data dates back to the 1980s, leading to research that proved that spectral differences due to aquatic vegetation were possible to detect (Raitala and Lampinen, 1985). An important early study on Finnish lakes also approached the configurations of ETM+ sensor for lake water quality estimations (Kallio et al., 2005). Feasibility studies conducted in Finland in the early 2000s have identified that it is possible to estimate the average Chl-a level of an individual lake through matchups of airborne sensing data from another lake (Pulliainen et al., 2001). Notwithstanding the limitation on spectral and radiometric resolutions, other previous efforts outlined the importance of ETM+ data on monitoring small lakes for coloured dissolved organic materials (CDOM), turbidity and Secchi disk transparency (Kallio et al., 2008). We find that these approaches should be revisited with LT data for two reasons, first taking the advantages of long data series is paramount for studying change (Maeda et al., 2019), secondly, exploring alternative high-resolution imagery is a necessary step to enhance the monitoring of small water bodies. Previous studies used semi-empirical approaches to conclude that Chl-assessment is limited by the band configuration of LT and this type of activity goes beyond the design of the TM sensor (Härmä et al., 2001). Our study revisits this assumption by gathering more *in situ* data and a vast collection of imagery.

Studies of single lakes using LT data are well described in the literature (Brivio et al., 2001; Giardino et al., 2001; Allan et al., 2011). For example, imagery from LT and samples from a transect were combined achieving a $R^2 = 0.9$ over Lake Erken, Sweden (Östlund et al., 2001). Another study, Isenstein et al. (2014) used the band ratio of B2/B1 (green/blue) for Chl-assessment on Lake Champlain, USA, reporting a R of 0.82. Having such space-derived estimates has been proved useful to study the changing patterns. Nevertheless, the challenges increase with smaller lakes. For example, a set of 131 small lakes (averaging 100 ha) in Maine revealed an R^2 of 0.25 (Boucher et al., 2018). LT5-TM and LT7-ETM+ are not ideal for waterbodies, but they are the only available dataset at enough resolution with a significant temporal span.

The models derived in these previous studies were limited by validation campaigns carried at specific validation campaigns, in specific time frames. Our approach is to engage on an innovative *in situ* and remote sensing match up. We used many years of consistent *in situ* data, collected at different locations, and created a validation method using more than 3 decades of satellite data. To take full advantage of the long LT time series, models should robustly incorporate data from both LT5-TM and LT7-ETM+. Vicent et al. argued that a model developed for LT5 cannot be applied to LT7 images (Vincent et al., 2004). Nonetheless, their methods involved the use of dark-object-subtracted radiance instead of surface reflectance. Hence, further studies are still needed to fully explore the combined use of LT5-TM and LT7-ETM+, using surface reflectance derived from state-of-the-art atmospheric correction algorithms (Masek et al., 2006).

The focus of our study is to demonstrate whether Chl-assessments using surface reflectance retrieved from LT sensors can be generalised for these different circumstances. In other words, we aim to understand how different Chl-a might affect LT reflectance, as a preliminary approach to develop advanced bio-optical models for inland and coastal waters. Such models, in turn, are an essential tool not only for global water quality monitoring, but to also study temporal dynamics of phytoplankton across large areas, allowing the identification of shifts in the temporal characteristics of phytoplankton blooms related to climate variability and land-use changes (IOCCG, 2018).

The water-leaving signal is especially complex for the case of inland waters due to the high concentrations of CDOM, tripton, floating and submerged aquatic vegetation, suspended matter (e.g clay) and finally phytoplankton. The tripton component, composed of detritus and minerals from dead phytoplankton and decaying organic matter, varies significantly in optical signatures and concentration ranges. High concentrations of humic and fulvic acids from surrounding vegetation are leached into lakes and reduce the light availability in the blue spectral region in boreal and brackish waters (Gorelick et al., 2017), both the case of most of Finland's lakes. The lakes considered in this paper are thus some of the most difficult cases for bio-optical models of phytoplankton proxying from space.

Our objective is to better understand spatiotemporal factors affecting the relationship between LT reflectance data and surface Chl-a concentration over high latitude lakes. We drive our research by asking: 1) how does the performance of models based on LT data vary with different lakes' trophic state? 2) how does the performance of models based on LT data vary at different temporal scales? 3) Can the LT data archive be used to assess the spatial and temporal variability of lakes' average Chl-a levels across large areas?

3.2. Material and Methods

3.2.1. Study area and *in situ* data

The lakes included in this study belong to the intensively monitored lakes of the national routine monitoring network of Finland (Figure 16). Lake Saimaa, along the Salpausselkä system, is the only lake with two sampling spots. Water samples for turbidity were taken from 1 m depth, and Chl-a was determined from a composite sample of 0 – 2 m depth. The concentration of Chl-a was measured with a spectrophotometer after extraction with hot ethanol (ISO 10260, GF/C filter). Turbidity, measured in Formazin Nephelometric Units, was determined by the nephelometric method (EN 27027), based on measurement of light (860 nm) scattered within a 90° angle from a beam directed at the water sample, with formazine used as a standard matching solution.

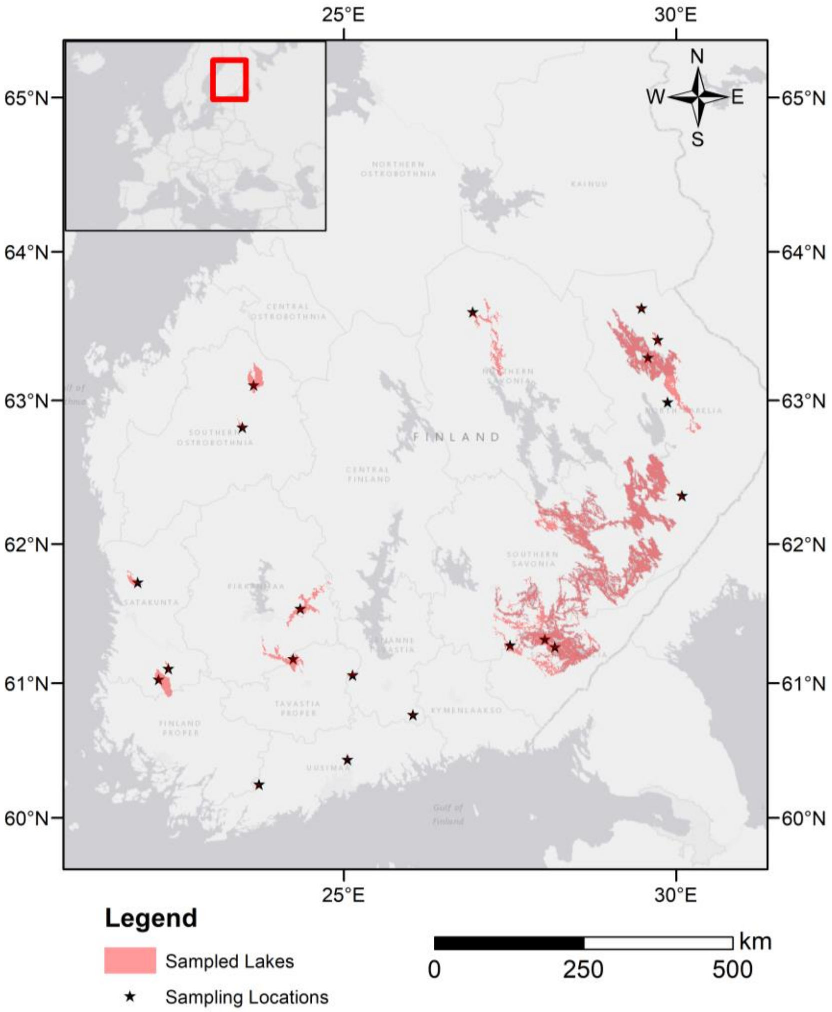


Figure 16 Distribution of the 19 sampled lakes and the 20 sampling locations. Two sampling locations were defined for lake Saimaa, the biggest lake in Finland.

3.2.2. Landsat Imagery

We used the Surface Reflectance Collection — Tier 1 from LT 5 and 7 provided by the United States Geological Survey (USGS) to the Google Earth Engine archives. Both satellites' lifespans include all our *in situ* sampling dates. These products are processed through the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction — a radiative transfer model that includes water vapor, ozone, geopotential height, aerosol optical thickness and digital elevation (Greb et al., 2018). Only images with the highest quality factor were used summing a total of 3865. Images are predominantly from summer months; no images were selected from December and January due to high cloud coverage and low – or null – sun elevation. The dates of the images span from February 1999 to April 2017 (Figure 17). We have used bands 1-5 from the LT collection corresponding to all visible bands, Near Infrared (NIR-band 4) and Shortwave Infrared (SWIR -band 5).

3.2.3. Data methods

We evaluated multivariate regression models to identify which LT bands, or band combinations, are more suitable for estimating Chl-a concentrations. We also evaluated how time differences between the date of Chl-a field samples and the date of LT images acquisition affect the performance of the models.

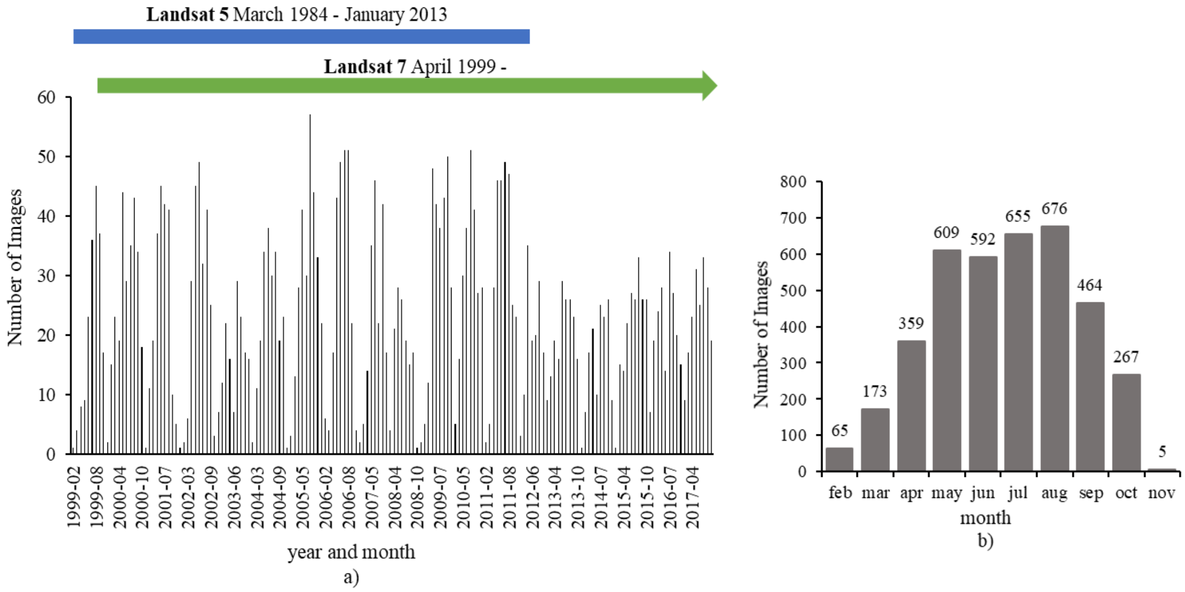


Figure 17 Number of images used for this study throughout the whole imagery collection a) and the distribution per month b).

Our code was developed in Google Earth Engine (Gorelick et al., 2017), which provides the entire dataset from LT imagery and the possibility to define the regions of interest according to our specific needs. The collection of LT data into band reflectance time series over the lakes was carried through two main stages: quality assurance of the images and matching of spatially averaged water reflectance with the *in situ* samples.

Next, we gathered and filtered the image collection. The filter removed cloud cover, cloud shadowing and ice pixels, all masked out based on the C Function of Mask (*cfmask)* algorithm described by Foga et al. (2017). Nevertheless, the *cfmask* cannot account for all imagery artefacts. To solve the issue, we added a normalised difference chlorophyll index (NDCI) to the resulting LT collection. We calculated the 25th and 75th percentiles from the resulting index distribution, thus eliminating pixels with NDCI outside the interquartile range (IQR) and bullet-proofing the *cfmask* filtering.

Daily aggregated data

Daily aggregated data is relative to the match up of a satellite image with the *in situ* collection around that date. We spatially averaged the resulting valid pixels per image, as laid down in the area buffer defined by a permanent water mask. We gathered data according to the temporal averaging of images collections within ± n days from the date of *in situ* collection. Previous validation studies indicated an ideal time gap between satellite overpass and field measurement of ± 1-2 days (Stadelmann et al., 2001). We have chosen a time gap of maximum ± 1-2 days, from the hour of sampling, to estimate the Chl-a concentration of all the 19 inland water bodies.

Seasonally aggregated data

Our analysis also evaluated seasonally aggregated data, in which we lose the temporal aspect of remote sensing concentration to assess the spatial distribution of the lakes' trophic status. For this, we used the average Chl-a during spring and summer (day of year [DOY] from 100 to 280) in all lakes, considering all LT pixels within a 500-m buffer of sampling collection. This procedure resulted in a total of 126 validation pairs.

All procedures were carried out in GEE and the data exported for further statistical analysis in R (Sasaki et al., 2005) as detailed in section 2.4. For statistical purposes, *in situ* Chl-a data was primarily filtered to remove outliers. To detect these outliers, we used Tukey's method which targets values above and below 1.5 of the interquartile range (IQR). This study also includes an assessment of the relationship between turbidity and Chl. We have calculated the overall correlation between both variables and narrowed it down to summer data (DOY 200 to 280).

Defining a permanent water mask.

It is paramount that the spatial average of water-leaving reflectance values is performed over permanent water surfaces. Preliminary lake boundaries were defined according to the GLOWABO dataset (Verpoorter et al., 2014). However, this layer can include small lake islets or areas of intermittent water presence. To further ensure that the imagery corresponds to permanent water surfaces, we intersected the GLOWABO dataset with the Global Surface Water Data from a Joint Research Center study (Pekel et al., 2016). By intersecting these datasets, we ensure that the selected pixels correspond to permanent water surfaces in the period between 1984 and 2017. Our methodology results in the definition of detailed and high-resolution surfaces on which reflectance spatial averaging can be performed. Within these areas, we overlaid a circle, centred around the sampling location, with varying a radius (Figure 18). Additionally, to avoid interference from land vegetation and other types of aquatic plants, we have applied a buffer of 50 m away from land when the circle of extraction is above 500 m.

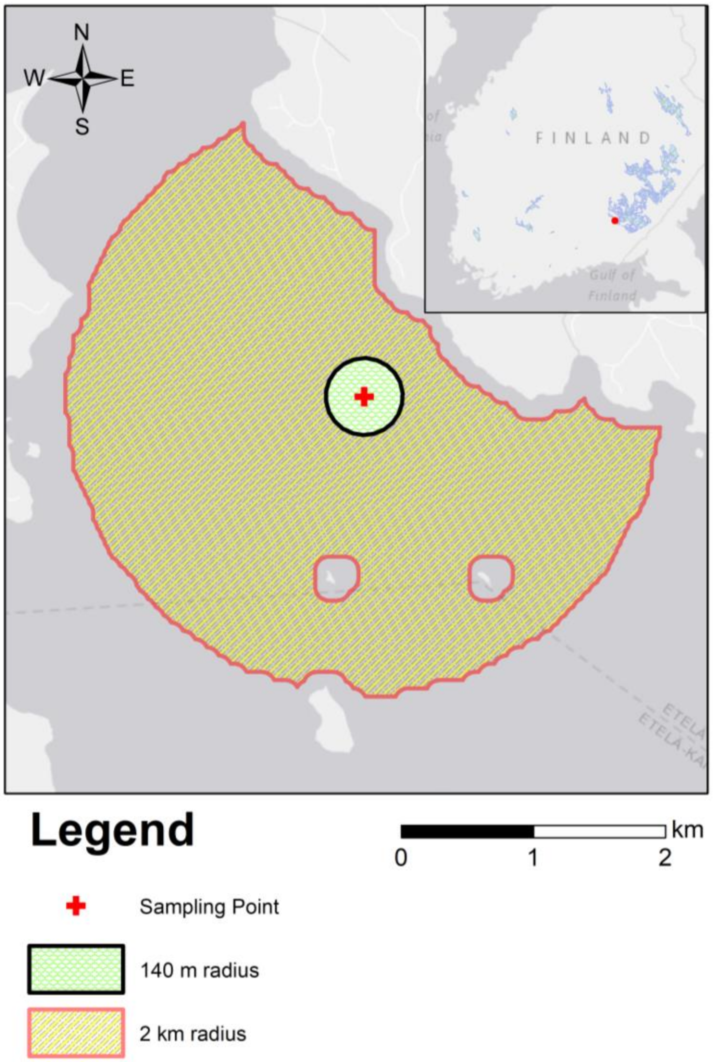


Figure 18 One of the sampled locations at the centre of the area for satellite reflectance band extraction (shaded). Such areas are a variable radius circle around the sampling site and avoiding land.

All shaded areas on the map (Figure 18) depict the surfaces over which the reflectance bands were collected in this manner. After creating a time-series collection of surface reflectance for each lake, we have generated a database for *in situ* Chl-a match-up and derived the models.

3.2.4. Model Selection through Relative Importance Metrics

We assessed the performance of a linear model by merging data from both LT 5 and 7 and all lakes. Multiple linear fits are presented in this analysis, providing a measure on how the different band combinations perform on detecting Chl-a. To have an overview of the variables to incorporate into the model, we used the "Leaps: regression subset selection" exhaustive search, the routine for the best subsets of predictors which uses a linear regression through an efficient branch-and-bound algorithm. The resulting combinations of regressors can be analyzed by either the R^2 of the model or its Schwartz's information criterion or Bayesian information criterion (BIC). The BIC is a criterion for model selection among a finite set of models (Neath and Cavanaugh, 2012) . While fitting models, it is possible to increase the likelihood of a good fitting by adding parameters but doing so may result in overfitting. The BIC resolves this problem by introducing a penalty term for the number of parameters in the model. Lower values of BIC are then preferred for the best model assessment.

Multivariate models for Chl-a were designed using each reflectance band as a regressor. Secondly, we evaluated model performance through relative importance metrics. Relative importance metrics is the quantification of the individual regressor's contributions to a multivariable regression model. For uncorrelated predictors, the multivariate coefficient of determination (R^2) is simply the cumulative result of each R^2 of the single-variate linear model. However, bands of satellite optical imagery are deeply correlated, raising the necessity for a relative importance classification. We have used the *relaimpo* package from R that provides six different methods for assessing relative importance in linear regression (Grömping, 2006). Among these methods, the one from Lindeman, Merenda and Gold (LMG) (Sen, 1968) is one of the most computationally intensive but highly recommended.

3.2.5. Spectral indices

Previous studies have demonstrated the usefulness of spectral indices, rather than individual bands, on the detection of vegetation both in land and water. Besides the individual bands, we used two spectral indices to derive our models; the LT adapted version of the normalized difference chlorophyll index, NDCI, and another index, BRG, based on the relative difference of blue and red bands relative to the green band.

The NDCI is given by:

$$NDCI = \frac{\rho_{NIR\ (B4)} - \rho_{red\ (B3)}}{\rho_{NIR\ (B4)} + \rho_{red\ (B3)}}$$

$[eq1]$

where ρ is the reflectance of the specific band.

The BRG model was adapted from (Brivio et al., 2001) who achieved an $R^2 = 0.818$ in Lake Garda, Italy. In such a model, Chl-a is directly proportional to the reflectance index given by:

$$BRG = \frac{\rho_{blue\ (B1)} - \rho_{red\ (B3)}}{\rho_{green\ (B2)}}$$

[eq2]

The same BRG index led to satisfactory results for other small water bodies as in the Malilangwe Reservoir, Zimbabwe with $R^2 = 0.81$ (Dalu et al., 2015).

3.3. **Results**

Of all models derived through intra-annual data, the best performance was achieved with a buffer of 700 m and a time-window of ± 1 day from the satellite acquisition. For this configuration, the results of the LEAPS exhaustive variable search are presented in Figure 19. The R^2 varied from 0.16, using only one explanatory variable (band 4 - NIR), to 0.55, using all possible bands and indices. The highest R^2 value could also be achieved when excluding band 2 (green) and including all other variables. The BIC values varied from -30, using only band 4, to -150, using bands 1, 3, 4 and 5.

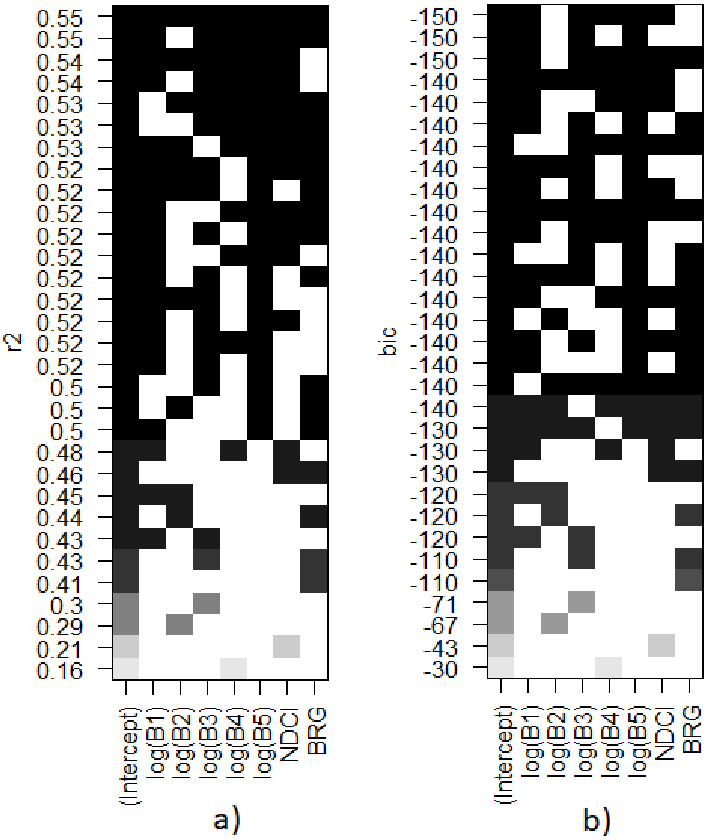


Figure 19 Best linear model assessment through LEAPS variable search. In a) the R2 for the models for the different regressors combinations. In b) the BIC for the respective models.

Figure 20 depicts the relative importance of each band for the overall R^2 of the achieved model. All bands 1-4 are significant ($p\text{-value} < 0.05$) for the construction of the model,

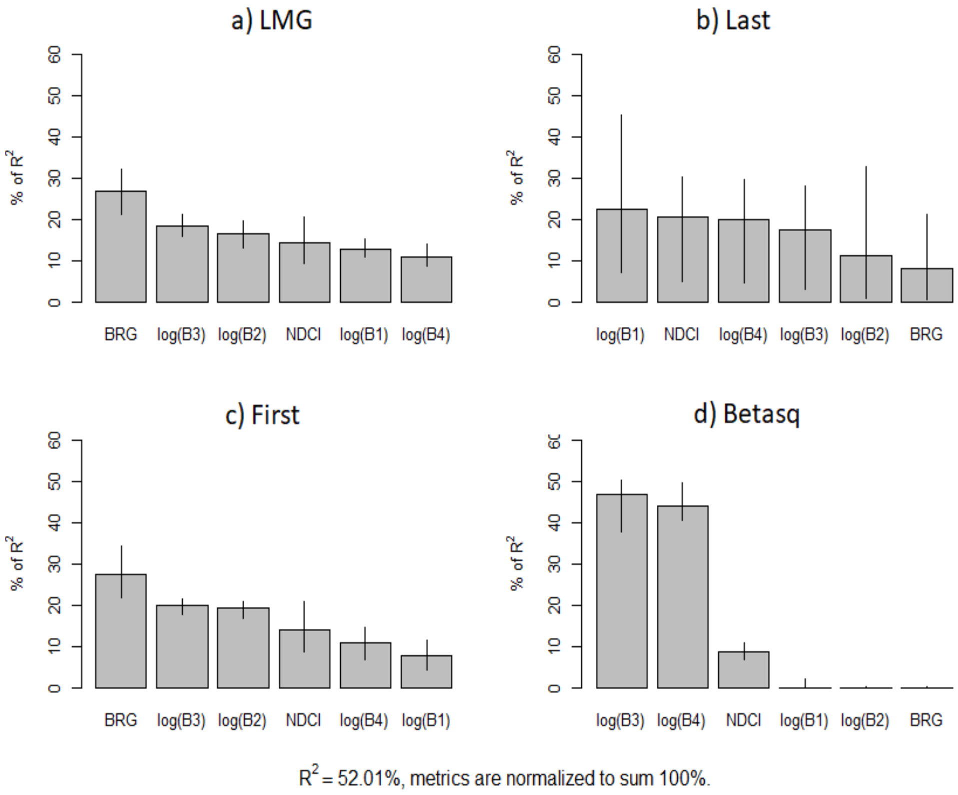


Figure 20 Metric of relative importance using the 700-m radius and a time window of ± 1 day. All bands and the spectral indices included. Relative importance of each LT band with 95% bootstrap confidence intervals.

although the different models used to evaluate their relative importance did not always agree on the most important variables. Across all methods, band 3 and BRG index has the strongest explanatory power. Band 2 was selected as the second-best explanatory variable by two methods (LMG and First).

Figure 21 provides the correlations matrix of all bands and the NDCI and BRG indices. As evidenced, relationships between individual explanatory variables and Chl-a are not linear. Pearson's coefficient of correlation (R) is shown for each band, and indices, with relation to the Chl-a concentration.

Because of the small contribution of the Short-wave Infrared (SWIR) band 5, we have considered a final model for the daily aggregated data comprising all these bands and indices.

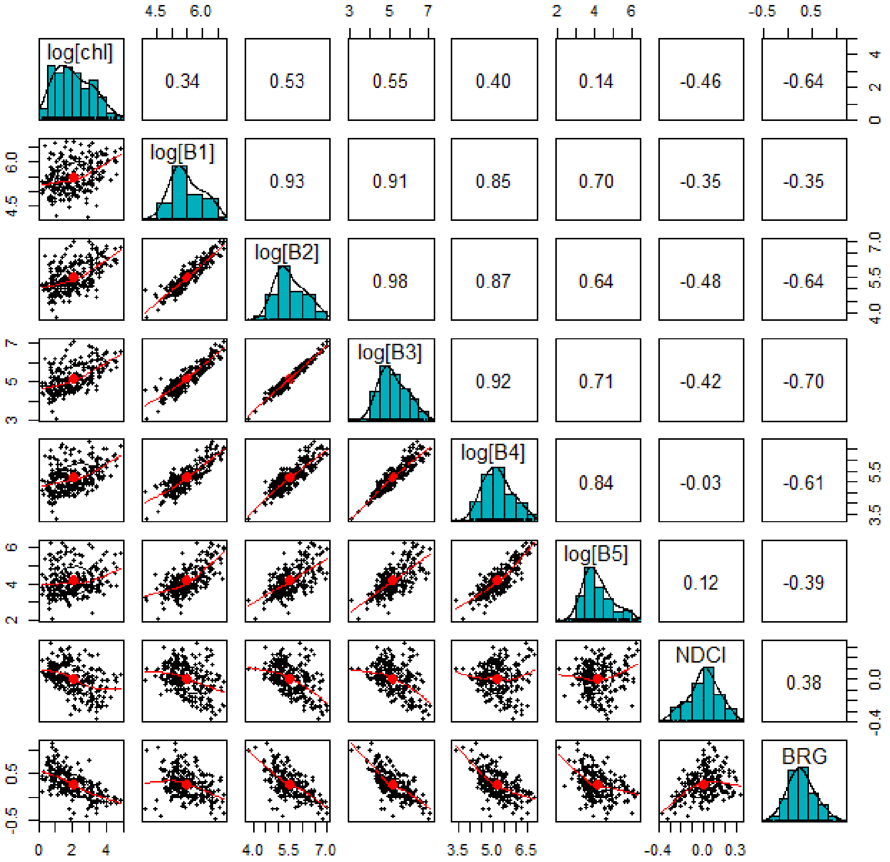


Figure 21 Scatterplots matrix with field measured Chl-a and LT bands the numbers on the diagonal part are the coefficients of correlation, R. The red lines depict polynomial fits to the individual band scatterplots.

All individual bands 1-5 correlate positively with *in situ* Chl-a but bands 2 (R = 0.53) and band 3 (R = 55) are more strongly correlated. Both indices NDCI and BRG are negatively correlated with *in situ* Chl.

