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Steps towards a status classification of Norwegian lakes using satellite data - method development and case studies

Norwegian Institute for Water Research

REPORT

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Summary

Sentinel 2 & 3 data for 2016 to 2020 were processed with C2RCC processor for six lakes in the ØKOSTOR monitoring program: Mjøsa, Selbusjøen, Gjende, Røssvatnet, Snåsavatnet and Femunden. In this report we have taken steps towards an operational remote sensing (RS) service for Norwegian lakes. Maps of multi-year chlorophyll-*a* concentrations (chl-*a*) were produced. Chl-*a* status classification based on RS was assessed and compared with the status based on in-situ sampling. The chl-*a* satellite data was variable over month, year and for an assessment period of 4-5 years It worked well for some lakes but overestimations of the chl-a retrieval can most likely be improved by the use of other algorithms or by finding a more correct conversions factor between chl-a concentration and chl-a absorption. The amount of data for each lake increases with satellite observations, on average 15 observations per year (Sentinel 2) and 19 (Sentinel 3), compared to 4-6/year or every 4th year with in-situ observations. RS can provide new knowledge of spatial and temporal dynamics and is thus a good complement to ordinary sampling for water quality classifications of Norwegian lakes, but it needs more in-depth work for possible adjustments and corrections.

Four keywords	Fire emneord
1. Lakes	1. Innsjøer
2. Remote sensing	2. Fjernmåling
3. Water quality	3. Vannkvalitet
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Steps towards a status classification of Norwegian lakes using satellite data –

Method development and case studies

Preface

This project was carried out by the Norwegian Institute for Water Research (NIVA) on behalf of the Norwegian Environment Agency in the period June 2020 to October 2021.

Several colleagues and local field assistants have been involved in the sampling campaigns, sample preparation and analysis for the six different lakes and the extra sampling in Mjøsa and the project was conducted in a joint effort with ØKOSTOR monitoring. In particular, we would like to thank Anna-Birgitta Ledang (formerly employed at NIVA) and Elizaveta Protsenko (NIVA) for downloading and processing all the remote sensing data used within this study;
Anna- Birgitta Ledang and Louise Valestrand (NIVA) for planning and execution of the optical in-situ sampling; Anna- Birgitta Ledang, Louise Valestrand, Sabine Marty (NIVA), Marit Norli (NIVA), Pierre Franqois Jaccard (NIVA), Asle Økelsrud (NIVA), Henriette Kildahl (NIVA) and Jan-Erik Thrane (NIVA) for collecting and processing various field data (data and lab analyses), and especially the work with collecting the match-up data set.

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Copenhagen, 3 October 2021
E. Thérèse Harvey
(project manager)

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Summary

This project is a continuation of the previous research and development project 'Performance and applications of satellite remote sensing data for water quality in Norwegian lakes', evaluation of MERIS, Sentinel-2 and Sentinel-3 products for the Norwegian Environmental Agency (Miljødirektoratet), conducted between 2017-2019. The final report had a focus on the theoretical and technical aspects of water quality assessment from remote sensing data as well as the state-of-the- art for the methods used. Future needs and steps for an operational service and a road map were also identified. The current study takes further steps towards the use of remote sensing data from Sentinel 2 and Sentinel 3 for operational monitoring of water quality in Norwegian lakes. In 2020, six lakes spread over Norway, that are included in the ØKOSTOR monitoring program, were investigated; Mjøsa, Selbusjøen, Gjende, Røssvatnet, Snåsavatnet and Femunden. Remote sensing (RS) data from the Sentinel 2A and 2B satellites as well as the Sentinel 3A and 3B satellites from the European Commission´s Copernicus satellite program was used. The RS data was downloaded and processed with the C2RCC atmospheric correction algorithm for each lake between 2016 or 2017 to 2020, during the growth season in May-September. Surface in-situ measurements of optical parameters (chlorophyll-*a* concentration (chl-*a)* and absorption, humic substances, turbidity, absorbance, attenuation and back-scattering) were collected from each lake by a joint effort from the monitoring team. In Mjøsa dedicated in-situ match-up data was collected by water samples and in-situ reflectance measurements were done at the same time as satellite overpasses. The time-series of both monitoring and RS data at monitoring stations show similar variability of chl-*a* and the seasonal patterns are clearly seen. The spatial time-series data from the satellite was used to calculate a spatial chl-*a* average for the full lake area and for the area corresponding to each monitoring station. The averages over several years showed that the lakes have consistent spatial patterns, and that the spatial variability can be large in some of the lakes. The RS results from Gjende were very patchy and the full area of the lake could not be processed. This was most likely due to strong adjacency effects and mountain shadows from the surrounding high mountains and high turbidity. The multi-year chl-*a* average for each lake was used to estimate the chl-*a* status classification *sensu* the Water Framework Directive (WFD) using the same thresholds as for the integrated 0-10 m depth in-situ samples from the monitoring stations. The results showed good agreements for Mjøsa and Selbusjøen, but the RS chl-*a* data was overestimated for Gjende, Røssvatnet, Snåsavatnet and Femunden. This can be due to several reasons, e.g. the difference between the RS estimate down to about half the Secchi depth compared to the integrated 0-10 m in-situ sample. Another explanation can be that the relationship used to estimate the chl-*a* concentration from the chl-*a* absorption differs from the actual relationships found in the lakes, as indicated by the preliminary results from this study. To find a robust relationship, more detailed studies would be required. However, the in-situ data set was relatively small for the lakes where the largest differences were observed, which makes it difficult to draw conclusions. For the lakes with more data e.g. Selbusjøen, an empirical relationship could be made and used for corrections of the RS data. Hence, the use of RS data makes it possible to follow both the temporal and spatial variability and can therefore contribute with new insights and knowledge for lakes that are sampled infrequently, or not at all, by providing data in between sampling occasions and years. By gathering the RS data, it is possible to follow changes in the variability and concentrations although the exact chl-*a* values may need to be improved. The amount of data available from Sentinel 2 and 3 is vast and for an operational system to be in place for all Norwegian lakes, many of the processing, quality assurance and the analytical steps need to be automated, but still with manually made quality checks on a regular basis. NIVA is a partner of EODataBee (i.e. European RS consortium for customizable service for water quality information derived from Earth Observation and other source), and have access to current developments, expertise and collaboration.

Sammendrag

Tittel: Utviklingstrinnene mot klassifisering av tilstand i norske innsjøer med satellittdata – metodeutvikling og eksempel
År: 2023
Forfatter(e): E. Thérèse Harvey, Kai Sørensen
Utgiver: Norsk institutt for vannforskning, ISBN 978-82-577-7395-3

Dette prosjektet er en videreføring av forsknings- og utviklingsprosjektet 'Bruk av satellittdata til overvåking av innsjøer', vurdering av MERIS-, Sentinel-2- og Sentinel-3-produkter, for Miljødirektoratet gjennomført mellom 2017-2019. Sluttrapporten hadde fokus på teoretiske og tekniske aspekter ved vannkvalitetsvurdering fra fjernmålingsdata (RS) og de mest aktuelle metodene ble brukt. Fremtidige behov og trinn for en operasjonell driftstjeneste og et veikart ble identifisert. Denne studien har tatt ytterligere skritt mot bruk av RS fra Sentinel satellittene for operasjonell overvåking av vannkvaliteten i norske innsjøer. I 2020 ble seks innsjøer spredt over hele Norge, som inngår i ØKOSTOR-overvåkingsprogrammet, undersøkt; Mjøsa, Selbusjøen, Gjende, Røssvatnet, Snåsavatnet og Femunden. Fjernmålingsdata fra Sentinel 2A- og 2B-satellittene samt Sentinel 3A- og 3B-satellittene fra Europakommisjonens Copernicus-satellittprogram ble brukt. RS-dataene ble lastet ned og behandlet med C2RCC atmosfærisk korreksjonsalgoritme for hver innsjø mellom 2016 eller 2017 til 2020, i vekstsesongen mai-september. Overflate in-situ målinger av optiske parametere (klorofyll-a konsentrasjon (chl-*a*) og absorpsjon, humus stoffer, turbiditet, absorbans, lysvekning og spredning) ble samlet inn fra hver innsjø ved en felles innsats fra overvåkingstemaet. I Mjøsa ble det samlet inn dedikerte in-situ match-up-data av vannprøver og in-situ reflektansemålinger samtidig med satellittpasseringeringene. Tidsserien med både overvåkings- og RS-data på overvåkingsstasjoner viser tilsvarende variasjon av chl-*a* og sesongvariasjonen kommer tydelig frem. Spatiale tidsseriedata fra satellitten ble brukt til å beregne et romlig chl-*a* gjennomsnitt for hele innsjøområdet og for området som tilsvarer hver overvåkingsstasjon. Flerårige gjennomsnitt viste at innsjøene har konsistente romlige mønstre og at romlig variasjon kan være stor i noen av dem. RS-resultatene fra hele innsjøområdet i Gjende kunne ikke behandles. Dette skyldtes mest sannsynlig skyggeeffekter eller tilbakestråling til atmosfæren fra de omkringliggende fjellene som påvirker vannpikselene samt for høye mengde partikler for satellitten. Det flerårige chl-*a* gjennomsnittet for hver innsjø ble brukt til å estimere chl-*a* statusklassifiseringen *sensu* Water Framework Directive med samme grenseverdi som for de integrerte 0-10 m dybde in-situ-prøvene fra overvåkingsstasjonene. Resultatene var gode for Mjøsa og Selbusjøen, men RS-dataene overestimerte chl-*a* for Gjende, Røssvatnet, Snåsavatnet og Femunden. Dette kan skyldes flere årsaker, for eksempel forskjellen mellom RS-estimatet ned til omtrent halvparten av siktedypet sammenlignet med integrert 0-10 m dybde in-situ prøven. En annen forklaring kan være at forholdet som brukes i algoritmen for å estimere chl-*a* konsentrasjonen fra chl-*a* absorpsjonen er forskjellig fra de faktiske forholdene i innsjøene, hvilket de foreløpige resultater basert på datasettet for denne studien indikerer. Dette emnet vil imidlertid trenge detaljerte studier med et større datasett for å finne et robust forhold som kan testes for å bruke det til behandling av RS-dataene. For innsjøene med høyest forskjell var in-situ-datasettet lite, hvilket gjør det vanskelig å trekke konklusjoner. For innsjøer med mer data, f.eks. Selbusjøen, kan det gjøres et empirisk forhold som kan brukes til korreksjoner av RS-dataene. Bruken av RS-data gjør det mulig å følge både tidsmessig og romlig variasjon og kan derfor bidra med ny innsikt og kunnskap for innsjøer som ikke overvåkes eller sjelden prøvetas, gjennom å gi data mellom prøvetakinger og år og endringene i variabiliteten og konsentrasjonene ville være mulig å følge selv om de nøyaktige verdiene kan trenge justeringer. Datamengden som er tilgjengelig fra Sentinel 2 og 3 er meget stort, og for at et operativt system skal være på plass, som kan gi data for alle norske innsjøer, må mange av behandlingene, kvalitetssikringen og de analytiske trinnene bli mer automatiserte, men fortsatt med regelmessige manuelle kvalitetskontroller. NIVA er partner i EODataBee (dvs. et europeisk RS-konsortium som utvikler tilpassede service for vannkvalitetsinformasjon avledet fra Jordobservasjon og andre kilder), og har dermed tilgang til aktuell utvikling, kompetanse og samarbeid.

1 Introduction

1.1 Background

This project is a continuation of the previous research and development project ‘Bruk av satellittdata til overvåking av innsjøer’ (Ledang et al., 2019). The main goal of this continuation is to examine a service development towards a more operational use of remote sensing (RS) data for the environmental monitoring and status classification of water quality, conducted in Norwegian lakes by the Norwegian Environmental Agency (Miljødirektoratet).

The Norwegian lakes are many, variable and some are very remotely located, making it challenging to observe the dynamic processes on appropriate time and spatial scales. A few stations, or in some cases one station within a relatively large lake, cannot be expected to represent the full variability in both time and space. Other methods are needed in order to gain better knowledge about the spatial dynamics in the lakes, such as satellite remote sensing. Since the lakes are not sampled yearly, satellite data can provide a good complementary dataset to the in-situ data so that the developments can be followed during the times of the year when in-situ sampling is not taking place and/or in the years without in-situ sampling.

Miljødirektoratet have expressed a need for a complementary dataset of water quality that could be used for deriving the water quality status classification for the EU Water Framework Directive (WFD) according to Vannforskriften for Norwegian lakes (Direktoratsguppen, 2018). Remote sensing data from satellites can provide robust data which makes it possible to monitor the changes in optical properties and water quality for water bodies that change rapidly in space and time. With the Copernicus program and the two twin-satellite sets of Sentinel 2 and Sentinel 3, the possibilities for remote sensing monitoring have never been better, and there are several ongoing efforts for research and application development within Europe to continuously improve the data quality. Satellite observations from Sentinel 3 sensor OLCI (Ocean and Land Colour Instrument, 300 m spatial resolution) take place daily in the summer period in Norway and every 4-5 days from the Sentinel 2 sensor MSI (Multi-Spectral Instrument (MSI), 60 m spatial resolution). This means that during cloud free days remote sensing-based data can provide a valuable collection of supplementary data for water quality data. Relevant products for the WFD classifications are e.g. seasonal or monthly averages of chlorophyll-*a* (chl-*a*), total suspended matter (TSM) and Secchi depth. Once the RS data has been collected by the sensors it is possible to derive data from previous years for use in e.g. an averaged classification of water status.

In the previous study by Ledang et al. (2019) there was a focus on the theoretical and technical aspects of water quality assessment from remote sensing data as well as the state-of-the-art methods used. The future needs for an operational service and a road map were also identified (Figure 1) (Ledang et al., 2019). Both the current and the previous project have focused on the first two steps in the conceptual model: R&D of remote sensing products. In this study a dedicated ground-truthing campaign was carried out in Mjøsa and a further 5 lakes with variable conditions and locations were selected where the regular monitoring program was supplemented with extra sampling of in-situ optical parameters.

To be able to use remote sensing data of water quality parameters, such as chl-*a*, as well as for status classifications it is necessary to test different algorithms and satellite sensors to find out which ones are the most suitable for the lake conditions studied and which variables that can be retrieved for the different lakes. The most common approach is to collect optical in-situ data simultaneously with a satellite over-pass, so-called match-up sampling (IOCCG, 2000). These special campaigns are called ground-truthing and aim to gather as much match-up data as possible under favorable conditions with clear skies. Data commonly collected for a match-up are in-situ optical parameters (Water leaving reflectance (Lu), Remote sensing reflectance (R_{rs}), light attenuation coefficient (K_d)) and bio-optical parameters (chl-*a*), coloured dissolved organic matter (Humic substances, cDOM) and total suspended matter (TSM). The in-situ data is collected simultaneously with a satellite over-pass, within a time window optimally 30 min but can be extended to 2 hours if the water masses are relatively stable. Since all remote sensing products are derived from the R_{rs} product (see Ledang et al. 2019 and references therein), the match-up data is needed to be able to conduct a validation of the satellite derived R_{rs} from the atmospheric corrections. The dataset can also be used for testing regional empirical algorithms and conversion factors for chl-*a*. Optical data are rarely collected on a regular basis and the data collected within this project are valuable for evaluating the satellite products, even though not all of them are dedicated match-up data.

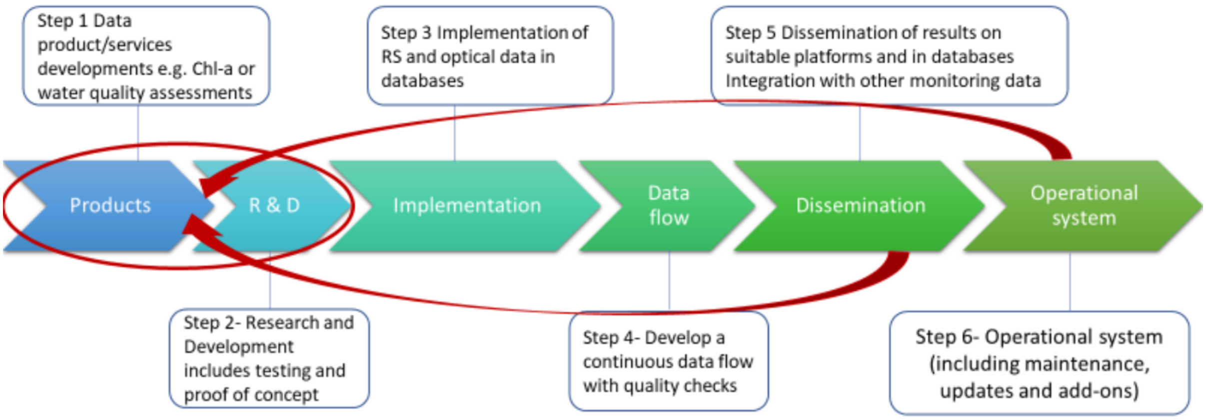

Figure 1. *Road map for an operational system of remote sensing data in Norwegian lakes. The red ring marks the steps covered by the previous (Ledang et al., 2019) and the current projects and the two arrows represents feedback on the system for developments.*

1.2 Project objectives

This study has several purposes and examines different questions related to chl-*a* retrieval from Sentinel 2 and takes further steps towards a status classification of Norwegian lakes using satellite data by method developments and sampling and evaluation of 6 case studies. The specific objectives of the study were;

- To collect in-situ optical parameters for a wide range of Norwegian lakes
- To collect dedicated match-up data including reflectance data on Mjøsa
- Derive the chl-*a* classification for each lake based on historical RS data from 4-5 years back
- Further develop the method towards a use of an operational remote sensing service as a complementary method within Miljødirektoratet´s regular monitoring and water classification of Norwegian lakes
- Evaluate the results from the different satellite sensors, Sentinel 2A & B and Sentinel 3A &B
- Provide a first analysis and assessment of what is good enough in relation to using satellite data for monitoring of Norwegian lakes
- Evaluate the next steps towards classification for based on remote sensing data

2 Methods

2.1 Lakes included in 2020

The field study included six selected lakes included in the ØKOSTOR monitoring program in 2020, two lakes in northern Norway (Røssvatnat and Snåsavatnet), one in central Norway (Gjende), two in eastern central Norway (Selbusjøen and Femunden) and one lake in southern Norway (Mjøsa) (Figure 2). The different water type definitions based on monitoring categories within the WFD for each of the lakes are found in Table 1.

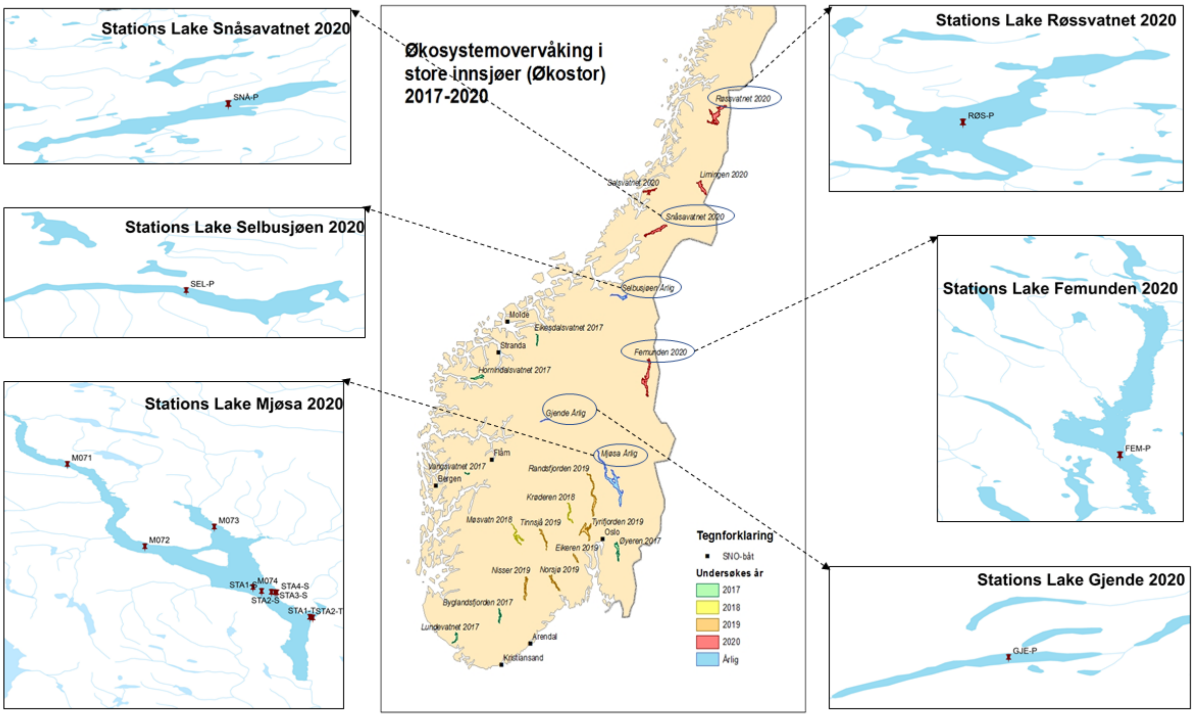

Figure 2. *Location of the six lakes included in the study. The color coding in the maps indicates how often the lakes are sampled during a 4-year period.*

Table 1. *Characteristics based on water type definitions (VannNett-Portal, 2021), 2016-2020. * indicates the official chl-a status reported on Vannet-Portal in 2021.*

Lake	Water Type	Areal, km²	Status chl-*a* *	Average depth, m	Chl-*a*, µg/l	Secchi depth, m	Colour, mg Pt/l	Turbidity, FNU
Mjøsa 2014-2020	**L107:** Very large, moderate Calcium, clear	366	High	155	2.1	7.8	11.9	0.54
Selbusjøen 2013-2020	**L105b:** Large, low Calcium, clear	57	High	70	0.8	-	26	0.3
Gjende 2013-2020	**L204:** Middel, low Calcium, very clear	16	High	66	0.96	6.7	3	1.8
Røssvatnet 2016, 2020	**L207:** Large, moderate Calcium, clear	219	High	66	0.4	-	7	-
Snåsavatnet 2016, 2020	**L107:** Large, moderate Calcium, clear	122	High	46	0.9	-	34	0.5
Femunden 2016, 2020	**L205:** Large, moderate Calcium, clear	204	High	15	0.7	8.5	11.3	0.1/0.3

2.2 In-situ data

2.2.1 In-situ sampling

In-situ sampling within this project had two objectives:

1) To increase the dataset of optical parameters, such as cDOM, chl-*a*, chlorophyll pigment absorption ($a_{Chl\text{-}a}$) and non-algal particles (a_{NAP}) for a wider range of Norwegian lakes that later can be used for e.g. algorithm developments and tuning
2) Conduct a dedicated match-up dataset for validation of the satellite products, such as the water leaving reflectance

2.2.1.1 Lake monitoring data

Data for each lake was collected under the framework of ØKOSTOR (17078025, Lyche Solheim et al., 2020), which is the national monitoring program for large Norwegian lakes led by NIVA and conducted by NIVA and partners. The monitoring program analyses an integrated mixed water sample between 0- 10 m depth, collected by a hose. Additional surface water samples, as recommended for match-up data (Zibordi et al., 2019) were collected at 0-0.5 m depth for bio-optical analyses within this study. The sampling was coordinated with the current field work to be able to collect data from a range of different lakes in an efficient way and was analysed by NIVA. The monitoring data was used when assessing the chl-*a* water quality status.

2.2.1.2 Match-up data

A main priority identified in the previous study (Ledang et al., 2019) was to collect match-up data and in-situ water leaving reflectance, so this was a focus in 2020. Collection of good quality match-up data is dependent on optimal conditions for sampling with clear skies and preferably calm weather.

Lake Mjøsa was therefore chosen to be studied based on the good accessibility for fieldwork, which makes it easy to go out and sample with a short notice when the conditions are correct and there is a satellite overpass. As one or sometimes both of the Sentinel 3 sensors pass every day the focus was to match the in-situ sampling with the Sentinel 2 sensors, as those include data from both sensors. We installed a new reflectance rig that could be mounted on a small boat which was kept at NIVA's Hamar office the whole season. The ordinary monitoring program sampling in Mjøsa takes place at 4 stations, Brøttum (MO71), Kise (MO72), Furnesfjorden (MO73) and Skreia (MO74) (Figure 3, Table 2), every month during the full season and with an additional station (M074 – Skreia) monitored bi-weekly.

Surface samples taken at approximately 0.5 m depth and reflectance measurements were collected during the ordinary monitoring program sampling. In 2020 we were able to collect match-up for 30 observations. A test run to set up the reflectance rig and training for the team performing the sampling took place on 16/6-2020. We managed to complete four dedicated match-up sampling campaigns following a transect from land to open water on 10/8-2020, 11/8-2020, 25/8-2020 and 17/9-2020 (Figure 3, Figure 4).

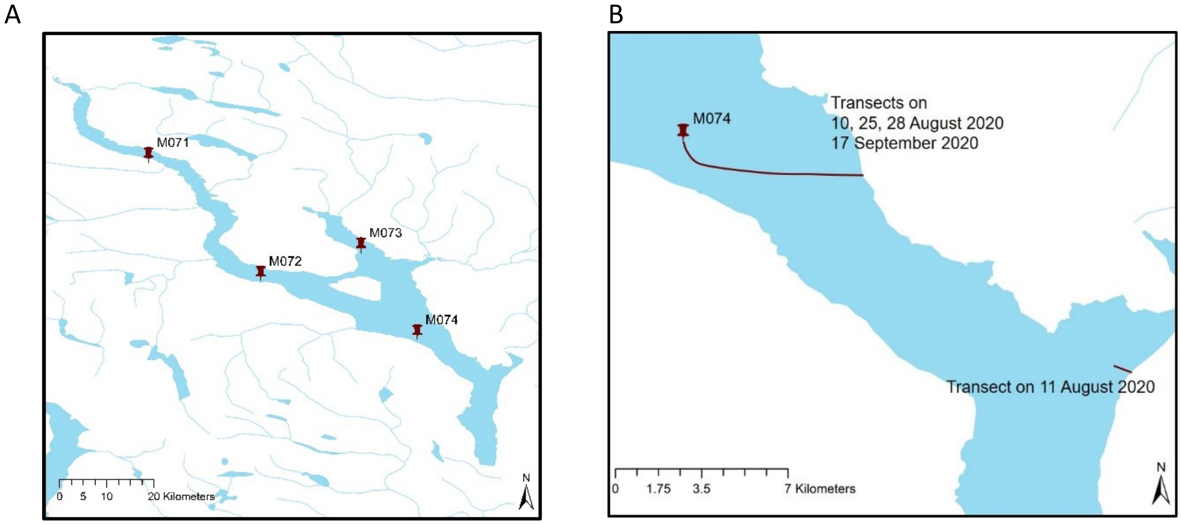

Figure 3. *A: the monitoring stations in Mjøsa. B: the match-up transects for satellite validation.*

Figure 4. *Images of the in- situ campaign in Mjøsa 2020. Photos by Henriette Kildahl and Asle Økelsrud/NIVA.*

Table 2. *Sampling day of the month for the in-situ campaign 2020, a * indicates either a match up point or a match-up transect (Mjøsa).*

Month/Lake	Mjøsa	Gjende	Selbusjøen	Røssvatnet	Snåsavatnet	Femunden
June	16, 23		25		23	30
July	7, 8, 15, 20	1, 28	22, 26	6	15,21	27
August	10*, 11*, 15*, 20*, 25*, 26, 28*		24	11	27	
September	17*	1	21	7	23	1
Stations,	8	1	1	1	1	1
Observations, n	30	3	5	3	5	3

2.2.1.3 Sampling methods

All water samples were collected from a boat at the surface (0-0.5 m depth) and kept cold and dark until analysis. The in-situ methods used for chl-*a*, cDOM, Secchi depth, turbidity follow the same procedures and protocols as the ordinary national monitoring program conducted by NIVA in the framework of ØKOSTOR (Lyche Solheim et al., 2020), and the method for deriving attenuation, total absorption, backscattering, $a_{Chl\text{-}a}$ and a_{NAP} are described in the earlier report (Ledang et al., 2019).

Reflectance data

A new rig with a TriOS RAMSES light sensors for measuring the above-water reflectance was establish in June 2020 for mounting on small boats used for monitoring in calm waters. Images of the set up are shown in Figure 5. Reflectance data is a light measurement that uses 3 sensors: one sensor for detecting the total incoming light from the atmosphere (Irradiance sensor, Ed); one sensor for the downwelling light that enters the water, which is not reflected at the surface (Downwelling sensor, Ld); and one sensor for the light coming back from the water to the atmosphere (Radiance, upcoming light, Lu). The information from the 3 sensors are used to calculate the remote sensing reflectance, R_{rs}, which is a proxy for the light that reaches the satellite sensor. The R_{rs} data from the satellite is used within the algorithms to derive e.g. the chl-*a* concentrations, see Ledang et al. (2019) for details. The sensors measure the full light spectra between 350-900 nm and are regularly calibrated against NIST standard lamps at the radiometric calibration laboratory at NIVA.

Figure 5. *Set up of the rig and computer with TriOS RAMSES light sensors measuring the above reflectance for Mjøsa, 1) Irradiance sensor; incoming light, Ed 2) downwelling, Ld and 3) radiance sensor; upcoming light, Lu. Photo: Sørensen/NIVA.*

2.2.1.4 Processing and data analysis

All the bio-optical parameters were analyzed from June to September 2020 and the results are presented in section 3. Chl-*a* was analyzed according to standard and accredited methods (Lyche Solheim et al., 2020). Absorption of cDOM was measured spectrophotometrically and the absorption values at 443 nm (a_{cDOM}) and the slope values (S_{cDOM}) were derived. The S_{cDOM} indicates the optical signal of the cDOM pool where higher values represents a steeper exponential curves, often associated with less degraded terrestrial material (Stedmon et al., 2000; Vodacek et al., 1997). cDOM parameters were calculated by a least square fitting between 350 and 500 nm with the program "cdom" in R (Loiselle et al., 2009; Massicotte & Markager, 2016; R Core Team, 2013). The mean turbidity (Turb) values were based on triplicate measurements from each station. The chl-*a* pigment absorption ($a_{Chl\text{-}a}$) and absorption of non-algal particles (a_{NAP}) were analyzed according to the Tassan & Ferrari (1995) method, with adjustments (Ledang et al., 2019). The results for a_{NAP} are not presented.

2.3 Satellite remote sensing data - Sentinel 2 and Sentinel 3

The coding solutions for a smooth data flow and processing schemes, including downloading that NIVA developed during the previous project and EU DCS4COP (DataCube Service for Copernicus) project (DCS4COP, 2021; EODataBee, 2021), were modified to the current lakes and were used for this study as well. All available RS scenes from Sentinel 2 and Sentinel 3 for the regions of interests (i.e. the lake polygons) were automatically downloaded from the Norwegian ColHub data center and processed in house and manually with the C2RCC (Case 2 Regional CoastColour RS processor) atmospheric correction (Brockmann et al., 2016). For details on the satellite sensors used and the atmospheric corrections applied please see details in Ledang et al. (2019) and references therein.

Quality assurance of data

The remote sensing reflectance data is used in the algorithms to derive the estimated concentrations of the parameters, e.g. chl-*a*. It is therefore important that the shape, range and magnitude of the reflectance spectra is correct. The retrieval is affected by various factors including e.g. clouds or cirrus clouds (high thin clouds), bottom reflectance, too-high concentrations of the bio-optical parameters, which all can interfere with the signal in a negative way. A standardized data sorting was used to ensure high quality data and various quality flags were applied to all the RS scenes to exclude non-valid data (i.e. flags for clouds, cloud shadow, high concentration of bio-optical parameters as well as sun glint). All data that was used in the analyses were also tested to pass the criteria set by the reflectance value at around 443 nm to be lower than at 490 nm (band 1 and 2 for Sentinel 2 and band 3 and 4 for Sentinel 3), which means that the R_{rs} spectra should have a normal shape with values at 443 nm lower than at 490 nm.

Pixel extraction

For each valid scene and for each monitoring station in the lakes the satellite data from a 3*3 matrix around the station was derived and the average was calculated. These values were used to compare with the in-situ data and used to assess the water quality status of chl-*a* for each station or lake.

Binning

Binning of remote sensing data is when several scenes for the same location but from different times are temporally averaged to e.g. retrieve the average monthly, yearly or assessment period (here 2016-2020 and 2017-2020 for Mjøsa) mean values. The results from the assessment period for each lake were used for the WFD water quality assessment based on remote sensing data. The binning was done for Sentinel-2 data and is presented as integrated chl-a maps in chapter 4.

Mosaicking

Mosaicking is applied when one lake needs two Sentinel 2 scenes to cover the full lake, with some overlaps. One can say that mosaicking is stitching the two scenes together using correct georeferencing and averaging the overlapping pictures. This was applied to Sentinel 2 data for Mjøsa, Røssvatnet and Femunden. This is illustrated for Røssvatnet in Figure 6. The Sentinel 3 images cover each lake in one tile.

Analyses

The Sentinel 2 and Sentinel 3 data were used for deriving time-series of data from the full area of all lakes (Sentinel-2) and for each of the monitoring stations and match-up stations in Mjøsa (Sentinel 2 and Sentinel 3). The data was used for time-series comparisons with the in-situ chl-*a* monitoring data and for as well as for the WFD assessment analyses.

Northern scenes **Southern scenes**

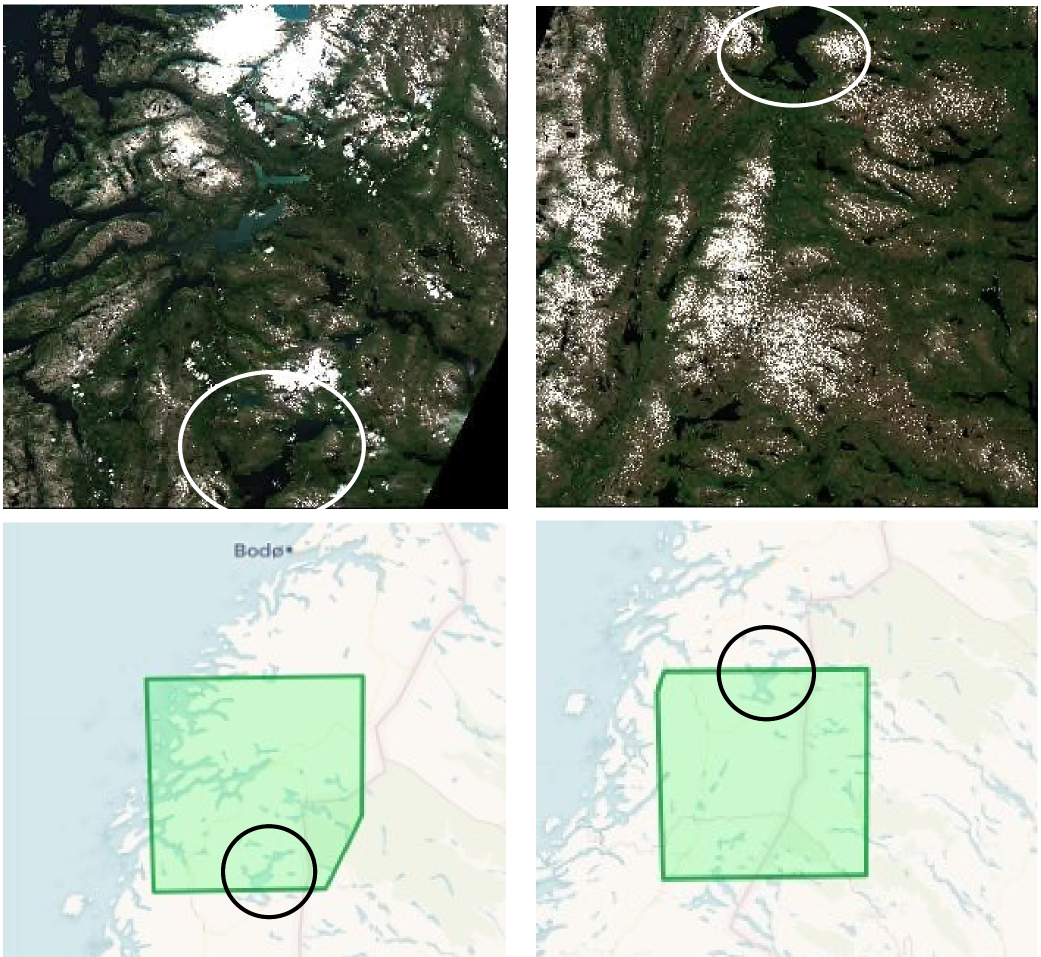

Figure 6. *RGB images of Røssvatnet from Level-2 S2MSI2A data and schematic images showing the coverage of each scene from Creodias/Copernicus* (*Home Page - CREODIAS*, 2021). *The left panel shows an example of the northern scenes, and the right-hand panel shows an example of the southern scenes. The results from the 2 scenes are stitched together by mosaicking. The white and black rings show the location of the lake.*

3 Results and discussion

The results of the in-situ 0.5 m depth surface samples for each of the hydrographic and optical parameters collected during June to September in 2020 for all six lakes are presented and the findings are discussed. Data from Mjøsa was collected more often and at different stations and are presented in more detail in a chapter 3.2. The remote sensing data are focused on chl-*a* and reflectance data from Sentinel 2, the results from Sentinel 3 are presented in a separate stand-alone Appendix.

3.1 In-situ data: Hydrographic and optical parameters

3.1.1 Chlorophyll-*a* concentration and chlorophyll-*a* pigment absorption

All lakes had relatively low concentrations of chl-*a* but it was higher in Mjøsa, with distinctive peaks of higher concentrations compared to periods with lower data (Figure 7A). The other lakes showed more stable chl-*a* concentrations over the season, with slightly higher concentrations in June for Snåsavatnet, Gjende and Femunden. It should be noted that the data in Mjøsa is from 4 different stations, whilst the other 5 lakes each have observations from a single station.