Model Performance

As expected, short-wave Infrared (SWIR) band 5 of LT 5 and 7 provided only a marginal contribution to the overall performance of the model by 0.04 in the R^2 coefficient. Extracting that band to assess the performance of only visible and NIR bands, also produced important results summarized in Table 7. All models derived from single bands 1 – 4 were significant but not all models that included reflectance indices, NDCI and BRG, are significant. Henceforth, for the best models, we checked if all coefficients are significant, i.e., we checked if all variables significantly contribute for the resulting model. For the best performing model, a R^2 = 52.01 was achieved, including bands 1-4 and both indices. Reducing the time-window between satellite collection and *in situ* sampling has a relevant impact on the overall performance of the model, as it increases the R^2, whilst maintaining a p-value < 0.05.

Table 7 Buffer size and R2 for time-windows of ±1 and ±2 days. All tests were performed for the model with bands 1-4, we excluded band 5 as in some cases it leads to non-significant models (p-value 0.05). All bands were significant.

Buffer Size / t-window	***60 m***	***90 m***	***100 m***	***140 m***	***180 m***	***300 m***	***500 m***	***600 m***	***700 m***	***800 m***	***900 m***
Model including bands 1 – 4:											
± 1 day	47.81 %	46.82 %	47.15 %	47.68 %	43.70 %	42.87 %	48.27 %	47.80 %	**48.75 %**	48.7%	48.47 %
± 2 days	45.15 %	37.71 %	36.95 %	37.51 %	37.34 %	38.63 %	41.4%	41.05 %	41.13 %	41.77 %	41.95 %
Model including bands and indices:											
± 1 day	49.96 % [Du]	50.89 %	50.77 %	50.19 %	47.16 %	45.15 %	51.26 %	50.98 %	**52.01 %**	51.66 %	51.92 %
± 2 days	45.87 % [B2, B3, B4, NDCI, BRG]	39.38 % [B1, B2, BRG]	38.83 % [B1, BRG]	39.89 % [BRG]	39.88 %	40.28 %	42.53 % [B3]	44.39 %	44.66 %	44.93 %	45.21 %

The choice of the size of the buffer around the sampling location has a small impact when compared to the choice of the time-windows (Table 7). It is advisable to maintain a buffer size of either 60 m or above 500 meters. Between 90 m to 300 m, we observed that the number of additional pixels has created more noise than valuable signal from Chl-a content, thus creating a lower performing model.

Figure 22 shows the best performing model found with a buffer of 700 m and ± 1 day time window; this model includes all visible bands plus Near Infrared (NIR, band 4) and Shortwave Infrared (SWIR, band 5). The inclusion of SWIR slightly increases the overall correlation but also the p-value of the model.

Table 8 Individual band/index importance for the model in figure 19.

	log(B1)	**log(B2)**	**log(B3)**	**log(B4)**	**log(B5)**	**NDCI**	**BRG**
LMG	0.110009	0.149998	0.18466	0.106984	0.075028	0.128362	0.244957

Using satellite images from ± 1 day of *in situ* sampling comes with the disadvantage of a small number of data pairs (Figure 22).

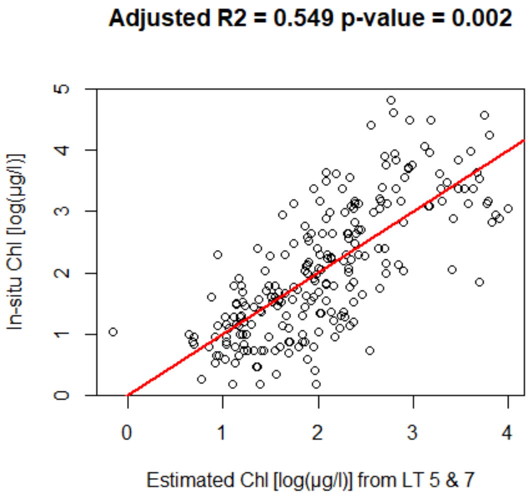


Figure 22 Scatterplot with modelled vs observed Chl-a using the best model (with R2 and p-value). This model was achieved in the conditions of Table 2: all five bands, NDCI and BRG for a time window of ± 1 day and 700 m buffer.

The tests in Table 7 and the model in Table 8 incorporate data from 6-11 out of the 19 lakes – for the remaining lakes, there are no satellite passes free of cloud cover, enough quality control standards, sun elevation or snow-free for the match-up. To assess Chl-a detection levels from different lakes, we have widened the time-window to ± 4 days and lowered the radius to 500 m and included band 5 (SWIR). We have compared results obtained for individual lakes by addressing the lakes' characteristics like depth, size and proximity of the sampling to the lakes' margins.

In Figure 23 we show that the coefficient of determination, R^2, varies depending on the mean Chl-a concentration of each lake. For each trophic state of a lake, the accuracy of the estimates from satellite imagery can vary greatly but there are significantly better performances for eutrophic lakes.

Model performance and trophic state

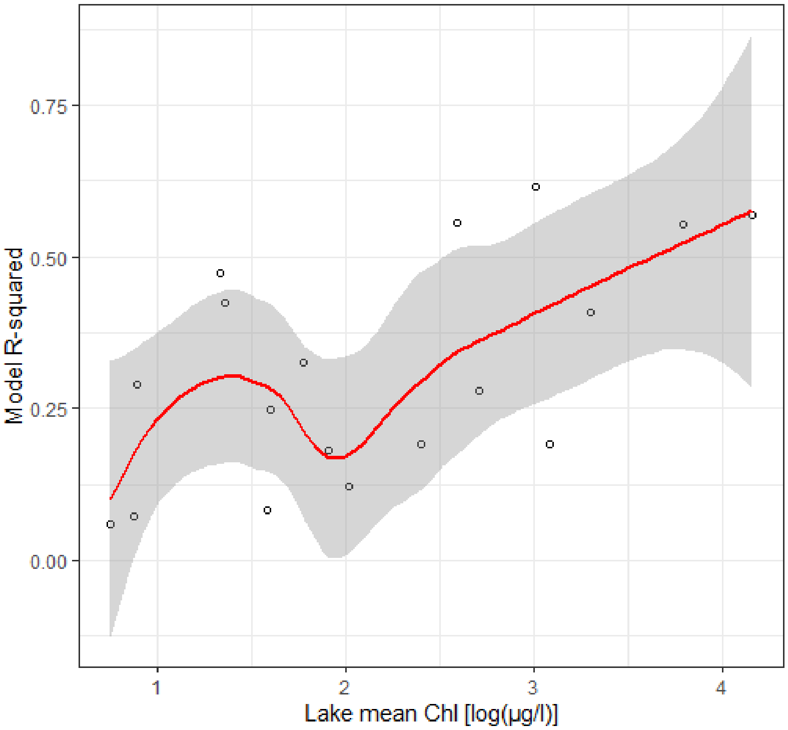


Figure 23 Scatterplot of individual lakes R2 vs average Chl-a concentration in each lake. Results were achieved using Scatterplot of individual lakes R2 vs average Chl-a concentration in each lake. The graph also shows the root-mean-square error (RMSE) as shadowed area and the blue line calculated as the locally weighted least squares regression. Results were achieved using individual multivariate models for each lake and a time-window of ±4 days.

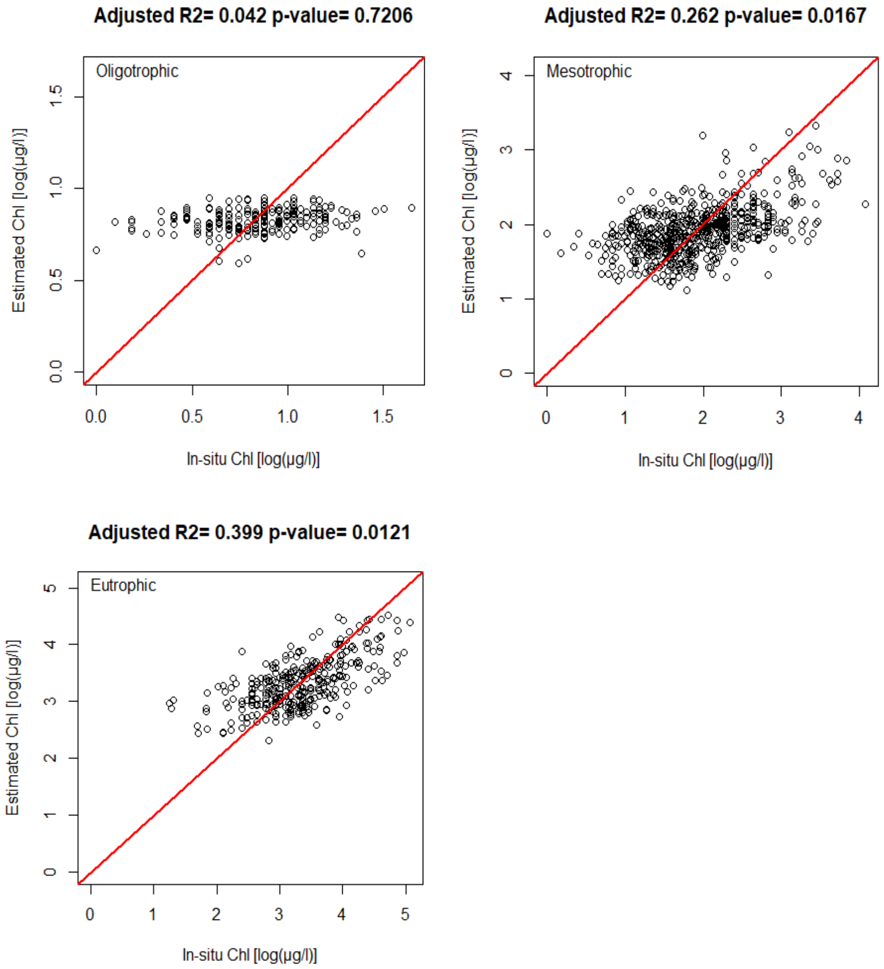


Figure 24 Model performance according to the trophic class of the lakes.

The trophic state of lakes greatly influences the performance of the model built on the individual samples match-up. According to our results in Figure 24, eutrophic lakes have better-resolved Chl-a estimations. Our results show that for eutrophic lakes the model performs twice as better as for mesotrophic lakes. All data points in Figure 25 were filtered to the spring and summer season, i.e., DOY = [100: 280].

Model performance against *in situ* measurements of Chl-and turbidity

Our results show that turbidity and Chl-are strongly correlated during summer months, i.e. DOY = [200:280]. Turbidity is therefore highly coupled with Chl-a during ~2.5 months of the year and before that the relationship is not present. The fact that during spring and until

July the Chl-a is decoupled from turbidity provides a ground for phenology studies on phytoplankton blooms in lakes. Even in summer period, a model of LT reflectance and turbidity does not perform nearly as well as for Chl.

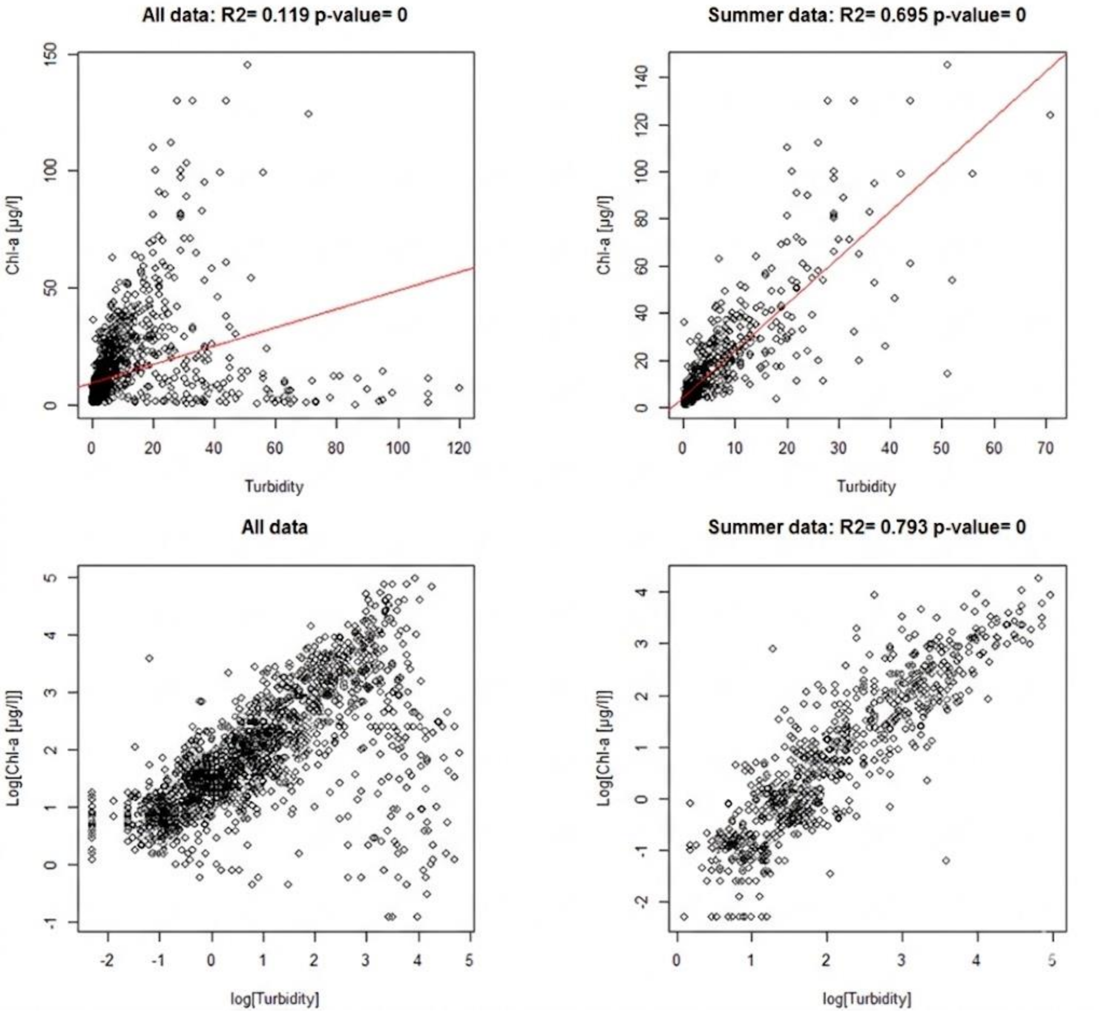


Figure 25 The relationship between Chl-a and turbidity for all data (left) and summer months (right).

Performance of the model vis-a-vis sampling location and geophysical characteristics

Sample collection set-up greatly influenced how well Chl-a concentrations at particular locations can be estimated using remote sensing (Figure 26). Therefore, model performance is likely to vary within lakes that are close to each other. There is no linear trend relating depth and R^2, but the smaller the lake the better this model performs. Indeed, small lakes of less than 40 km^2, are better suited to be studied under this model. The relationship between the small lakes signal and the surrounding vegetation will be discussed further. Sampling locations that are very close to the shore (less than 200 m) have poor relation with the model estimates. On the other hand, the performance of the model is better for sampling locations between 200 and 700 m to the lakes' margins (Figure 26-c). As it will be discussed further, proximity to a lake's margins can imply higher Chl-a if surrounding vegetation does not interfere with the optical characteristics of a lake's water.

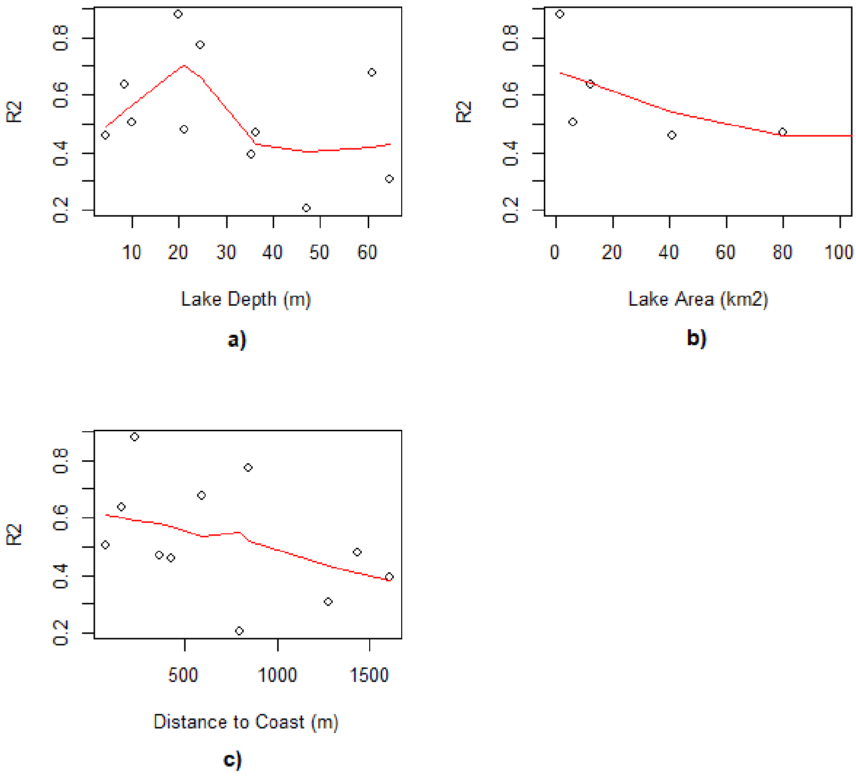


Figure 26 Scatterplot matrix R2 vs lake depth a), lake size b) and distance from the sampling collection site to the coast c).

3.2. Seasonally Aggregated Data

We showed that the signal-to-noise ratio on the remotely sensed Chl-a is higher on the spring and summer period for eutrophic lakes. Hence, we aggregated images collected only during the summer period, i.e., between DOY 200 and 280. These images, when matched-up with the *in situ* samples, produce a well-performing model.

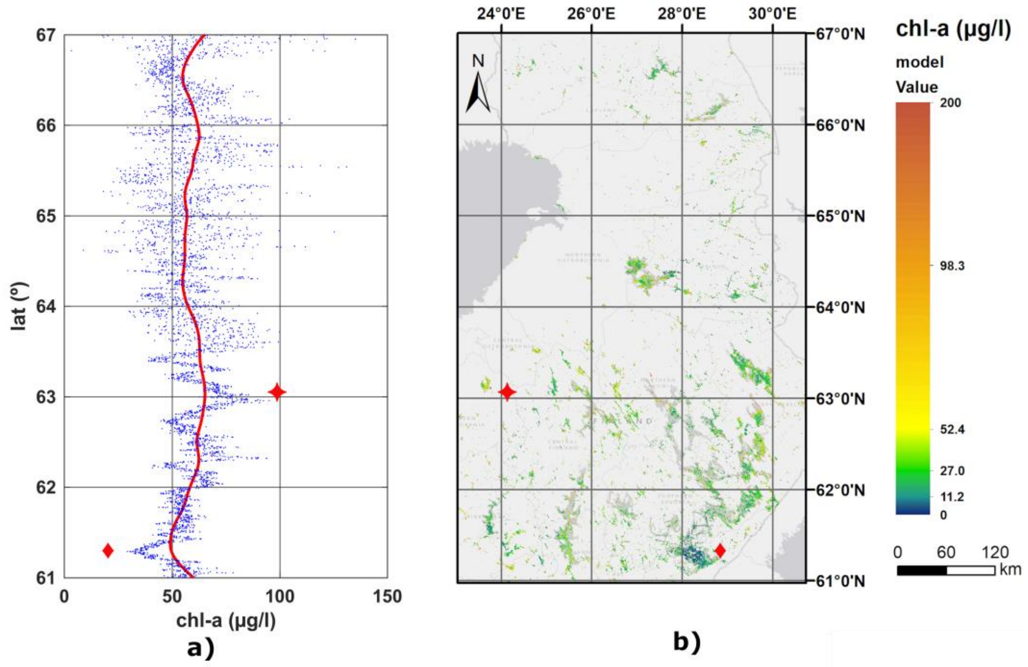


Figure 27 a) blue dots represent the average Chl-a per latitude pixel (0.0013º) and the red line represents the smoothed average per degree in latitude. b) Map with predicted values of mean Chl-a for the Finnish lakes. Lake Saimaa is indicated by the symbol ◆ and lake Lappajärvi by ✦.

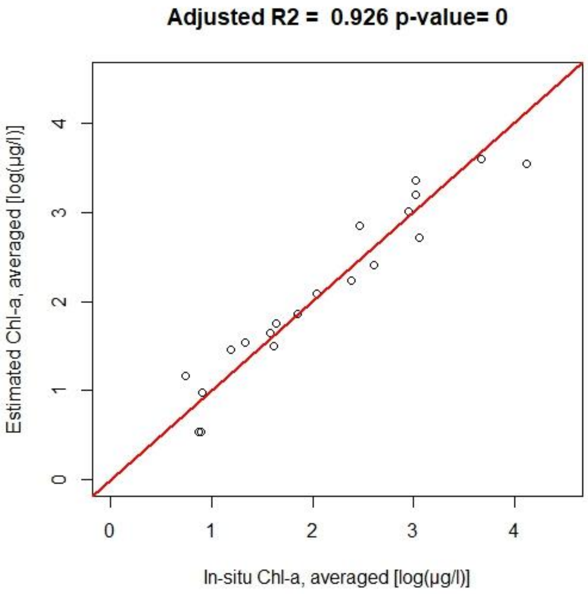


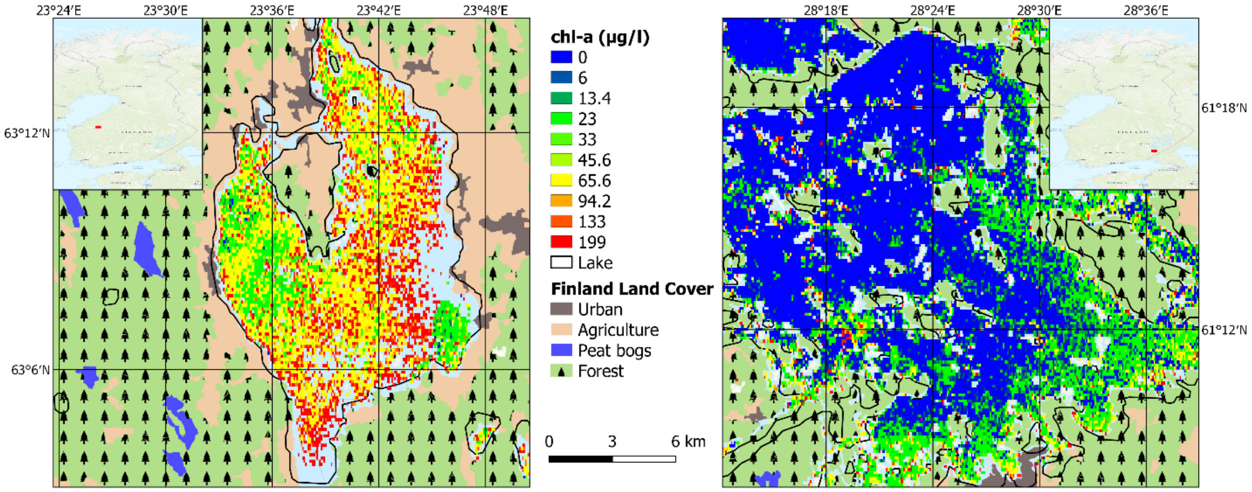
Figure 28 Predicted values of lakes mean surface Chl, using multivariate regression.

The seasonally aggregated model (Figure 28) is the result of using a 500-m buffer with a ±2 day with averaged summer results for each lake. This result shows that the model performs well for large-scale estimation of Chl-a between DOY 100 and 280. The results of the Chl-a estimation for the entire Finland, using the corresponding model, is shown in Figure 27. As we expect that a gradient of rising latitudes has a large influence on the primary production of the lakes, we averaged the mean Chl-a in our model for the same latitude. For latitudes between 61.5º N to 63.5º N there seems to be a clear positive trend on the increase of seasonal Chl. Lake Saimaa (red diamond in Figure 27) is one of the less eutrophic ones, which contributes to the lowest average Chl-a concentration at the 61.2º N parallel. On the other hand, Lappajärvi (red star in Figure 27 and detailed in Figure 29) is Finland's largest crater lake, it has been given by our model as a very eutrophic lake which corresponds to the same concerns in the literature.

The clear trend contrasts with the northernmost areas where lakes are less abundant, smaller or sparser. Above 63.5 º N, extreme variance of Chl-a can be seen. Under 63.5ºN latitude, the model correctly identifies lakes that are typically eutrophic, due to the presence of agriculture or arable land.

3.4. Discussion

In this paper, we aim to better understand how statistical models based on LT perform considering different lakes across an extended time period, from 1984 to mid-2017 and an extended area. There are several differences between the TM and ETM+ sensors, onboard LT 5 and 7, respectively. TM is a multispectral scanning radiometer and ETM+ a whiskbroom scanning radiometer with an additional panchromatic band of 15 m resolution and two 8-bit "gain" ranges. ETM+ also features a 60-m resolution thermal band, replacing the one of 120-m resolution of TM. Nevertheless, these differences do not affect the bands considered in this paper and we assume we can merge data from both sensors. Regarding the bands used in this study, it should be noted that, as land sensors, most of LT sensing capability (256 grey-levels) is used for the highly reflective surface of the land. Dark lakes are therefore harder to discern, and results are highly dependent on turbidity and trophic levels – benchmarking the differences between these sensing regimes (as the ones in Figure 29) leads



a) b)

Figure 29 a) Lake Lappajärvi is a eutrophic lake surrounded by arable land and some agriculture. b) Lake Saimaa is an oligotrophic lake surrounded by forest and some urban areas to the south. Both maps are provided in the same scale.

to the discussion of whether using atmospheric correction would lead to different results. Previous results showed that using atmospherically corrected data improved models only slightly (Kallio et al., 2008).

The choice of the spatial buffer around the sampling location has a small effect on the relationship between Chl-and satellite data, but a buffer of 500-700 m was found to be the best choice for the models tested in this study. Additionally, a time window of ± 1 day performs better than a ± 2 day, meaning that satellite observations closer to the date when the field samples were collected are preferred. This is in line with previous studies that have assessed Chl-a over lakes, even in different geographic conditions (*e.g.* Minnesota, USA) (Stadelmann et al., 2001). We also assessed the impact of extending this time-window up to ±10 days. By doing so, the goodness of predictive Chl-a estimations has decreased significantly. The same is described by other authors, pointing out the decrease in certainty of the model with a longer time-window (Boucher et al., 2018). Despite this, our models for non-averaged data performed better than other match-up activities for lakes at lower latitudes. As an example, the best model for a selection of water bodies in Maine, USA provided a correlation coefficient of at most 0.25 (Boucher et al., 2018).

As expected, the use of the SWIR 1 band did not improve the performance of the model derived from intra-annual data. In fact, SWIR bands have been used on the enhancement of the atmospheric correction algorithms for ocean colour (Vanhellemont and Ruddick, 2015) and their calibration for inland and coastal waters (Wang et al., 2016). But under certain circumstances the direct use of SWIR bands for Chl-a detection is fruitful, applicable to floating-bloom events, typical of cyanobacterial communities where most of the biomass is at surface level (Wang et al., 2019) . In the oceans, MODIS data from SWIR bands has also been used on the concept of a floating algae index (Hu, 2009) . Our study does not focus on depth-resolved data and thus the use of SWIR was omitted.

On the other hand, our results demonstrate that we can determine, with good confidence, the lake specific mean Chl-a concentration in Finnish lakes (Figure 28). This general model for all lakes must be used carefully. From Figure 26 we see that the model performance varies amongst the sampled lakes on the daily aggregation approach. However, it is the level of Chl-a concentration that has the most significant impact on model accuracy. For timely estimations of Chl, the LT bands are not ideal as turbidity has a significant influence on the estimated Chl. Specifically, during the spring months, it was not possible to detect how turbidity is affecting our results. Studies have concluded that turbidity detection was feasible through TM data but not Chl-a (Härmä et al., 2001). It should be noted that if a lake is oligotrophic or CDOM-dominated (like most Finnish lakes) the radiometric resolution of LT data is insufficient to detect different Chl-a levels – lakes must be eutrophic for signal on both LT5-TM and LT7-ETM+ to be discerned (Figure 29). Authors have argued that high CDOM levels shadow the optical signature of phytoplankton in the blue region of the spectrum rendering the blue/green ratio based Chl-algorithms useless (Kallio et al., 2005). Despite this, we have seen that seasonally aggregating data from satellite and *in situ* campaigns provides a reliable model. In this model, some concerns must be addressed. For example, the land adjacency effect is particularly relevant in small lakes. As seen in Figure 26-c, preliminary results on the performance of the model with respect to how close the sampling locations are to the margins provide insights that need to be further studied.