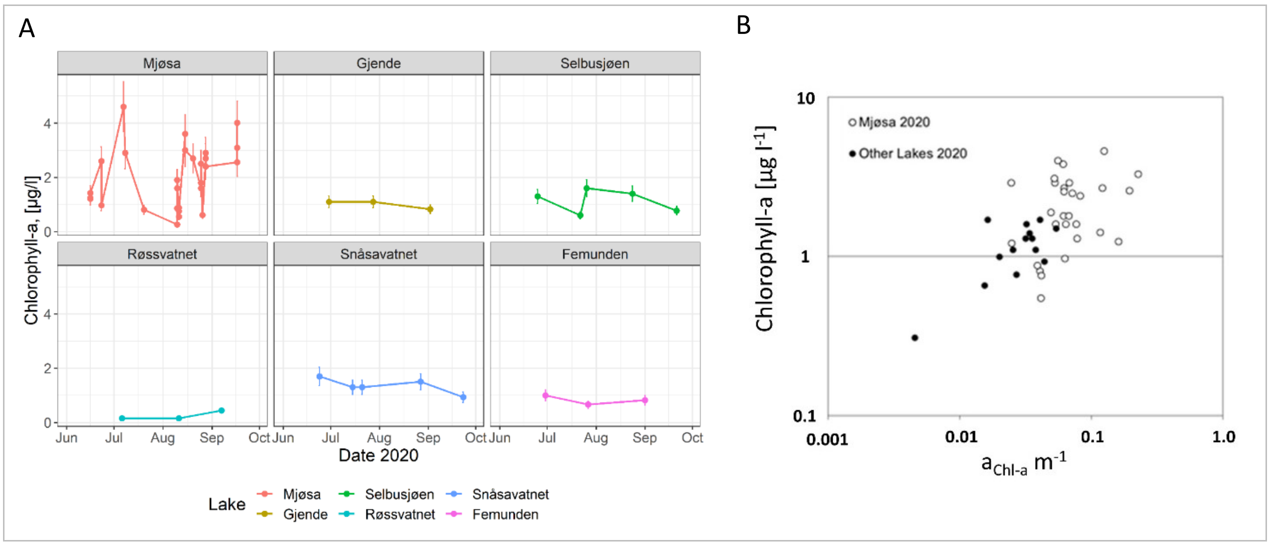

Figure 7. *A: Surface (0.5 m depth) chl-a data (µg/l) from each lake between June- September 2020. Error bars represent a general 20% uncertainty of the method. Mjøsa includes 4 stations and the other lakes 1 station each. B): Chl-a specific absorption, a_{Chl-a}, m^{-1} from this study in relation to the chl-a concentration on a log-log scale. The black circles are data from the other lakes; Gjende; Snåsavatnet; Selbusjøen; Røssvatnet and Femunden and the open circles are data from Mjøsa.*

The chl-*a* pigment absorption was analyzed for all lakes and the relationship to the chl-*a* concentrations is presented in Figure 7B. Standard relationships between the chl-*a* concentration and the chl-*a* specific absorption is used in the remote sensing algorithms. It is important that the conversion factors used are as close as possible to the natural conditions and based on the natural variability, to be able to retrieve high quality chl-*a* data from satellite sensors. The collection of this data is tedious with a high workload, both in terms of measurements as well as data processing. There are not many bio-optical studies of Norwegian lakes and therefore the data from this study is an important initial data set that with potential to be used for more detailed studies of algorithm developments and tuning. The data set is too small to allow us to draw conclusions, but when the data from this study was placed in a broader perspective in comparision with other studies and the chl-*a* absorption (a_{Chl-a}) ~chl-*a* concentration relationship from (Sørensen et al., 2007) (Figure 8A) they agree well. However, when calculating the chl-*a* values based on the relationship from all lakes and all lakes without Mjøsa in 2020 (Figure 8B) the relationship differs from Sørensen et al. (2007) at concentrations above 2 µg/l, and is gives much lower chl-*a* values (2-4 times). Since the conversion factor in the C2RCC equals the Sørensen et al. (2007) factors, this algorithm will most likely overestimate the chl-*a* values. The chl-*a* concentrations retreived from the 2020 data also show an overestimation. It should be noted that these are preliminary results as there are very few data points ($a_{Chl\text{-}a}$ and chl-*a*) on which to base the models. The results of the models should ideally also be validated against an independent in-situ data set.

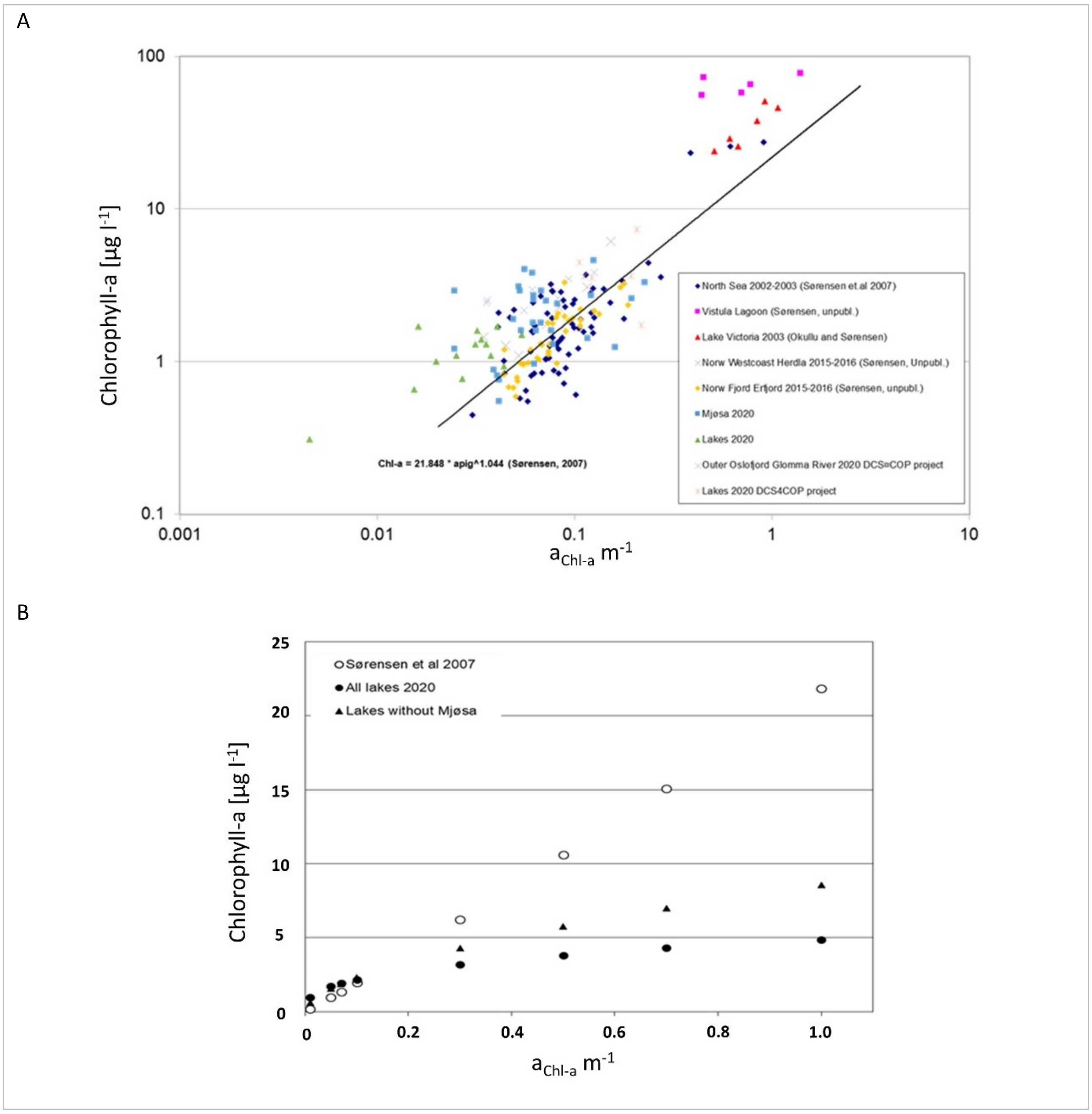

Figure 8. *A: Chlorophyll specific absorption from this study in comparison with data from other studies and areas on a log-log scale. The relationship between chl-a concentration and the chlorophyll specific absorption from this study (blue squares and green triangles) lines up well with the other studies. B: shows the chl-a concentrations if we calculated based on the 2020 relationships for the lakes compared to Sørensen et al. (2007). The* $a_{Chl\text{-}a}$ *are the output from the processor. The open circles are based on Sørensen et al. (2007), the black dots are based on all lakes in 2020 and the triangles are based on all lakes except Mjøsa.*

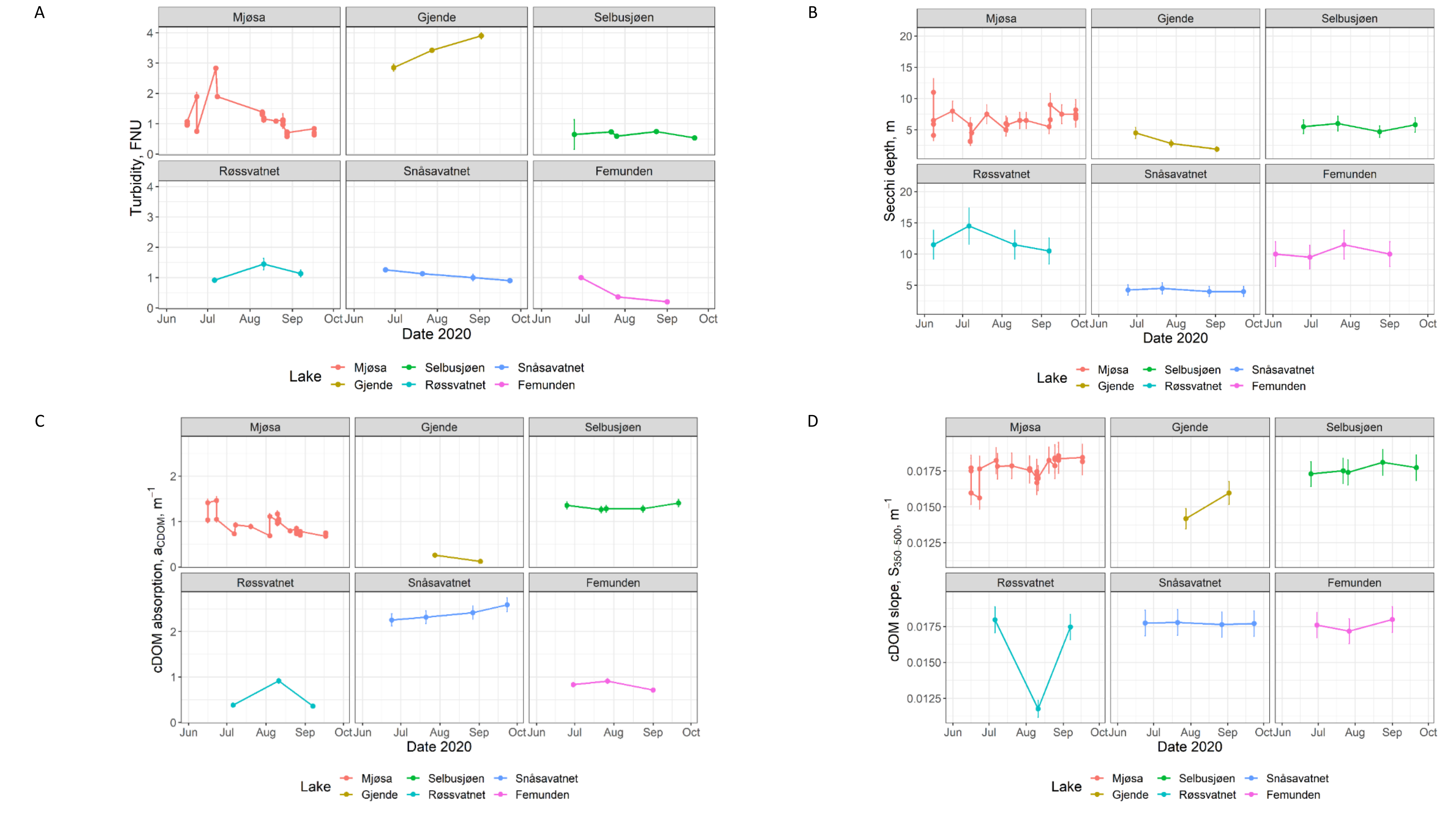

Figure 9. *Surface data (0.5 m depth) from each lake between June - September 2020, several stations in Mjøsa and 1 station in each of the other lakes. A: Turbidity (FNU). Error bars represent 1 standard deviation calculated from the sample variability and mean, B: Secchi depth (m). Error bars represent a general 20% uncertainty of the method, C: Absorption of cDOM, m^{-1} at 443 nm. Error bars represent 6% error of the method and D: cDOM slopes, m^{-1}, between 350 and 500 nm. Error bars represent 5% error of the method.*

3.1.2 Turbidity

The turbidity values were highest in Gjende (Figure 9A) with an increase over the season, while Snåsavatnet and Femunden showed a decrease with season. The variable data in Mjøsa are attributed to the 4 different stations with variable inflows from larger rivers.

3.1.3 Secchi depth

The Secchi depth varied between about 2 to 14m (Figure 9B), with clearer waters in Røssvatnet, Femunden and Mjøsa, which is on average a bit higher than the reported values for Femunden and Mjøsa (Table1). Snåsavatnet and Selbusjøen had low Secchi depth which corresponds to the high colour values of 34 and 26 (Table 1). However, Gjende has a colour number of 3 but had very low Secchi depths, especially at the end of the season.

3.1.4 cDOM absorption and cDOM slopes

The cDOM absorption was analyzed for all lakes (Figure 9C), and the low absorption found in Gjende and Femunden correspond to the low colour numbers, 3 and 11.3 respectively (Table 1). The colour value of 34 for Snåsavatnet follows the pattern with high cDOM absorption and the low Secchi depth, followed by Selbusjøen, Mjøsa and Røssvatnet, although the cDOM absorption was more variable. The cDOM slopes (Figure 9D) are usually less variable than the cDOM absorption as they depend on the structure and characteristics of the cDOM molecules, although it can vary with season (Harvey et al., 2015). The slope in Røssvatnet was lower in August than in July and September, where both the cDOM absorption and turbidity were higher. This can be connected to e.g. heavy rainfall that increased the runoff to the lake. The other lakes showed less variability, except Mjøsa, which include data from more than one station. If the slopes values are known the cDOM absorption at other wavelengths can easily be calculated.

3.1.5 Total absorption, attenuation and backscattering

Samples of attenuation (c), total absorption (a) and backscatter (bb) were measured at 9 different wavelengths (412, 440, 488, 510, 532, 555, 650, 676 and 715 nm) by an ac9 instrument in the lab. The absorption (Figure 10A) and attenuation (the extinction or the gradual loss of light through the water) (Figure 10B) declines with wavelength. Corrections for pure water contribution and temperature and salinity effects were applied according to Röttgers et al. (2013) and Sullivan et al. (2006). Total absorption includes all absorption in the water column, i.e. including cDOM and chl-*a* specific absorption and non-algal absorption. The magnitude of the absorption differs between lakes and between months. The attenuation also varies in the same way as the total absorption between the sampling months and the magnitude between the stations, where Snåsavatnet stands out with a much higher attenuation in the blue than the others, probably connected to the high cDOM absorption and the high "Farge”. The total backscattering (Figure 10C) is a measure of how much the particles scatters the light within the water column and is related to the turbidity (which is a proxy for scatter) and the suspended particles within the water. The backscattering is not as pronounced wavelength dependent as the absorption and attenuation, which is seen in the graph, but the scattering is still wavelength dependent. The highest scattering is seen in Gjende, which is expected as it has a glacial connection and the melt water from glaciers are known to bring high loads of sediments to the water, and thus increasing the scattering. High scattering usually affects the chl-*a* retrieval from the sensors.

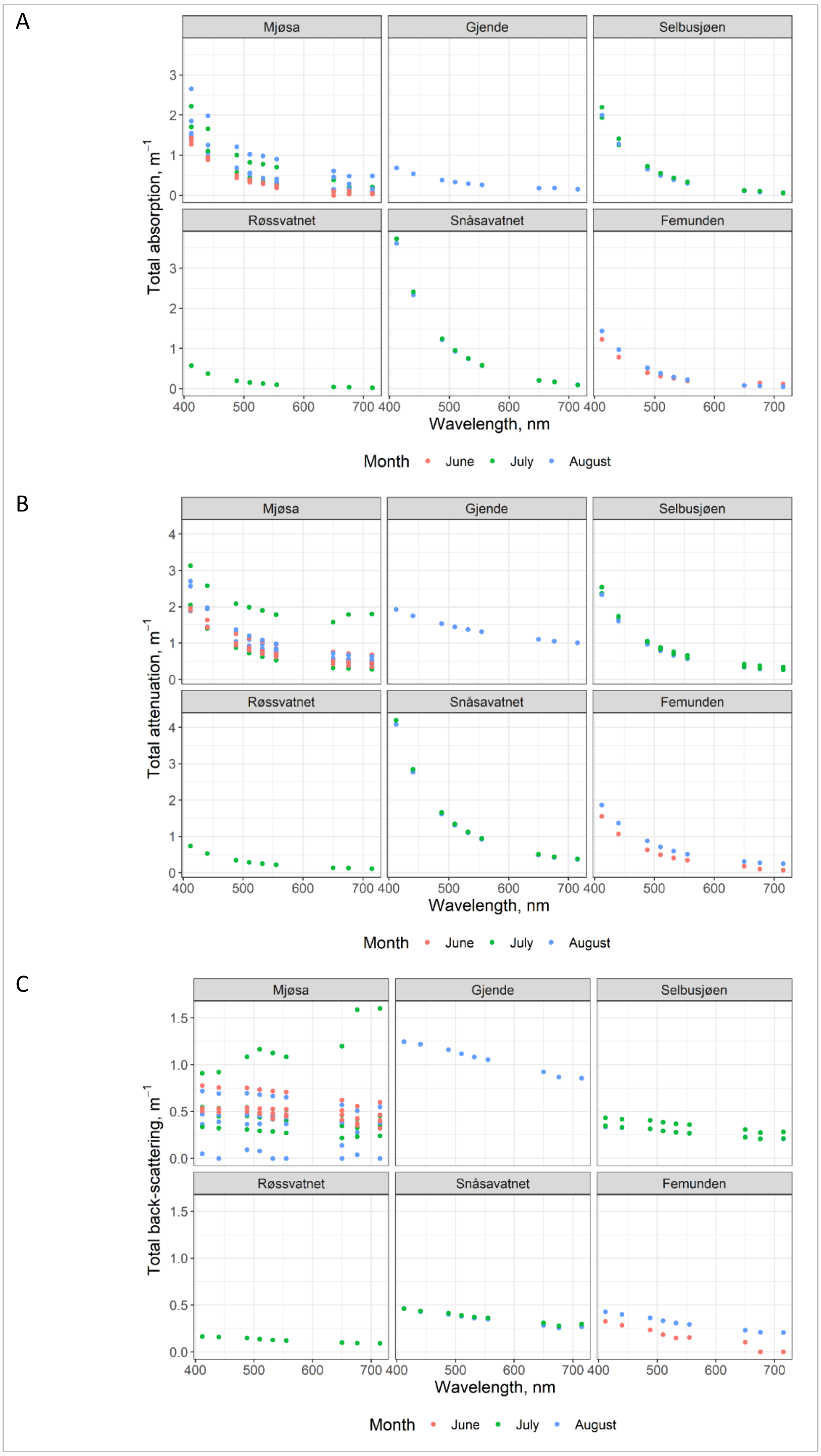

Figure 10. *A: Total absorption, a_{tot}, m^{-1}. B: total attenuation, m^{-1} from ac9 data per wavelength, nm (x-axis) from each lake between June- August 2020. C: backscattering, b_b, m^{-1} from ac9 data per wavelength, nm (x-axis) from each lake between June- August 2020.*

3.2 Lake Mjøsa

As there was an extra focus on collecting data in Mjøsa at different stations and with more frequent observations in the 2020 season, these data are presented separately and analysed further. Monitoring data from previous years are also presented for comparisons with RS data. Two types of in-situ data were gathered 1) monitoring data based on an integrated mix-sample (0-10 m depth) and 2) surface (0.5 m depth) match-up data for the satellite overpasses at station Brøttum, Skreia and along the transects (see maps, Figure 3). In 2020 was the match-up data set 30 observations (Table 2). This is a unique data set for Norwegian lakes and will be used in more detailed studies in the future.

3.2.1 Chlorophyll-*a*

The monitoring data in Mjøsa have been collected regularly and a time-series between 2016 and 2020 for the summer months are presented for each monitoring station in Figure 11A. The chl-*a* concentration is based on an integrated sample of water from mixed depths. The time-series shows several summer blooms and the concentrations in 2020 seem to be a bit higher in August at both Skreia and Kise. Surface samples were collected in 2020 and the chl-*a* concentrations are presented in Figure 11B. For station Brøttum and Skreia both the surface and the mix-sample data are plotted, where the mix-samples at station Skreia sometimes was as much as 2 times higher than the surface samples.

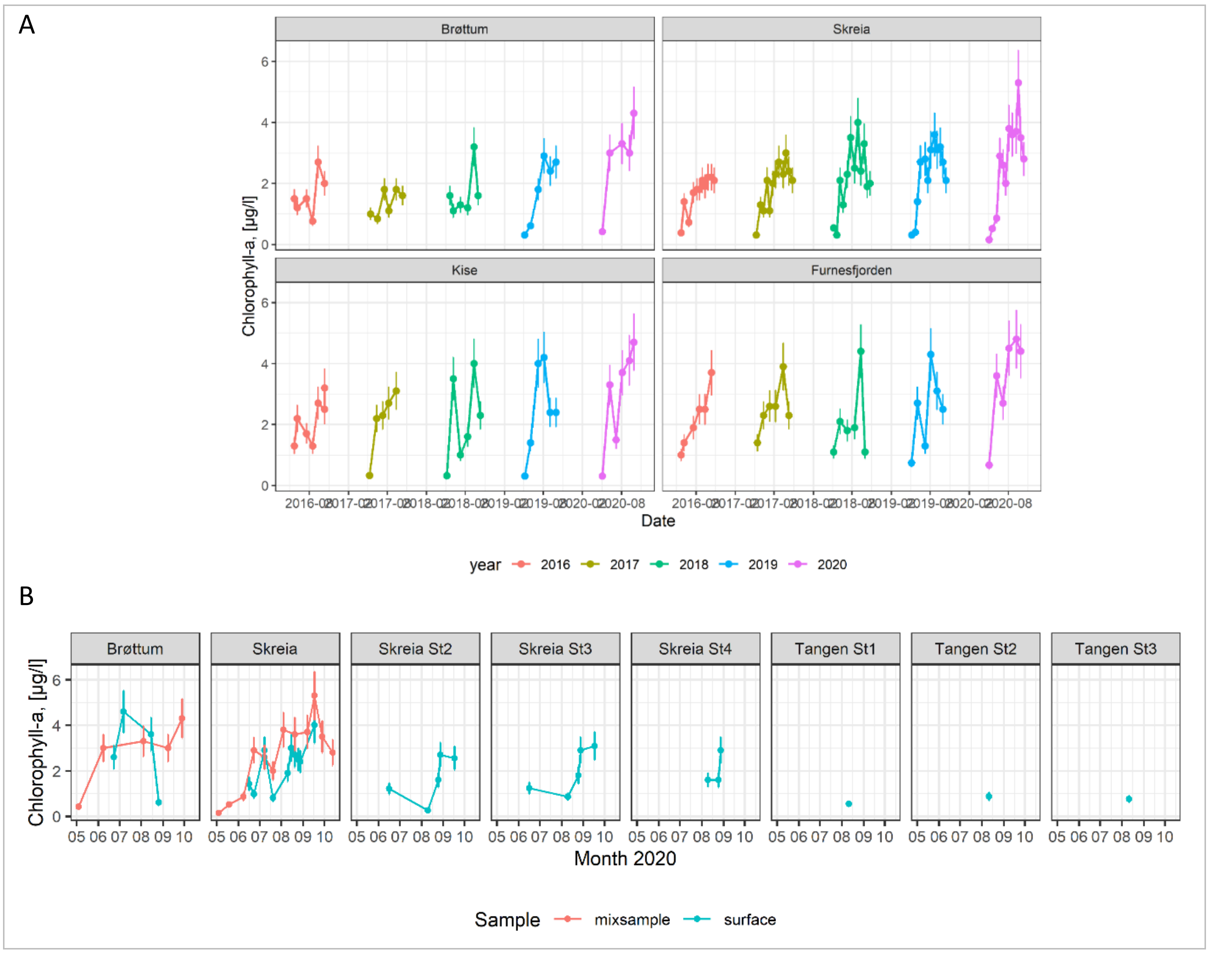

Figure 11. *A: Time-series of chl-a (µg/l) from 0-10 m, at the 4 monitoring stations (Brøttum, Skreia, Kise and Furnesfjorden), May- October 2016-2020. B: chl-a (µg/l) for surface match-up data 0.5 m (blue) and monitoring mix-sample 0-10 m (red) for stations Brøttum and Skreia and the transect stations (Skreia St2-St4 and Tangen St1-St3), May/June- September 2020. Error bars represent a general 20% uncertainty of the method.*

3.2.2 Turbidity

The turbidity data is measured in the monitoring program from the integrated mix-sample between 0-10 m at 2 stations, Brøttum and Skreia. Time-series between 2017-2020 are shown in Figure 12A. The turbidity was generally higher at station Brøttum, which also shows a higher variability than station Skreia, especially in 2018. In 2020 the turbidity values seemed to be higher at stations Skreia, like with the chl-*a* concentration, especially in July (Figure 12A). Results from the 2020 match-up surface samples shows that the turbidity has a peak in the summer months and a slightly decrease in September (Figure 12B). The turbidity at the surface was higher than the mix-sample at Skreia.

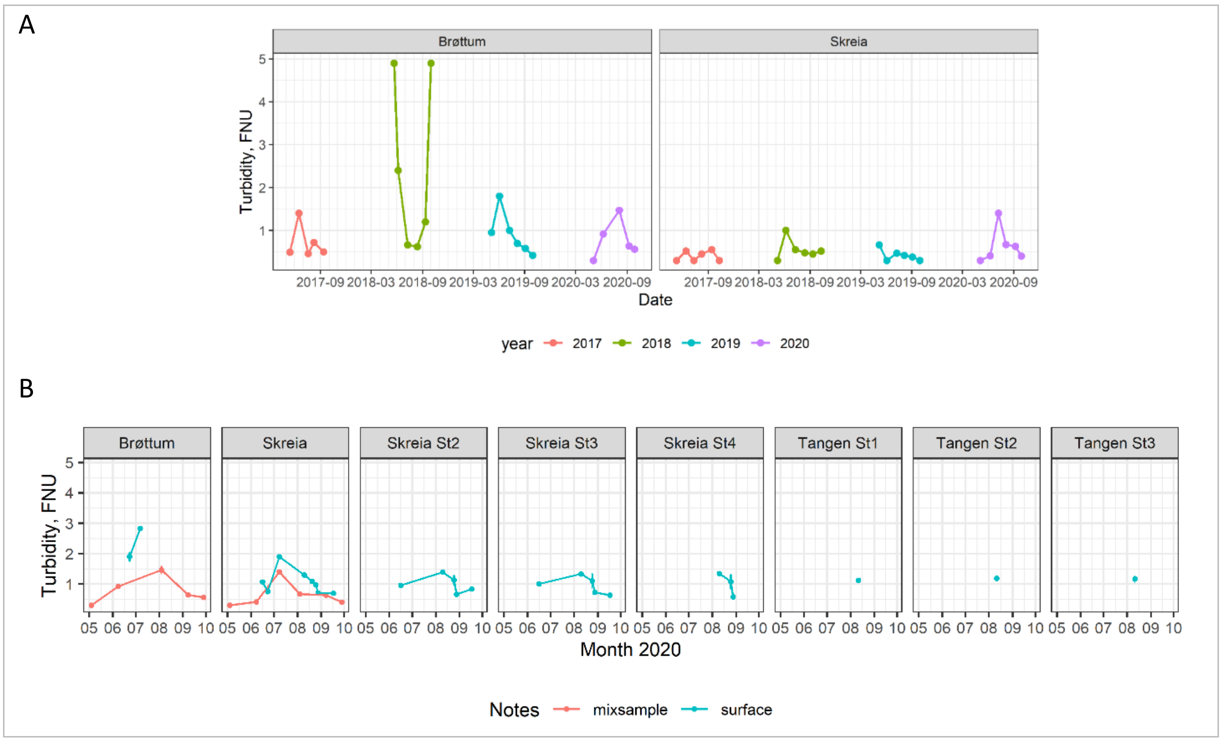

Figure 12. *A: Turbidity data (FNU) for the 2 of the monitoring stations (Brøttum and Skreia) in Mjøsa between June- September 2017-2020. B: Turbidity data (FNU) for surface match-up data 0.5 m (blue) and monitoring integrated mix-sample data 0-10 m (red), including the monitoring stations Brøttum and Skreia and the transect stations (Skreia St2-St4 and Tangen St1-St3). Error bars in fig B represent a general 20% uncertainty of the method.*

3.2.3 Secchi depth

Time series of Secchi depth show that it varies between the stations, season and year (Figure 13). The highest values are found in spring and the lowest during the summer months. Secchi depth is a parameter that can be assessed by remote sensing data from satellites and is one of the supporting parameters for the status assessment within the WFD. It has a long record of monitoring data, which makes it good to use for long term studies. However, the parameter is itself a proxy for the light availability in the water column which is affected by the absorption and scattering of the constituents within the water. Secchi depth is therefore strongly related to several bio-optical parameters, like the cDOM absorption, the amount of total suspended matter and chl-*a* absorption, the turbidity as well as the total attenuation and total back-scattering. In this study the focus has been on chl-*a*, but more dedicated studies of remote sensing and light and Secchi depth would be valuable.

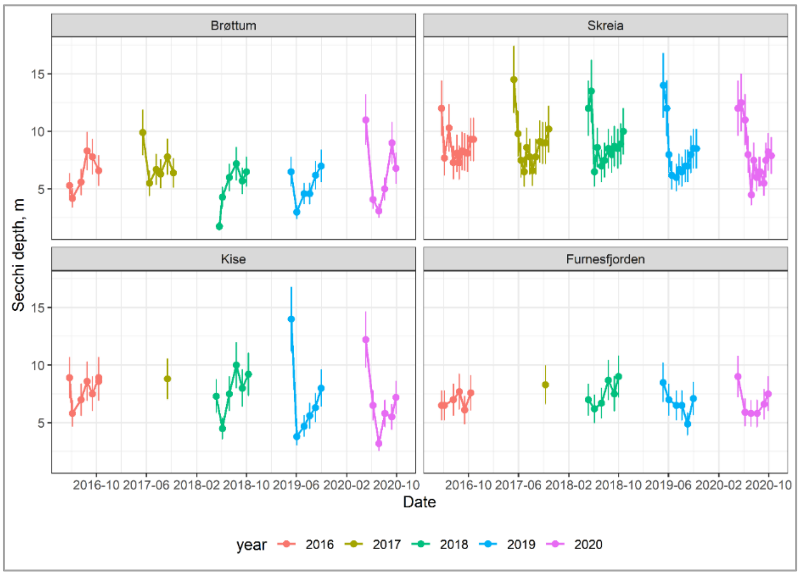

Figure 13. *Secchi depth data, for the 4 of the monitoring stations (Brøttum, Skreia, Kise and Furnesfjorden) in Mjøsa between May- October 2016-2020. Error bars represent a general 20% uncertainty of the method.*

3.2.4 cDOM absorption and cDOM slope

Absorption by cDOM is not included in the monitoring program, instead 'Farge' i.e. the colour, is measured which is related to cDOM, see Ledang et al. (2019) for an estimated relationship between the two parameters. In 2020 cDOM absorption was measured for all surface match-up samples and the data set for the stations in Mjøsa are presented in Figure 14A. The variability in Mjøsa is large during the season with highest values in spring and lower absorption in autumn. The high spring absorption is most likely related to river-run off, which has been shown in other studies (Harvey et al., 2015). The slope values varied in the same way as the cDOM absorption (Figure 14B).

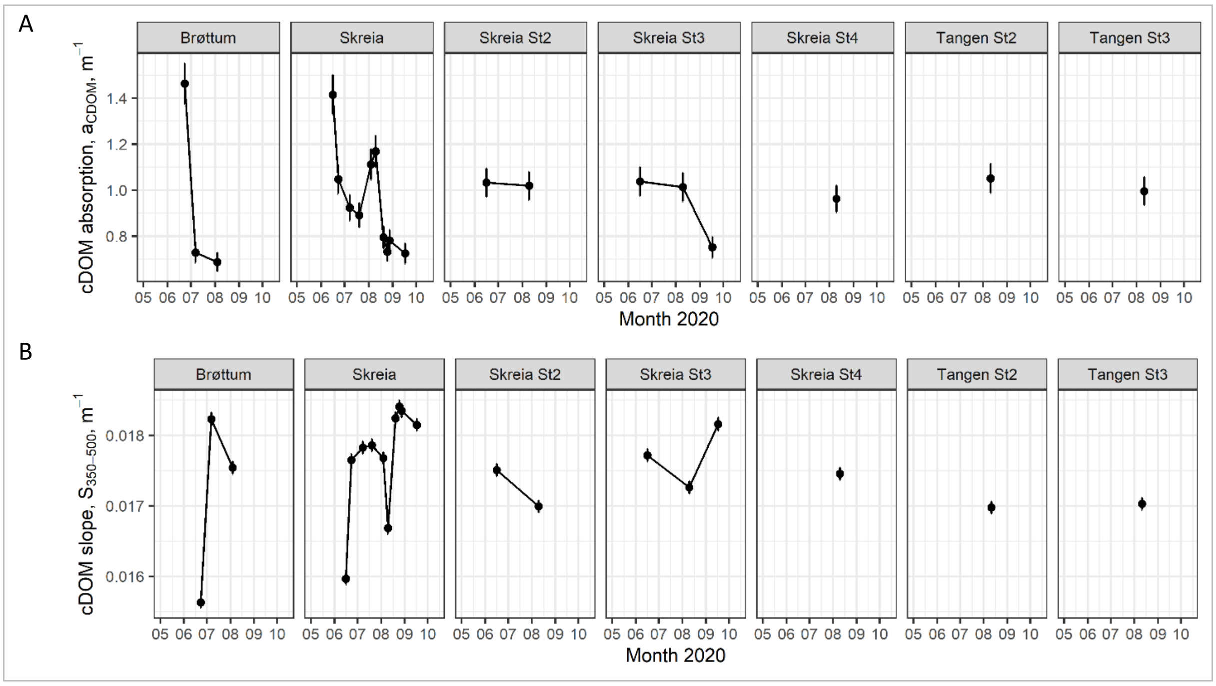

Figure 14. *A: Absorption of cDOM, m^{-1} at 443 nm and B: cDOM slopes, m^{-1}, between 350 and 500 nm in Mjøsa 2020. Error bars represent a 6 % and 5% error, respectively of the method.*

3.2.5 Reflectance, absorption, attenuation and back-scattering

Remote sensing reflectance, R_{rs} (sr^{-1}) were calculated from data sampled continuously by the RAMSES sensors, whilst collecting the water samples, with the newly installed rig on the Hamar office boat. The data was filtered for QA based on the ratio between 750 nm/550 nm. If the ratio was above 1, the spectra was excluded. In general, reflectance data collected in Mjøsa looks good, but the magnitude is in the lower range, which is expected when the waters are clear (Figure 15). The shapes of the spectra show some differences between stations and days, indicating that there are differences in the optical parameters across the lake. The R_{rs} data from the dedicated match-up campaigns are presented as separate figures so that the variability within the lake, i.e. per station can be seen (Figure 16A, B, C and D). The bump around 680 nm is likely a combination of a chl-a fluorescence peak and chl-a absorption.

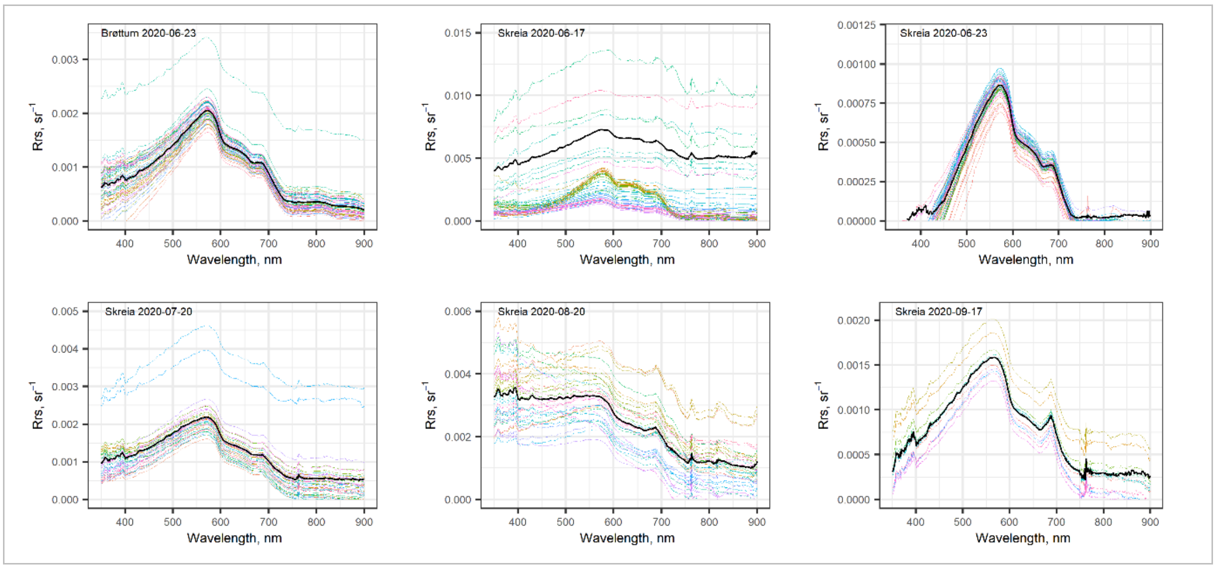

Figure 15. *In-situ remote sensing reflectance data between 350-900 nm at different stations and dates from 2020, sampled during monitoring campaigns. The black line represents the average R_{rs}.*

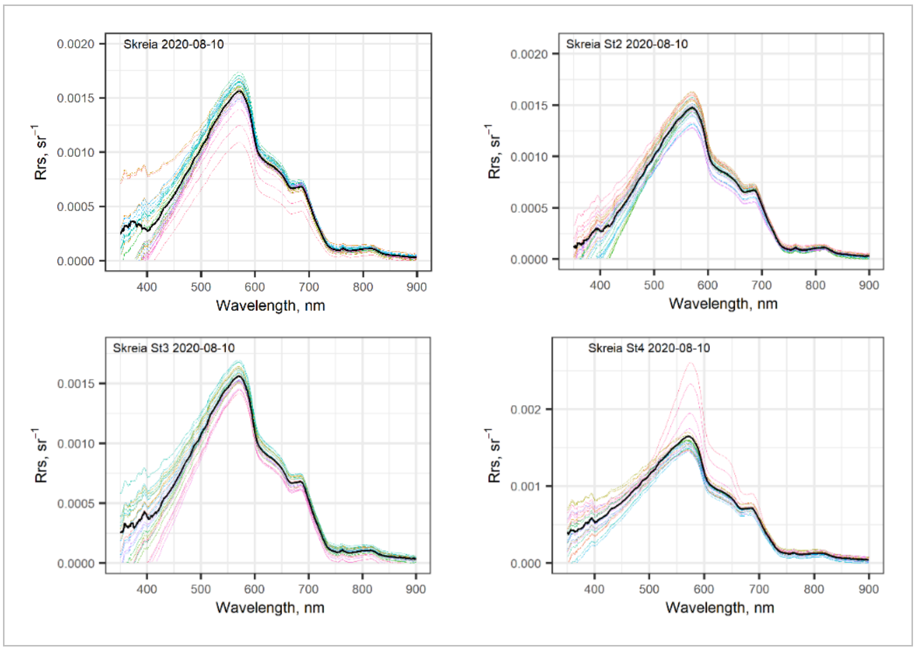

Figure 16A. *In-situ remote sensing reflectance data between 350-900 nm at different stations on 2020-08-10. The black line represents the average R_{rs}.*