The adjacency effect is known to reduce apparent surface contrast (Richter et al., 2006) and is particularly severe in the case of dark water bodies surrounded by dense vegetation. As LT imagery is developed mostly for land applications, there is a mask for the lakes' adjacency effect to land but not the converse. In areas near the lakes' margins, the adjacency effect can overestimate Chl-a concentration as it acts by changing reflectance at shorter wavelengths (IOCCG, 2018). Boreal waters are known for their high concentrations of humic and fluvic acids (CDOM) leached from the surrounding vegetation and soils. These, in turn, reduce the light availability in the blue spectral region (IOCCG, 2018). In Finnish lakes, high CDOM absorbs nearly all water leaving radiance. Thus, the radiance measured above lakes consist of radiation backscattered from the atmosphere, radiation reflected from the water surface and the radiation backscattered from the adjacent land. Water signal is often negligible in the blue band and can be discarded for such lakes. It is paramount to have *in situ* studies that sample a lake at different distances from the coast – such results would greatly improve our capability to quantify the adjacency effect in these types of lakes where sun elevation is low and most of their waters are brown. From our results, one factor that seems to ameliorate detection performance – including the minimization of the adjacency effect – is the trophic level of the lake. Another evident source of error is the potential effect of shallow lake grounds. Our methodology is robust on defining the lakes' margins by creating a permanent water mask. The use of a buffer away from the lakes margins and small islets can render unlikely the presence of shallow banks under water – nor can we guarantee the avoidance of underwater vegetation. Some of these banks can also appear and disappear over the extensive timespan of this study. The revision of earlier studies on aquatic vegetation could influence resolving phytoplankton from our detection methodology (Raitala and Lampinen, 1985).

As seen in lakes Lappajärvi (⟨Chl⟩ = 86.95 µg/l) and Saimaa (⟨Chl⟩ = 10.1 µg/l), the model correctly identified them as eutrophic and oligotrophic lakes, respectively. Lappajärvi, being a brown water lake, contains humic material and has a high phosphorus content. The phosphorus load into Lappajärvi comes from agriculture and cattle farming and measures have been considered to decrease the impact of eutrophication and mitigate algae bloom occurrence (Räike et al., 2003). Our results also corroborate the trends in eutrophication such as Lake Keurusselkä (⟨Chl⟩ = 31.83 µg/l) reported as having an increasing trophic status which corresponded to 10 µg/l in 2010 (Räike et al., 2003). In Lake Saimaa, depicted in Figure 29-b), the average Chl-a during the summer period is 10.1 µg/l which also corresponds to the literature, as this is a typical oligotrophic lake (Malve et al., 2016). The results of this study are particularly timely now that new data is emerging and Finnish lakes like Kallavesi, Näsijärvi and Vesijärvi have already been reported to experience later freeze dates and earlier ice break-up dates (Woolway et al., 2020). Understanding the impact of such geophysical

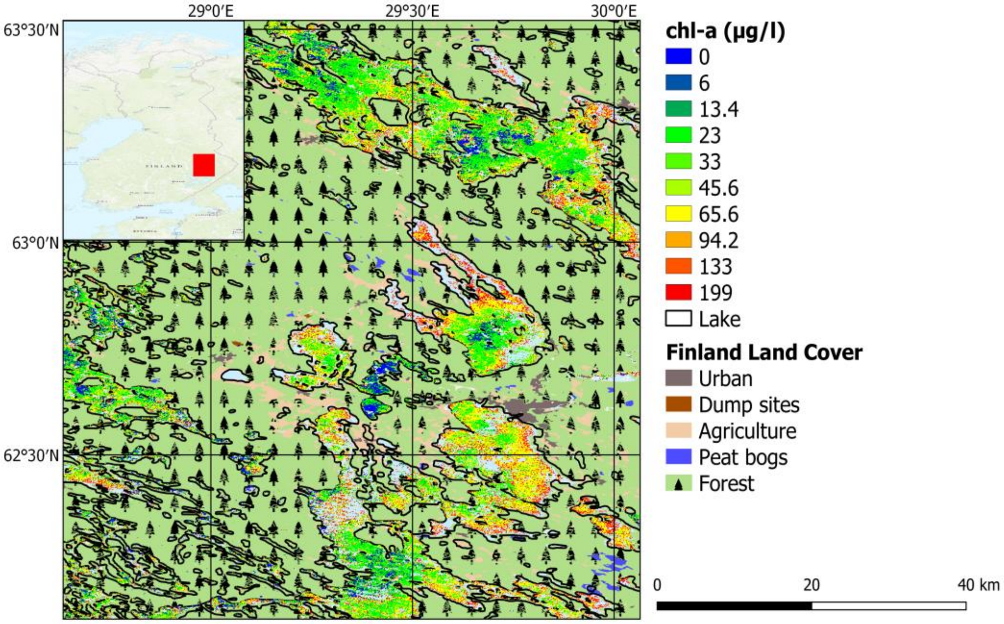


Figure 30 Eastern area of Finland with plenty of small lakes surrounded by dense vegetation and thus where the adjacency effect is most prominent. Land Cover is simplified: "urban" is discontinuous urban fabric, industrial or commercial units; "agriculture" is taken as agriculture and natural vegetation but also non-irrigated arable land; and "forest" comprises transitional woodland-shrub, broad-leaved forest, coniferous forest, mixed forest, and natural grasslands.

changes on lake Chl-a content is of utmost importance and can be applied to better understand phenology changes of phytoplankton in freshwater systems (Maeda et al., 2018).

Early semi-operative approaches pointed out the possibility of studying small lakes (and their small details, Figure 30) if not for the medium and low resolution of conventional ocean colour sensors (Pulliainen et al., 2001). Our study also revisits the application of *in situ* data reference data in the conception of empirical Chl-a models (Flink et al., 2001; Koponen et al., 2001;Östlund et al., 2001;Pulliainen et al., 2001) by applying new cloud computing

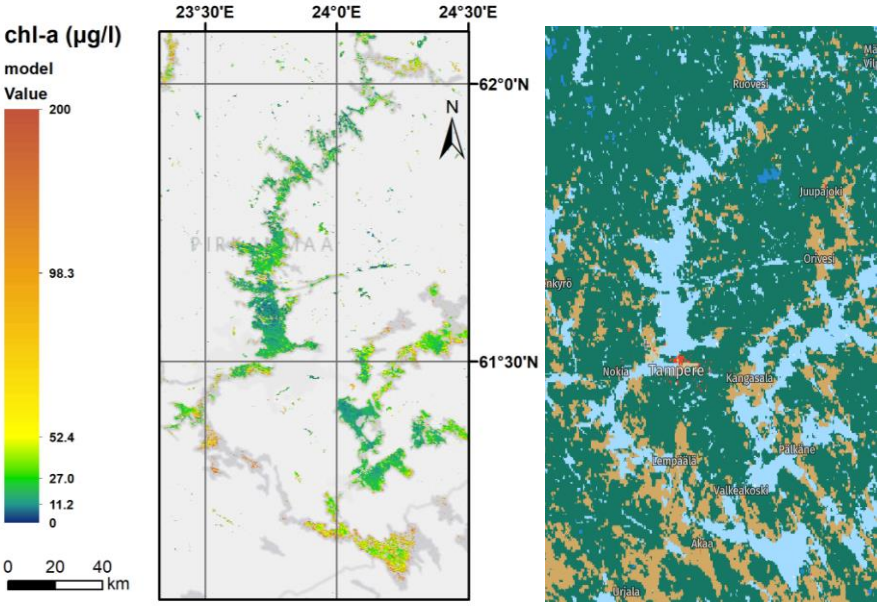


Figure 31 Map with predicted values of mean Chl-a (left) for Pirkanmaa lake and corresponding area for land use: light brown indicating arable land or agriculture, dark green represents forest.

technology like Google Earth Engine (Gorelick et al., 2017) to the analysis of thousands of images and *in situ* measurements corresponding to long time series of data. The use of our methodology can allow for the application of a model to smaller lake, more remote, or simply less studied than a bigger "control" lake used for in the validation campaign.

Additionally, we underline the acute need to monitor Boreal lakes. In other regions, like Alberta, Canada, variations of trophic levels have been linked to climate, biotic variations and geology (Sass et al., 2007). A similar approach based on a model for all Finnish lakes is of the utmost importance.

3.5. **Conclusions**

Despite its relatively high spatial resolution, LT imagery is often overlooked for remote sensing of Chl, due to the low spectral resolution of the sensors. Nevertheless, our results demonstrate that estimations over aggregated time windows can be done with high accuracy.

Our results show that LT imagery can fill the resolution gap when it comes to monitoring the small, numerous and adjacent lakes found in the Finnish geophysical context.

Reducing imagery over monthly means can produce useful results of the model allowing for higher correlations and typical characterizations of the different water bodies within specified timeframes. Assessing Chl-a is possible due to its strong relationship with turbidity although multi-linear models of LT data to estimate turbidity do not produce as good results as the Chl-a models. The relationship between Chl-and turbidity is most robust during summer, and since the model performs better during this period, the derived model can be used for further studies of phenology shifts during the blooming seasons.

The adjacency effect, when quantified, could explain the high variations of our model when applied to the calculation of Chl-a concentration in small lakes. During this study we came across the difficulty of identifying the impacts of the adjacency effect both through our analysis and the timely literature. Therefore, we believe that the work here can open the discussion for retrieving more sophisticated models for Chl-a estimation, giving a better suited measurement of adjacency effects from land on small water bodies remotely sensed through Landsat imagery. Similar studies have already been carried for the adjacency effect on MODIS, SeaWiFS, MERIS, OLCI, OLI and MSI for the case of mid-latitude coastal environments (Bulgarelli and Zibordi, 2018). Although our methodology features a buffer from the lakes' margins, this might not be enough to completely eradicate the impact of the adjacency effect.

Satellites can provide valuable information in cases where required sampling density is high, or field surveys are expensive or even impossible to carry out. Especially, satellite images may provide informative prior information for field sampling estimates, in a Bayesian setting. As lakes are sensitive to many climate factors, they are certainly useful in climate change monitoring.

Notes:

ISO 10260. Water quality – Measurement of biochemical parameters – Spectrometric determination of the chlorophyll a concentration. International Organization for Standardization, Geneva, 1992.

EN 27027. Water quality. Determination of turbidity. European Committee for Standardization, Strasbourg, 1994.

Chapter 4. Temporal patterns of phytoplankton phenology across high latitude lakes unveiled by long-term time series of satellite data

Abstract. Monitoring temporal changes in phytoplankton dynamics in high latitude lakes is particularly timely for understanding the impacts of warming on aquatic ecosystems. In this study, we analysed 33-years of high resolution (30 m) Landsat (LT) data for reconstructing seasonal patterns of Chl-a concentration in four lakes across Finland, between 60ºN and 64ºN. Chl-a models based on LT spectral bands were calibrated using 17-years (2000-2016) of field measurements collected across the four lakes. These models were then applied for estimating Chl-a using the entire LT-5 and 7 archives. Approximately 630 images, from 1984 to 2017, were analysed for each lake. The Chl-a seasonal patterns were characterized using phenology metrics, and the time-series of LT-based Chl-a estimates were used for identifying temporal shifts in the seasonal patterns of Chl-a concentration. Our results showed an increase in the length of phytoplankton growth season in three of the lakes. The highest increase was observed in Lake Köyliönjärvi, where the length of growth season has increased by 28 days from the baseline period of 1984-1994 to 2007-2017. The increase in the length of season was mainly attributed to an earlier start of phytoplankton blooms. We further analysed surface temperature (Ts) and precipitation data to verify if climatic factors could explain the shifts in the seasonal patterns of Chl-a. We found no direct relationship between Ts and Chl-a seasonal patterns. Similarly, the phenological metrics of Ts, in particular length of season, did not show significant temporal trends. On the other hand, we identify potential links between changes in precipitation patterns and the increase in the phytoplankton season length. We verified a significant increase in the rainfall contribution to the total precipitation during the autumn and winter, accompanied by a decline in snowfall volumes. This could indicate an increasing runoff volume during the beginning of spring, contributing to an earlier onset of the phytoplankton blooms, although further assessments are needed to analyse historical streamflow values and nearby land cover data. Likewise, additional studies are needed to better understand why Chl-a patterns in some lakes seem to be more resilient than in others.

Keywords: Chlorophyll *a*, Landsat, eutrophication, remote sensing, Finland.

4.1. Introduction

Monitoring phytoplankton dynamics in inland waters is critical for understanding environmental changes in aquatic ecosystems. At the base of the food web, phytoplankton provide energy for the entire aquatic trophic system by fixing carbon through photosynthesis (Wetzel, 2001). Phytoplankton further play a fundamental role in the biogeochemical cycles with high ecological importance (Behrenfeld and Boss, 2014b). Similarly, changes in phytoplankton biomass can lead to profound environmental impacts. Studies have shown that most freshwater systems on the planet experience undesirable increases in planktonic and benthic biomass, mostly caused by anthropogenic eutrophication (Vincent et al., 2004; Smith et al., 2006). Such changes may lead to reduced dissolved oxygen, increased fish mortality, and potential health risks due to the release of toxins (Rabalais et al., 2009; Oliver et al., 2017; Padedda et al., 2017).

In general, satellite data offers an online data possibility, and relatively cheaper way to assess changes than *in situ* estimates. Moreover, it offers a possibility to understand the temporal patterns of phytoplankton blooms, which is particularly interesting for assessing the ecological status of aquatic ecosystems. Information on phytoplankton phenology can provide scientific support for policies related to water resources management and environmental impacts mitigation (Anderson, 2009; Mitrovic et al., 2011). Furthermore, understanding the phytoplankton seasonal patterns helps identifying drivers of environmental changes in aquatic ecosystems. The timing of the onset of phytoplankton blooms is mainly driven by the physicochemical conditions of the water column, such as thermal stratification and water column mixing conditions, variation in solar radiation and the extent of the possible ice cover (Bleiker and Schanz, 1989; Adrian et al., 1999; Vehmaa and Salonen, 2009). Phytoplankton blooms have been shown to be closely associated with climatic variables, the surrounding land use, and nutrients flow (Gittings et al., 2018). Nonetheless, currently the temporal and spatial dynamics of phytoplankton blooms across inland waters have not yet been comprehensively studied.

Due to the phenomenon of Arctic amplification, climate change is happening faster at high-latitudes (Yamanouchi, 2011; Cohen et al., 2014). Studies indicate that the Arctic region has warmed more than twice as fast as the global average (Screen and Simmonds, 2010). High latitude lakes are thus particularly interesting for studying environmental changes in aquatic ecosystems. Furthermore, in northern countries, such as Finland, we can observe lakes with vast range of trophic states and distributed along a large latitudinal gradient.

However, the impacts of climate change on the temporal dynamics of phytoplankton in lakes are not well understood. Although several studies using time-series analysis have been undertaken in the marine environment (Racault et al., 2012;Ji et al., 2013;Blondeau-Patissier et al., 2014), much less has been done over inland water (Thackeray et al., 2008; Palmer et al., 2015). Many factors contribute for the lack of multi-temporal assessments of phytoplankton dynamics over lakes, including scarce information on the spatial variability of phytoplankton concentration and limited time series of field data (Oliver et al., 2017).

Remote sensing (RS) can potentially provide a powerful tool for improving phytoplankton monitoring, given its ability to collect data over large areas and the existence of multi-decadal imagery archives. Several satellite sensors can collect data at spectral wavelengths that allow estimating Chl-a concentrations in aquatic ecosystems. All phytoplankton species contain Chl-a as the key photosynthetic pigment, which is used as the most common proxy for monitoring phytoplankton. For instance, ocean color satellite instruments, such as the NASA’s Sea-viewing Wide Field-of-view Sensor (SeaWiFS, 1997-2010) and Moderate Resolution Imaging Spectroradiometer (MODIS, 1999-), onboard Aqua satellite, collect(ed) data at wavelengths spanning from 0.44 to 0.67 µm, supporting widely used algorithms for Chl-a estimates particularly in ocean water (Werdell and Bailey, 2005; Bailey and Werdell, 2006; Hu et al., 2012b). More recently, in 2016, the European Space Agency has launched the Ocean and Land Colour Instrument (OLCI) onboard the Sentinel-3A satellite. The OLCI collects data in 21 spectral bands, from 0.4 to 1.02 µm, allowing the development of products such as estimates of algal pigment and total suspended matter concentrations.

Nonetheless, the application of the above-mentioned tools in lakes remains challenging due to the coarse spatial resolution of the longer-run missions (*e.g.* MODIS: 500-1000 m, MERIS 300 m) and/or the short time-series of the new generation of satellites (*e.g.* Sentinel-3A, Sentinel 2A and B). In northern countries (*e.g.* Finland, Sweden, and Norway), the complex shapes and often small size of lakes require the use of high spatial resolution sensors. However, high spatial resolution often comes at the expense of coarser temporal resolutions, requiring the acquisition of images throughout longer periods to reliably capture the seasonal patterns of Chl-a. In this context, the sensors onboard the Landsat (LT) satellites family presents an interesting alternative. The LT sensors provide a long and continuous time series, running from 1972 (LT-1) to the present date (LT-8). Since the launch of LT-4, in 1982, the program provides high spatial resolution data at 30 m.

Although LT sensors have relatively low spectral resolution, several studies have been successful in assessing Chl-a concentration using LT imagery. Vincent et al. (2004) applied LT data for mapping cyanobacterial blooms in Lake Erie. Using linear models, they were able to estimate phycocyanin concentration with accuracy up to 77%. Allan et al. (2011) used LT data for estimating Chl-a concentrations in central North Island lakes of New Zealand, reporting classification accuracies up to 95%. Also applying LT data, Isenstein et al., 2014 used multivariate models to retrieve Chl-a concentrations, reporting that models accounted for 72 to 83% of the variability in Chl-a observations.

Although recent studies have used LT time-series for assessing phytoplankton long-term trends in lakes (Ho et al., 2017; Tan et al., 2017), it is still broadly unknown how the temporal dynamics of lake's Chl-a (i.e., seasonality, phenology) have changed over time. Similarly, the temporal trends of Chl-a concentration in high latitude lakes, where climate change is reportedly occurring faster, remain poorly understood.

Some challenges still exist in using LT imagery for assessing Chl-a seasonal dynamics. The low temporal resolution of LT (*e.g.*, 16 days for LT-5 and -7) makes it difficult for obtaining cloud free observations in some seasons of the year. In some cases, it can be difficult to precisely capture the temporal characteristics of Chl-a blooms. However, as the first LT satellite was launched back in 1972, we now have available an extensive archive of imagery, which combined, can provide a dense time-series for observing seasonal patterns. Yet, the high spatial resolution of LT imagery implies in relatively large file sizes and analysing over 30 years of data is computationally expensive. Until now this has been an important bottleneck in using high resolution RS data for time-series assessments. The dissemination of high-performance computational tools for geospatial analysis, such as Google Earth Engine (Gorelick et al., 2017), has largely facilitated the usage of so called "big-data" in environmental assessments, leading to new and unprecedented opportunities for assessing long time-series of satellite data (Pekel et al., 2016).

In this study we use the extensive LT imagery archive and high-performance computational tools for addressing the following objectives: a) to characterize seasonal patterns of phytoplankton phenology at high latitude Finnish lakes; b) to identify shifts or trends in the temporal dynamics of phytoplankton phenology during the past 30 years, and c) to examine the role of climatic variation on phytoplankton seasonal patterns.

4.2. Material and methods

4.2.1. Study areas and field data

We carried out analysis in four Finnish lakes: Haapajärvi, Kuortaneenjärvi, Köyliönjärvi and Tuusulanjärvi (Figure 32). The lakes are spread across a latitudinal gradient varying from 60^o to 64^o north. Haapajärvi is a shallow humic-rich lake with a maximum depth of 8,5 m. Kuortaneenjärvi is humic-rich with an average depth of 3.3 m and a maximum depth of 16m. Köyliönjärvi is a eutrophic nutrient-rich lake with an average depth of 2.6 m and a maximum depth of 12,8 m. Tuusulanjärvi is a hypereutrophic lake, with a mean depth of 3.2 m and one main basin reaching 10 m depth. Tuusulanjärvi is naturally eutrophic, and with the predominant clay soils in the catchment the water is greyish brown in color.

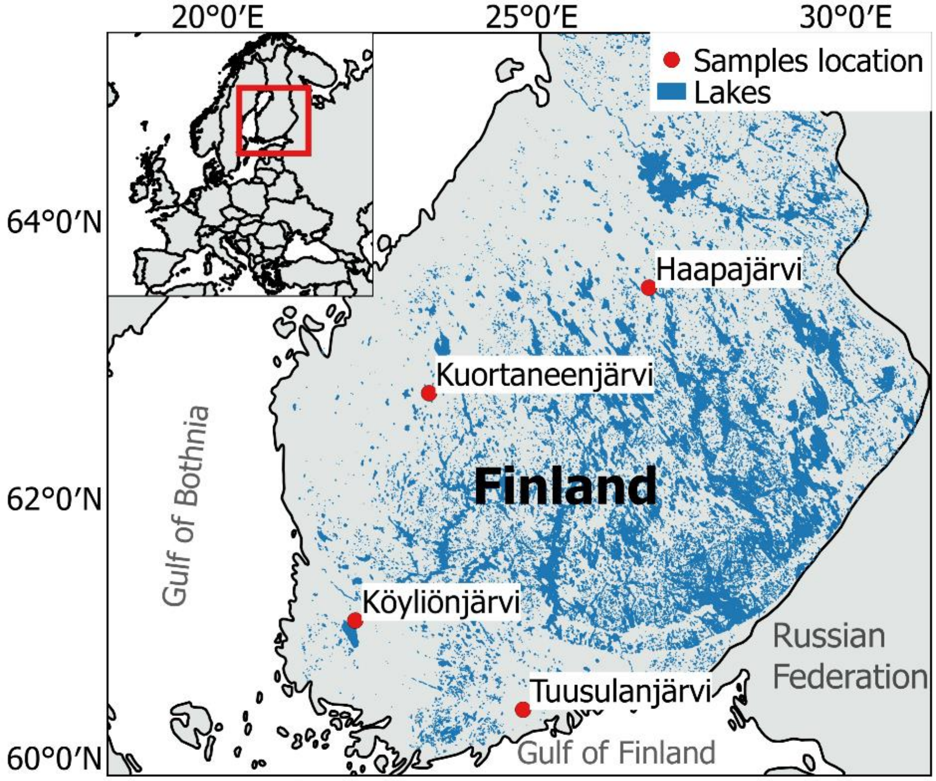


Figure 32 Geographical distribution of the *in situ* Chl-a observations.

Here we use 17-years (2000-2016) of Chl-a field measurements collected in each of the four lakes (see Figure 32 for samples location). The field measurements (*in situ* knowledge) were mostly collected between May and October, without a fixed interval. The number of field measurements varied between lakes, being 42 for Lake Haapajärvi, 68 for Lake Kuortaneenjärvi, 89 for Lake Köyliönjärvi and 255 for Lake Tuusulanjärvi.

All the lakes belong to the intensively monitored lakes of the national routine monitoring network of Finland. Chl-a concentrations were determined from water samples taken by a tube sampler from 0–2 m. The concentration of Chl-a was measured in laboratory with a spectrophotometer after extraction with hot ethanol (ISO10260, 1992).

4.2.2. Landsat imagery

All imagery from the LT-5 and 7 archives, until December 2017, were analysed in this study. All pre-processing procedures, as well as data extraction, were carried out using the high-performance cloud computing tools offered by Google Earth Engine (Gorelick et al., 2017). The LT-5 collection contains images collected from Jan 1, 1984 to May 5, 2012, while LT-7 imagery was obtained from Jan 1, 1999 – December 30, 2017. Approximately 630 images were analysed for each lake. For both, LT-5 and 7, we used the USGS Surface Reflectance Tier 2 product. This dataset contains surface reflectance imagery from the LT-5 Thematic Mapper (TM) and LT-7 Enhanced Thematic Mapper Plus (ETM+) sensors. The images contain 4 visible and near-infrared bands and 2 short-wave infrared bands. In this study, we used bands 1 (blue, 0.45-0.52 μm), 2 (green, 0.52-0.60 μm), 3 (red, 0.63-0.69 μm), 4 (near-infrared, 0.77-0.90 μm) and 5 (shortwave infrared 1.55-1.75 μm). All bands were processed to orthorectified surface reflectance. The imagery of both, LT-5 and LT-7, have spatial resolution of 30 m, radiometric resolution of 8-bits, as well as consistent spectral resolution in the bands used for this study.

The images were atmospherically corrected using the LEDAPS (Landsat Ecosystem Disturbance Adaptive Processing System) method, providing radiometrically consistent surface reflectance data (Masek et al., 2013). We carried out quality control assessment in every image using cloud, shadow, water and snow masks produced using CFMASK (Zhu et al., 2015; Foga et al., 2017), as well as a per-pixel saturation mask. However, the CFMASK has difficulties to operate over bright targets such as snow/ice, and optically thin clouds have a higher probability of being omitted by the algorithm. Hence, to further eliminate pixels containing artefacts associated to cloud or ice, we removed outliers in the surface reflectance values extracted for each lake, using the 25th and 75th percentiles as threshold.

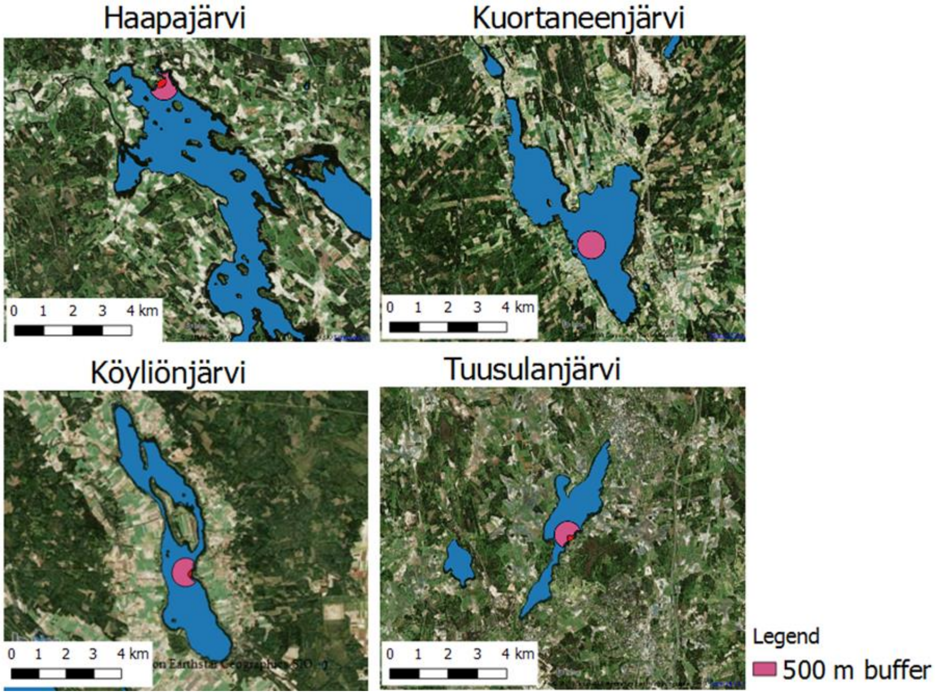


Figure 33 Location of the sampling sites used in this study. The red areas indicate the 500 m buffer around the sampling location, from where the Landsat data was extracted.

To extract the surface reflectance values at each site, we averaged all (quality controlled) pixels inside a 500 m radius buffer around the location where the *in situ* samples were collected (Figure 33). To certify that only permanent water surfaces were contained inside the 500 m buffer, we use the high-resolution Global Surface Water Data (Pekel et al., 2016) to mask out any land surface inside the buffers.

We have chosen the 500 m buffer based on a preliminary analysis of the model accuracy, where differently sized buffers were tested.

Table 9 Model accuracy using different buffer sizes to spatially aggregate the Landsat pixels, considering a general model for all lakes.

Buffer size	60 m	90 m	100 m	140 m	180 m	300 m	500 m	600 m	700 m	800 m	900 m
	45.15%	37.71%	36.95%	37.51%	37.34%	38.63%	41.4%	41.05%	41.13%	41.77%	41.95%

All tests in Table 9 were performed using Landsat bands 1-4. All bands were significant and all models with $p\text{-value} < 0.05$.

4.2.3. Chlorophyll *a* modelling

Estimates of Chl-a concentration based on LT imagery were obtained using linear multi-variate models. Individual models were created for each lake. The explanatory variables used for the models were the surface reflectance values from LT bands 1 to 5, and two spectral indices designed specifically for assessing Chl-a concentration in aquatic ecosystems. The first index is the normalized difference chlorophyll index (*NDCI*), developed by (Mishra and Mishra, 2012). The *NDCI* is calculated as follow:

$$NDCI = \frac{\rho_{NIR\,(B4)} - \rho_{red\,(B3)}}{\rho_{NIR\,(B4)} + \rho_{red\,(B3)}} \qquad \text{Equation 1}$$

where ρ is the surface reflectance for the respective spectral band. It is important to note that the *NDCI* was initially developed using MERIS spectral bands (i.e. 660-670 nm and 704-714 nm), which differ in location and width from those of LT bands (i.e. 630-690 nm and 770-900 nm). The second spectral index, based on the red, blue and green reflectance bands, was defined as follow (Brivio et al., 2001):

$$BRG = \frac{\rho_{blue\,(B1)} - \rho_{red\,(B3)}}{\rho_{green\,(B2)}} \qquad \text{Equation 2}$$

Although the *BRG* index was initially developed to be used in ocean waters, it has been successfully applied by Brivio et al. (2001) in Lake Garda, Italy, achieving an $R^2 = 0.818$.

The same index led to satisfactory results for other small water bodies as in the Malilangwe Reservoir, Zimbabwe with $R^2 = 0.81$ (Dalu et al., 2015).

Given that LT bands were not originally designed for assessing Chl-a in inland waters, most lake studies applying LT data used empirical or semi-empirical approaches e, g (Vincent et al., 2004; Allan et al., 2011; Isenstein et al., 2014). Generally, there is no single solution available for defining the explanatory variables of the empirical models. For instance, (Tan et al., 2017) have tested simple linear models based on four different spectral indices (band arithmetic and band ratios) and a multi-linear regression using LT bands 1, 2 and 4. They found that the best accuracies were achieved using the multi-linear regression, with an R2 of up to 0.78. Isenstein et al. (2014) also compared different combination of bands and indices, and found the best results applying a multi-linear regression model composed of two band ratio (B2/B1 and B3/B1). Hence, given the lack of a common solution in the literature, we chose to test all the five LT bands and two indices described in

$$NDCI = \frac{\rho_{NIR\,(B4)} - \rho_{red\,(B3)}}{\rho_{NIR\,(B4)} + \rho_{red\,(B3)}} \qquad \text{Equation 1}$$

$$BRG = \frac{\rho_{blue\,(B1)} - \rho_{red\,(B3)}}{\rho_{green\,(B2)}} \qquad \text{Equation 2}$$

For each lake, we tested the significance and explanatory power of the variables.

The models were firstly tested using a 5-fold cross validation, and later all samples were used to generate the final model used for prediction. The models were tested and developed using the *in situ* data, which were merged with the LT data using an interval of ±8 days. That is, for each *in situ* sample, we searched for LT images obtained 8 days before or after the sample acquisition. A previous study has shown that, in comparison with smaller time-windows, the 8 days interval increases the chances of matching a LT observation with the field sample, without significantly affecting the model performance (Tan et al., 2017b).

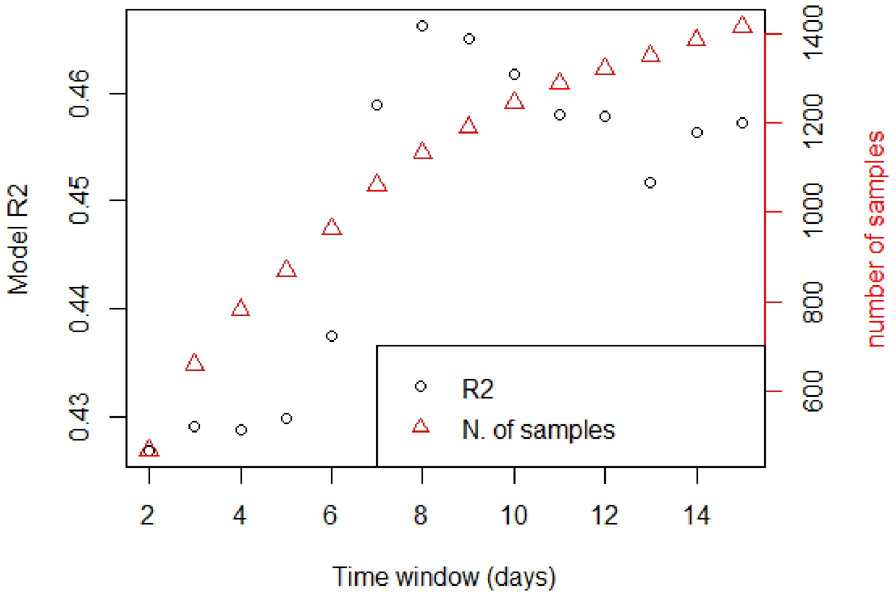


Figure 34 Model performance using different time windows to merge satellite observations and in situ samples. The secondary axis shows the number of samples resulting from the data merging. The tests were performed considering a general model for all four lakes assessed in this study.

Our preliminary assessments have confirmed these results, showing that time-windows below 8 days significantly reduces the number of matching observations, consequently decreasing the model performance (Figure 34). In case more than one image was available during this time-window, we considered the average of the surface reflectance values.

4.2.4. Climate variables

Although a full assessment of the drivers of Chl-a phenology goes beyond the scope of this study, we carry out preliminary assessments on key climate variables over the studied lakes. We used remotely sensed estimates of daytime and night-time land surface temperature obtained by the Moderate resolution Imaging Spectroradiometer (MODIS), onboard the TERRA satellite. The MODIS land surface temperature has been successfully applied to estimate lake surface water temperature (Ts) (Wan et al., 2017). The product used in our study was the MOD11A2, collection 6, which offers daytime and night-time Lake Surface

Temperature (LST) data stored on a 1 km sinusoidal grid as the average values of clear-sky LSTs during an 8-day period (Wang et al., 2008). MODIS Ts represents the radiometric temperature related to the thermal infrared radiation emitted from the lake surface observed by an instantaneous MODIS observation. The daytime Ts corresponds to measurements acquired around 10:30 am, while night-time Ts observations are acquired around 10:30 pm (local solar time). MODIS land surface temperature products have been validated over a broad range of representative conditions and extensively tested using comparisons with *in situ* values and radiance-based validation (Wang et al., 2008; Wan et al., 2017). The product uncertainties are currently well defined and, in most cases, LST error is estimated to be lower than 1 kelvin (Wang et al., 2008). We certified that only good quality data were used by applying filters based on the MOD11A2 quality control layer and, therefore, excluding pixels contaminated by clouds or with low confidence. All MOD11A2 data from March 5, 2000 to December 30, 2017 were analysed.

Furthermore, we analysed rainfall [kg m^{-2} s^{-1}], snowfall [kg m^{-2} s^{-1}] and total precipitation [kg m^{-2} s^{-1}] data obtained from the Global Land Data Assimilation System (GLDAS), version 2.1. This dataset ingests satellite and ground-based observational data products and, using advanced land surface modeling and data assimilation techniques, it generates optimal fields of land surface states and fluxes (Rodell et al., 2004). The spatial resolution is 0.25° and the original temporal resolution is 3 hours. However, to make this dataset consistent with the MODIS Ts data, we aggregate all GLDAS data into 8-day averages, using the same dates as the MODIS composites. Here, we analysed all GLDAS data from January 1, 2000 to December 30, 2017.

4.2.5. Time-series analysis

This study focused on assessing Chl-a intra-annual patterns between April and October (warm months), given that during the remaining months (cold months) the lakes are often frozen and LT imagery have high frequency of cloud coverage. Because of the low temporal resolution of the LT sensors, obtaining a dense enough time-series to reconstruct the Chl-a seasonal patterns requires aggregating several years of data. In this study, we used a 10-year sliding window, with 1 year incrementing steps. In other words, for the interval between years *n* and *n+9*, we aggregated all available LT imagery to reconstruct the average Chl-a seasonal pattern during this period, while the next interval would comprise the data between years *n+1* and *n+10*. This approach results in a temporal series with irregular steps between observations (i.e. the date of the observations are defined based on the individual observations of each year inside the sliding window), but with a higher density, allowing a more robust description of the Chl-a phenological patterns.

The analysis of the seasonal patterns followed a similar approach as proposed by Forkel et al., 2015, which was initially developed to assess land surface phenology and trends. The approach consisted in four main steps: i) filling of permanent gaps in the time-series (i.e. cold months), ii) time-series smoothing and interpolation, iii) detection of phenology metrics and iv) identification of temporal trends in the phenology metrics.

The first step consisted in filling the values from the cold months with a baseline value. The baseline value for each lake was defined as the minimum Chl-a concentration observed in the *in situ* time-series. In the second step, we used the Local Polynomial Regression Fitting (LOESS) method to perform a time-series smoothing. This procedure is necessary for removing high-frequency noise and optimize the calculation of the seasonal metrics. Simple linear interpolation was used to fill eventual data gaps.

In the third step, we used the resulting smoothed time-series for extracting three Chl-a phenology metrics: start of Chl-a season (SOS), end of Chl-a season (EOS) and length of season (LOS). We also calculated the position of Chl-a peak (POP) and position of Chl-a trough (POT), but given the large uncertainties in these two variables, we do not analyse them thoroughly in this study. The POP can be affected by remaining high frequency noise, while the POT is affected by the artificial temporal limits imposed to define the warm months and cold months. The SOS and EOS were calculated using 50% thresholds on the seasonal Chl-a curve (White et al., 1997), which is based on the definition of SOS and EOS as the mid-points of spring Chl-a bloom (equivalent to greening in land vegetation phenology) and autumn senescence, respectively (Forkel et al., 2015). Finally, after applying the phenology metrics for each 10-year window period, we evaluated if significant temporal trends could be observed. The significance of the trends was assessed using the Mann-Kendall trend test, as proposed by Hamed and Rao (1998) This modified version of the Mann-Kendall trend test (Mann, 1945) reduces the chances of false positives by accounting for serial correlation, often present in time-series data due to sub-sequent observations. The magnitude of the trends were assessed using the Sen's slope (Sen, 1968), which is less vulnerable to errors in comparison with least squares estimator of a regression coefficient ß, as well as less sensitive to nonnormality of the parent distribution and outliers.

A similar procedure for calculating phenology metrics was applied to the Ts time-series, aiming to evaluate if any trends observed in the Chl-a temporal dynamics could be explained by surface temperature changes. However, in the case of Ts, the metrics were calculated for each year, from 2001 to 2017, given that the higher temporal resolution of the MODIS sensor allows a solid delineation of the Ts intra-annual variation. The Mann-Kendall trend test was also applied to evaluate trends in rainfall, snowfall and total precipitation, between 2000 and 2017. However, the seasonality metrics were not calculated for the precipitation variables, given the lack of consistent seasonal patterns in this region (as will be demonstrated later in the results).

4.3. **Results**

The LT models for estimating Chl-a, fitted individually for each lake, showed satisfactory performance. The 5-fold cross validation of the models showed Mean Absolute Errors (MAE) of 2.39 µg/l (Haapajärvi, n=30), 1.43 µg/l (Kuortaneenjärvi, n=47), 5.61 µg/l (Köyliönjärvi, n=61) and 2.76 µg/l (Tuusulanjärvi, n=121). All final models used for the predictions were statistically significant ($p<0.01$), with R2 varying from 0.37 to 0.63. The relative importance and statistical significance of each explanatory variable varied between lakes. The BRG index and the blue reflectance did not show significant influence in any of the models ($p>0.05$), which is explained by the high chromophoric dissolved organic matter (CDOM) absorption, which shadows the optical signature of phytoplankton in the blue spectrum. Please refer to the supplementary material for detailed statistical summary of all models.

Figure 34 shows the seasonal pattern of Chl-a estimated using the LT model, in comparison with the observations for the same period. The red lines show the interpolation of in situ Chl-a concentrations observed from 2000 to 2016, without a regular temporal resolution. All models were able to capture the magnitude and seasonal variation of Chl-a. A perfect fit between the field samples and the satellite estimates is not expected, given the large range of fluctuations and uncertainties inherent to each acquisition level. The uncertainties and variation mainly stem from a better detection accuracy of the Chl-a measurements from water samples compared to satellite detected ones, differences in the spatial scale of detection, patchy distribution of phytoplankton assemblages in lakes, and the variation in the optical properties of the lakes. Furthermore, the number of satellite observations were considerably higher in comparison with field samples for the same period, which leads to slightly smoother curves for the modelled Chl-a dataset. For instance, for Lake Köyliönjärvi, there were 222 satellite observations between 2000 and 2016, while only 89 in situ observations during the same period. In some cases (*e.g.* Haapajärvi and Kuortaneenjärvi), there were no Chl-a field observations available before mid-May, which allowed the modeled Chl-a values to cover a larger period of the year.

Considering the *in situ* values, average Chl-a concentration were the highest in lake Köyliönjärvi (53.8 µg/l), followed by Haapajärvi (41.1 µg/l), Tuusulanjärvi (29.1 µg/l), and Kuortaneenjärvi (23.5 µg/l). Likewise, the largest seasonal range was observed in Lake Köyliönjärvi, where we observed a 58 µg/lvariation between the lowest and highest average Chl-a concentration. In comparison, the seasonal range in the lakes Kuortaneenjärvi and Tuusulanjärvi were much lower (20 and 25 µg/l respectively).

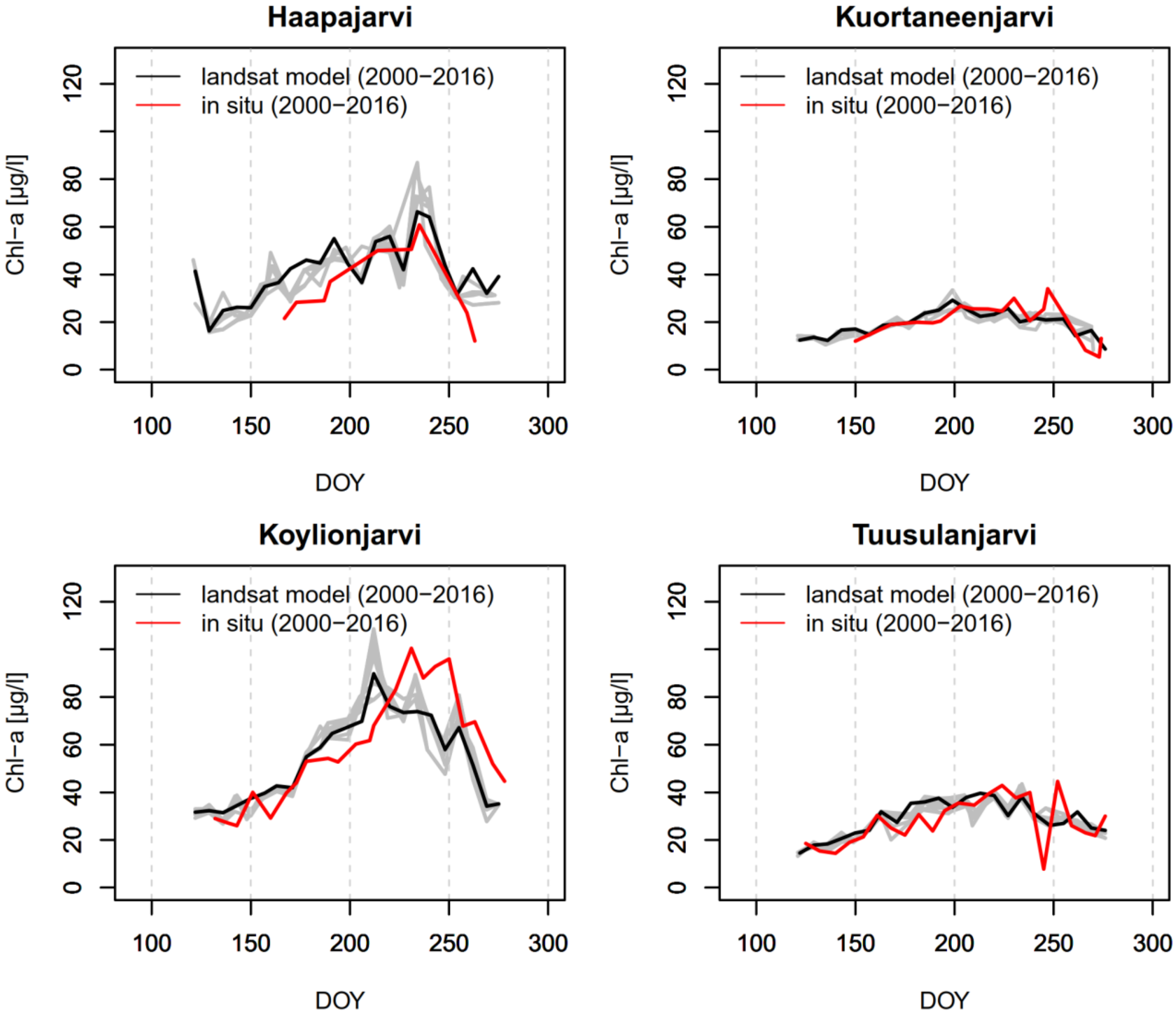


Figure 35 Chl-a seasonal variation estimated using Landsat data and from field measurements from 2000 to 2016. The gray lines represent the modeled Chl-a values within a 10-year time window, with time steps of one year. The solid black line is the average Chl-a values modelled using Landsat data for the same period, and the solid red line shows the Chl-a concentration estimated using field samples.

The results of the seasonal Chl-a curve fitting using the LOESS method, as well as the average phenological metrics for each lake, are presented in Figure 36. These results show estimates for the POP, POT, SOS, EOS and LOS. Nonetheless, we hereafter focus on assessing the LOS, SOS and EOS, as these metrics can be robustly estimated in our given conditions.

The average (1984-2017) SOS was observed between June and beginning of July, with small variations between lakes. The average EOS took place around September, also with slight variations between lakes. The mean LOS in all lakes was 83 days. The smallest LOS was observed in Lake Tuusulanjärvi (83 days), and the larger in Lake Köyliönjärvi (90 days).

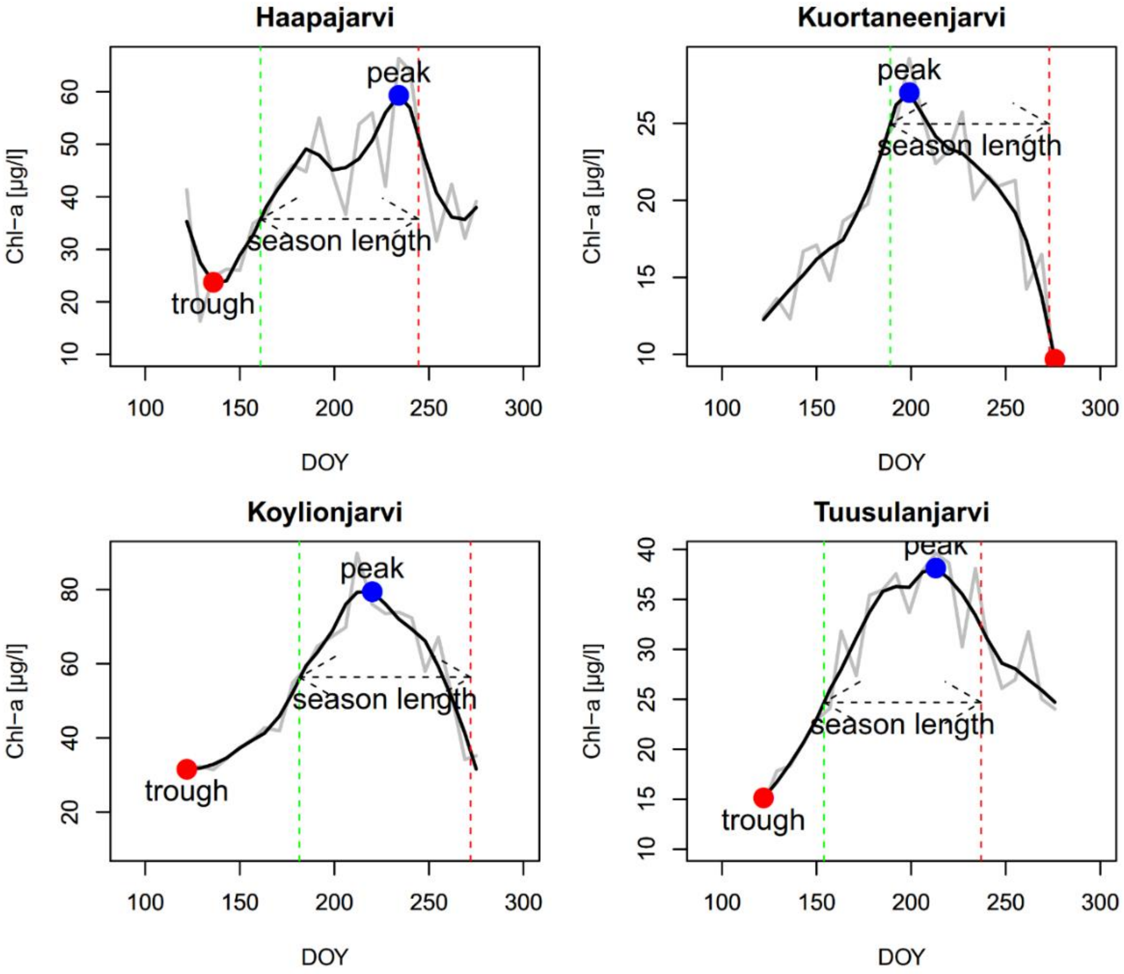


Figure 36 Time-series smoothing (solid black lines) and phenology metrics calculated using the average for the entire baseline period (1984-2017). Grey lines show the average seasonal variation of Chl-a, for the same baseline period, without smoothing.

Table 10 Summary of the average seasonal metrics for the four analysed lakes, considering the baseline period between 1984 and 2017. POP = position of peak; POT = position of trough; SOS = start of season; EOS = end of season; and LOS= length of season. All values are expressed in day number of year (DOY).

Lake	POP	POT	SOS	EOS	LOS
Haapajärvi	234	136	161	244.5	83.5
Kuortaneenjärvi	199	276	189	273	84
Köyliönjärvi	220	122	181.5	272	90.5
Tuusulanjärvi	213	122	154	237	83

The analysis of the temporal trends of the Chl-a seasonal metrics is presented in Figure 37 and Table 10. We observed significant ($p<0.01$) increasing trends in the LOS across Lakes Kuortaneenjärvi, Köyliönjärvi and Tuusulanjärvi. Comparing the average LOS from 1984-1994 with the period of 2007-2017, we observed an increase in LOS of 26.5 days in Kuortaneenjärvi, 28.5 days in Köyliönjärvi, and 14 days in Tuusulanjärvi (Table 11). The increasing trend in LOS was mostly explained by a decreasing trend in the SOS, while no significant trends were seen in the EOS. In Lake Kuortaneenjärvi, the SOS during the period 1984-1994 was in average observed around 16 of June, while during the period 2007-2017, it has shifted to 14 of May, that is, 32 days earlier. In Lake Köyliönjärvi, the SOS has decreased 23 days during the same period (from June 29 to June 6).

In Lake Haapajärvi, we report a decreasing, but not significant trend in the LOS. Such decrease was mostly caused by an increase in the SOS. Nonetheless, although to trend in EOS was significant considering the entire time-series, we observe that the EOS increase took place between 1984 and 2004, after which, the EOS remained stable.

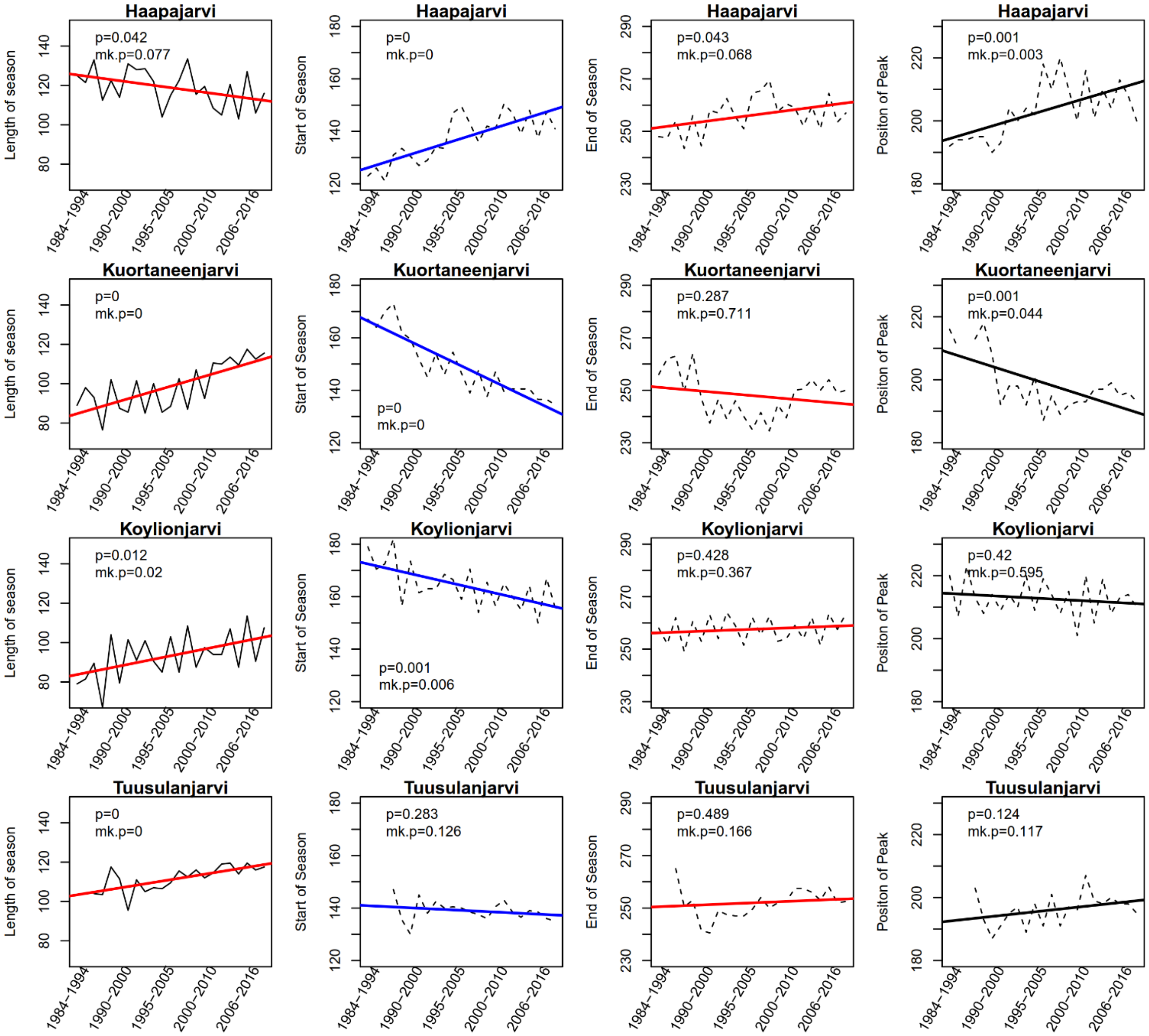


Figure 37 Trends for length of season (LOS), start of season (SOS), end of season (EOS) and position of peak (POP), from 1994 to 2017 for lakes Haapajärvi (row 1), Kuortaneenjärvi (row 2), Köyliönjärvi (row 3) and Tuusulanjärvi (row 4). The metrics were calculated considering a 10-year window. The p-value of the modified Mann-Kendall test, as well as the Sen’s slope indicating the magnitude of the trends, are displayed in each panel.

Table 11 Temporal changes in the seasonality metrics extracted from the Chl-a time-series

	Start of Season [DOY]		End of Season [DOY]		Length of Season [days]	
Lake	**1984-1994**	**2007-2017**	**1984-1994**	**2007-2017**	**1984-1994**	**2007-2017**
Haapajarvi	123	141	248	257	125	116
Kuortaneenjarvi	167	134.5	256	250	89	115.5
Koylionjarvi	179	156	258	263.5	79	107.5
Tuusulanjarvi	147	135	259.5	252.5	103.5	117.5

To better understand the factors driving the changes in the Chl-a seasonal patterns observed in Figure 38, we further examine the Ts and precipitation over the studied lakes. The seasonal patterns of Ts, between 2001 and 2017, are presented in Figure 38 and Table 12. Both daytime and night-time Ts showed a clear and consistent seasonal pattern, with relatively small inter-annual variability. On average, the warm season started in April and ended in October in all four lakes. The maximum Ts was generally observed during July, for both daytime and night-time Ts. The peak of Ts did not coincide with the peak of Chl-a concentration in any lake, as other factors are likely to drive the timing of Chl-a peak (as will be discussed later).