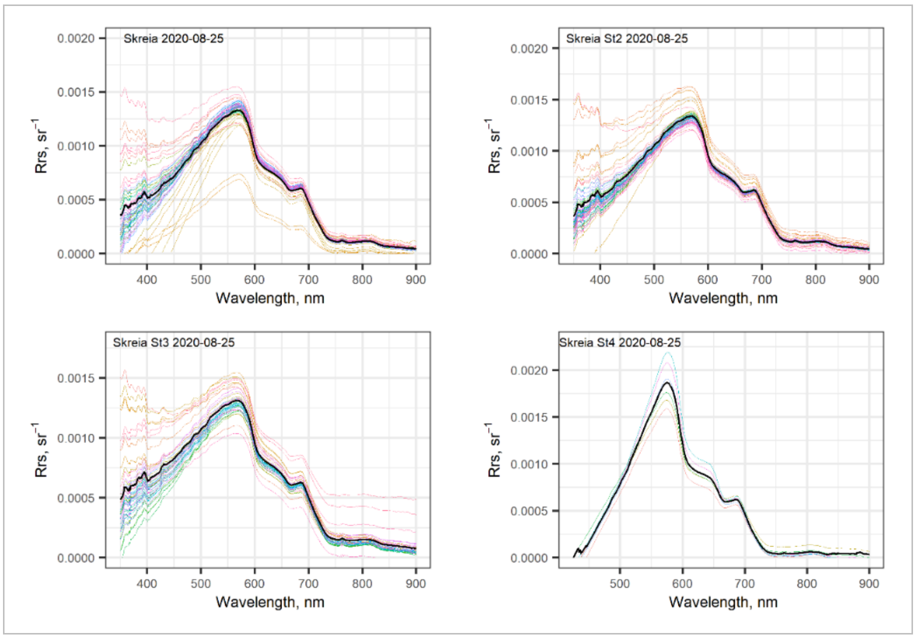

Figure 16B. *In-situ remote sensing reflectance data between 350-900 nm at different stations on 2020-08-25. The black line represents the average R_{rs}.*

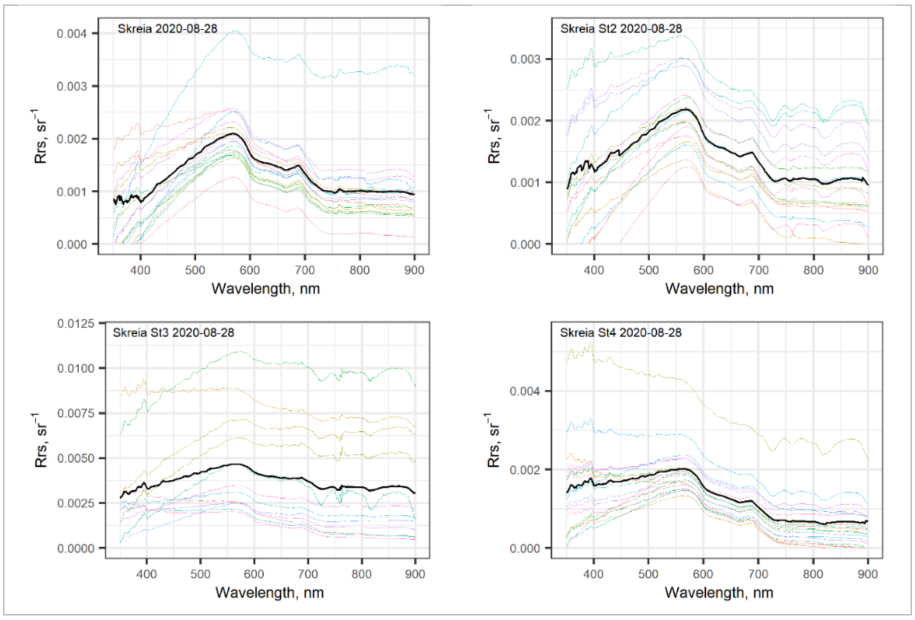

Figure 16C. *In-situ remote sensing reflectance data between 350-900 nm at different stations on 2020-08-28. The black line represents the average R_{rs}.*

Figures 16A-C represent transects from Skreia towards land and figure 16D shows a more coastal transect at Tangen. At Tangen St3 it seems to be some noise or 2 different types of waters that was measured during the transect, as the reflectance data shows two different peaks, possibly due to drifting of the boat.

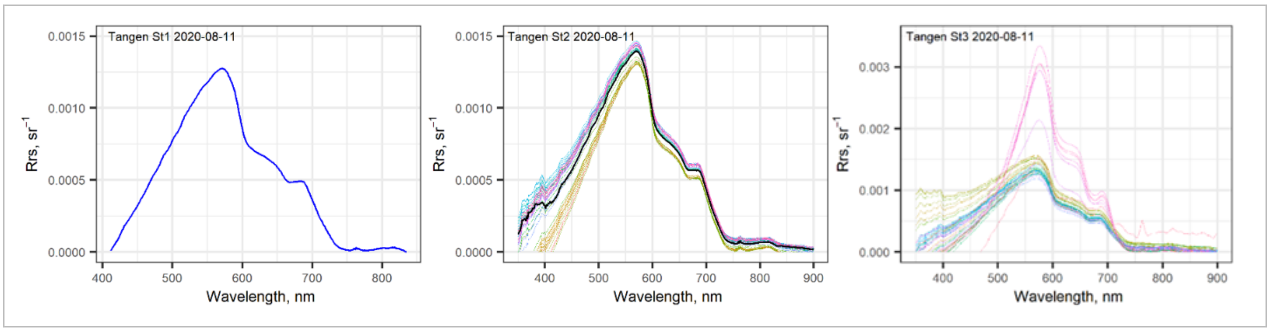

Figure 16D. *In-situ remote sensing reflectance data between 350-900 nm at different stations on 2020-08-11. The black line represents the average* R_{rs}.

The total absorption, attenuation and backscattering from the ac9 measurements in surface waters between May to September 2020 are presented in Figure 17. The difference between June and August is mostly seen at station Brøttum, but the differences between months can also be seen at Skreia. At station Skreia 2 on 16/6-2020 all values are higher, which would need an extra evaluation for an explanation, it could e.g. be more particles in the water or a faulty measurement.

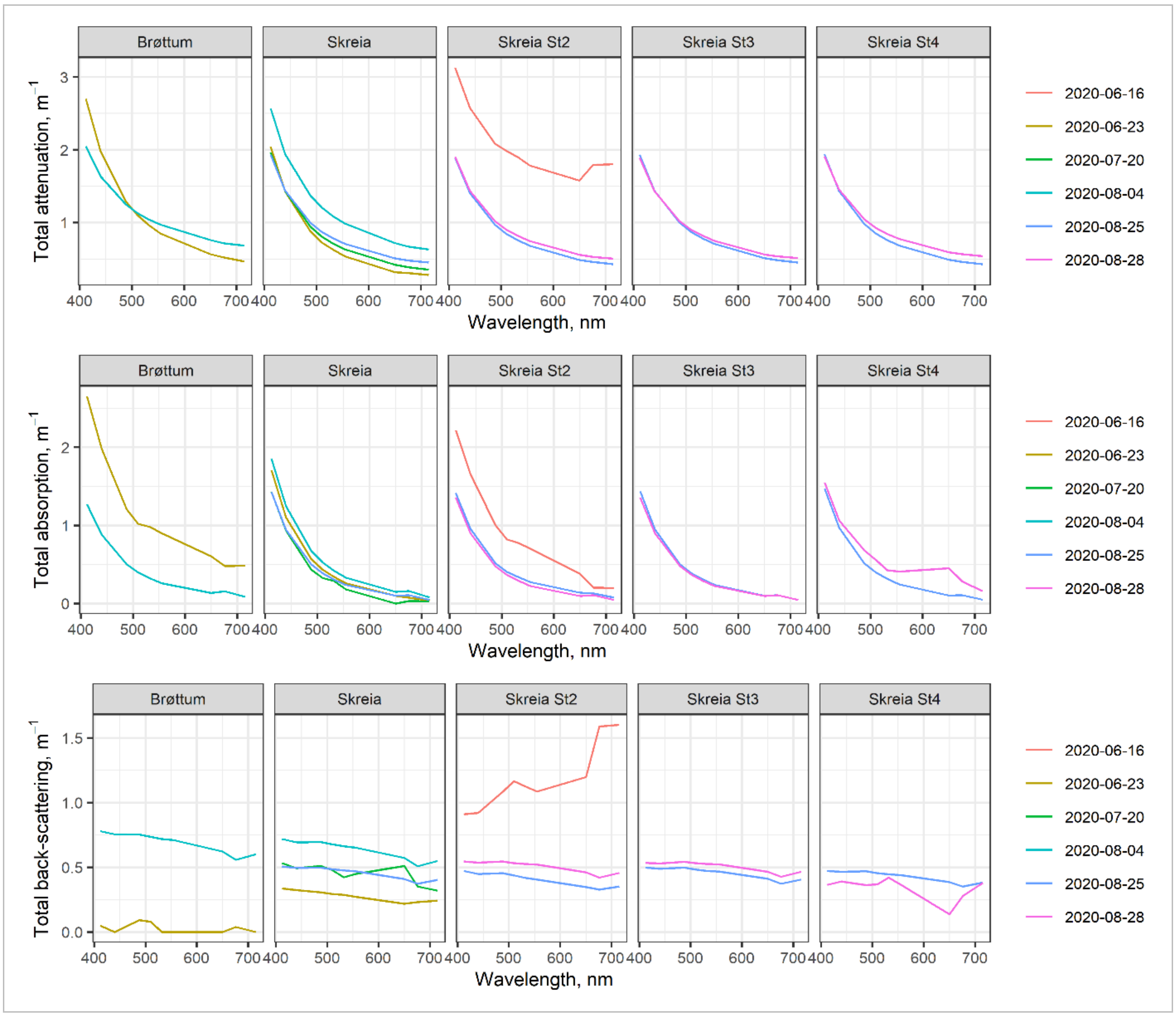

Figure 17. *Total absorption (*a_{tot}*),* m^{-}*, total attenuation (c),* m^{-1} *and backscattering (bb),* m^{-1} *from ac9 data per wavelength, nm (x-axis) from each station within Mjøsa. Each line represents a different date.*

3.2.6 Remote sensing data

Sentinel 2 and Sentinel 3 time-series and reflectance data are presented for Mjøsa. The other lakes were analysed, and the data was quality assured and used for the chl-*a* status assessment quality in Chapter 4, but the individual time-series are not presented here.

3.2.7 Time-series of chlorophyll-*a* in Lake Mjøsa

Lake Mjøsa is covered by two different tiles of Sentinel-2 data so the downloading and processing were done separately for the southern and the northern part. In total 335 Northern scenes and 326 Southern scenes between 1 April to 30 Sep. 2017-2020 where downloaded and processed for Sentinel 2 A and B. Out of those 28-32 scenes were selected for further analyses, based on their cloud cover, reflectance spectra, and outliers defined as; chl-*a* values above 25 µg/l, TSM above 30 mg/l and Euphotic depth above 15 m. Either Sentinel 3 A or B passes Mjøsa every day and on some days both do. In total 1150 scenes between 1 March to 31 Oct. 2017-2020 were downloaded and processed for Sentinel 3 A and B and 12.7 %- 19.4% scenes (147-223) were used for further analyses based on the same quality criteria as for Sentinel-2. Cloud cover is the most common reason for excluding a scene.

The phenology of the chl-*a* concentrations at station Brøttum (Figure 18) station Skreia (Figure 19A) from in-situ measurements (open circles) aligns in general very well with the S2 data (black circles) and is capturing the seasonal variation well. Some S2 observations overestimate the chl-*a* concentrations, which might be due to a to high signal-to-noise ratio. However, both the dedicated match-up surface samples in 2020 (marked as red triangles in the figure) and the monitoring mix-sample data show higher concentrations than the S2 data (Figure 19B and 19C). For sentinel-3 data the results for Brøttum (Figure 20A) are similar, although it seems like Sentinel 3 capture higher chl-a concentrations both in spring and during autumn due to more days of observations than both Sentinel 2 and in situ data. This is also seen for station Skreia (Fig. 20B), but 2019 shows variable results. In the figures the error bars for the in-situ data represents a general 20 % error of the method but the variability is usually higher during spring and autumn. For the RS data the standard deviations from the pixels are used. Time series for stations Furnesfjorden and Kise but without match-up data are found in Appendix A.

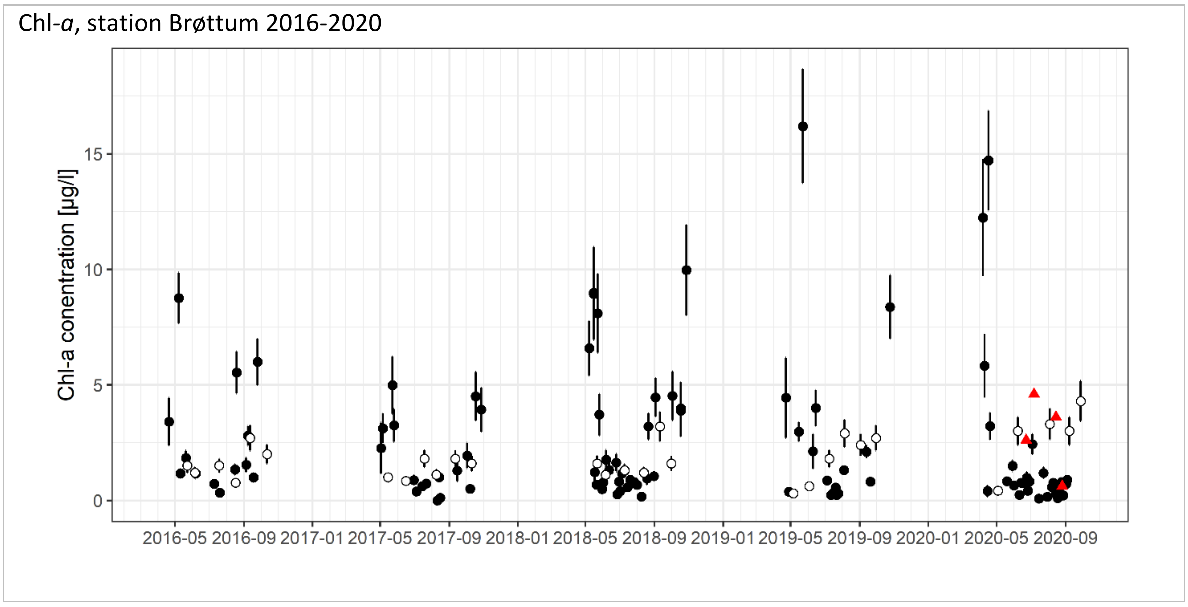

Figure 18. *Time-series Sentinel 2 chl-a and in situ data for Brøttum in Mjøsa from 2016-2020. The black circles show the Sentinel 2 data and the open circles the in-situ data taken by a mix-sample sample from the surface down to 10 m depth. The red triangles are surface samples from 0.5 m depth, collected during the current project in 2020.*

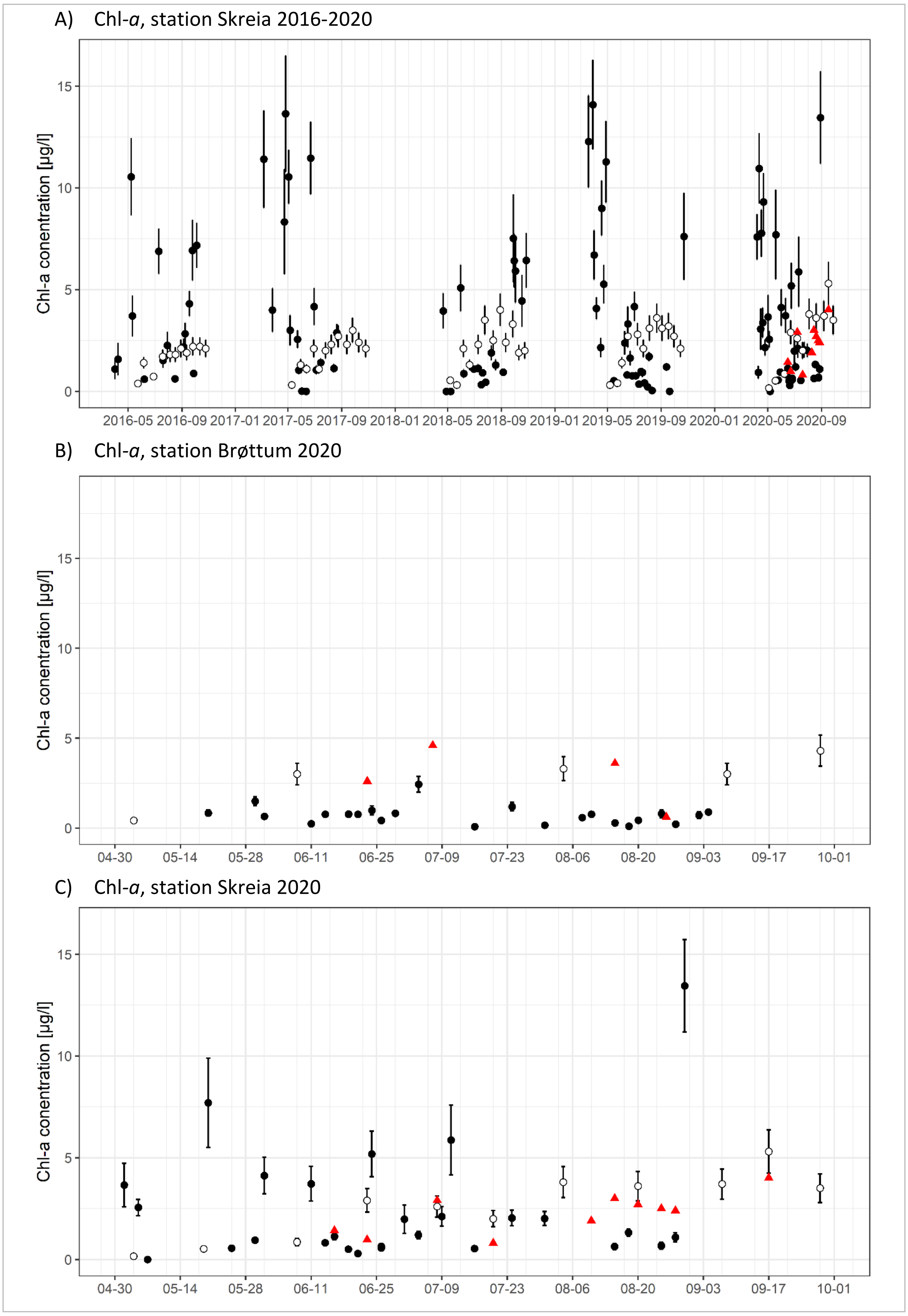

Figure 19. A*: Time-series Sentinel 2 chl-a and in situ data in in Mjøsa for station Skreia 2016-2020, B: Time-series of chl-a for station Brøttum from April to September 2020, C: Time-series of chl-a for station Skreia in Mjøsa from April to September 2020. The black circles show the Sentinel 2 data and the open circles the in-situ data taken by a mix-sample from the surface down to 10 m depth. The red triangles are surface samples from 0.5 m depth, collected during the current project in 2020.*