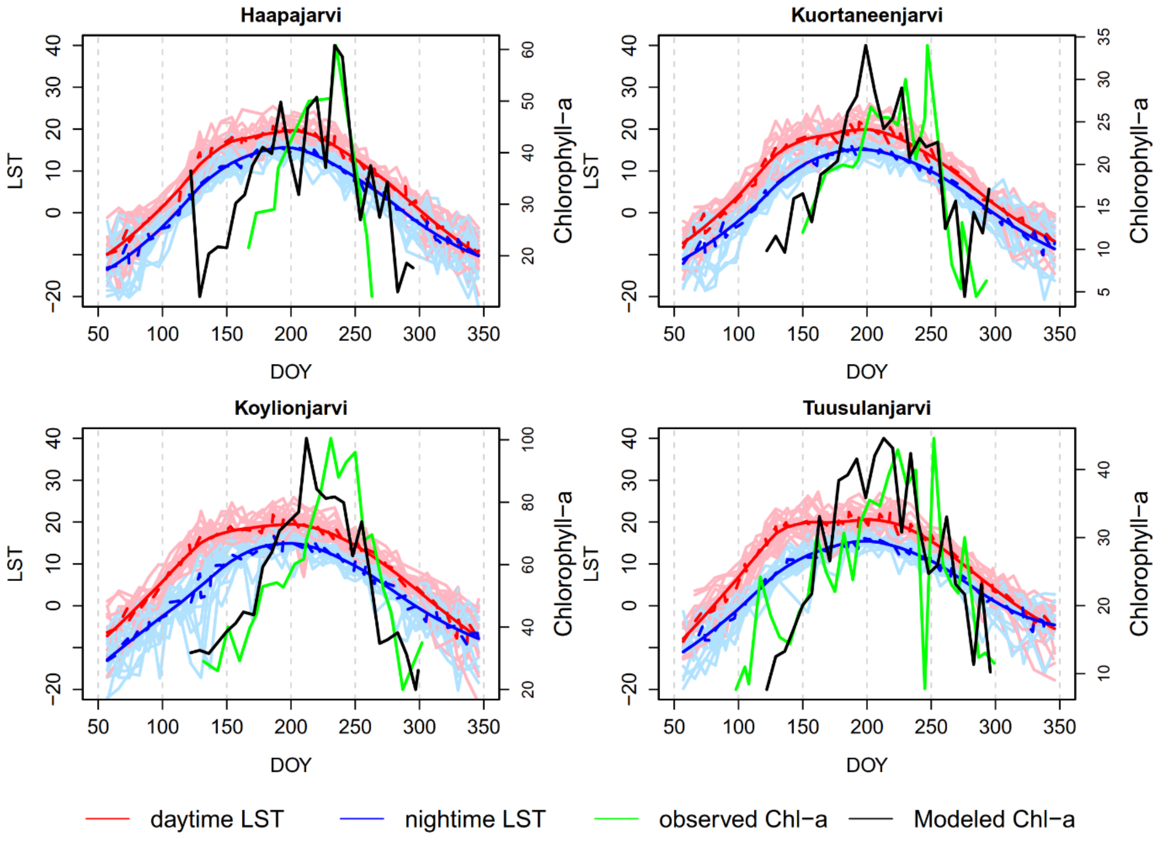


Figure 38 Seasonal patterns of daytime and nighttime lake surface temperature estimated by the MODIS sensor. The mean values from 2001 to 2017 are represented by the dark red (daytime) and dark blue (nighttime) lines, while the light red and light blue lines represent the individual observations of daytime and nighttime surface temperatures, respectively. The *in situ* and modelled Chl-a are shown in the green and black lines, respectively.

Table 12 Average seasonal metrics for surface temperature (Ts) estimated using the MODIS sensor, considering the baseline period between 2001 and 2017.

	Haapajärvi	Kuortaneenjärvi	Köyliönjärvi	Tuusulanjärvi
Start of warm season [DOY]	100	97	91	93
End of warm season [DOY]	290	290	300	290
Length of warm Season [days]	190	190	210	200
Position of maximum Ts [DOY]	190	190	190	180

We did not observe statistically significant trends in average Ts, or in any of the seasonal metrics. The time-series of the length of warm season is presented in Figure 39. The standard deviation of the length of warm season between 2001 and 2017 varied from 9 to 15 days in the four lakes. Hence, the seasonal patterns were shown to be consistent and stable during this period and, therefore, cannot be attributed as a cause for the changes in the Chl-a LOS previously reported.

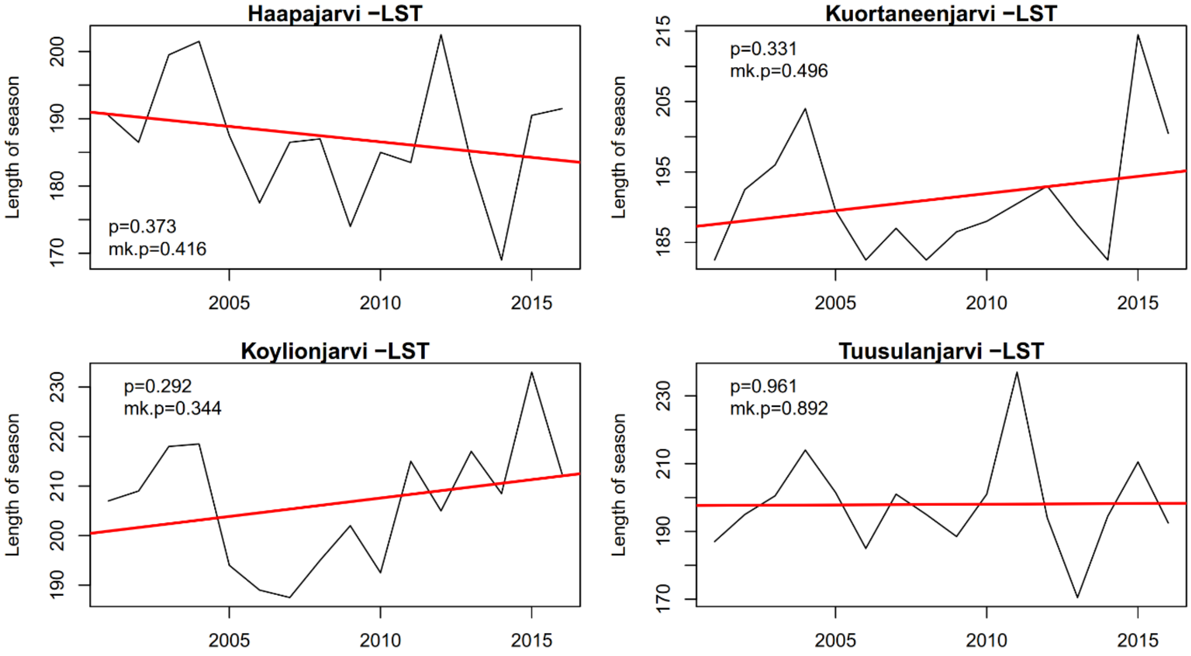


Figure 39 Trends on the time-series of the length of warm season calculated using the lake surface temperature obtained from the MODIS sensor.

The intra-annual precipitation patterns for the four lakes are illustrated in Figure 40. Although the total precipitation did not present clear seasonality, some temporal patterns could be observed in the rainfall and snowfall components. In average (2000-2017) the snowfall rate tended to zero after April, increasing again after October. The rainfall seasonality showed inverse pattern, with average peak occurring around July. Nonetheless, rainfall showed very high inter-annual variability, and its seasonal dynamics cannot be robustly characterized.

These results show that the beginning of the phytoplankton bloom generally takes place after the snowfall contribution to the total precipitation has vanished (Figure 40). This is explained by higher runoff volumes at the end of winter, when melting snow and rainfall carry sediments and nutrients to the lakes, contributing for increasing productivity. Phytoplankton blooms end usually in September with decreasing temperature and light. Once again, multiple other factors are likely to contribute to the temporal dynamics of blooms.

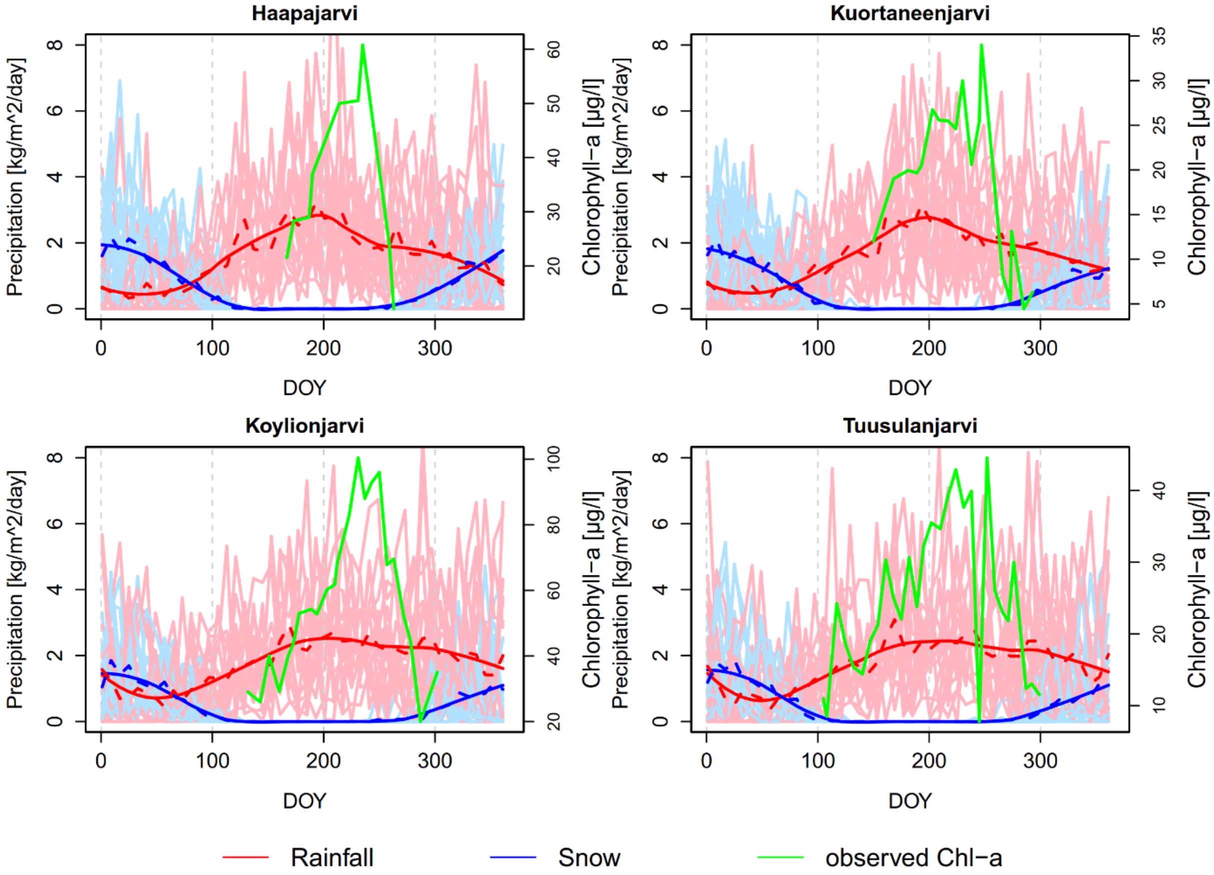


Figure 40 Average intra-annual patterns of rainfall (dark red) and snowfall (dark blue) obtained from the Global Land Data Assimilation System (GLDAS), version 2.1. Data from January 1, 2000 to December 30, 2017. The light red and light blue lines represent the monthly rainfall and snowfall observations, respectively. *In situ* values of Chl-*a* are shown in the green.

The temporal trends in precipitation from 2000 to 2017 are presented in Figure 41 and Table 13. We report a strong consistent decrease in snow rates in all lakes during winter months (Oct-Dec and Jan-Mar). With the decrease in snow rates, we see an increase in the relative rainfall contribution to the total precipitation, although rainfall did not show significant trends during winter. On the other hand, changes in rainfall were observed mostly during spring (Apr-Jun), with significant increasing rates in lakes Kuortaneenjärvi and Köyliönjärvi.

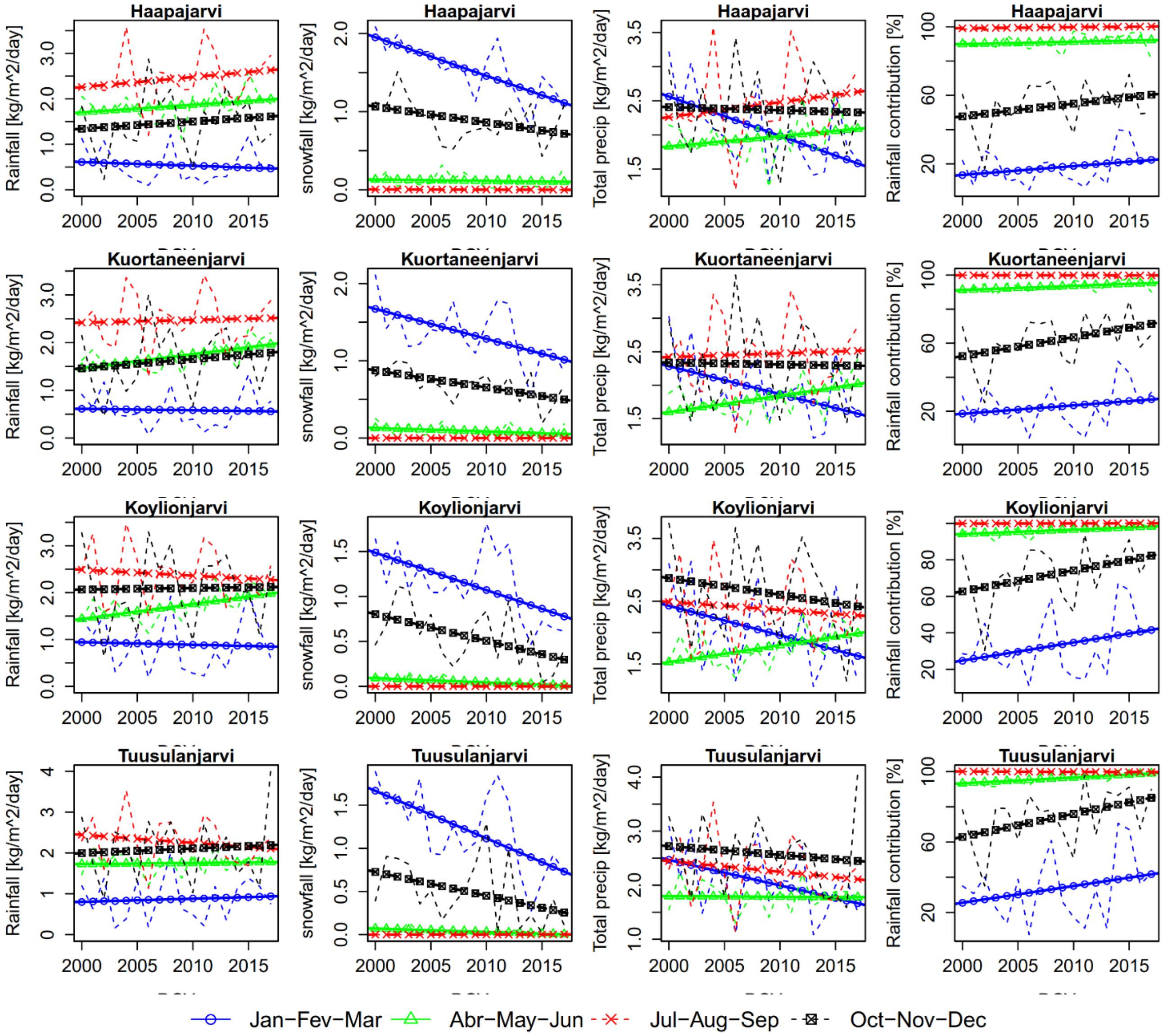


Figure 41 Trends in precipitation from 2000 to 2017. The columns from left to right represent, rainfall, snowfall, total precipitation and rainfall contribution to total precipitation, respectively.

Table 13 Slope estimate of the precipitation time-series presented in Figure 41. ***$p<0.01$; **$p<0.05$: *$p<0.1$

lake		Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec
Haapajärvi	Rainfall [kg m^{-2} day^{-1} / year]	-0,008	0,017	0,022	0,016
	Snowfall [kg m^{-2} day^{-1} / year]	-0,049 ***	-0,002	0,000	-0,020*
	total precipitation [kg m^{-2} day^{-1} / year]	-0,058**	0,015	0,022	-0,005
	Rainfall contribution [% / year]	0,513	0,136	0,061**	0,742
Kuortaneenjärvi	Rainfall [kg m^{-2} day^{-1} / year]	-0,003	0,029**	0,006	0,019
	Snowfall [kg m^{-2} day^{-1} / year]	-0,039**	-0,005	0,000	-0,022**
	total precipitation [kg m^{-2} day^{-1} / year]	-0,042	0,025*	0,006	-0,003
	Rainfall contribution [% / year]	0,496	0,239*	-0,006	1,116*
Köyliönjärvi	Rainfall [kg m^{-2} day^{-1} / year]	-0,005	0,032**	-0,013	0,003
	Snowfall [kg m^{-2} day^{-1} / year]	-0,042**	-0,005**	0,000	-0,030**
	total precipitation [kg m^{-2} day^{-1} / year]	-0,047	0,027**	-0,013	-0,027
	Rainfall contribution [% / year]	0,993	0,238**	0,007**	1,148
Tuusulanjärvi	Rainfall [kg m^{-2} day^{-1} / year]	0,008	0,003	-0,020	0,011
	Snowfall [kg m^{-2} day^{-1} / year]	-0,055**	-0,004**	0,000	-0,028
	total precipitation [kg m^{-2} day^{-1} / year]	-0,047*	-0,001	-0,020	-0,016
	Rainfall contribution [% / year]	0,950	0,333***	-0,022	1,307*

4.4. Discussion

Our results indicate a tendency for increasing length of phytoplankton growth season in high latitude lakes in Finland. The magnitude of these temporal trends was, however, not consistent between lakes. To better understand these discrepancies, further studies are necessary to clarify the biophysical drivers of environmental changes across these lakes and the sources of temporal variation in their optical properties. Currently there are only few studies on the temporal trends of phytoplankton blooms in lakes. A study using long-term (1955–2003) physical, chemical and biological data from the North Basin of Windermere, UK, reported an advancing trend on spring peak biomass of two diatom taxa, *Asterionella formosa* and *Cyclotella spp* (Thackeray et al., 2008). They concluded that phytoplankton phenological shifts can be caused by local processes, as well as by climate change. While changes in *Cyclotella spp*. seasonal patterns were a result of earlier thermal stratification, the advancement of the *Asterionella formosa* spring peak was linked with both progressive nutrient enrichment and lake warming (Thackeray et al., 2008). Our results did not show evidence of a linkage between lake surface temperature and long-term trends of phytoplankton phenology. However, these results cannot discard an underlining process related to temporal changes in the thermal stratification of lakes. Moreover, challenges persist for separating climate driven changes in primary production dynamics from other anthropogenic forcing, such as changes in land-use and nutrient runoff (Moss et al., 2011).

Shifts in phytoplankton phenology associated with changes in the thermal stratification of lakes were reported by (Winder and Schindler, 2004), who investigated the effects of climatic and biotic drivers on lake processes using a historical dataset of 40 years from Lake Washington, USA. They reported that, in 2002, phytoplankton spring bloom occurred about 19 days earlier than it did in 1962. These changes were tightly linked to an increase in the thermal stratification period (by 25 days over the last 40 years), which was mainly caused by an earlier spring stratification (Winder and Schindler, 2004). In this aspect, our results confirm previous evidence indicating that shifts in lakes' phytoplankton phenology are being mostly driven by an early spring onset. A study over New England shelf, between 2003 and 2016, has shown that phytoplankton blooms in this area now occur 20 days earlier than at the start of observations (Hunter-Cevera et al., 2016). They concluded that earlier springtime warming stimulates cell division earlier each year. Nonetheless, the drivers of phytoplankton dynamics over coastal waters can differ significantly from those in high latitude lakes.

An earlier onset of phytoplankton blooms and longer growing season may potentially result in higher biomass (Domis et al., 2013). Variation in the timing of phytoplankton blooms in lakes affects the species composition by favouring certain taxa (Sommer and Lengfellner, 2008) and further has an impact on competition within the phytoplankton community as well as on trophic interactions with other organisms. Combined with the increased nutrient loading from anthropogenic sources, a longer phytoplankton growth season may further have an impact on the recreational values provided by lakes, with possible implications of toxic phytoplankton species on human health (Lam et al., 1995).

Our results also present evidence that, at higher latitudes, the earlier spring onset is likely to suffer influence from changes in precipitation patterns. In particular, we observed a decrease in snow rates during winter, and consequent increase in the relative rainfall contribution to the total precipitation. We also show significant increase in rainfall during spring. These changes in the precipitation pattern can impact the hydrological regime in the basins draining to the lakes, strongly affecting the timing and magnitude of nutrients discharge. In fact, (Thackeray et al., 2008) have shown that, over the North Basin of Windermere, UK, nutrient enrichment explained more variation in phytoplankton phenology than water temperature. Hence, more detailed studies will help to assess the complexity of the interacting factors driving phytoplankton phenology in inland waters, including land use change and geomorphological characteristics of the basins.

The discrepant results between lakes observed in our study are likely associated with different basin characteristics, such as surrounding land cover, temporal variation in nutrient runoff, and different phytoplankton assemblages. Natural bodies of water present high temporal variation in their chemical characteristics due to the runoff they receive from both anthropogenic and natural sources, as well as the temperature stratification and water mixing. While the examined lakes present different optical characteristics that challenge modelling Chl-a dynamics accurately, our approach provides a new insight into in examining phytoplankton phenologies in boreal lakes that could not be captured by snapshot water sampling by monitoring programmes.

4.4.1. Model performance and uncertainties

Studies aiming to estimate phytoplankton/Chl-a concentration in lakes using LT imagery have reported a large range of model performances, with R^2 varying from 0.30 to 0.95 (Vincent et al., 2004; Allan et al., 2011; Isenstein et al., 2014; Tan et al., 2017) these accuracies are higher than those obtained in our study (0.37 to 0.63), particularly considering our results for mesotrophic lakes (Tuusulanjärvi, Kuortaneenjärvi). Nonetheless, we highlight that there are significant differences in the design of our study. More importantly, in some of the previous studies reporting high model accuracies, models were calibrated to assess the spatial variability of Chl-a within lakes, but did not account for temporal variability (Vincent et al., 2004; Allan et al., 2011). On the other hand, the goal of our models was to estimate Chl-a temporal variability (i.e. how Chl-a concentrations varied throughout time in a same location). This latter task is technically more challenging, given that the spectral differences between sampling dates can be quite subtle, particularly in oligotrophic and mesotrophic lakes. A recent study by Tan et al. (2017), in which LT models were created to assess phytoplankton temporal variability, has reported R^2 from 0.39 to 0.7, which is consistent with our results.

We therefore emphasize that our approach may not be applicable to lakes with low Chl-a concentration. In oligotrophic lakes, the seasonal changes in phytoplankton biomass are considerably smaller, so that the spectral and radiometric resolution of LT5 and 7 are likely to be too coarse to capture this temporal variability. In such cases, newer high-resolution sensors as the Sentinel-2 multi-spectral instrument (MSI), with 13 spectral bands and 12-bits radiometric resolution, is likely to provide more promising results in the longer run, when a denser time-series archive becomes available. MSI includes the bands 0.646-0.684 µm and 0.695-0.714 µm, which are close to the MERIS bands 0.660 – 0.670 µm and 0.704 – 0.714 µm used in the original NDCI index (Mishra and Mishra, 2012). These MERIS bands have been shown to be optimal for the estimation of Chl-a by band ratio algorithms in lakes in Finland (Kallio, 2012). Chl-a was estimated with good accuracy from Sentinel 2 data in Estonian lakes (Toming et al., 2016) with trophic status ranging mainly from mesotrophic to eutrophic. The algorithm was based on the height of the 705 nm reflectance peak.

The new OLI sensor (Operational Land Imager), onboard LT-8, also offers important improvements in comparison with its predecessors. The LT-8 OLI sensor includes additional bands that allow a more confident assessment of data quality, and the radiometric resolution has been improved to 12-bits (in comparison to 8-bits in LT-5 and 7).

As pointed out by (Oliver et al., 2017), assessments on environmental changes over lakes are often limited by temporal and spatial availability of observation data. The capability of remote sensing to overcome such bottlenecks is limited by sensors' resolution or the length of time-series. As exemplified in our study, solving these problems requires dealing with high computation costs, and a careful management of uncertainties, such as cloud contamination and the low spectral signal over freshwater bodies. Here, we used the high-performance cloud computing tools offered by Google Earth Engine (Gorelick et al., 2017) to process and analyse over 30-years of high-resolution satellite data. The processing involved using imagery converted from top-of-atmosphere irradiance to surface reflectance using stated-of-the-art atmospheric correction (Masek et al., 2013), as well as cloud, cloud shadow, and snow/ice masking in each image, using algorithms based on decision trees (Zhu et al., 2015; Foga et al., 2017).

In this study, we carried out this analysis in more than 600 images for each lake. Such procedure would have been extremely laborious or unrealistic just few years ago.

Our results indicate a tendency for increasing length of phytoplankton season in high latitude lakes. The magnitude of these temporal trends was, however, not consistent between lakes. To better understand these discrepancies, further studies are critical to clarify the biophysical drivers of environmental changes across these lakes. Currently there are only few studies on the temporal trends of phytoplankton blooms in lakes. A study using long-term (1955–2003) physical, chemical and biological data from the North Basin of Windermere, UK, reported an advancing trend on spring peak biomass of two diatom taxa, *Asterionella formosa* and *Cyclotella spp* (Thackeray et al., 2008). They concluded that phytoplankton phenological shifts can be caused by local processes, as well as by climate change. While changes in *Cyclotella spp*. seasonal patterns were a result of earlier thermal stratification, the advancement of the *Asterionella formosa* spring peak was linked with both progressive nutrient enrichment and lake warming (Thackeray et al., 2008). Our results did not show evidence of a linkage between lake surface temperature and long-term trends of phytoplankton phenology. However, these results cannot discard an underlining process related to temporal changes in the thermal stratification of lakes, which should be investigated in further studies.

Shifts in phytoplankton phenology associated with changes in the thermal stratification of lakes were also reported by (Winder and Schindler, 2004), who investigated the effects of climatic and biotic drivers on lake processes using a historical dataset of 40 years from Lake Washington, USA. They reported that, in 2002, phytoplankton spring bloom occurred about 19 days earlier than it did in 1962. These changes were tightly linked to an increase in the thermal stratification period (by 25 days over the last 40 years), which was mainly caused by an earlier spring stratification (Winder and Schindler, 2004). In this aspect, our results confirm previous evidence indicating that shifts in lakes' phytoplankton phenology are being mostly driven by an early spring onset. A study over New England shelf, between 2003 and 2016, has shown that phytoplankton blooms in this area now occur 20 days earlier than at the start of observations (Hunter-Cevera et al., 2016). They concluded that earlier springtime warming stimulates cell division earlier each year. Nonetheless, the drivers of phytoplankton dynamics over coastal waters can differ significantly from those in high latitude lakes.

An earlier onset of phytoplankton blooms and longer growing season may potentially result in higher biomass (Domis et al., 2013). Variation in the timing of phytoplankton blooms in lakes affects the species composition by favouring certain taxa (Sommer and Lengfellner, 2008) and further has an impact on competition within the phytoplankton community as well as on trophic interactions with other organisms. Combined with the increased nutrient loading from anthropogenic sources, a longer phytoplankton growth season may further have an impact on the recreational values provided by lakes, with possible implications of toxic phytoplankton species on human health (Lam et al., 1995).

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4.5. Conclusions

In this study we evaluated 33-years of satellite data for characterizing the phytoplankton phenology and long-term trends across four lakes in Finland. Our approach could successfully characterize the average Chl-a seasonal patterns in all lakes, providing a novel baseline for evaluating environmental changes. We present evidence of increasing length in phytoplankton bloom seasons in high latitude Finnish lakes, mostly caused by an earlier onset of phytoplankton growth. We report an increase up to 28 days in the length of Chl-a season (Lake Köyliönjärvi) over the past three decades. Nonetheless, the magnitude of changes in the Chl-a seasonal patterns varied between lakes, with one of the lakes showing no significant changes. The observed changes in Chl-a temporal patterns are unlikely to be explained by changes in surface temperature (Ts), as we could not detect significant trends on average Ts, or in the Ts phenological metrics from 2001 to 2017. However, changes in the thermal stratification of the lakes cannot be discarded. We also point out for important shifts in the precipitation patterns over the past decades that could potentially drive the observed changes in Chl-a seasonal patterns. Our results show a significant decrease in snowfall rates during winter, with a consequent increase in the rainfall contribution to total precipitation. Finally, we suggest that further studies will decrease the uncertainties related to the biophysical factors driving the temporal patters in Chl-a, allowing a robust explanation for the shifts in Chl-a seasonality reported here. Particularly, it is crucial for climate variables to be accounted in combination with a comprehensive assessment of the hydrological characteristics of the drainage basins contributing to the lakes' influx.

Chapter 5. Discussion – The Role of Earth Observation in Managing Aquatic Ecosystems in a Changing Climate

Earth Observation (EO) technologies are becoming increasingly important as tools for monitoring and managing aquatic ecosystems, providing critical information that underpins effective management decisions in the context of the challenges of climate change. This discourse addresses the relevance of EO, grounded in evidence from three large-scale studies (Maeda et al., 2019; Lisboa et al., 2020, 2024). Together, the studies detail the widespread impact of EO technologies on marine and freshwater ecosystems.

Marine Protected Areas (MPAs) are important for the conservation of marine biodiversity and sustainable utilization of marine resources. Earth Observation (EO) technologies, especially through satellite remote sensing, have revolutionized the management and monitoring of MPAs by providing continuous and large-scale datasets that are beyond the capability of traditional monitoring methods. It is well known that the synoptic and temporal extent of satellites is unmatched in its capability to scan large oceanic areas, providing information regarding diverse ecological indicators like sea surface temperature, chlorophyll-a concentration, and turbidity levels. The extensive covering is essential for the detection of large-scale environmental changes and trends over long intervals. However, technological resources for covering smaller MPAs and freshwater lakes are still inadequate. In comparison to traditional field-based monitoring methods, EO technologies provide an economical alternative, especially in monitoring distant or large marine areas. This ability allows for more intensive and comprehensive monitoring without the enormous costs typically required for ship-based surveys (Lisboa et al., 2024).

5.1 Case Applications and Studies

Coral Reef Monitoring: Advanced high-resolution sensors in satellites have been used in an attempt to quantify the health status of coral reef systems. Colour alterations in reefs as well as certain water quality parameters can be detected to track bleaching events and overall health of coral communities.

Fisheries Management: EO information on sea surface temperature and chlorophyll-a concentration is critical in managing fish stocks. The information aids in the detection of productive fishing grounds and the effects of climate variability on fish distribution.

5.2 EO in Freshwater Systems

Freshwater ecosystems, such as lakes, rivers, and wetlands, have been significantly enhanced by EO technologies. These ecosystems are highly dynamic and sensitive to climatic as well as anthropogenic drivers and therefore require strong monitoring approaches.

5.2.1 Advancements in EO for Freshwater Monitoring

High-Resolution Imaging: Modern satellites offer high-resolution imagery that can detect minor changes in spatial variations within water bodies. This is needed for the determination of the factors like water clarity, chlorophyll-a levels, and surface temperature.

Multispectral and hyperspectral sensors are capable of recording a broad range of wavelengths and therefore can perform an extensive analysis of water quality parameters and detect specific constituents like dissolved organic matter and suspended sediments.

5.3 Case Analyses

Chlorophyll-a Monitoring: Lisboa et al. (2020) illustrate the potential of applying multi-source remote sensing methods for the quantification of chlorophyll-a concentration in Finnish lakes. The method offers high spatial resolution data that is vital in the process of understanding eutrophication and the effects of nutrient loading on lake ecosystems.

Phytoplankton Phenology: Long-term satellite observations are used by Maeda et al. (2019) to study phytoplankton phenology in high-latitude lakes. Observing the patterns over a long time is crucial in establishing the effects of climate change on primary production and ecosystem integrity.

5.4 Challenges and Opportunities

Notwithstanding the immense progress, a number of challenges are encountered for the widespread adoption and utilization of EO technologies in aquatic ecosystem management.

5.4.1 Challenges

Data Integration and Accessibility: Accessing the EO data and integrating it with *in situ* measurements and making the data available to a large audience, such as policymakers and local managers, is still a challenge.

Technical Limitations: Technical limitations still lie in the resolution and precision of EO data, especially for small lakes or highly variable complex environments.

5.4.2 Opportunities for Innovation

The launch of new satellites such as ICESat-2 that are capable of retrieving vertical profiles of chlorophyll-a concentration holds the promise of improved Earth Observation (EO) capabilities (Lisboa et al., 2024).

The integration of machine learning and artificial intelligence with Earth Observation data can enhance data analysis capabilities to detect patterns and anomalies automatically. Therefore, the integration can significantly enhance the efficiency and accuracy of monitoring tasks (Lisboa et al., 2024).

Interdisciplinary Strategies: Integrating EO data with ecological models and socioeconomic data could yield a more integrated understanding of ecosystem dynamics and support more optimal management.

5.5. Governance and Policy Implications

The provision of timely and precise environmental information by EO technologies is essential to good government and policymaking in aquatic ecosystem management. The inaugural study emphasizes the importance of EO informing policymaking and facilitating ecosystem-based management approaches.

5.5.1 Policy Integration

International Programmes: European Space Programme and Copernicus programmes are central to providing key climate variables and other environmental data to inform international and national policymaking. These programmes facilitate the harmonization of

Earth Observation (EO) data into governance, enabling more effective and better-informed management policies (Lisboa et al., 2024) – *e.g.* the European Space Programme.

Local and Regional Management: Environmental observation technologies help local and regional management programs by providing information that can be used to assess the success of management intervention, such as restoration activities and the establishment of conservation practices. Conclusion The longer discussion highlights the critical role of EO in the management of aquatic ecosystems in the context of climate change. The application of EO technologies in marine and freshwater ecosystems has resulted in significant enhancement in monitoring capacity, enabling more effective and timely action in management. However, overcoming data integration, accessibility, and technical limitations is crucial to realize the full potential of EO. Continued innovation and integration of inter-disciplinary approaches will improve our ability to monitor, understand, and manage aquatic ecosystems and make them resilient and sustainable in the context of climate change.

Chapter 6. Final remarks – Earth Observation in Aquatic Ecosystem Management

The use of Earth Observation (EO) technologies in aquatic ecosystem management is underscored in all three articles as a paradigmatic approach. Generally, the three papers emphasize EO as the key to enhanced observation, assessment, and management of climate change-impacted marine and freshwater ecosystems. Below, we present the common conclusions derived from these studies.

6.1 Improved Surveillance Proficiencies

All three studies refer to the great improvement in monitoring capacity offered by EO technologies, best complemented by *in situ* observations. Conventional methods of monitoring aquatic ecosystems are hampered by spatial and temporal coverage limitations, cost, and resource requirements. EO technologies, especially satellite remote sensing, overcome these deficiencies through the offering of:

Synoptic Coverage: The ability to collect extensive and worldwide datasets, providing wide views of whole ecosystems, which is particularly valuable for remote or inaccessible locations.

Temporal Frequency: Continuous and periodic data gathering allows one to track temporal changes and trends necessary for the detection and understanding of the dynamics of ecosystems.

Cost-Effectiveness: Lower cost compared to other traditional *in situ* monitoring techniques, enabling wider and more comprehensive data collection.

6.2 Enhanced Understanding of Ecosystem Cycles

EO technologies have greatly improved our knowledge base on ecosystem dynamics, especially how ecosystems respond to climate change. The research identifies a number of areas where EO has improved our knowledge base:

Phenology and Temporal Patterns: Long-term satellite records have identified temporal patterns and phenological trends in phytoplankton and other primary producers and have accounted for impacts of climate change on primary production and ecosystem health (Maeda et al., 2019).

Water Quality Monitoring: Multi-source remote sensing has proven to be useful in water quality parameter monitoring, including chlorophyll-a concentration, which is utilized as an indicator of freshwater nutrient enrichment and eutrophication (Lisboa et al., 2020).

Marine Ecosystem Health: Continuous sea surface temperature, chlorophyll concentration, and other parameter monitoring is necessary to establish the health of marine ecosystems, detect events like coral bleaching and blooms, and effectively manage Marine Protected Areas (MPAs).

6.3 Policy and Management Implications

As a whole, the study emphasizes the value of EO data in guiding policy and management decisions. The incorporation of EO in governance frameworks is at the heart of successful ecosystem-based management:

Evidence-Informed Policy: Reliable and timely Earth observation data facilitate the development of evidence-informed policies, thereby allowing more efficient responses to environmental changes and improved management of aquatic resources (Lisboa et al., 2024).

International and National Programs: Copernicus and EU Space Programme are some of the programs that are important in offering vital environmental data, which are very important for international and national policymaking. These programs demonstrate the potential of EO for improving governance and management strategies.

6.4 Challenges and Future Directions

Although EO technologies have come a long way, the research also identifies some future challenges and areas of development:

Data Integration and Accessibility: Making EO data available in conjunction with *in situ* measurements and to a wide community, including policymakers and local managers, is an issue to be resolved.

Technical Advances: Ongoing advances in high-resolution sensors and sophisticated satellites like ICESat-2, which can take vertical profiles of the concentration of chlorophyll-a, are the need of the hour in order to offer more precise and integrated data (Lisboa et al., 2024).

Interdisciplinary Approaches: Merging Earth Observation (EO) data with ecological modelling, socioeconomic data, and machine learning techniques can give a more holistic view of ecosystem processes and enhance management (Pham et al., 2023).

Shared Conclusions

1. Revolutionizing Effect of EO Technologies: The emergence of EO technologies has radically transformed the monitoring and management functions of aquatic ecosystems, providing comprehensive, timely, and cost-effective data that form the basis of effective regulation under changing climatic conditions.

2. Increased Ecosystem Understanding: EO's capacity to observe large-scale and long-term environmental change has profoundly enhanced our understanding of ecosystem processes, especially of the effects of climate change on marine and freshwater ecosystems.

3. Use in Policy and Management: EO data are essential to evidence-based policy and management decision-making, enabling more efficient governance systems and allowing evidence-based management of ecosystems.

4. Challenges and Opportunities: Overcoming data integration, access, and technical constraints, and taking advantage of technological innovation and interdisciplinary opportunities, will be critical to taking full advantage of EO in aquatic ecosystem management. Not addressed in the papers is that the capability to access near-real-time data enables the quick detection of change in the marine environment. For example, an abrupt

change in sea surface temperature or in chlorophyll-a concentration can signal events such as coral bleaching or harmful algal blooms, allowing timely management response. In our study we were constrained by the examination of phytoplankton variability with the aid of satellite imagery in the very challenging case of small lakes. We did not investigate variation of phytoplankton communities in such changes. Such data are very important, and it was initiated in some cases like the Baltic semi-open sea (Seppälä and Olli, 2008).

Additionally, it is reported that temperature increase has a strong impact on phytoplankton peak biomass (declining with temperature), mean cell size (declining with temperature) and on the percentage of microplankton diatoms (declining with temperature). All these changes will lead to deteriorating feeding conditions for copepod zooplankton and, hence, to less effective energy transfer from primary to fish production in a warmer climate (Sommer and Lengfellner, 2008). Examination of those dynamics in the trophic chain is also a line to be pursued further.

References

Acevedo-Trejos, E., Brandt, G., Steinacher, M., and Merico, A. (2014). A glimpse into the future composition of marine phytoplankton communities. *Front Mar Sci* 1, 15. doi: 10.3389/fmars.2014.00015

Adrian, R., O'Reilly, C. M., Zagarese, H., Baines, S. B., Hessen, D. O., Keller, W., et al. (2009a). Lakes as sentinels of climate change. *Limnol Oceanogr* 54, 2283–2297. doi: 10.4319/lo.2009.54.6_part_2.2283

Adrian, R., O'Reilly, C. M., Zagarese, H., Baines, S. B., Hessen, D. O., Keller, W., et al. (2009b). Lakes as sentinels of climate change. *Limnol Oceanogr* 54, 2283–2297. doi: 10.4319/lo.2009.54.6_part_2.2283

Adrian, R., Walz, N., Hintze, T., Hoeg, S., and Rusche, R. (1999a). Effects of ice duration on plankton succession during spring in a shallow polymictic lake. *Freshw Biol* 41, 621–634. doi: 10.1046/j.1365-2427.1999.00411.x

Adrian, R., Walz, N., Hintze, T., Hoeg, S., and Rusche, R. (1999b). Effects of ice duration on plankton succession during spring in a shallow polymictic lake. *Freshw Biol* 41, 621–634. doi: 10.1046/j.1365-2427.1999.00411.x

Allan, M. G., Hamilton, D. P., Hicks, B. J., and Brabyn, L. (2011a). Landsat remote sensing of chlorophyll a concentrations in central North Island lakes of New Zealand. *Int J Remote Sens* 32, 2037–2055. doi: 10.1080/01431161003645840

Allan, M. G., Hamilton, D. P., Hicks, B. J., and Brabyn, L. (2011b). Landsat remote sensing of chlorophyll a concentrations in central North Island lakes of New Zealand. *Int J Remote Sens* 32, 2037–2055. doi: 10.1080/01431161003645840

Anderson, D. M. (2009a). Approaches to monitoring, control and management of harmful algal blooms (HABs). *Ocean Coast Manag* 52, 342–347. doi: 10.1016/j.ocecoaman.2009.04.006

Anderson, D. M. (2009b). Approaches to monitoring, control and management of harmful algal blooms (HABs). *Ocean Coast Manag* 52, 342–347. doi: 10.1016/j.ocecoaman.2009.04.006

Aoyama, T. (2010). Algorithm for estimating the chlorophyll-a concentrations in water areas with different qualities from satellite data., in *Remote Sensing of the Coastal Ocean, Land, and Atmosphere Environment*, (SPIE), 236–243. doi: 10.1117/12.869442

Appleby, T., Studley, M., Moorhouse, B., Brown, J., Staddon, C., and Bean, E. (2021). Sea of possibilities: Old and new uses of remote sensing data for the enforcement of the Ascension Island marine protected area. *Mar Policy* 127, 103184. doi: 10.1016/j.marpol.2018.06.012

Bada, J. L. (2004). How life began on Earth: A status report. *Earth Planet Sci Lett* 226. doi: 10.1016/j.epsl.2004.07.036

Bailey, S. W., and Werdell, P. J. (2006). A multi-sensor approach for the on-orbit validation of ocean color satellite data products. *Remote Sens Environ* 102, 12–23. doi: 10.1016/j.rse.2006.01.015

Baker, J. C., and Williamson, R. A. (2006a). Satellite imagery activism: Sharpening the focus on tropical deforestation. *Singap J Trop Geogr* 27, 4–14. doi: 10.1111/J.1467-9493.2006.00236.X

Baker, J. C., and Williamson, R. A. (2006b). Satellite imagery activism: Sharpening the focus on tropical deforestation. *Singap J Trop Geogr* 27, 4–14. doi: 10.1111/J.1467-9493.2006.00236.X

Ballari, D., Vilches-Blázquez, L. M., Orellana-Samaniego, M. L., Salgado-Castillo, F., Ochoa-Sánchez, A. E., Graw, V., et al. (2023a). Satellite Earth Observation for Essential Climate Variables Supporting Sustainable Development Goals: A Review on Applications. *Remote Sens (Basel)* 15. doi: 10.3390/rs15112716

Ballari, D., Vilches-Blázquez, L. M., Orellana-Samaniego, M. L., Salgado-Castillo, F., Ochoa-Sánchez, A. E., Graw, V., et al. (2023b). Satellite Earth observation for essential climate variables supporting Sustainable Development Goals: A review on applications. *Remote Sens (Basel)* 15, 2716. doi: 10.3390/rs15112716

Beck, R., Zhan, S., Liu, H., Tong, S., Yang, B., Xu, M., et al. (2016). Comparison of satellite reflectance algorithms for estimating chlorophyll-a in a temperate reservoir using coincident hyperspectral aircraft imagery and dense coincident surface observations. *Remote Sens Environ* 178, 15–30. doi: 10.1016/J.RSE.2016.03.002

Beggs, H., Karagali, I., and Castro, S. (2023). Sea surface temperature: An introduction to users on the set of GHRSST formatted products. doi: 10.5281/zenodo.7762412

Behrenfeld, M. J., and Boss, E. S. (2014a). Resurrecting the ecological underpinnings of ocean plankton blooms. *Ann Rev Mar Sci* 6, 167–194. doi: 10.1146/annurev-marine-052913-021325

Behrenfeld, M. J., and Boss, E. S. (2014b). Resurrecting the ecological underpinnings of ocean plankton blooms. *Ann Rev Mar Sci* 6, 167–194. doi: 10.1146/annurev-marine-052913-021325

Blasiak, R., and Yagi, N. (2016). Shaping an international agreement on marine biodiversity beyond areas of national jurisdiction: lessons from high seas fisheries. *Mar Policy* 71, 210–216. doi: 10.1016/j.marpol.2016.06.004

Bleiker, W., and Schanz, F. (1989a). Influence of environmental factors on the phytoplankton spring bloom in Lake Zürich. *Aquat Sci* 51, 47–58. doi: 10.1007/BF00877780

Bleiker, W., and Schanz, F. (1989b). Influence of Environmental-Factors on the Phytoplankton Spring Bloom in Lake Zurich. *Aquat Sci* 51, 47–58.

Blondeau-Patissier, D., Gower, J. F. R., Dekker, A. G., Phinn, S. R., and Brando, V. E. (2014). A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans. *Prog Oceanogr* 123, 123–144. doi: 10.1016/j.pocean.2013.12.008

Bojinski, S., Verstraete, M., Peterson, T. C., Richter, C., Simmons, A., and Zemp, M. (2014). The concept of essential climate variables in support of climate research, applications, and policy. *Bull Am Meteorol Soc* 95, 1431–1443. doi: 10.1175/BAMS-D-13-00047.1

Borics, G., Abonyi, A., Salmaso, N., and Ptacnik, R. (2021). Freshwater phytoplankton diversity: models, drivers and implications for ecosystem properties. *Hydrobiologia* 848, 53–75. doi: 10.1007/s10750-020-04332-9

Boucher, J., Weathers, K. C., Norouzi, H., and Steele, B. (2018a). Assessing the effectiveness of Landsat 8 chlorophyll a retrieval algorithms for regional freshwater monitoring. *Ecological applications* 28, 1044–1054. doi: 10.1002/EAP.1708

Boucher, J., Weathers, K. C., Norouzi, H., and Steele, B. (2018b). Assessing the effectiveness of Landsat 8 chlorophyll a retrieval algorithms for regional freshwater monitoring. *Ecological Applications* 28, 1044–1054. doi: 10.1002/eap.1708

Brando, V. E., Dekker, A. G., Park, Y. J., and Schroeder, T. (2012). Adaptive semianalytical inversion of ocean color radiometry in optically complex waters.

Applied Optics, Vol. 51, Issue 15, pp. 2808-2833 51, 2808–2833. doi: 10.1364/AO.51.002808

Briggs, D. E. G. (2015). The cambrian explosion. *Current Biology* 25, R864–R868. doi: 10.1016/j.cub.2015.04.047

Brivio, P. A., Giardino, C., and Zilioli, E. (2001a). Determination of chlorophyll concentration changes in Lake Garda using an image-based radiative transfer code for Landsat TM images. *Int J Remote Sens* 22, 487–502. doi: 10.1080/014311601450059

Brivio, P. A., Giardino, C., and Zilioli, E. (2001b). Determination of chlorophyll concentration changes in Lake Garda using an image-based radiative transfer code for Landsat TM images. *Int J Remote Sens* 22, 487–502. doi: 10.1080/014311601450059

Brotas, V., Brewin, R. J. W., Sá, C., Brito, A. C., Silva, A., Mendes, C. R., et al. (2013). Deriving phytoplankton size classes from satellite data: Validation along a trophic gradient in the eastern Atlantic Ocean. *Remote Sens Environ* 134, 66–77. doi: 10.1016/j.rse.2013.02.013

Bulgarelli, B., and Zibordi, G. (2018). On the detectability of adjacency effects in ocean color remote sensing of mid-latitude coastal environments by SeaWiFS, MODIS-A, MERIS, OLCI, OLI and MSI. *Remote Sens Environ* 209, 423–438. doi: 10.1016/j.rse.2017.12.021

Calamita, E., Lever, J. J., Albergel, C., Woolway, R. I., and Odermatt, D. (2024). Detecting climate-related shifts in lakes: A review of the use of satellite Earth Observation. *Limnol Oceanogr* 69, 723–741. doi: 10.1002/LNO.12498

Campbell, J. W., and Feng, H. (2005). The empirical chlorophyll algorithm for MODIS: Testing the OC3M algorithm using NOMAD data.

Carder, K. L., Arnone, R. A., and Lee, Z. (2002). Deriving inherent optical properties from water color: a multiband quasi-analytical algorithm for optically deep waters. *Applied Optics, Vol. 41, Issue 27, pp. 5755-5772* 41, 5755–5772. doi: 10.1364/AO.41.005755

Carr, H., Abas, M., Boutahar, L., Caretti, O. N., Chan, W. Y., Chapman, A. S. A., et al. (2020). The Aichi Biodiversity Targets: achievements for marine conservation and priorities beyond 2020. *PeerJ* 8, e9743. doi: 10.7717/PEERJ.9743/TABLE-2

Catry, P., Senhoury, C., Sidina, E., El Bar, N., Bilal, A. S., Ventura, F., et al. (2023). Satellite tracking and field assessment highlight major foraging site for green turtles in the Banc d'Arguin, Mauritania. *Biol Conserv* 277, 109823. doi: 10.1016/j.biocon.2022.109823

Chang, C. H., Liu, C. C., Wen, C. G., Cheng, I. F., Tam, C. K., and Huang, C. S. (2009a). Monitoring reservoir water quality with Formosat-2 high spatiotemporal imagery. *Journal of Environmental Monitoring* 11. doi: 10.1039/b912897b

Chang, C.-H., Liu, C.-C., Wen, C.-G., Cheng, I.-F., Tam, C.-K., and Huang, C.-S. (2009b). Monitoring reservoir water quality with Formosat-2 high spatiotemporal imagery. *Journal of Environmental Monitoring* 11, 1982–1992. doi: 10.1039/b912897b

Charlson, R. J., Lovelock, J. E., Andreae, M. O., and Warren, S. G. (1987a). Oceanic phytoplankton, atmospheric sulphur, cloud albedo and climate. *Nature* 326, 655–661. doi: 10.1038/326655a0

Charlson, R. J., Lovelockt, J. E., and Warren, S. G. (1987b). Oceanic phytoplankton, atmospheric sulphur, cloud albedo and climate.

Chisholm, S. W. (1992). "Phytoplankton size," in *Primary Productivity and Biogeochemical Cycles in the Sea*, (Springer, Boston, MA), 213–237. doi: 10.1007/978-1-4899-0762-2_12

Choi, K. T. H. (2018). Space, satellite and solutions: essential climate variables and the future of climate monitoring from space. *Weather* 73. doi: 10.1002/wea.3306

Clarke, G. L., Ewing, G. C., and Lorenzen, C. J. (1970). Spectra of Backscattered Light from the Sea Obtained from Aircraft as a Measure of Chlorophyll Concentration. *Science (1979)* 167, 1119–1121. doi: 10.1126/science.167.3921.1119

Coffer, M. M. A., Schaeffer, B. A., Urquhart, E. A., Darling, J. A., and Salls, W. B. (2018). A method for quantifying the number of US lakes with cyanobacterial harmful algal blooms using satellite remote sensing., in *Remote Sensing and Modeling of Ecosystems for Sustainability XV*, (SPIE), 60–72. doi: 10.1117/12.2319669

Cohen, J., Screen, J. A., Furtado, J. C., Barlow, M., Whittleston, D., Coumou, D., et al. (2014). Recent Arctic amplification and extreme mid-latitude weather. *Nat Geosci* 7, 627–637. doi: 10.1038/ngeo2234

Conway Morris, S. (2006). Darwin's dilemma: the realities of the Cambrian 'explosion.' *Philosophical Transactions of the Royal Society B: Biological Sciences* 361, 1069–1083. doi: 10.1098/rstb.2006.1846

Cristina, S., Icely, J., Goela, P. C., DelValls, T. A., and Newton, A. (2015). Using remote sensing as a support to the implementation of the European Marine Strategy Framework Directive in SW Portugal. *Cont Shelf Res* 108, 169–177. doi: 10.1016/j.csr.2015.03.011

Cubaynes, H. C., and Fretwell, P. T. (2022). Whales from space dataset, an annotated satellite image dataset of whales for training machine learning models. *Sci Data* 9, 245.

Cury, P. M., Shin, Y.-J., Planque, B., Durant, J. M., Fromentin, J.-M., Kramer-Schadt, S., et al. (2008). Ecosystem oceanography for global change in fisheries. *Trends Ecol Evol* 23, 338–346. doi: 10.1016/j.tree.2008.02.005

Dalu, T., Dube, T., Froneman, P. W., Sachikonye, M. T. B., Clegg, B. W., and Nhiwatiwa, T. (2015). An assessment of chlorophyll-a concentration spatio-temporal variation using Landsat satellite data, in a small tropical reservoir. *Geocarto Int* 30, 1130–1143. doi: 10.1080/10106049.2015.1027292

Darroch, S. A. F., Smith, E. F., Laflamme, M., and Erwin, D. H. (2018). Ediacaran extinction and Cambrian explosion. *Trends Ecol Evol* 33, 653–663. doi: 10.1016/j.tree.2018.06.003

Delfour-Samama, O., and Leboeuf, C. (2014). Review of potential legal frameworks for effective implementation and enforcement of MPAs in the high seas. *ICES Journal of Marine Science* 71, 1031–1039. doi: 10.1093/icesjms/fsu024

Deppeler, S. L., and Davidson, A. T. (2017). Southern Ocean phytoplankton in a changing climate. *Front Mar Sci* 4, 40. doi: 10.3389/fmars.2017.00040

Dias, J. M., Babanin, A., Teresa De Castro Rodríguez, M., and Soldatenko, S. (2022). On the Effects of Mixed and Deep Ocean Layers on Climate Change and Variability. *J Mar Sci Eng* 10, 1216. doi: 10.3390/jmse10091216

Domis, D. S., Lisette, N., Elser, J. J., Gsell, A. S., Huszar, V. L. M., IBELINGS, B., et al. (2013). Plankton dynamics under different climatic conditions in space and time. *Freshw Biol* 58, 463–482. doi: 10.1111/fwb.12053

Donato, D. C., Kauffman, J. B., Murdiyarso, D., Kurnianto, S., Stidham, M., and Kanninen, M. (2011a). Mangroves among the most carbon-rich forests in the tropics. *Nature Geoscience 2011 4:5* 4, 293–297. doi: 10.1038/ngeo1123

Donato, D. C., Kauffman, J. B., Murdiyarso, D., Kurnianto, S., Stidham, M., and Kanninen, M. (2011b). Mangroves among the most carbon-rich forests in the tropics. *Nat Geosci* 4, 293–297. doi: 10.1038/ngeo1123

Doney, S. C. (2006). Plankton in a warmer world. *Nature* 444, 695–696. doi: 10.1038/444695a

Downing, J. A., Prairie, Y. T., Cole, J. J., Duarte, C. M., Tranvik, L. J., Striegl, R. G., et al. (2006a). The global abundance and size distribution of lakes, ponds, and impoundments. *Limnol Oceanogr* 51, 2388–2397. doi: 10.4319/LO.2006.51.5.2388

Downing, J. A., Prairie, Y. T., Cole, J. J., Duarte, C. M., Tranvik, L. J., Striegl, R. G., et al. (2006b). The global abundance and size distribution of lakes, ponds, and impoundments. *Limnol Oceanogr* 51, 2388–2397. doi: 10.4319/LO.2006.51.5.2388

Duarte, C. M., Prairie, Y. T., Montes, C., Cole, J. J., Striegl, R., Melack, J., et al. (2008a). CO2 emissions from saline lakes: A global estimate of a surprisingly large flux. *J Geophys Res Biogeosci* 113, 4041. doi: 10.1029/2007JG000637

Duarte, C. M., Prairie, Y. T., Montes, C., Cole, J. J., Striegl, R., Melack, J., et al. (2008b). CO2 emissions from saline lakes: A global estimate of a surprisingly large flux. *J Geophys Res Biogeosci* 113. doi: 10.1029/2007JG000637

Eakin, C. M., Nim, C. J., Brainard, R. E., Aubrecht, C., Elvidge, C., Gledhill, D. K., et al. (2010). Monitoring coral reefs from space. *Oceanography* 23, 118–133. doi: 10.5670/oceanog.2010.10

European Commission (2012). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, and the Committee of the Regions: Blue Growth opportunities for marine and maritime sustainable growth. Brussels. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52012DC0494 (Accessed May 2, 2025).