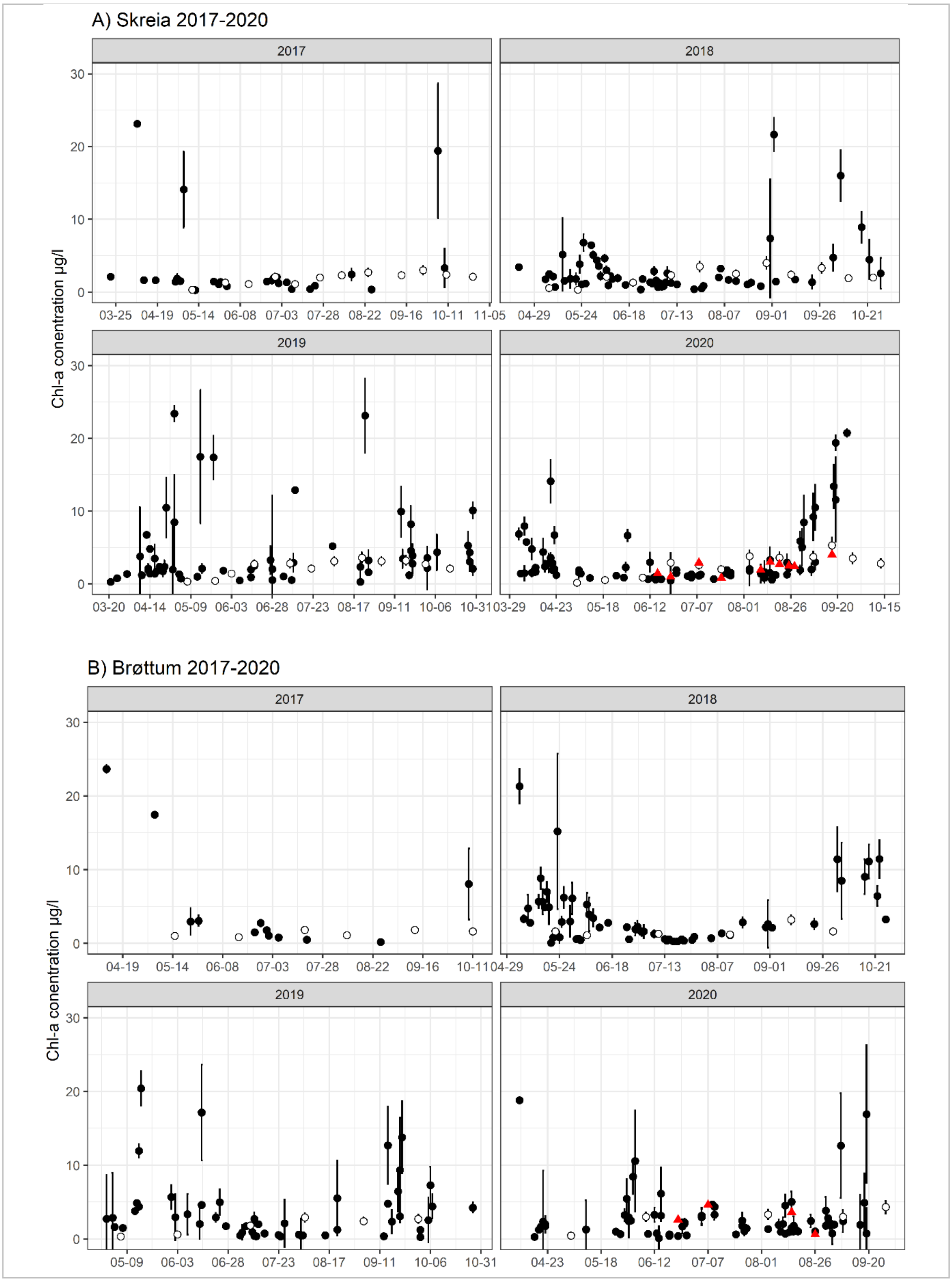

Figure 20. *Time-series of Sentinel 3 chl-a and in situ data in Mjøsa for A) station Brøttum and B) station Skreia from March to October 2017-2020. The black circles show the Sentinel 3 data and the open circles the in-situ data taken by a mix-sample from the surface down to 10 m depth. The red triangles are surface samples from 0.5 m depth, collected during the current project in 2020.*

3.2.8 Sentinel 2 reflectance data 2020

Remote sensing reflectance from Sentinel 2 is important to study as it is one of the main inputs to the C2RCC algorithm. The data for Brøttum (Figure 21) shows a general good pattern over the seasons while some data seems to be erroneous with high R_{rs} values in the blue wavelengths. For Skreia the data shows a similar pattern (Figure 22).

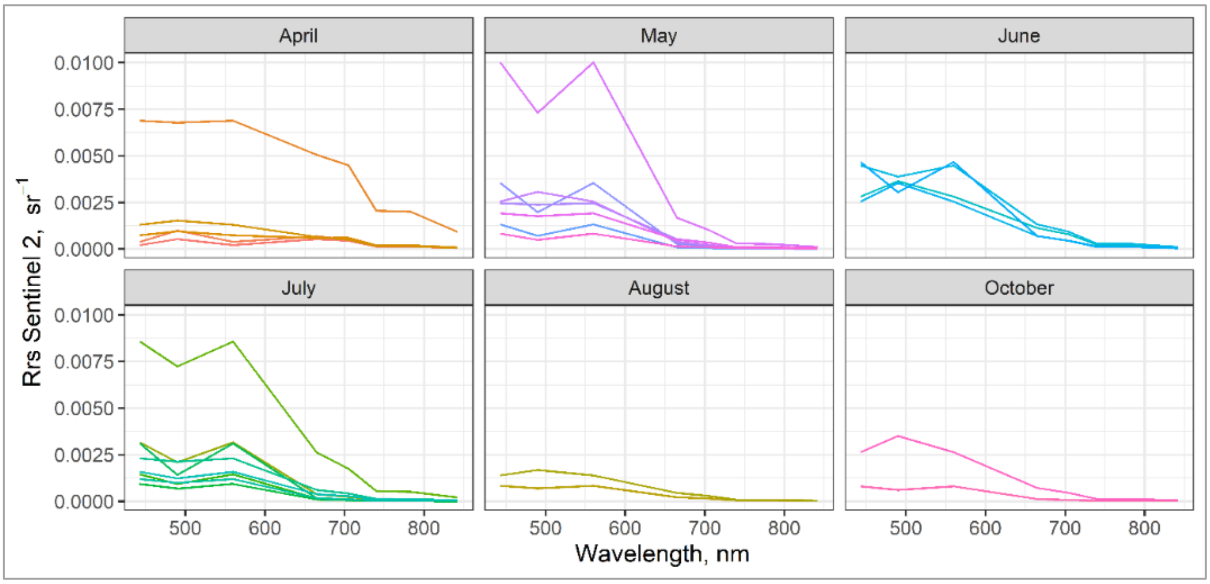

Figure 21. *Remote sensing reflectance data,* R_{rs} *sr*$^{-1}$*, from Sentinel 2, C2RCC, April to October at station Brøttum 2020. The different lines for each month represent different days.*

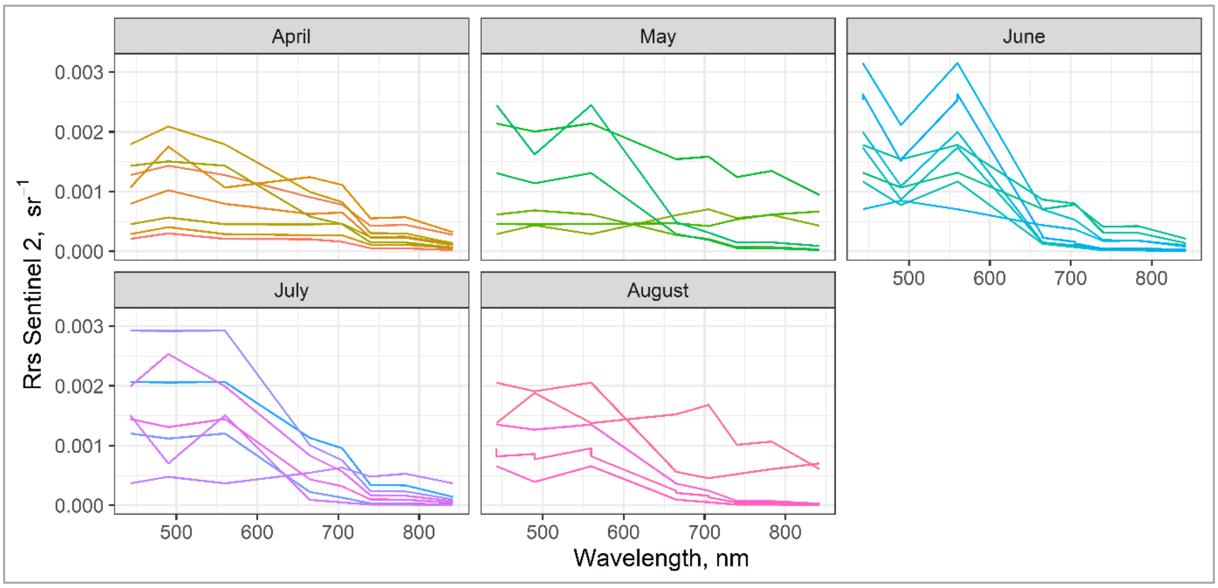

Figure 22. *Remote sensing reflectance data,* R_{rs} *sr*$^{-1}$*, from Sentinel 2, C2RCC, April to October at station Skreia 2020. The different lines for each month represent different days.*

4 Chl-*a* status classification *sensu* WFD

4.1 Remote sensing integrated chlorophyll-*a* concentration

Sentinel 2

All available scenes of Sentinel 2A and 2B, between 1 May to 30 September, were downloaded and processed with the C2RCC algorithm (Brockmann et al., 2016 and Ledang et al., 2019) for each lake between 2017-2020 and for Mjøsa between 2016-2020. Mjøsa, Femunden and Røssvatnet are relatively large and in order to have a full coverage over the lakes, two different tiles of Sentinel 2 data need to be processed, doubling the amount of time and storage needed to obtain all the relevant Sentinel 2 data to be for the analyses. The other three lakes, Gjende, Selbusjøen and Snåsavatnet are all covered by one Sentinel 2 tile. The maximum number of scenes covering each lake ranged between 292 (Gjende) and 377 (Røssvatnet north), depending on the revisiting times, average cloud cover, placements (e.g. adjacency effects or mountain shadow) and latitude (Table 3). Although the number of scenes is high the number of pixels used for the average chl-*a* concentration and status classification ranged between 4.1% to 17.5%. The lowest value was attributed to Gjende (Table 3a) which seems to be a major challenge for retrieving RS data with high adjacency effects from the mountains and possibly scattering from the sediments. In Figure 23 and 24 this is seen by large areas with many pixels filtered out and thus without data for Gjende. The most probable reason is that it is surrounded by high mountains, which interfere with the water leaving reflectance.

Table 3a. *S2 C2RCC data used in this study for each lake between May-September 2016/7-2020*

	Scenes	Scenes used			Total pixels	Pixels used	
Lake	**processed**	**min**	**mean**	**max**	**n**	**n**	**%**
Mjøsa north	341	1	**97**	**127**	379 712	34 576	9.1
Mjøsa south	335	1	82	112	280 924	49 135	**17.5**
Gjende	292	2	64	75	21 720	891	**4.1**
Selbusjøen	369	1	41	94	62 460	9 871	15.8
Røssvatnet north	377	1	54	87	24 190	30 711	12.7
Røssvatnet south	366	1	53	83	242 190	31 748	13.1
Snåsavatnet	371	1	46	77	182 245	25 275	13.9
Femunden north	363	1	**38**	68	177 366	26 380	14.9
Femunden south	326	1	39	72	177 366	27 622	15.6
Average (Gjende excluded)			**59**				

All valid pixels were binned, and an integrated chl-*a* value was calculated between 1 May to 30 September for all years for each of the six lakes (Figure 23). The averaged spatial distribution of the lakes is clearly seen as well as areas with higher concentrations connected to e.g. river inflows. RS data from October was excluded as the sun angle may be too low to retrieve reliable data.

Sentinel 3

Also all available scenes of Sentinel 3A and 3B, between 1 May to 30 September, were downloaded and processed with the C2RCC algorithm (Brockmann et al., 2016 and Ledang et al., 2019) for each lake between 2017-2020. All six lakes are covered in one Sentinel 3 tile. The maximum number of scenes covering each lake ranged between 1016 (Femunden) and 1756 (Selbusjøen), depending on the revisiting times, average cloud cover, placements (e.g. adjacency effects or mountain shadow) and latitude (Table 3b). The spatial resolutions are compensated by the higher visiting time with between 64 to 79% more available scenes for Sentinel 3 are than for sentinel 2. The spatial binning for each lake was only made for Sentinel 2 data so the number of pixels used was not estimated for the Sentinel 3, however the value will be less than for Sentinel 2 data, as the resolution is lower. The lowest number of observations was attributed again to Gjende (Table 3b) with only 10 scenes used after filtration, which is 540% less than for Sentinel 2. Here we can see that Sentinel 3 has major challenged retrieving data whereas for all other lakes than Femunden (63% less than Sentinel 2) Sentinel 3 provides between 22-61% more observations than Sentinel 2.

Table 3b. *S3 C2RCC data used in this study for each lake between May-September 2017-2020*

Lake	Scenes prosessed	Scenes used	Percentage difference to S2	
			Available	Used
Mjøsa, Skreia	1150	159	70	43
Gjende	1029	10	72	-540
Selbusjøen	1756	77	79	47
Røssvatnet	1626	69	77	22
Snåsavatnet	1591	117	77	61
Femunden	1016	24	66	-63
Average		**79**		

4.2 Chlorophyll-*a* status classification

The chl-*a* status for each pixel in every lake was assessed by comparing the integrated chl-*a* value to the thresholds based on the defined water type definitions and according to the method described in 'Vanndirektivet 2018. Veileder 02:2018 Klassifisering av miljøtilstand i vann' (Direktoratsguppen, 2018). According to the method shall all indexes be based on a minimum of monthly observations during the growth season, i.e. 6 samples between May and October in the southern Norway and four observations between June and September in Northern Norway, north of Saltfjellet. The status value for chl-*a*, EQR are calculated as:

$$EQR_{Chla} \frac{Chla_{ref}}{Chla_{Obs}}$$

Where chl-a_{ref} is the pre-defined reference value for that waterbody or lake and chl-a_{Obs} is the observed averaged chl-*a* concentration. The parameter value, chl-a_{Obs} are then compared to the specific class boundary value for High, Good, Moderate, Poor or Bad classes for the current water type of the lake. The class the EQR value falls within defines the status classification (Direktoratsguppen, 2018). The EQR were calculated for 1) the average of all pixels covered by the lake for Sentinel 2 data, 2) the monitoring stations based on the average chl-*a* value derived from Sentinel 2 and Sentinel 3 RS data by pixel extraction and 3) the in-situ data at each monitoring station based on the average in-situ chl-*a* values. Data between May-September from 2016-2020 and 2017-2020 was used for the Sentinel 2 RS derived EQR average values and for Sentinel 3 the data from May-September 2017-2020 was used (Table 4a & 4b). The in-situ data observations were between May-October 2016-2020. The standard deviation was calculated based on yearly average data for in-situ samples and pixel variability for the RS data. The standard deviation for the full lake average is based on all pixels used, also presented in Table 4.

The chl-*a* status classification of the lakes was compared to the lake specific chl-*a* threshold limits for each class and divided in the corresponding class depending on the chl-*a* value, and the calculations were done in different ways. First, pixel by pixel assessment of the Sentinel 2 RS data, providing a spatial map of the classification within each lake (Figure 24). This illustrates that the classes are distributed differently over the lake, either with separate basins or areas or differences between the coastal and open sea waters. Secondly the chl-*a* average was calculated for *1)* the full lake based on

Sentinel 2 RS data and *2)* 3 by 3 pixels around each monitoring station based on Sentinel 2 or Sentinel 3 RS data and *3)* for each monitoring station based on in-situ monitoring data.

Table 4a. *Status classification of the lakes based on all pixels from Sentinel 2 compared to in-situ observations. The average chl-a concentrations are presented for Sentinel 2 data of the whole lake and per station and the in-situ data per station with standard deviation in brackets and italics, [µg l⁻¹] (stdev, µg l⁻¹).*

	Chl-*a* S2 average Lake		**Chl-*a* average stations**				**Status S2 mean Lake**	**Status average stations**	
			S2		**In-situ**				
Lake	**µg l⁻¹**	***StDev***	**µg l⁻¹**	***StDev***	**µg l⁻¹**	***StDev***	**S2**	**S2**	**In-situ**
Mjøsa, Skreia	**1.93**	*0.62*	**2.37**	*0.26*	**2.44**	*0.51*	High	Good	Good
Gjende	**na**	*na*	**3.07**	*0.76*	**1.17**	*0.34*	NA	Mod.	High
Selbusjøen	**2.60**	*1.01*	**2.13**	*0.48*	**0.96**	*0.19*	Good	Good	High
Røssvatnet	**3.05**	*1.06*	**5.06**	*0.83*	**0.34**	*0.03*	Good	Mod.	High
Snåsavatnet	**3.95**	*1.52*	**4.91**	*0.10*	**0.94**	*0.20*	Good	Mod.	High
Femunden	**4.01**	*2.02*	**6.77**	*0.18*	**0.70**	*0.18*	Mod.	Mod.	High
Mjøsa other monitoring stations									
Brøttum			1.58	*0.31*				High	
Furnesfjorden			1.78	*0.11*				High	
Kise			1.32	*0.19*				High	

Table 4b. *Status classification of the lakes based on all pixels from Sentinel 3 compared to in-situ observations. The average chl-a concentrations are presented for Sentinel 3 per station and the in-situ data per station with standard deviation in brackets and italics, [µg l⁻¹] (stdev, µg l⁻¹).*

	Chl-*a* average stations				**Status average stations**	
	S3		**In-situ**			
Lake	**µg l⁻¹**	***StDev***	**µg l⁻¹**	***StDev***	**S3**	**In-situ**
Mjøsa, Skreia	**3.03**	*0.98*	**2.44**	*0.51*	Good	Good
Gjende	**1.19**	*0.41*	**1.17**	*0.34*	High	High
Selbusjøen	**3.07**	*1.72*	**0.96**	*0.19*	Good	High
Røssvatnet	**1.54**	*0.34*	**0.34**	*0.03*	High	High
Snåsavatnet	**5.70**	*0.91*	**0.94**	*0.20*	Mod.	High
Femunden	**6.49**	*2.01*	**0.70**	*0.18*	Mod.	High
Mjøsa other monitoring stations						
Brøttum	3.21	*1.11*			Good	
Furnesfjorden	3.49	*1.79*			Good	
Kise	2.39	*0.92*			Good	

The 2 first methods (i.e. RS data) class boundaries and averages were compared to the last method (i.e. in-situ monitoring data), presented in Table 4. For the full lake assessment based on Sentinel 2 RS, the status was defined as 1 class higher for Mjøsa (Skreia) and one lower for Selbusjøen. The Sentinel 2 RS data from the same station location were in the same class for Mjøsa (Skreia) and one class lower for Selbusjøen. For Gjende, the RS status was based on data approximately 600 m west of the monitoring station as there were no valid data from the same coordinates as the station and the assessment for the full lake was excluded as the retrieval was not optimal for the lake, and would need to be studied more detailed for a proper evaluation, e.g. if some specific adjacency effect filters can be applied. The assessment for the monitoring station of RS data was 2 classes lower than the in-situ samples (Table 4a). The classifications based on the Sentinel 3 data were more aligned with the in situ monitoring datasets and much improved for Gjende and Røssvatnet, classified in the same class (Table

4b). For direct comparisons between a station the amount of data is based on the days of observations, where Mjøsa had 59 in-situ observations and 90 observations from Sentinel 2 and 159 from Sentinel 3, which is almost twice and three times as many days with observations. For Selbusjøen the number of observations were 29, 41 and 77, respectively. The number of RS observations was more than 3 times higher than from in-situ (64 compared to 19 observations) in Gjende for Sentinel 2. For Røssvatnet, Snåsavatnet and Femunden the differences between the in-situ and RS were larger with lower status for both Sentinel 2 and 3 data. In these 3 lakes the number of observations for Sentinel 2 was an order of magnitude greater than those from in-situ measurements, making direct comparison difficult (Table 4 and 5). However, when using about 85 000 observations compared to 59 observations (every Sentinel 2 pixel used for Mjøsa) and almost 10 000 observations compared to 29 for Selbusjøen, differences are to be expected. Perhaps direct comparisons like this should be avoided as it does not provide the same type of data (Table 3 and 5 and Figure 25). Nevertheless, can data from Sentinel 2 and 3 be used to fill out the days in-between sampling days, and provide better knowledge on the variations over time.