European Environment Agency (2015a). *State and Outlook 2015 the European Environment*. doi: 10.2800/944899

European Environment Agency (2015b). State and Outlook 2015: The European Environment. Copenhagen. doi: 10.2800/944899

Falkowski, P. (2012). Ocean science: The power of plankton. *Nature* 483, S17–S20. doi: 10.1038/483S17A;SUBJMETA

Falkowski, P. G., and Raven, J. A. (2013). *Aquatic photosynthesis*. Princeton University Press.

Fasnacht, Z., Joiner, J., Haffner, D., Qin, W., Vasilkov, A., Castellanos, P., et al. (2022). Using Machine Learning for Timely Estimates of Ocean Color Information From Hyperspectral Satellite Measurements in the Presence of Clouds, Aerosols, and Sunglint. *Frontiers in Remote Sensing* 3, 846174. doi: 10.3389/FRSEN.2022.846174/BIBTEX

Field, C. B., Behrenfeld, M. J., Randerson, J. T., and Falkowski, P. (1998a). Primary production of the biosphere: Integrating terrestrial and oceanic components. *Science (1979)* 281. doi: 10.1126/science.281.5374.237

Field, C. B., Behrenfeld, M. J., Randerson, J. T., and Falkowski, P. (1998b). Primary production of the biosphere: integrating terrestrial and oceanic components. *Science (1979)* 281, 237–240. doi: 10.1126/science.281.5374.237

Flink, P., Lindell, L. T., and Östlund, C. (2001). Statistical analysis of hyperspectral data from two Swedish lakes. *Science of the total environment* 268, 155–169. doi: 10.1016/S0048-9697(00)00686-0

Foga, S., Scaramuzza, P. L., Guo, S., Zhu, Z., Dilley Jr, R. D., Beckmann, T., et al. (2017a). Cloud detection algorithm comparison and validation for operational Landsat data products. *Remote Sens Environ* 194, 379–390. doi: 10.1016/j.rse.2017.03.026

Foga, S., Scaramuzza, P. L., Guo, S., Zhu, Z., Dilley, R. D., Beckmann, T., et al. (2017b). Cloud detection algorithm comparison and validation for operational Landsat data products. *Remote Sens Environ* 194, 379–390. doi: 10.1016/j.rse.2017.03.026

Forel, F.-A. (1890). *Le Léman: Monographie Limnologique*. Lausanne: F. Rouge.

Forkel, M., Migliavacca, M., Thonicke, K., Reichstein, M., Schaphoff, S., Weber, U., et al. (2015a). Codominant water control on global interannual variability and trends in land surface phenology and greenness. *Glob Chang Biol* 21, 3414–3435. doi: 10.1111/gcb.12950

Forkel, M., Migliavacca, M., Thonicke, K., Reichstein, M., Schaphoff, S., Weber, U., et al. (2015b). Codominant water control on global interannual variability and trends in land surface phenology and greenness. *Glob Chang Biol* 21, 3414–3435. doi: 10.1111/gcb.12950

GCOS (2016). The Global Observing System for Climate: Implementation Needs. Geneva. Available at: https://library.wmo.int/doc_num.php?explnum_id=3417

Giardino, C., U, C. G., Pepe, M., Brivio, P. A., Ghezzi, P., and Zilioli, E. (2001). Detecting chlorophyll , Secchi disk depth and surface temperature in a sub-alpine lake using Landsat imagery Detecting chlorophyll , Secchi disk depth and surface temperature in a sub-alpine lake using Landsat imagery. doi: 10.1016/S0048-9697(00)00692-6

Gittings, J. A., Raitsos, D. E., Krokos, G., and Hoteit, I. (2018a). Impacts of warming on phytoplankton abundance and phenology in a typical tropical marine ecosystem. *Sci Rep* 8, 2240. doi: 10.1038/s41598-018-20560-5

Gittings, J. A., Raitsos, D. E., Krokos, G., and Hoteit, I. (2018b). Impacts of warming on phytoplankton abundance and phenology in a typical tropical marine ecosystem. *Sci Rep* 8, 2240. doi: 10.1038/s41598-018-20560-5

Gordon, H. R., Clark, D. K., Brown, J. W., Brown, O. B., Evans, R. H., and Broenkow, W. W. (1983). Phytoplankton pigment concentrations in the Middle Atlantic Bight: comparison of ship determinations and CZCS estimates. *Appl Opt* 22, 20. doi: 10.1364/AO.22.000020

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017a). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens Environ* 202, 18–27. doi: 10.1016/j.rse.2017.06.031

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017b). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens Environ* 202, 18–27. doi: 10.1016/j.rse.2017.06.031

Greb, S., Dekker, A., and Binding, C. (2018). IOCCG 2018 Earth Observations in Support of Global Water Quality. Available at: https://repository.oceanbestpractices.org/handle/11329/535

Gregg, W. W., Rousseaux, C. S., and Franz, B. A. (2017). Global trends in ocean phytoplankton: a new assessment using revised ocean colour data. *Remote Sensing Letters* 8, 1102–1111. doi: 10.1080/2150704X.2017.1354263

Grömping, U. (2006). Relative Importance for Linear Regression in R: The Package relaimpo. *J Stat Softw* 17. doi: 10.18637/jss.v017.i01

Groom, S. B., Sathyendranath, S., Ban, Y., Bernard, S., Brewin, B., Brotas, V., et al. (2019a). Satellite ocean colour: Current status and future perspective. *Front Mar Sci* 6. doi: 10.3389/fmars.2019.00485

Groom, S., Sathyendranath, S., Ban, Y., Bernard, S., Brewin, R., Brotas, V., et al. (2019b). Satellite ocean colour: current status and future perspective. *Front Mar Sci* 6, 485. doi: 10.3389/fmars.2019.00485

Hadjal, M., Paterson, R., and McKee, D. (2023). Neural networks to retrieve in water constituents applied to radiative transfer models simulating coastal water conditions. *Frontiers in Remote Sensing* 4, 973944. doi: 10.3389/FRSEN.2023.973944/BIBTEX

Halpern, B. S., Lester, S. E., and McLeod, K. L. (2010a). Placing marine protected areas onto the ecosystem-based management seascape. *Proc Natl Acad Sci U S A* 107. doi: 10.1073/pnas.0908503107

Halpern, B. S., Lester, S. E., and McLeod, K. L. (2010b). Placing marine protected areas onto the ecosystem-based management seascape. *Proc Natl Acad Sci U S A* 107, 18312–18317. doi: 10.1073/PNAS.0908503107

Halpern, B. S., Lester, S. E., and McLeod, K. L. (2010c). Placing marine protected areas onto the ecosystem-based management seascape. *Proceedings of the National Academy of Sciences* 107, 18312–18317. doi: 10.1073/pnas.0908503107

Halpern, B. S., Walbridge, S., Selkoe, K. A., Kappel, C. V, Micheli, F., d'Agrosa, C., et al. (2008). A global map of human impact on marine ecosystems. *Science (1979)* 319, 948–952. doi: 10.1126/science.1149345

Hamed, K. H., and Rao, A. R. (1998). A modified Mann-Kendall trend test for autocorrelated data. *J Hydrol (Amst)* 204, 182–196. doi: 10.1016/S0022-1694(97)00125-X

Hamel, M. A., and Andréfouët, S. (2010). Using very high resolution remote sensing for the management of coral reef fisheries: Review and perspectives. *Mar Pollut Bull* 60, 1397–1405. doi: 10.1016/J.MARPOLBUL.2010.07.002

Härmä, P., Vepsäläinen, J., Hannonen, T., Pyhälahti, T., Kämäri, J., Kallio, K., et al. (2001a). Detection of water quality using simulated satellite data and semi-empirical algorithms in Finland. *Science of the Total Environment* 268, 107–121. doi: 10.1016/S0048-9697(00)00688-4

Härmä, P., Vepsäläinen, J., Hannonen, T., Pyhälahti, T., Kämäri, J., Kallio, K., et al. (2001b). Detection of water quality using simulated satellite data and semi-empirical algorithms in Finland. *Science of the Total Environment* 268, 107–121. doi: 10.1016/S0048-9697(00)00688-4

Harris, R., and Baumann, I. (2015). Open data policies and satellite Earth observation. *Space Policy* 32, 44–53. doi: 10.1016/J.SPACEPOL.2015.01.001

Henson, S. A., Cael, B. B., Allen, S. R., and Dutkiewicz, S. (2021). Future phytoplankton diversity in a changing climate. *Nat Commun* 12, 5372. doi: 10.1038/s41467-021-25699-w

Ho, J. C., Stumpf, R. P., Bridgeman, T. B., and Michalak, A. M. (2017). Using Landsat to extend the historical record of lacustrine phytoplankton blooms: A Lake Erie case study. *Remote Sens Environ* 191, 273–285. doi: 10.1016/j.rse.2016.12.013

H.-O. Pörtner, D.C. Roberts, Masson-Delmotte, V., Zhai, P., Tignor, M., Poloczanska, E., et al. (2022). IPCC, 2019: IPCC Special Report on the Ocean and Cryosphere in a Changing Climate. *The Ocean and Cryosphere in a Changing Climate*.

Holgerson, M. A., and Raymond, P. A. (2016). Large contribution to inland water CO2 and CH4 emissions from very small ponds. *Nat Geosci* 9, 222–226. doi: 10.1038/ngeo2654

Hood, R. R., Laws, E. A., Armstrong, R. A., Bates, N. R., Brown, C. W., Carlson, C. A., et al. (2006). Pelagic functional group modeling: Progress, challenges and prospects. *Deep Sea Research Part II: Topical Studies in Oceanography* 53, 459–512. doi: 10.1016/j.dsr2.2006.01.025

Hu, C. (2009). A novel ocean color index to detect floating algae in the global oceans. *Remote Sens Environ* 113, 2118–2129. doi: 10.1016/j.rse.2009.05.012

Hu, C., Lee, Z., and Franz, B. (2012a). Chlorophyll aalgorithms for oligotrophic oceans: A novel approach based on three-band reflectance difference. *J Geophys Res Oceans* 117, 1011. doi: 10.1029/2011JC007395

Hu, C., Lee, Z., and Franz, B. (2012b). Chlorophyll aalgorithms for oligotrophic oceans: A novel approach based on three-band reflectance difference. *J Geophys Res Oceans* 117. doi: 10.1029/2011JC007395

Hunter-Cevera, K. R., Neubert, M. G., Olson, R. J., Solow, A. R., Shalapyonok, A., and Sosik, H. M. (2016). Physiological and ecological drivers of early spring blooms of a coastal phytoplankter. *Science (1979)* 354, 326–329. doi: 10.1126/science.aaf8536

Ilmavirta, V. (1982). Dynamics of phytoplankton in Finnish lakes., in *Lakes and Water Management: Proceedings of the 30 Years Jubilee Symposium of the Finnish Limnological Society, held in Helsinki, Finland, 22–23 September 1980,* (Springer), 11–20. doi: 10.1007/BF00005782

IOCCG (2014). Phytoplankton Functional Types from Space. Dartmouth. Available at: https://ioccg.org/wp-content/uploads/2015/10/IOCCG-Report-15.pdf

IOCCG (2018a). Earth Observations in Support of Global Water Quality Monitoring. Dartmouth. Available at: https://research.utwente.nl/en/publications/earth-observations-in-support-of-global-water-quality-monitoring (Accessed September 6, 2020).

IOCCG (2018b). Earth Observations in Support of Global Water Quality Monitoring. IOCCG Report Series, No. 17, International Ocean Colour Coordinating Group, Dartmouth, Canada. *Reports and Monographs of the International OceanColour Coordinating Group*.

Irrgang, C., Saynisch, J., and Thomas, M. (2019). Estimating global ocean heat content from tidal magnetic satellite observations. *Sci Rep* 9, 7893.

Isenstein, E. M., Trescott, A., and Park, M. (2014a). Multispectral remote sensing of harmful algal blooms in Lake Champlain, USA. *Water environment research* 86, 2271–2278. doi: 10.2175/106143014X13975035526149

Isenstein, E. M., Trescott, A., and Park, M.-H. (2014b). Multispectral Remote Sensing of Harmful Algal Blooms in Lake Champlain, USA. *Water Environment Research* 86, 2271–2278. doi: 10.2175/106143014X13975035526149

Jayne, S. R., Wahr, J. M., and Bryan, F. O. (2003). Observing ocean heat content using satellite gravity and altimetry. *J Geophys Res Oceans* 108.

Ji, R., Jin, M., and Varpe, Ø. (2013). Sea ice phenology and timing of primary production pulses in the Arctic Ocean. *Glob Chang Biol* 19, 734–741. doi: 10.1111/gcb.12074

Joshi, I. D., and D’Sa, E. J. (2018). An estuarine-tuned quasi-analytical algorithm (QAA-V): Assessment and application to satellite estimates of SPM in Galveston Bay following Hurricane Harvey. *Biogeosciences* 15, 4065–4086. doi: 10.5194/BG-15-4065-2018

Kahru, M., Brotas, V., Manzano-Sarabia, M., and Mitchell, B. G. (2011). Are phytoplankton blooms occurring earlier in the Arctic? *Glob Chang Biol* 17, 1733–1739. doi: 10.1111/j.1365-2486.2010.02312.x

Kallio, K. (2012a). *Monographs of the Boreal Environment Research*.

Kallio, K. (2012b). Water quality estimation by optical remote sensing in boreal lakes. Helsinki: University of Helsinki. Available at: https://helda.helsinki.fi/server/api/core/bitstreams/94d4a3ca-cce0-45ab-ae81-4cf7db8b6a9c/content

Kallio, K., Attila, J., Härmä, P., Koponen, S., Pulliainen, J., Hyytiäinen, U.-M., et al. (2008). Landsat ETM+ images in the estimation of seasonal lake water quality in boreal river basins. *Environ Manage* 42, 511–522. doi: 10.1007/s00267-008-9146-y

Kallio, K., Pulliainen, J., and Ylöstalo, P. (2005a). MERIS, MODIS and ETM+ channel configurations in the estimation of lake water quality from subsurface reflectance using semi-analytical and empirical algorithms. *Geophysica* 41, 31–55.

Kallio, K., Pulliainen, J., and Ylöstalo, P. (2005b). MERIS, MODIS and ETM+ channel configurations in the estimation of lake water quality from subsurface reflectance using semi-analytical and empirical algorithms. *Geophysica* 41, 31–55. Available at: https://www.geophysica.fi/pdf/geophysica_2005_41_1-2_031_kallio.pdf

Kirk, J. T. O. (1983). *Light and Photosynthesis in Aquatic Ecosystems*. Cambridge: Cambridge University Press.

Kloiber, S. M., Brezonik, P. L., Olmanson, L. G., and Bauer, M. E. (2002). A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sens Environ* 82, 38–47. doi: 10.1016/S0034-4257(02)00022-6

Koponen, S., Pulliainen, J., Servomaa, H., Zhang, Y., Hallikainen, M., Kallio, K., et al. (2001). Analysis on the feasibility of multi-source remote sensing observations for chl-a monitoring in Finnish lakes. *Science of the total environment* 268, 95–106. doi: 10.1016/S0048-9697(00)00689-6

Kraemer, B. M., Chandra, S., Dell, A. I., Dix, M., Kuusisto, E., Livingstone, D. M., et al. (2017). Global patterns in lake ecosystem responses to warming based on the temperature dependence of metabolism. *Glob Chang Biol* 23, 1881–1890. doi: 10.1111/gcb.13459

Kratzer, S., Harvey, E. T., and Philipson, P. (2014). The use of ocean color remote sensing in integrated coastal zone management—A case study from Himmerfjärden, Sweden. *Mar Policy* 43, 29–39. doi: 10.1016/j.marpol.2013.03.023

Lam, A. K.-Y., Prepas, E. E., Spink, D., and Hrudey, S. E. (1995). Chemical control of hepatotoxic phytoplankton blooms: implications for human health. *Water Res* 29, 1845–1854. doi: 10.1016/0043-1354(94)00348-B

Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning, A. C., et al. (2018a). Global Carbon Budget 2017. *Earth Syst Sci Data* 10, 405–448. doi: 10.5194/essd-10-405-2018

Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning, A. C., et al. (2018b). Global carbon budget 2017. *Earth Syst Sci Data* 10, 405–448. doi: 10.5194/essd-10-405-2018

Lenton, T. M., Rockström, J., Gaffney, O., Rahmstorf, S., Richardson, K., Steffen, W., et al. (2019). Climate tipping points—too risky to bet against. *Nature* 575, 592–595. doi: 10.1038/d41586-019-03595-0

Lisboa, F., Brotas, V., and Santos, F. D. (2024a). Earth Observation—An Essential Tool towards Effective Aquatic Ecosystems' Management under a Climate in Change. *Remote Sens (Basel)* 16, 2597. doi: 10.3390/rs16142597

Lisboa, F., Brotas, V., and Santos, F. D. (2024b). Earth Observation—An Essential Tool towards Effective Aquatic Ecosystems' Management under a Climate in Change. *Remote Sens (Basel)* 16, 2597. doi: 10.3390/rs16142597

Lisboa, F., Brotas, V., Santos, F. D., Kuikka, S., Kaikkonen, L., and Maeda, E. E. (2020a). Spatial variability and detection levels for chlorophyll-a estimates in high latitude lakes using landsat imagery. *Remote Sens (Basel)* 12, 2898. doi: 10.3390/rs12182898

Lisboa, F., Brotas, V., Santos, F. D., Kuikka, S., Kaikkonen, L., and Maeda, E. E. (2020b). Spatial Variability and Detection Levels for Chlorophyll-a Estimates in High Latitude Lakes Using Landsat Imagery. *Remote Sens (Basel)* 12, 2898. doi: 10.3390/rs12182898

Liu, C.-C., Shieh, C.-L., Lin, J.-C., and Wu, A.-M. (2011). Classification of non-vegetated areas using Formosat-2 high spatiotemporal imagery: the case of Tseng-Wen Reservoir catchment area (Taiwan). *Int J Remote Sens* 32, 8519–8540. doi: 10.1080/01431161.2010.542200

Longhurst, A. (1995). An estimate of global primary production in the ocean from satellite radiometer data. *J Plankton Res*.

Longhurst, A., Sathyendranath, S., Platt, T., and Caverhill, C. (1995). An estimate of global primary production in the ocean from satellite radiometer data. *J Plankton Res* 17, 1245–1271. doi: 10.1093/plankt/17.6.1245

Lovelock, J. E. (2006). *The Revenge of Gaia: Earth's Climate in Crisis and the Fate of Humanity*. London: Allen Lane.

Maeda, E. E., Lisboa, F., Kaikkonen, L., Kallio, K., Koponen, S., Brotas, V., et al. (2018). Temporal patterns of phytoplankton phenology across high latitude lakes unveiled by long-term time series of satellite data.

Maeda, E. E., Lisboa, F., Kaikkonen, L., Kallio, K., Koponen, S., Brotas, V., et al. (2019a). Temporal patterns of phytoplankton phenology across high latitude lakes unveiled by long-term time series of satellite data. *Remote Sens Environ* 221, 609–620. doi: 10.1016/j.rse.2018.12.006

Maeda, E. E., Lisboa, F., Kaikkonen, L., Kallio, K., Koponen, S., Brotas, V., et al. (2019b). Temporal patterns of phytoplankton phenology across high latitude lakes unveiled by long-term time series of satellite data. *Remote Sens Environ* 221, 609–620. doi: 10.1016/j.rse.2018.12.006

Maeda, E. E., Lisboa, F., Kaikkonen, L., Kallio, K., Koponen, S., Brotas, V., et al. (2019c). Temporal patterns of phytoplankton phenology across high latitude lakes unveiled by long-term time series of satellite data. *Remote Sens Environ* 221, 609–620. doi: 10.1016/j.rse.2018.12.006

Malve, O., Hjerppe, T., Tattari, S., Väisänen, S., Huttunen, I., Kotamäki, N., et al. (2016). Participatory operations model for cost-efficient monitoring and modeling of river basins—A systematic approach. *Science of the total environment* 540, 79–89. doi: 10.1016/j.scitotenv.2015.06.105

Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica* 13, 245–259. doi: 10.2307/1907187

Mansaray, A. S., Dzialowski, A. R., Martin, M. E., Wagner, K. L., Gholizadeh, H., and Stoodley, S. H. (2021a). Comparing PlanetScope to Landsat-8 and Sentinel-2 for Sensing Water Quality in Reservoirs in Agricultural Watersheds. *Remote Sensing 2021, Vol. 13, Page 1847* 13, 1847. doi: 10.3390/RS13091847

Mansaray, A. S., Dzialowski, A. R., Martin, M. E., Wagner, K. L., Gholizadeh, H., and Stoodley, S. H. (2021b). Comparing PlanetScope to Landsat-8 and Sentinel-2 for sensing water quality in reservoirs in agricultural watersheds. *Remote Sens (Basel)* 13, 1847. doi: 10.3390/RS13091847

Margulis, L., and Sagan, D. (2023). *Microcosmos: Four Billion Years of Evolution from Our Microbial Ancestors*. University of California Press. doi: 10.1525/9780520340510

Marine Protection Atlas (n.d.). Marine Protection Atlas. *https://mpatlas.org/*. Available at: https://mpatlas.org/ (Accessed May 2, 2025).

Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., et al. (2006). A Landsat surface reflectance dataset for North America, 1990-2000. *IEEE Geoscience and Remote sensing letters* 3, 68–72. doi: 10.1109/LGRS.2005.857030

Masek, J. G., Vermote, E. F., Saleous, N., Wolfe, R., Hall, F. G., Huemmrich, F., et al. (2013). LEDAPS calibration, reflectance, atmospheric correction preprocessing code, version 2. *Model product*. doi: 10.1109/LGRS.2005.857030

Maturi, E. M., Shay, L. N., Donahue, D. R., and Byrne, D. A. (2024). NOAA’s operational satellite ocean heat content products. *Journal of operational oceanography* 17, 93–102.

Mayer, K. J., Wang, X., Santander, M. V, Mitts, B. A., Sauer, J. S., Sultana, C. M., et al. (2020). Secondary marine aerosol plays a dominant role over primary sea spray aerosol in cloud formation. *ACS Cent Sci* 6, 2259–2266. doi: 10.1021/acscentsci.0c00793

McLeod, E., Chmura, G. L., Bouillon, S., Salm, R., Björk, M., Duarte, C. M., et al. (2011). A blueprint for blue carbon: Toward an improved understanding of the role of vegetated coastal habitats in sequestering CO2. *Front Ecol Environ* 9, 552–560. doi: 10.1890/110004

Mcleod, E., Chmura, G. L., Bouillon, S., Salm, R., Björk, M., Duarte, C. M., et al. (2011). A blueprint for blue carbon: toward an improved understanding of the role of vegetated coastal habitats in sequestering CO2. *Front Ecol Environ* 9, 552–560. doi: 10.1890/110004

Mikkonen, S., Laine, M., Mäkelä, H. M., Gregow, H., Tuomenvirta, H., Lahtinen, M., et al. (2015). Trends in the average temperature in Finland, 1847–2013. *Stochastic Environmental Research and Risk Assessment* 29, 1521–1529. doi: 10.1007/s00477-014-0992-2

Mishra, S., and Mishra, D. R. (2012a). Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. *Remote Sens Environ* 117, 394–406. doi: 10.1016/j.rse.2011.10.016

Mishra, S., and Mishra, D. R. (2012b). Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. *Remote Sens Environ* 117, 394–406. doi: 10.1016/j.rse.2011.10.016

Mitrovic, S. M., Hardwick, L., and Dorani, F. (2011a). Use of flow management to mitigate cyanobacterial blooms in the Lower Darling River, Australia. *J Plankton Res* 33, 229–241. doi: 10.1093/plankt/fbq094

Mitrovic, S. M., Hardwick, L., and Dorani, F. (2011b). Use of flow management to mitigate cyanobacterial blooms in the Lower Darling River, Australia. *J Plankton Res* 33, 229–241. doi: 10.1093/plankt/fbq094

Mobley, C. D. (1989). A numerical model for the computation of radiance distributions in natural waters with wind-roughened surfaces. *Limnol Oceanogr* 34, 1473–1483. doi: 10.4319/LO.1989.34.8.1473

Mobley, C. D. (1999). Estimation of the remote-sensing reflectance from above-surface measurements. *Applied Optics, Vol. 38, Issue 36, pp. 7442-7455* 38, 7442–7455. doi: 10.1364/AO.38.007442

Mobley, C. D., Bissett, P., Walsh, J. J., Dieterle, D. A., Carder, K. L., and Bissett, W. P. (2011). Fast light calculations for ocean ecosystem and inverse models. *Optics Express, Vol. 19, Issue 20, pp. 18927-18944* 19, 18927–18944. doi: 10.1364/OE.19.018927

Moore, J. K., Doney, S. C., Glover, D. M., and Fung, I. Y. (2001). Iron cycling and nutrient-limitation patterns in surface waters of the World Ocean. *Deep Sea Research Part II: Topical Studies in Oceanography* 49, 463–507.

Morel, A., and Prieur, L. (1977). Analysis of variations in ocean color. *Limnol Oceanogr* 22, 709–722. doi: 10.4319/lo.1977.22.4.0709

Moss, B., Kosten, S., Meerhoff, M., Battarbee, R. W., Jeppesen, E., Mazzeo, N., et al. (2011). Allied attack: climate change and eutrophication. *Inland waters* 1, 101–105. doi: 10.5268/IW-1.2.359

Murakami, H., and Dupouy, C. (2013). Atmospheric correction and inherent optical property estimation in the southwest New Caledonia lagoon using AVNIR-2 high-resolution data. *Appl Opt* 52, 182–198. doi: 10.1364/AO.52.000182

Nair, A., Sathyendranath, S., Platt, T., Morales, J., Stuart, V., Forget, M.-H., et al. (2008). Remote sensing of phytoplankton functional types. *Remote Sens Environ* 112, 3366–3375. doi: 10.1016/j.rse.2008.01.021

Neath, A. A., and Cavanaugh, J. E. (2012). The Bayesian information criterion: background, derivation, and applications. *Wiley Interdiscip Rev Comput Stat* 4, 199–203. doi: 10.1002/wics.199

Notaro, M., Holman, K., Zarrin, A., Fluck, E., Vavrus, S., and Bennington, V. (2013). Influence of the Laurentian Great Lakes on regional climate. *J Clim* 26, 789–804. doi: 10.1175/JCLI-D-12-00140.1

Olejarz, J., Iwasa, Y., Knoll, A. H., and Nowak, M. A. (2021). The Great Oxygenation Event as a consequence of ecological dynamics modulated by planetary change. *Nat Commun* 12, 3985. doi: 10.1038/s41467-021-23286-7

Oliveira, M. C., and Siqueira, L. (2022a). Digitalization between environmental activism and counter-activism: The case of satellite data on deforestation in the Brazilian Amazon. *Earth System Governance* 12, 100135. doi: 10.1016/J.ESG.2022.100135

Oliveira, M. C., and Siqueira, L. (2022b). Digitalization between environmental activism and counter-activism: The case of satellite data on deforestation in the Brazilian Amazon. *Earth system governance* 12, 100135. doi: 10.1016/J.ESG.2022.100135

Oliver, S. K., Collins, S. M., Soranno, P. A., Wagner, T., Stanley, E. H., Jones, J. R., et al. (2017a). Unexpected stasis in a changing world: Lake nutrient and chlorophyll trends since 1990. *Glob Chang Biol* 23, 5455–5467. doi: 10.1111/gcb.13810

Oliver, S. K., Collins, S. M., Soranno, P. A., Wagner, T., Stanley, E. H., Jones, J. R., et al. (2017b). Unexpected stasis in a changing world: Lake nutrient and chlorophyll trends since 1990. *Glob Chang Biol* 23, 5455–5467. doi: 10.1111/gcb.13810

Onoda, M., and Young, O. R. (2017). *Satellite earth observations and their impact on society and policy*. Springer Nature. doi: 10.1007/978-981-10-3713-9

Osman, M. B., Coats, S., Das, S. B., McConnell, J. R., and Chellman, N. (2021). North Atlantic jet stream projections in the context of the past 1,250 years. *Proceedings of the National Academy of Sciences* 118, e2104105118. doi: 10.1073/pnas.2104105118

Östlund, C., Flink, P., Strömbeck, N., Pierson, D., and Lindell, T. (2001a). Mapping of the water quality of Lake Erken, Sweden, from Imaging Spectrometry and Landsat Thematic Mapper. *Science of the Total Environment* 268, 139–154. doi: 10.1016/S0048-9697(00)00683-5

Östlund, C., Flink, P., Strömbeck, N., Pierson, D., and Lindell, T. (2001b). Mapping of the water quality of Lake Erken, Sweden, from imaging spectrometry and Landsat Thematic Mapper. *Science of the Total Environment* 268, 139–154. doi: 10.1016/S0048-9697(00)00683-5

Pace, M. L., and Prairie, Y. T. (2005a). Respiration in lakes. *Respiration in Aquatic Ecosystems*. doi: 10.1093/ACPROF:OSO/9780198527084.003.0007

Pace, M. L., and Prairie, Y. T. (2005b). Respiration in lakes. *Respiration in aquatic ecosystems* 1, 103–122. doi: 10.1093/ACPROF:OSO/9780198527084.003.0007

Padedda, B. M., Sechi, N., Lai, G. G., Mariani, M. A., Pulina, S., Sarria, M., et al. (2017). Consequences of eutrophication in the management of water resources in Mediterranean reservoirs: A case study of Lake Cedrino (Sardinia, Italy). *Glob Ecol Conserv* 12, 21–35. doi: 10.1016/j.gecco.2017.08.004

Pahlevan, N., Chittimalli, S. K., Balasubramanian, S. V, and Vellucci, V. (2019). Sentinel-2/Landsat-8 product consistency and implications for monitoring aquatic systems. *Remote Sens Environ* 220, 19–29. doi: 10.1016/j.rse.2018.10.027

Palmer, S. C. J., Odermatt, D., Hunter, P. D., Brockmann, C., Présing, M., Balzter, H., et al. (2015). Satellite remote sensing of phytoplankton phenology in Lake Balaton using 10years of MERIS observations. *Remote Sens Environ* 158, 441–452. doi: 10.1016/j.rse.2014.11.021

Parsons, T. R., and Lalli, C. M. (2002). Jellyfish population explosions: revisiting a hypothesis of possible causes. *La mer* 40, 111–121.

Pekel, J.-F., Cottam, A., Gorelick, N., and Belward, A. S. (2016a). High-resolution mapping of global surface water and its long-term changes. *Nature* 540, 418–422. doi: 10.1038/nature20584

Pekel, J.-F., Cottam, A., Gorelick, N., and Belward, A. S. (2016b). High-resolution mapping of global surface water and its long-term changes. *Nature* 540, 418–422. doi: 10.1038/nature20584

Peltomaa, E., Ojala, A., Holopainen, A.-L., and Salonen, K. (2013). Changes in phytoplankton in a boreal lake during a 14-year period. *Boreal environment research* 18, 387–400. doi: 10138/165157

Pham, T. D., Ha, N. T., Saintilan, N., Skidmore, A., Phan, D. C., Le, N. N., et al. (2023a). Advances in Earth observation and machine learning for quantifying blue carbon. *Earth Sci Rev* 243, 104501. doi: 10.1016/j.earscirev.2023.104501

Pham, T. D., Ha, N. T., Saintilan, N., Skidmore, A., Phan, D. C., Le, N. N., et al. (2023b). Advances in Earth observation and machine learning for quantifying blue carbon. *Earth Sci Rev* 243, 104501. doi: 10.1016/j.earscirev.2023.104501

Pi, X., Luo, Q., Feng, L., Xu, Y., Tang, J., Liang, X., et al. (2022a). Mapping global lake dynamics reveals the emerging roles of small lakes. *Nat Commun* 13, 5777. doi: 10.1038/s41467-022-33239-3

Pi, X., Luo, Q., Feng, L., Xu, Y., Tang, J., Liang, X., et al. (2022b). Mapping global lake dynamics reveals the emerging roles of small lakes. *Nat Commun* 13, 5777.

Platt, T. (1978). The structure of pelagic marine ecosystems. *Rpp. P.-v. Cons. int. Explor. Mer.* 173, 60–65.

Platt, T., and Denman, K. (1977). Organisation in the pelagic ecosystem. *Helgoländer Wissenschaftliche Meeresuntersuchungen* 30, 575–581. doi: 10.1007/BF02207862

Platt, T., and Jassby, A. D. (1976). The relationship between photosynthesis and light for natural assemblages of coastal marine phytoplankton 1. *J Phycol* 12, 421–430. doi: 10.1111/j.1529-8817.1976.tb02866.x

Pörtner, H.-O., Roberts, D. C., Masson-Delmotte, V., Zhai, P., Tignor, M., Poloczanska, E., et al. (2019). The ocean and cryosphere in a changing climate. *IPCC special report on the ocean and cryosphere in a changing climate* 1155, 10–1017. doi: 10.1017/9781009157964.

Prasetya, J. D., and Purwanti, F. (2017). Diversity based sustainable management for seagrass ecosystem: Assessing distribution and Diversity of Seagrass in marine protected area. *Adv Sci Lett* 23, 2413–2415. doi: 10.1166/asl.2017.8665

Preisendorfer, R. W. (1961). Application of radiative transfer theory to light measurements in the sea. Washington, D.C.

Prizibisczki, C. (2020). Brasil precisa comprar imagens privadas de satélite? Entenda a polêmica. *https://oeco.org.br/reportagens/brasil-precisa-comprar-imagens-privadas-de-satelite-entenda-a-polemica/*.

Pulliainen, J., Kallio, K., Eloheimo, K., Koponen, S., Servomaa, H., Hannonen, T., et al. (2001a). A semi-operative approach to lake water quality retrieval from remote sensing data. *Science of the Total Environment* 268, 79–93. doi: 10.1016/S0048-9697(00)00687-2

Pulliainen, J., Kallio, K., Eloheimo, K., Koponen, S., Servomaa, H., Hannonen, T., et al. (2001b). A semi-operative approach to lake water quality retrieval from remote sensing data. *Science of the Total Environment* 268, 79–93. doi: 10.1016/S0048-9697(00)00687-2

Rabalais, N. N., Turner, R. E., Díaz, R. J., and Justić, D. (2009). Global change and eutrophication of coastal waters. *ICES Journal of Marine Science* 66, 1528–1537. doi: 10.1093/icesjms/fsp047

Racault, M.-F., Le Quéré, C., Buitenhuis, E., Sathyendranath, S., and Platt, T. (2012). Phytoplankton phenology in the global ocean. *Ecol Indic* 14, 152–163. doi: 10.1016/j.ecolind.2011.07.010

Räike, A., Pietiläinen, O.-P., Rekolainen, S., Kauppila, P., Pitkänen, H., Niemi, J., et al. (2003). Trends of phosphorus, nitrogen and chlorophyll a concentrations in Finnish rivers and lakes in 1975–2000. *Science of the Total Environment* 310, 47–59. doi: 10.1016/S0048-9697(02)00622-8

Raitala, J., and Lampinen, J. (1985). A landsat study of the aquatic vegetation of the lake luodonjärvi reservoir, Western Finland. *Aquat Bot* 21, 325–346. doi: 10.1016/0304-3770(85)90075-0

Raven, J. A. (1998). The twelfth Tansley Lecture. Small is beautiful: the picophytoplankton. *Funct Ecol* 12, 503–513. doi: 10.1046/j.1365-2435.1998.00233.x

Reichle, D. E. (2023). *The global carbon cycle and climate change: Scaling ecological energetics from organism to the biosphere*. Elsevier. doi: 10.1016/C2022-0-00267-1

Richter, R., Bachmann, M., Dorigo, W., and Muller, A. (2006). Influence of the adjacency effect on ground reflectance measurements. *IEEE Geoscience and Remote Sensing Letters* 3, 565–569. doi: 10.1109/LGRS.2006.882146

Robinson, I. S. (2004). *Measuring the Oceans from Space: The Principles and Methods of Satellite Oceanography*. Springer Praxis Books.

Rodell, M., Houser, P. R., Jambor, U. E. A., Gottschalck, J., Mitchell, K., Meng, C.-J., et al. (2004). The global land data assimilation system. *Bull Am Meteorol Soc* 85, 381–394. doi: 10.1175/BAMS-85-3-381

Rolland, A., Bertrand, F., Maumy, M., and Jacquet, S. (2009). Assessing phytoplankton structure and spatio-temporal dynamics in a freshwater ecosystem using a powerful multiway statistical analysis. *Water Res* 43, 3155–3168. doi: 10.1016/j.watres.2009.03.049

Rouse, W. R., Oswald, C. M., Binyamin, J., Blanken, P. D., Schertzer, W. M., and Spence, C. (2003a). Interannual and seasonal variability of the surface energy balance and temperature of central Great Slave Lake. *J Hydrometeorol* 4. doi: 10.1175/1525-7541(2003)004

Rouse, W. R., Oswald, C. M., Binyamin, J., Blanken, P. D., Schertzer, W. M., and Spence, C. (2003b). Interannual and Seasonal Variability of the Surface Energy Balance and Temperature of Central Great Slave Lake. *J Hydrometeorol* 4, 720–730. doi: 10.1175/1525-7541(2003)004<0720:IASVOT>2.0.CO;2

Rowlands, G., Brown, J., Soule, B., Boluda, P. T., and Rogers, A. D. (2019a). Satellite surveillance of fishing vessel activity in the Ascension Island Exclusive Economic Zone and Marine Protected Area. *Mar Policy* 101. doi: 10.1016/j.marpol.2018.11.006

Rowlands, G., Brown, J., Soule, B., Boluda, P. T., and Rogers, A. D. (2019b). Satellite surveillance of fishing vessel activity in the ascension island exclusive economic zone and marine protected area. *Mar Policy* 101, 39–50. doi: 10.1016/j.marpol.2018.11.006

Rühland, K., Paterson, A. M., and Smol, J. P. (2008a). Hemispheric-scale patterns of climate-related shifts in planktonic diatoms from North American and European lakes. *Glob Chang Biol* 14, 2740–2754. doi: 10.1111/j.1365-2486.2008.01670.x

Rühland, K., Paterson, A. M., and Smol, J. P. (2008b). Hemispheric-scale patterns of climate-related shifts in planktonic diatoms from North American and European lakes. *Glob Chang Biol* 14, 2740–2754. doi: 10.1111/j.1365-2486.2008.01670.x

Sakuno, Y., Miño, E. R., Nakai, S., Mutsuda, H., Okuda, T., Nishijima, W., et al. (2014). Chlorophyll and suspended sediment mapping to the Caribbean Sea from rivers in the capital city of the Dominican Republic using ALOS AVNIR-2 data. *Environ Monit Assess* 186, 4181–4193. doi: 10.1007/S10661-014-3689-6

Sasaki, T., Massaki, N., and Kubo, T. (2005). Wolbachia variant that induces two distinct reproductive phenotypes in different hosts. *Heredity (Edinb)* 95, 389–393. doi: 10.1038/sj.hdy.6800737

Sass, G. Z., Creed, I. F., Bayley, S. E., and Devito, K. J. (2007a). Understanding variation in trophic status of lakes on the Boreal Plain: A 20 year retrospective using Landsat TM imagery. *Remote Sens Environ* 109, 127–141. doi: 10.1016/j.rse.2006.12.010

Sass, G. Z., Creed, I. F., Bayley, S. E., and Devito, K. J. (2007b). Understanding variation in trophic status of lakes on the Boreal Plain: A 20 year retrospective using Landsat TM imagery. *Remote Sens Environ* 109, 127–141. doi: 10.1016/j.rse.2006.12.010

Sayers, M. J., Grimm, A. G., Shuchman, R. A., Bosse, K. R., Fahnenstiel, G. L., Ruberg, S. A., et al. (2019). Satellite monitoring of harmful algal blooms in the Western Basin of Lake Erie: A 20-year time-series. *J Great Lakes Res* 45, 508–521. doi: 10.1016/J.JGLR.2019.01.005

Schellnhuber, H. J. (1999a). ‘Earth system’ analysis and the second Copernican revolution. *Nature 1999 402:6761* 402, C19–C23. doi: 10.1038/35011515

Schellnhuber, H. J. (1999b). ‘Earth system’analysis and the second Copernican revolution. *Nature* 402, C19–C23. doi: 10.1038/35011515

Schiermeier, Q. (2006). Climate change: A sea change. *Nature* 439. doi: 10.1038/439256A

Schlesinger, W. H. (2006). Global change ecology. *Trends Ecol Evol* 21, 348–351. doi: 10.1016/J.TREE.2006.03.004

Screen, J. A., and Simmonds, I. (2010a). The central role of diminishing sea ice in recent Arctic temperature amplification. *Nature* 464, 1334–1337. doi: 10.1038/nature09051

Screen, J. A., and Simmonds, I. (2010b). The central role of diminishing sea ice in recent Arctic temperature amplification. *Nature* 464, 1334–1337. doi: 10.1038/nature09051

Searles Jones, J. (2019a). To solve climate change, remember the ocean. *Nature*. doi: 10.1038/D41586-019-02832-W

Searles Jones, J. (2019b). To solve climate change, remember the ocean. doi: 10.1038/D41586-019-02832-W

Secchi, A. (1866). Relazione delle esperienze fatte a bordo della pontificia pirocorvetta Immacolata Concezione per determinare la trasparenza del mare. *Bullettino del Collegio Romano* 1, 1–20.

Sen, P. K. (1968a). Estimates of the Regression Coefficient Based on Kendall's Tau. *J Am Stat Assoc* 63, 1379–1389. doi: 10.1080/01621459.1968.10480934

Sen, P. K. (1968b). Estimates of the regression coefficient based on Kendall's tau. *J Am Stat Assoc* 63, 1379–1389. doi: 10.1080/01621459.1968.10480934

Seppälä, J., and Olli, K. (2008). Multivariate analysis of phytoplankton spectral in vivo fluorescence: estimation of phytoplankton biomass during a mesocosm study in the Baltic Sea. *Mar Ecol Prog Ser* 370, 69–85. doi: 10.3354/meps07647

Sessions, A. L., Doughty, D. M., Welander, P. V, Summons, R. E., and Newman, D. K. (2009). The continuing puzzle of the great oxidation event. *Current biology* 19, R567–R574. doi: 10.1016/j.cub.2009.05.054

Sieburth, J. M., Smetacek, V., and Lenz, J. (1978). Pelagic ecosystem structure: Heterotrophic compartments of the plankton and their relationship to plankton size fractions 1. *Limnol Oceanogr* 23, 1256–1263. doi: 10.4319/lo.1978.23.6.1256

Siegel, D. A., Maritorena, S., and Peterson, A. R. (2002). Optimization of a semianalytical ocean color model for global-scale applications. *Applied Optics, Vol. 41, Issue 15, pp. 2705-2714* 41, 2705–2714. doi: 10.1364/AO.41.002705

Smale, D. A., and Wernberg, T. (2009). Satellite-derived SST data as a proxy for water temperature in nearshore benthic ecology. *Mar Ecol Prog Ser* 387, 27–37.

Smith, R. C., Eppley, R. W., and Baker, K. S. (1982). Correlation of primary production as measured aboard ship in Southern California Coastal waters and as estimated from satellite chlorophyll images. *Mar Biol* 66, 281–288. doi: 10.1007/BF00397033

Smith, V. H., Joye, S. B., and Howarth, R. W. (2006). Eutrophication of freshwater and marine ecosystems. *Limnol Oceanogr* 51, 351–355. doi: 10.4319/lo.2006.51.1_part_2.0351

Soldatenko, S. A., and Yusupov, R. M. (2017). Sensitivity and feedback loops of a zero-dimensional climate model in the context of the weather and Earth's climate control. *Informatics and Automation* 52, 5–31. doi: 10.15622/SP.52.1

Sommer, U., and Lengfellner, K. (2008). Climate change and the timing, magnitude, and composition of the phytoplankton spring bloom. *Glob Chang Biol* 14, 1199–1208. doi: 10.1111/j.1365-2486.2008.01571.x

Stadelmann, T. H., Brezonik, P. L., and Kloiber, S. (2001). Seasonal patterns of chlorophyll a and Secchi disk transparency in lakes of East-Central Minnesota: Implications for design of ground-and satellite-based monitoring programs. *Lake Reserv Manag* 17, 299–314. doi: 10.1080/07438140109354137

Striebel, M., Behl, S., and Stibor, H. (2009). The coupling of biodiversity and productivity in phytoplankton communities: consequences for biomass stoichiometry. *Ecology* 90, 2025–2031. doi: 10.1890/08-1409.1

Tan, W., Liu, P., Liu, Y., Yang, S., and Feng, S. (2017a). A 30-Year Assessment of Phytoplankton Blooms in Erhai Lake Using Landsat Imagery: 1987 to 2016. *Remote Sens (Basel)* 9, 1265. doi: 10.3390/rs9121265

Tan, W., Liu, P., Liu, Y., Yang, S., and Feng, S. (2017b). A 30-year assessment of phytoplankton blooms in Erhai Lake using Landsat imagery: 1987 to 2016. *Remote Sens (Basel)* 9, 1265. doi: 10.3390/rs9121265

Thackeray, S. J., Jones, I. D., and Maberly, S. C. (2008a). Long-term change in the phenology of spring phytoplankton: species-specific responses to nutrient enrichment and climatic change. *Journal of Ecology* 96, 523–535. doi: 10.1111/j.1365-2745.2008.01355.x

Thackeray, S. J., Jones, I. D., and Maberly, S. C. (2008b). Long-term change in the phenology of spring phytoplankton: species-specific responses to nutrient enrichment and climatic change. *Journal of Ecology* 96, 523–535. doi: 10.1111/j.1365-2745.2008.01355.x

The European Parliament and the Council of the European Union (2008). Directive 2008/56/EC of the European Parliament and of the Council of 17 June 2008 establishing a framework for community action in the field of marine environmental policy (Marine Strategy Framework Directive). *Official Journal of the European Union* L 164, 19–40. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32008L0056 (Accessed June 17, 2008).

Tilstone, G. H., Angel-Benavides, I. M., Pradhan, Y., Shutler, J. D., Groom, S., and Sathyendranath, S. (2011). An assessment of chlorophyll-a algorithms available for SeaWiFS in coastal and open areas of the Bay of Bengal and Arabian Sea. *Remote Sens Environ* 115, 2277–2291. doi: 10.1016/J.RSE.2011.04.028

Tin, H. C., Uyen, N. T., Hieu, D. V, Ni, T. N. K., Tu, N. H. C., and Saizen, I. (2020). Decadal dynamics and challenges for seagrass beds management in Cu lao cham marine protected area, central Vietnam. *Environ Dev Sustain* 22, 7639–7660. doi: 10.1007/S10668-019-00540-Z

Toming, K., Kutser, T., Laas, A., Sepp, M., Paavel, B., and Nõges, T. (2016). First experiences in mapping lake water quality parameters with Sentinel-2 MSI imagery. *Remote Sens (Basel)* 8, 640. doi: 10.3390/rs8080640

Toonen, H. M., and Bush, S. R. (2020). The digital frontiers of fisheries governance: fish attraction devices, drones and satellites. *Journal of environmental policy & planning* 22, 125–137. doi: 10.1080/1523908X.2018.1461084

Tranvik, L. J., Downing, J. A., Cotner, J. B., Loiselle, S. A., Striegl, R. G., Ballatore, T. J., et al. (2009a). Lakes and reservoirs as regulators of carbon cycling and climate. *Limnol Oceanogr* 54, 2298–2314. doi: 10.4319/LO.2009.54.6_PART_2.2298

Tranvik, L. J., Downing, J. A., Cotner, J. B., Loiselle, S. A., Striegl, R. G., Ballatore, T. J., et al. (2009b). Lakes and reservoirs as regulators of carbon cycling and climate. *Limnol Oceanogr* 54, 2298–2314. doi: 10.4319/LO.2009.54.6_PART_2.2298

Turekian, K. K., and Holland, H. D. (2014). *Treatise on Geochemistry.*, Second. Elsevier. doi: 10.1016/C2009-1-28473-5

van Eck, N. J., and Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* 84, 523–538. doi: 10.1007/s11192-009-0146-3

Vanhellemont, Q., and Ruddick, K. (2015). Advantages of high quality SWIR bands for ocean colour processing: Examples from Landsat-8. *Remote Sens Environ* 161, 89–106. doi: 10.1016/J.RSE.2015.02.007

Veerman, J., Kumar, A., and Mishra, D. R. (2022a). Exceptional landscape-wide cyanobacteria bloom in Okavango Delta, Botswana in 2020 coincided with a mass elephant die-off event. *Harmful Algae* 111, 102145. doi: 10.1016/J.HAL.2021.102145

Veerman, J., Kumar, A., and Mishra, D. R. (2022b). Exceptional landscape-wide cyanobacteria bloom in Okavango Delta, Botswana in 2020 coincided with a mass elephant die-off event. *Harmful Algae* 111, 102145. doi: 10.1016/J.HAL.2021.102145

Vehmaa, A., and Salonen, K. (2009a). Development of phytoplankton in Lake Pääjärvi (Finland) during under-ice convective mixing period. *Aquat Ecol* 43, 693–705. doi: 10.1007/s10452-009-9273-4

Vehmaa, A., and Salonen, K. (2009b). Development of phytoplankton in Lake Pääjärvi (Finland) during under-ice convective mixing period. *Aquat Ecol* 43, 693–705. doi: 10.1007/s10452-009-9273-4

Veron, J. E. N. (2008). Mass extinctions and ocean acidification: biological constraints on geological dilemmas. *Coral Reefs* 27, 459–472. doi: 10.1007/s00338-008-0381-8

Verpoorter, C., Kutser, T., Seekell, D. A., and Tranvik, L. J. (2014a). A global inventory of lakes based on high-resolution satellite imagery. *Geophys Res Lett* 41, 6396–6402. doi: 10.1002/2014GL060641

Verpoorter, C., Kutser, T., Seekell, D. A., and Tranvik, L. J. (2014b). A global inventory of lakes based on high-resolution satellite imagery. *Geophys Res Lett* 41, 6396–6402. doi: 10.1002/2014GL060641

Vigouroux, G., Kari, E., Beltrán-Abaunza, J. M., Uotila, P., Yuan, D., and Destouni, G. (2021). Trend correlations for coastal eutrophication and its main local and whole-sea drivers–Application to the Baltic Sea. *Science of the Total Environment* 779, 146367. doi: 10.1016/J.SCITOTENV.2021.146367

Vincent, R. K., Qin, X., McKay, R. M. L., Miner, J., Czajkowski, K., Savino, J., et al. (2004a). Phycocyanin detection from LANDSAT TM data for mapping cyanobacterial blooms in Lake Erie. *Remote Sens Environ* 89, 381–392. doi: 10.1016/j.rse.2003.10.014

Vincent, R. K., Qin, X., McKay, R. M. L., Miner, J., Czajkowski, K., Savino, J., et al. (2004b). Phycocyanin detection from LANDSAT TM data for mapping cyanobacterial blooms in Lake Erie. *Remote Sens Environ* 89, 381–392. doi: 10.1016/j.rse.2003.10.014

Wan, W., Li, H., Xie, H., Hong, Y., Long, D., Zhao, L., et al. (2017). A comprehensive data set of lake surface water temperature over the Tibetan Plateau derived from MODIS LST products 2001–2015. *Sci Data* 4, 1–10. doi: 10.1038/sdata.2017.95

Wang, D., Ma, R., Xue, K., and Loiselle, S. A. (2019). The assessment of Landsat-8 OLI atmospheric correction algorithms for inland waters. *Remote Sens (Basel)* 11, 169. doi: 10.3390/rs11020169

Wang, M., Shi, W., Jiang, L., and Voss, K. (2016). NIR-and SWIR-based on-orbit vicarious calibrations for satellite ocean color sensors. *Opt Express* 24, 20437–20453. doi: 10.1364/OE.24.020437

Wang, W., Liang, S., and Meyers, T. (2008). Validating MODIS land surface temperature products using long-term nighttime ground measurements. *Remote Sens Environ* 112, 623–635. doi: 10.1016/j.rse.2007.05.024

Wang, Z. (2009). *In Sputnik's Shadow: The President's Science Advisory Committee and Cold War America*. Rutgers University Press.

Werdell, P. J., and Bailey, S. W. (2005). An improved *in situ* bio-optical data set for ocean color algorithm development and satellite data product validation. *Remote Sens Environ* 98, 122–140. doi: 10.1016/j.rse.2005.07.001

Werdell, P. J., Franz, B. A., Bailey, S. W., Feldman, G. C., Boss, E., Brando, V. E., et al. (2013). Generalized ocean color inversion model for retrieving marine inherent optical properties. *Applied Optics, Vol. 52, Issue 10, pp. 2019-2037* 52, 2019–2037. doi: 10.1364/AO.52.002019

Westberry, T. K., Silsbe, G. M., and Behrenfeld, M. J. (2023). Gross and net primary production in the global ocean: An ocean color remote sensing perspective. *Earth Sci Rev* 237, 104322.

Wetzel, R. G. (2001). "Structure And Productivity Of Aquatic Ecosystem," in *Limnology*, (Elsevier), 129–150. doi: 10.1016/B978-0-08-057439-4.50012-5

White, L. D. (1952). Final report, Project Hermes V-2 Missile Program. Available at: https://archive.org/details/finalreportproje00whit/page/56/mode/2up (Accessed April 18, 2022).

White, M. A., Thornton, P. E., and Running, S. W. (1997). A continental phenology model for monitoring vegetation responses to interannual climatic variability. *Global Biogeochem Cycles* 11, 217–234. doi: 10.1029/97GB00330

Williams, P., Thomas, D., and Reynolds, C. (2003). Phytoplankton Productivity: Carbon Assimilation in Marine and Freshwater Ecosystems. *Fish and Fisheries* 4, 194–195. doi: 10.1046/j.1467-2979.2003.t01-3-00114.x

Winder, M., and Schindler, D. E. (2004). Climatic effects on the phenology of lake processes. *Glob Chang Biol* 10, 1844–1856. doi: 10.1111/j.1365-2486.2004.00849.x

Winder, M., and Sommer, U. (2012a). Phytoplankton response to a changing climate. *Hydrobiologia* 698, 5–16. doi: 10.1007/S10750-012-1149-2/METRICS

Winder, M., and Sommer, U. (2012b). Phytoplankton response to a changing climate. *Hydrobiologia* 698, 5–16. doi: 10.1007/S10750-012-1149-2/METRICS

(WMO), W. M. O., (WMO), W. M. O., Programme, (UNEP) United Nations Environment, Science, (ICSU) International Council for, (UNESCO) United Nations Educational, S. and C. O., and Change, (UNFCCC) United Nations Framework Convention on Climate (2003). *The second report on the adequacy of* *the global observing systems for climate in support of the UNFCCC*. Geneva: WMO.

Woolway, R. I., Kraemer, B. M., Lenters, J. D., Merchant, C. J., O'Reilly, C. M., and Sharma, S. (2020). Global lake responses to climate change. *Nat Rev Earth Environ* 1, 388–403. doi: 10.1038/s43017-020-0067-5

Yamanouchi, T. (2011). Early 20th century warming in the Arctic: A review. *Polar Sci* 5, 53–71. doi: 10.1016/j.polar.2010.10.002

Zhang, Z., Chen, P., Zhang, S., Huang, H., Pan, Y., and Pan, D. (2025). A Review of Machine Learning Applications in Ocean Color Remote Sensing. *Remote Sensing 2025, Vol. 17, Page 1776* 17, 1776. doi: 10.3390/RS17101776

Zheng, H., Ma, Y., Huang, J., Yang, J., Su, D., Yang, F., et al. (2022). Deriving vertical profiles of chlorophyll-a concentration in the upper layer of seawaters using ICESat-2 photon-counting lidar. *Opt Express* 30, 33320–33336. doi: 10.1364/oe.463622

Zhu, Z., Wang, S., and Woodcock, C. E. (2015a). Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. *Remote Sens Environ* 159, 269–277. doi: 10.1016/j.rse.2014.12.014

Zhu, Z., Wang, S., and Woodcock, C. E. (2015b). Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. *Remote Sens Environ* 159, 269–277. doi: 10.1016/j.rse.2014.12.014