Table 5. *Data used for status classification. There were no data for Røssvatnet, Snåsavatnet and Femunden from other years than 2020. The amount of days with an observation (n observations) is equivalent to an in-situ sample or a RS scene from one day. The average number per year is presented in italics in brackets.*

	Years, months			**n observations**		
Lake	**In-situ**	**Sentinel 2**	**Sentinel 3**	**In-situ**	**Sentinel 2**	**Sentinel 3**
Mjøsa, Skreia	5 (2016-2020), May-Oct	5 (2016-2020), May-Sep	4 (2017-2020), May-Sep	59 (*11.8*)	90 (*18*)	159 *(55)*
Gjende	5 (2016-2020), May-Oct	4 (2017-2020), May-Sep	4 (2017-2020), May-Sep	19 (*3.8*)	64 (*16*)	10 *(2.75)*
Selbusjøen	5 (2016-2020), May-Oct	4 (2017-2020), May-Sep	4 (2017-2020), May-Sep	29 (*5.8*)	41 (*10.25*)	77 *(26.25)*
Røssvatnet	1 (2020), June-Oct	4 (2017-2020), May-Sep	4 (2017-2020), May-Sep	5	54 (*13.5*)	69 *(18.5)*
Snåsavatnet	1 (2020), May-Oct	4 (2017-2020), May-Sep	4 (2017-2020), May-Sep	6	46 (*11.5*)	117 *(55.5)*
Femunden	1 (2020), June-Sept	4 (2017-2020), May-Sep	4 (2017-2020), May-Sep	4	39 (*9.75*)	24 *(6)*

The chl-*a* averages were higher from Sentinel than in-situ for all lakes, except for Sentinel 2 in Mjøsa and Sentinel 3 in Gjende (Table 4 and Figure 25). The comparison at station Skreia and Gjende are very good whereas the differences are larger for Selbusjøen. Selbusjøen has quite low chl-*a* values and low turbidity, and the cDOM absorption was the second highest for all lakes. The total absorption was also quite high and the scattering low. The high cDOM and the low scattering make it more difficult to retrieve a strong R_{rs} signal at the satellite sensor, which increases the uncertainty associated with the chl-*a* estimate. High cDOM is also known to affect the algorithms so that the chl-*a* is more easily overestimated, which can have affected the results in Selbusjøen. In Gjende the differences were smaller, but the large variation in observed values makes it difficult to evaluate potential sources of difference. The difference in chl-*a* for Røssvatnet, Snåsavatnet and Femunden was large but the amount of data is not equivalent. A better assessment would be to only include the data from 2020 from Sentinel 2 as any possible interannual variability is not captured by the in-situ data but can have been included in the Sentinel 2 data set. However, with so few in-situ measurements the uncertainty of the in-situ data is very high. For Gjende the spectral resolution was better with Sentinel 3, but even fewer days could be retrieved due to the lower spatial resolution over the narrow lake. Studies of the bi-weekly or monthly average from all the years from the Sentinel data could help reveal a more detailed picture of the variability within those less frequently sampled lakes.

One of the main questions is how the RS data should be applied. Should we look upon it with the same eyes as the in-situ data, which is represented by about 1 L of water from a whole lake or by using the signal from the top layer (i.e. half Secchi depth) of the whole water body? For water quality status classifications, it important that the actual status is correct as management are dependent on the results. Overestimated chl-*a* values from RS data will make actual assessment less accurate. However, for lakes that are so seldom measured or not measured at all the use of RS data is an invaluable source of information. It would provide the temporal and the spatial dynamics of the lakes and at their monitoring stations. If chl-*a* after more in-situ data is collected, and preferably from the surface down to 0.5 m, it appears that chl-*a* concentrations still are biased, then one could test new algorithms, adjust existing algorithms or simply apply a correction factor when the amount of the bias is known. Once such a relationship is established for one lake it is possible to process the RS data and analyze the actual variability in the chl-*a* concentrations. It would also be possible to apply similar relationships to similar kind of lakes, i.e. turbid, clear, high in humic substances, glacial inputs etc.

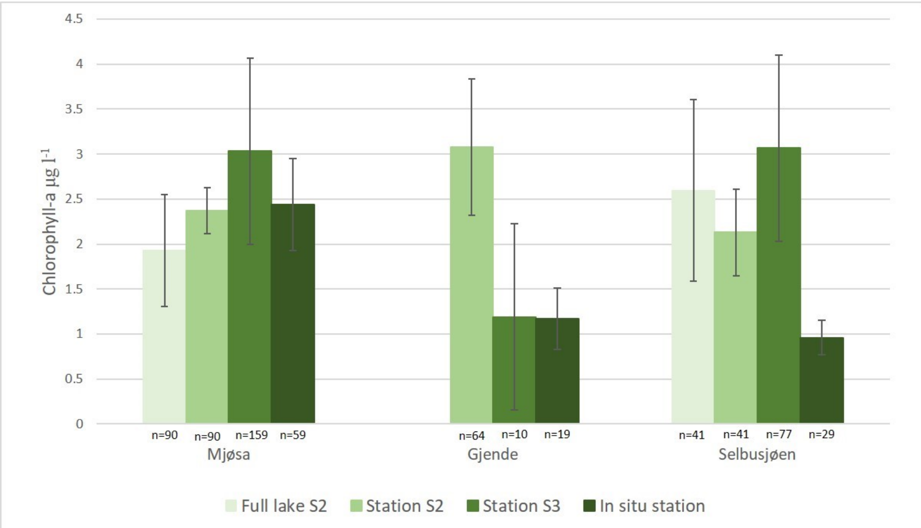

Figure 25. *Comparison between the average chl-a values used to calculate the EQR values at station Skreia in Mjøsa, Gjende and for Selbusjøen. The in-situ data are based on a mix-sample sample between 0-10 m. n stands for number of days with observations.*

Evaluation of the surface in-situ match-up samples for status assessment could improve the results as they e.g. for Snåsavatnet seems to be higher than the mix-sample and would therefore be more aligned with the RS data. In Ledang et al. (2019) it was shown that surface chl-*a* samples from 0.5 m depth corresponded better with RS data than the mix-sample. The surface samples usually represent the conditions that affects the reflectance reaching the satellite to a higher degree. The 'depth eye' of the satellite sensor depends on how deep the light reaches in the water column, and a rule of thumb that about 90% of the signal comes from half the Secchi depth. For these lakes that would mean somewhere between 3-5 m depth or as much as 7-8 m and for periods with up to up to 16 m Secchi depth. The integrated data reaching the satellites will rarely represent depths up to 10 m, which would require a Secchi depth of 20 m.

Another factor can be the difference found for the conversion factors/algorithms used to calculate the chl-*a* concentrations from the chl-*a* absorption (preliminary results shown in Figure 8B). The Chl-a data of the Sentinel data from the in-situ data is most often higher and could then be explained by this relationship, where the algorithm (C2RCC) used today would provide chl-*a* values 2-4 times higher than with the preliminary relationship based on the data from this study. If more suitable conversion factors/algorithms were used the chl-*a* values would likely be better approximate the in-situ data.

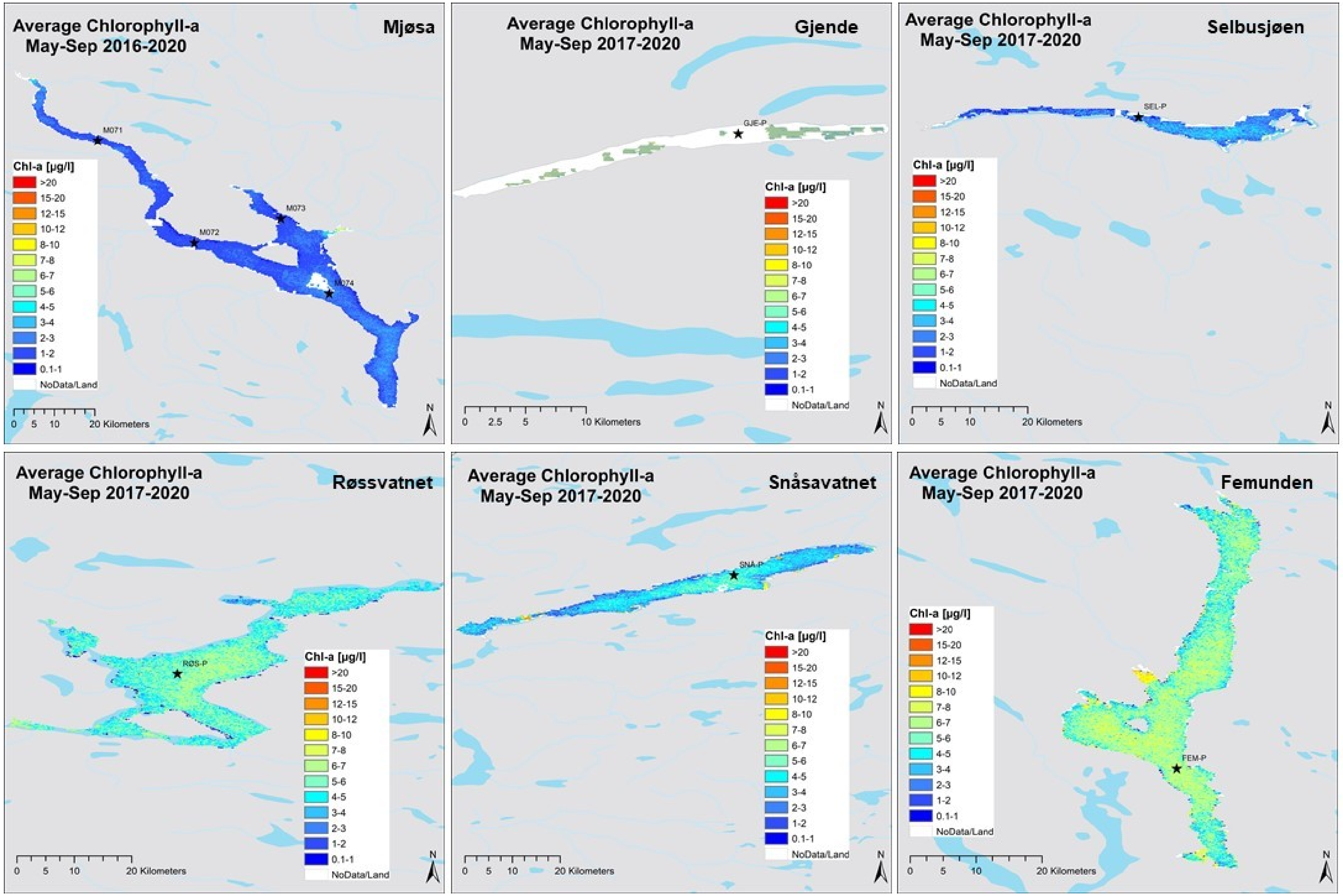

Figure 23. *Maps showing the 4- or 5- year chl-a average for each lake based on Sentinel 2A and 2B data. The placement of the monitoring stations within the regular program are showed with a black star.*

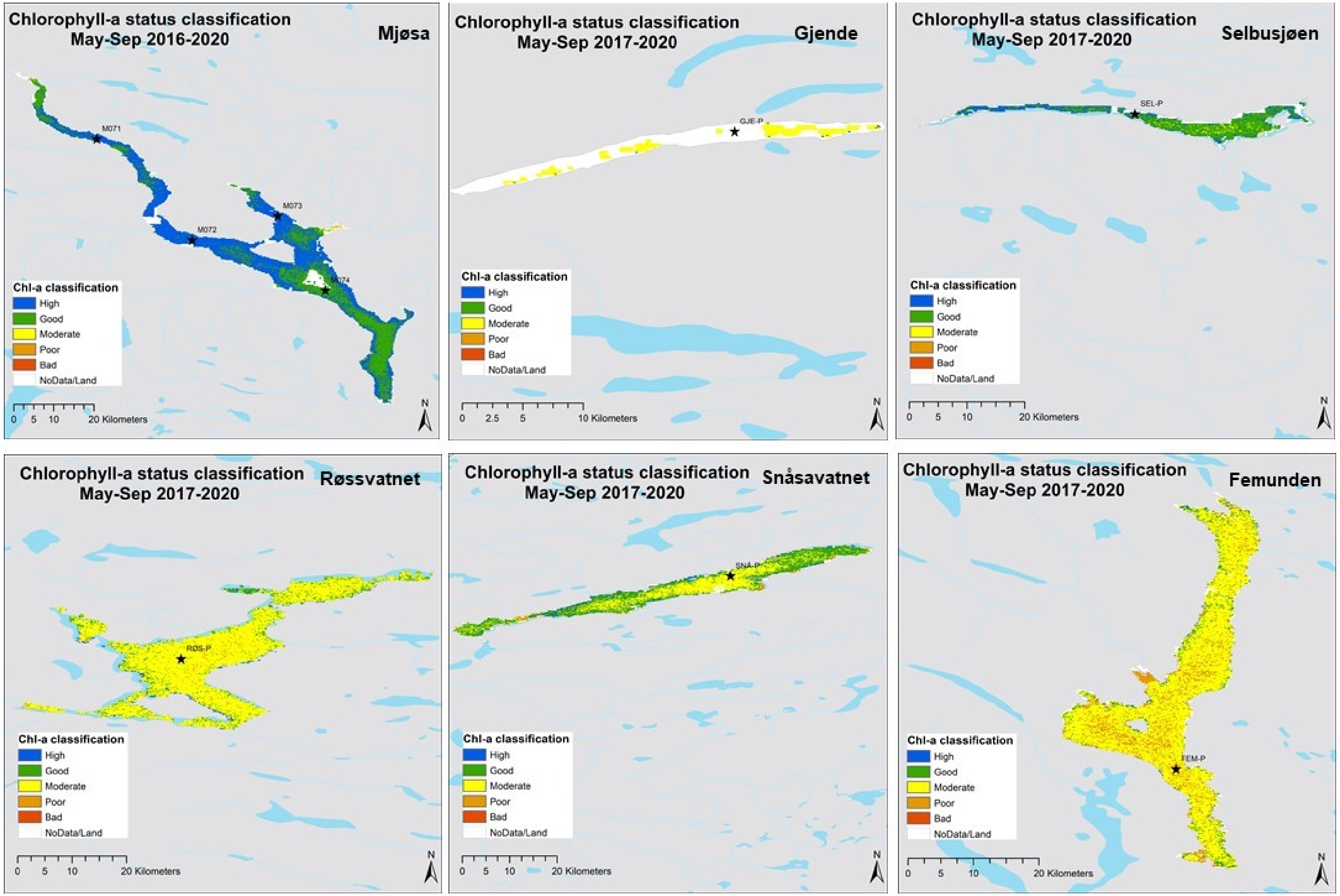

Figure 24. *Maps showing the 4- or 5- year chl-a status classification for each lake based on Sentinel 2A and 2B data. The placement of the monitoring stations within the regular program are showed with a black star.*

5 Future perspectives and research needs

The status of the lakes determined from Sentinel 2 data when using all available pixels are slightly worse than the classifications derived from in-situ data. This might be because there are more data included from near shore areas or areas of the lake where there is a higher inflow from land, leading to higher chl-*a* values. It could also be due to a bias in the RS products leading to an overestimation by the algorithm, caused by incorrect reflectance spectra e.g. caused by mountain shadows, strong scattering, bottom reflectance or adjacency effects or incorrect conversion factor for calculating the chl-a concentration. This could be solved by setting stricter maximum chl-*a* criteria for inclusion in the binned product based on the known variability within the lake. Another possibility is to buffer out the pixels that are close to land, and thereby assess only the ‘core’ open part of the lake. It was seen that some of the lakes also had very high cDOM absorption, that also can lead to overestimations of chl-*a*. For these lakes other RS algorithms might perform better.

However, comparing the chl-*a* average based on all pixels of a full lake area to the chl-*a* average based on in-situ data from one monitoring station is not very suitable. The average from the full lake captures all the variations taking place in the different areas within the lake, whereas the monitoring station represents one basin or the open part of the lake. Instead, the spatial information gained from the RS data should be utilised to a larger extent within the monitoring program to add another layer for understanding the dynamics of the lakes. The spatial and temporal information is very valuable for studies of e.g. the possible drivers of change, connected to e.g. temperature, rainfall, river inflow, snowmelt in spring, ice thawing and glacial run-off, when applicable. By placing the observations in a larger context, the knowledge of possible changes will be better known, and the understanding of the systems will improve, especially for lakes that are remote and/or seldom sampled. The RS data can also be used to study the differences between basins within one lake, e.g. the temporal variation of chl-*a* within each basin or if they are optically different, like the differences between e.g. the area around station Brøttum, Furnesfjorden and the area around station Skreia in Mjøsa. Further, RS data can provide a higher temporal resolution for lakes that are sampled bi-weekly during the summer season and reveal more insight into ecosystem dynamics.

Direct comparison between stations can be studied for lakes that have substantial in-situ data sets. Where there are differences between in-situ and RS estimates, and when they can be quantified in a systematic way, correction factors can be applied. We now have a better understanding of the lake’s optics and improvement of the algorithms should also be possible as a natural next step. This would e.g. be a possibility for the results in Selbusjøen, and maybe Gjende, although the in-situ data is presently limited for such an analysis. It becomes more difficult for lakes where the in-situ data are scarce and differences between the methods are great (Røssvatnet, Snåsavatnet and Femunden). For these types of lake, a 1-year comparison would be beneficial, so that the interannual variability is reduced, as well as dedicated tests of alternative or adjusted RS algorithms. One usual approach is to make a comparison for the same individual days or maximum of a few days difference instead of monthly means. The result from the study shows that the Sentinel 2 data for Røssvatnet, Snåsavatnet and Femunden (Table 4) overestimate to such a high degree that the use for chl-*a* status classifications presently cannot be recommended. The use of other atmospheric correction algorithms could improve the results and the full data set is processed with Acolite (Vanhellemont, 2019), but those results have not yet been analysed. Another way to improve the results can be to test how well the chl-*a* is in line with the in-situ data after tuning of the chl-*a* absorption coefficient in the algorithms. The empirical relationships between the chl-*a* concentration and the chl-*a* absorption based on the data that has been gathered for the lakes could be used to tune the C2RCC algorithm. Another factor affecting the results is the difference between the depth where the samples are measured and the depth to which the satellite measures. In clear lakes the signal reaching the satellite can come from as much as 10 m depth, and in such a situation the mixed-sample from the surface down to 10 m of the in-situ sample are more comparable than a surface sample from 0.5 m. Whereas, for a very turbid, euphotic or humic lake the depth of the RS signal is much less and the comparison to the 10 m mix-sample becomes problematic, such that corrections might be needed. But again, information of the changes and the relative variation would still be of high value and it should be possible to make generalisations for lakes that are not monitored in-situ but have similar conditions as other regularly monitored lakes.

Other products from the satellite sensors can provide highly valuable information of the lakes and their water quality. Secchi depth is a parameter that is included as a supporting parameter within the WFD. Different indicators of the light environment such as; 1) K_d(PAR)- Photosynthetic Active Radiation, i.e. the integrated light measurement between 350-700 nm; 2) the light attenuation coefficient (i.e. the reduction in light intensity as it travels through the water) and euphotic depth (Z_{eu}), (i.e. the depth in the water column, from the surface, where there is enough light for photosynthesis to occur) are all important factors to study in terms of e.g. coastal darkening or brownification (Frigstad et al., 2020).

5.1 Steps needed for an operational remote sensing service

To be able to fully incorporate remote sensing data into the Norwegian ecosystem monitoring program, it would be advisable to further test and tailor the algorithms to regional or local conditions. This could be achieved to some extent with the data set developed in this and previous projects, but that the work required work lies outside the scope of this project. A preliminary analysis of the relationship between chl-*a* absorption and chl-*a* concentration based on 2020 years data (Figure 8B) showed differences in the results based on different algorithms for that relationship. This is an important result as the algorithm used by C2RCC2 is based on the Sørensen et al. (2007) results from the North Sea and seems not to be as applicable to some of the lakes. The differences in the relationship between chl-*a* absorption and chl-*a* concentration is one example of why the retrieval of chl-*a* concentrations from satellites can be a challenge. Other parameters, such as suspended particles, turbidity, light attenuation (K_d) and Secchi depth, do not have these inherent uncertainties, but are based on more robust physical relationships and are therefore usually retrieved with higher accuracy than chl-*a* from the satellite sensors.

This project has gathered a substantial remote sensing and bio-optical in-situ data set that is not fully evaluated in terms of all the aspects mentioned above, as well as for time-series analyses for all lakes and other parameters than chl-*a*, e.g. Secchi depth, Kd (light), euphotic depth, turbidity, cDOM as well as the R_{rs} at different wavelengths. Statistical approaches to the match-up data and chl-*a* classifications would help evaluate the accuracy of the methods and could provide a more detailed evaluation of the comparability and potential differences between the methods, both for multi-year and single year analyses. Combined analysis based on all data from 2020 would also be able to show how the methods compare overall as well as for the different lakes. Other available optical data from Norwegian lakes were collected to a limited extent in 2019 for the earlier RS lake project (Ledang et al., 2019) and more extensively in 2019 and 2020 under the DCS4COP project (DCS4COP, 2021). It would also be very interesting to investigate the potential for development and test of an integrated method, resulting in hybrid products, where both data from the RS satellites and in-situ data are used. It is worth mentioning that in-situ data are also associated with errors so one should investigate the best approach to how RS and in-situ data should be used together.

5.2 Data processing and product developments

For a near-real time dataset and visualisation, it would be preferable to develop a more automated coding routine and cloud based set up for processing data, algorithm selection based on the R_{rs} etc., as done for both the Copernicus high resolution coastal data set and the OSPAR chl-*a* assessment based on RS data. Such a near-real time data product could provide updated information related to lake conditions to facilitate a faster management or reduced mitigation response time to possible issues. It would e.g. also be fundamental for a cyanobacteria alert system to be in place and operational that can provide citizens with cyanobacteria bloom reports before or when visiting a lake or bathing site. This could be achieved by the following steps:

- Automatization of downloading and processing in place which gives a smooth data flow, although some manual post-processing steps should be included.
- Automatization of quality assurance (QA)
- Automatization for producing level-3 products
- Visualisation and integration with in-situ data done for test cases
- Development of a cyanobacteria alert system

EODataBee is a newly establish European remote sensing consortium that is the continuation of the research team and product developed under the Horizon 2020 DCS4COP project (DCS4COP, 2020, 2021; EODataBee, 2021), of which NIVA is a partner. EODataBee provides a fully customizable data cube service for water quality information derived from Earth Observation and other sources. EODataBee comprises four core Service Elements:

- Water quality products
- Scientific consultancy
- Data Cube generation, operation, and visualization service
- Training for customers

As a partner in EODataBee, NIVA have access to the most current developments, expertise and collaboration within Europe for water quality data services and NIVA are able to design targeted products and solutions that are asked for.

6 Conclusions

This study shows a promising use of satellite derived chl-*a* data for several of the lakes included in the national monitoring program, especially in Mjøsa and Selbusjøen. The results from Gjende are more difficult to evaluate as the RS retrieval seems to have problems with high turbidity and mountain shadows. This was clearly seen for the Sentinel 2 data whereas the valid scenes from Sentinel 3 was fewer but with better results. For Røssvatnet, Snåsavatnet and Femunden the direct comparisons showed larger differences and the amount of in-situ data were very scarce compared to the RS data, making comparisons difficult.

Some main conclusions can be drawn:

- Sentinel 2 and Sentinel 3 works in general well for retrieving chl-*a* data per month, year and for an assessment period of 4-5 years in certain lakes
- The amount of data for each lake are increased as RS data increases the number of observations. Sentinel 3 measures the lakes ones or twice a day, which will increase the number of possible scenes, providing a daily temporal coverage during certain periods. Hence, RS data delivers a lot of spatial data and temporal data that is in between ordinary in-situ samplings, and this has a demonstrable impact on monitoring of the Norwegian lakes physical and chemical conditions
- The spatial patterns of both the chl-*a* concentration and the uniformity of lake status classifications can only be achieved with RS data and make a basis for new monitoring products as RS can provide new knowledge of the lakes' spatial and temporal dynamics
- This study shows that the results from both Sentinel 2 and Sentinel 3 are overestimating the chl-*a* values for monthly means for half of the lakes, which would give rise to a lower classification status of chl-*a* compared with in-situ data
- Sentinel 2 performs better for some lakes (Mjøsa), whereas Sentinel 3 is better for others (Gjende)

- The results suggest that the absolute value of chl-*a* retrieved by the RS data can be improved by better conversion factors between chl-*a* absorption and chl-*a* concentration
- Evaluation of other atmospheric correction algorithms, e.g. POLYMER or Acolite may improve chl-*a* retrieval
- Detailed comparisons based on observations from the same day for each lake should be done The lakes investigated here are low to moderate in chl-*a* and the Sentinel 2 sensor should have a higher potential for more eutrophic lakes where the reflected signal is higher
- RS data is a good complement to ordinary sampling for water quality classifications of Norwegian lakes, but for some lakes it needs some more in-depth work for possible adjustments and corrections
- Detailed studies of different basins or areas within the lake can be made to investigate how they differs in temporal changes and chl-*a* concentrations
- The RS data can also provide water quality information of lakes that are not a part of the monitoring programs as well as for the years in between in-situ sampling

- Not all lakes are suitable for RS data, depending on their locations or extreme bio-optical properties that are outside what the algorithm can handle, but in the study 3-4 out of 6 lakes were suitable with confidence and data could only be derived to a limited extent for one lake (Gjende).

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Appendix A.

Time-series Kise and Furnesfjorden

Time series from Mjøsa for Sentinel2 and in situ data in stations Kise and Furnesfjorden are presented in Figure A1 and A2. The equivalent time series for Sentinel 3 are shown in Figure A3.

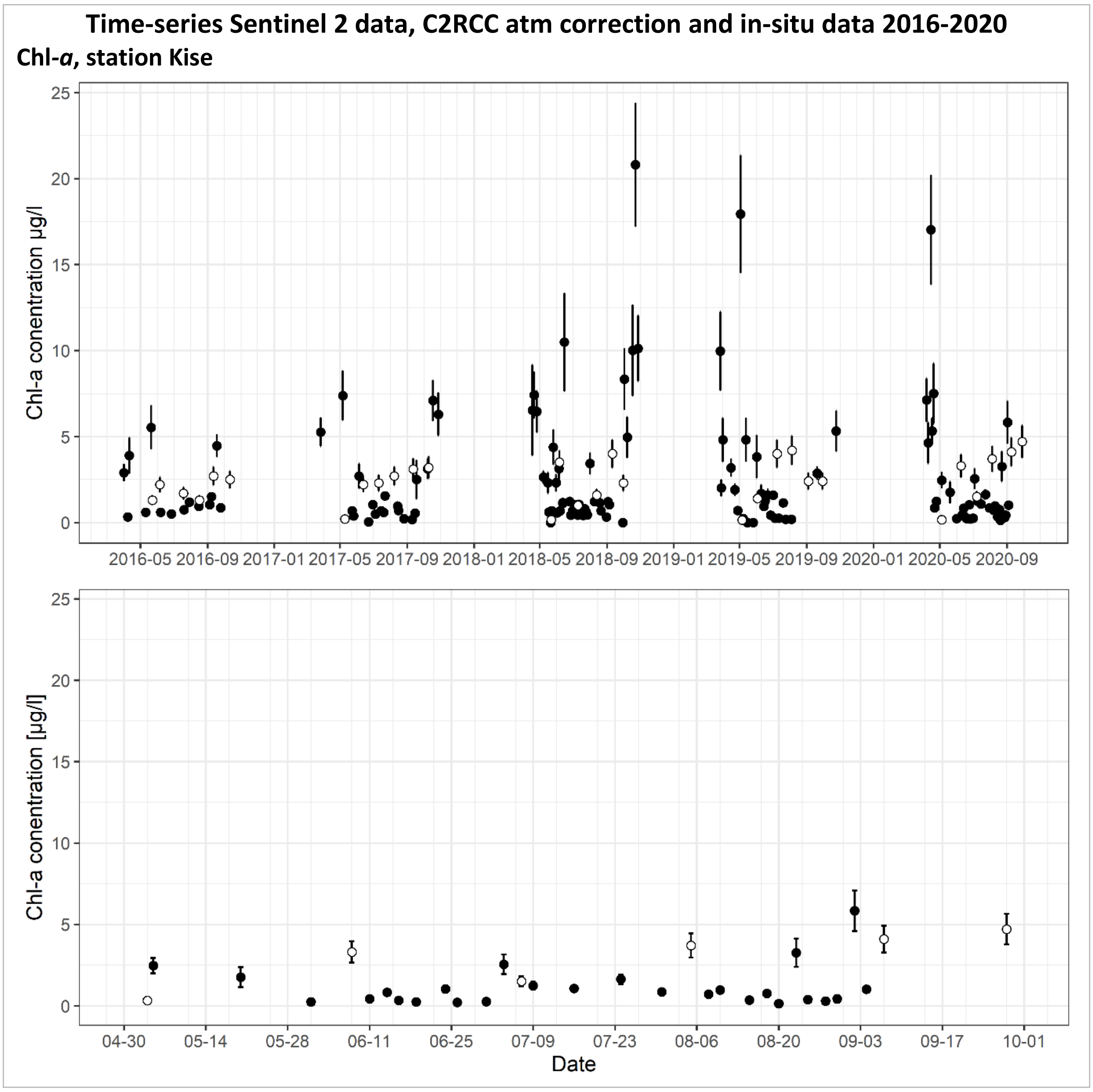

Figure A1. *Time-series Sentinel 2 chl-a and in situ data from 2016-2020 for station Kise in Mjøsa. The black circles show the Sentinel 2 data and the open circles the in-situ data taken by a mix-sample sample from the surface down to 10 m depth.*

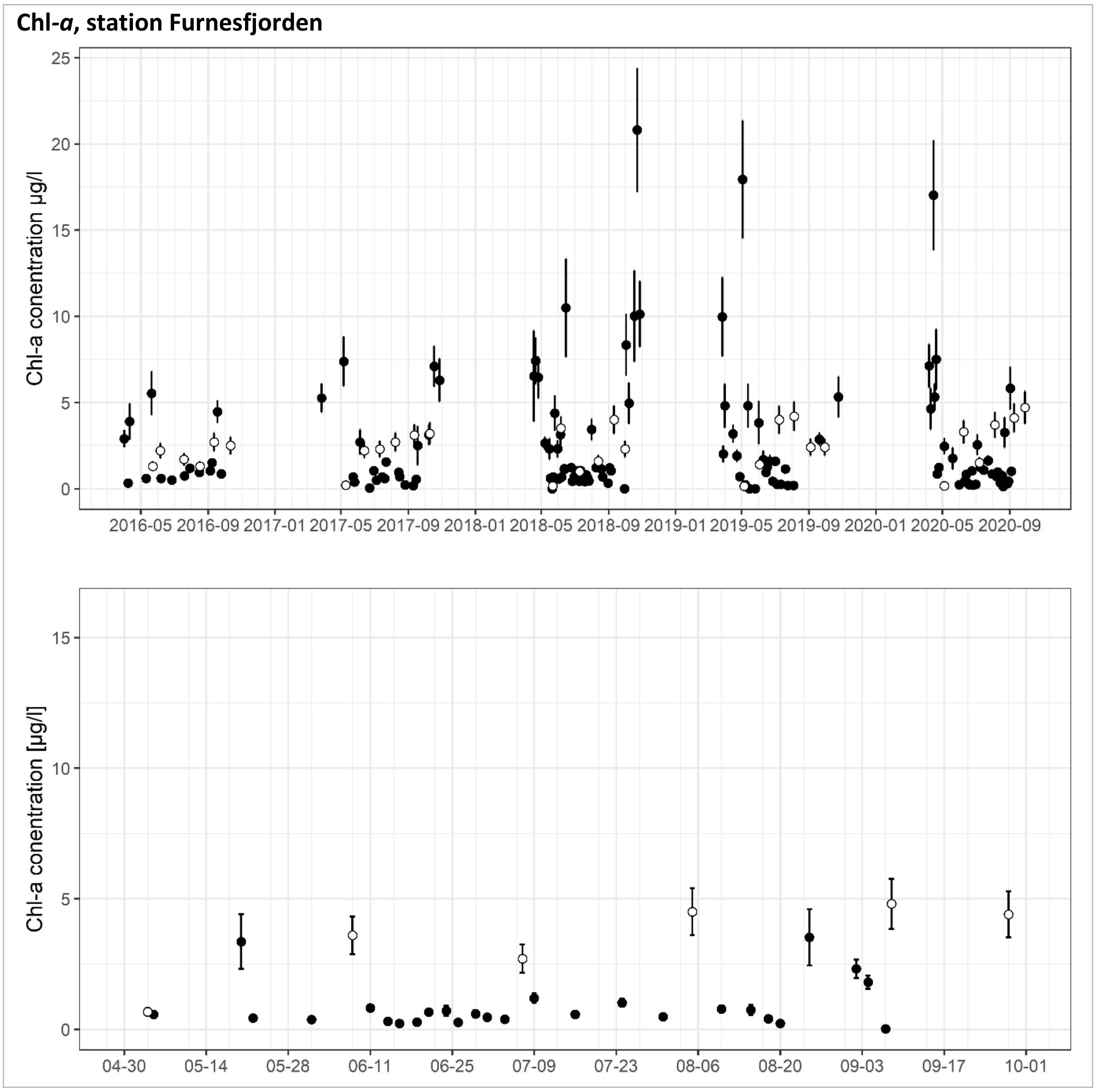

Figure A2. *Time-series Sentinel 2 chl-a and in situ data from 2016-2020 for station Furnesfjorden in Mjøsa. The black circles show the Sentinel 2 data and the open circles the in-situ data taken by a mix-sample sample from the surface down to 10 m depth.*

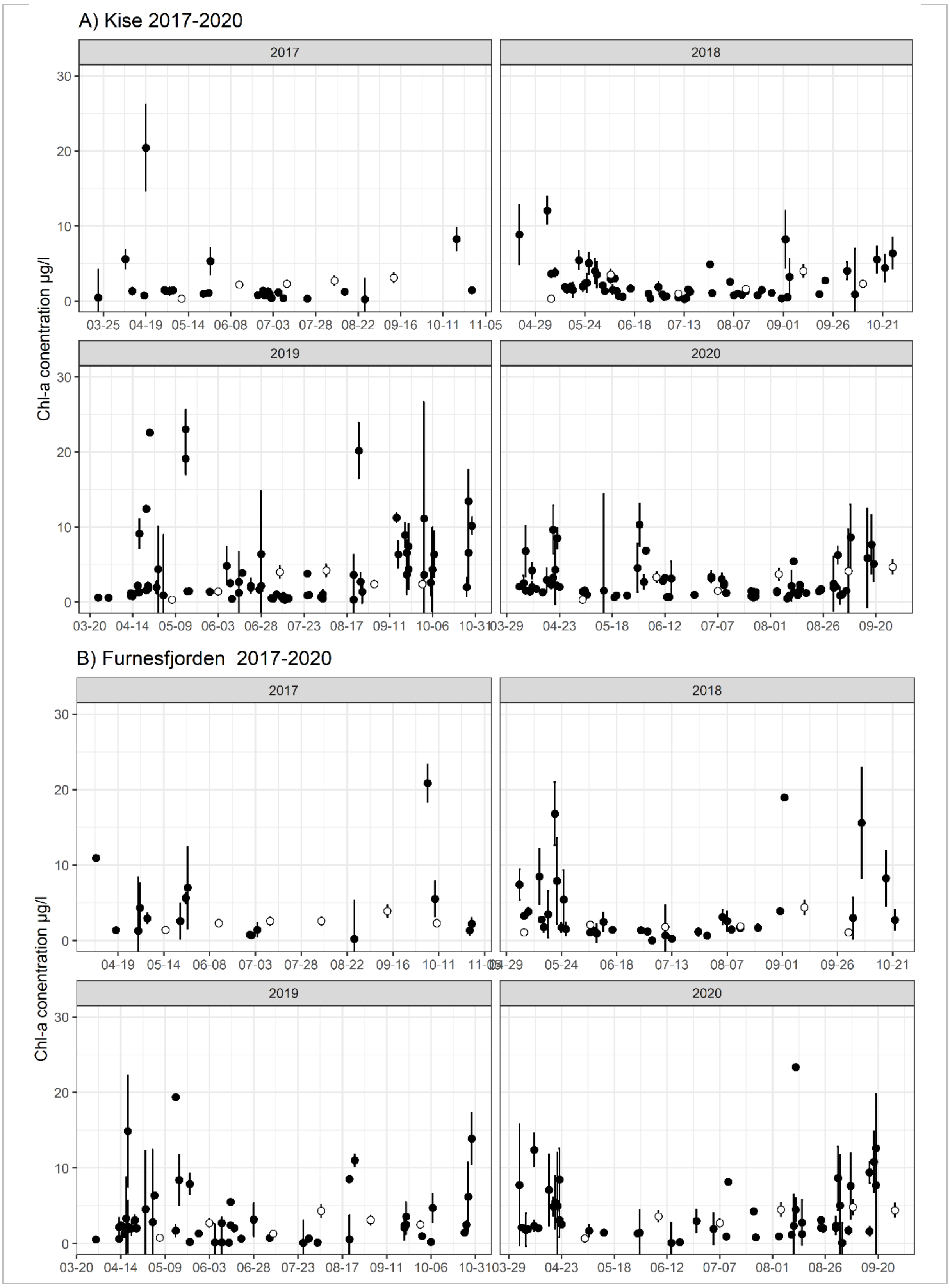

Figure A3. *Time-series of Sentinel 3 chl-a and in situ data in Mjøsa for A) station Kise and B) station Furnesfjorden from March to October 2017-2020. The black circles show the Sentinel 3 data and the open circles the in-situ data taken by a mix-sample from the surface down to 10 m depth. The red triangles are surface samples from 0.5 m depth, collected during the current project in 2020.*

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