USE OF REMOTE SENSING TECHNOLOGIES FOR MONITORING CHLOROPHYLL A AND SUBMERGED AQUATIC VEGETATION IN DANISH COASTAL WATERS

Part of the RESTEK project (Brug af remote sensing teknologier til opgørelse af klorofyl-a koncentrationer og vegetationsudbredelse i danske kystvande)

Technical Report from DCE – Danish Centre for Environment and Energy No. 139 2019

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Data sheet

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Abstract:	This report investigates the potential of using different remote sensing (RS) technologies to supplement the conventional national NOVANA programme for monitoring of water quality (chlorophyll a) and submerged aquatic vegetation (seagrasses and macroalgae) in Danish coastal waters. The potential of using drones, orthophotos and Sentinel 2+3 satellites are investigated in a number of test sites. From these results, strengths, weaknesses and knowledge gaps are discussed. Recommendations on future steps for integration of RS techniques for monitoring in Danish coastal waters and assessment of good ecological status according to the Water framework directive are also provided.
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Preface

This report is a deliverable to the Danish Environmental Protection Agency (Miljøstyrelsen, MST), who wanted an investigation of the potential of using different remote sensing (RS) technologies to assess coastal water quality, in line with the EU Water Framework Directive. The investigations provided in this technical report build on a more theoretical review report from DCE - Danish Centre for Environment and Energy (Harvey et al. 2018) where background information about the use of RS techniques for monitoring of coastal water quality is provided. The report has benefitted greatly from other ongoing projects which have contributed with valuable data and experiences.

Summary

This project investigated the abilities of different remote sensing (RS) techniques for monitoring water quality in the nearshore, shallow Danish coastal waters. Our analysis was divided into two parts: 1) monitoring of the cover of submerged aquatic vegetation (SAV: composed of eelgrass, other rooted macrophytes and macroalgae) and 2) monitoring of the water quality parameter chlorophyll a (Chl). The overall aim was to evaluate the potential of using different RS technologies as a replacement or supplement to the conventional Danish national NOVANA (National Monitoring and Assessment Programme for the Aquatic and Terrestrial Environment) monitoring programme for assessment of environmental targets (Good Ecological Status: GES) in the 119 bodies of water (Vandområder) included in the EU Water Framework Directive (WFD). The investigated RS techniques were Sentinel 2 and 3 satellites (S2, S3), summer orthophotos (SOPs) and unmanned aerial vehicles (UAVs, "drones"). Strengths, weaknesses and knowledge gaps were evaluated based on an investigation in nine shallow coastal systems, covering a total of 17 bodies of water from 2016 to 2018. In all systems, data collected with RS techniques were compared with *in situ* data. Based on the gained experiences, we analysed the costs and benefits of the different RS tools and provide suggestions on how to implement RS into the environmental monitoring framework of the coastal zone. Finally we present future work needed to facilitate integration of the different RS techniques into monitoring of Danish coastal waters. The main findings are presented below.

Part I: SAV monitoring with S2, SOP and drones:

- S2 is the most realistic approach for large-scale (national) annual SAV mapping in the coastal zone. SOPs are a good supplement providing valuable detailed information on patch development. The SOP archive from the 1950s furthermore allows for long-term change assessments in areal distribution, which can be used as a GES indicator.
- Both S2 and SOPs have limitations in estimating the maximum depth of SAV distribution, which for eelgrass is a key parameter in the assessment of coastal water quality and GES.
- The *in situ* drone technique is currently the only RS method capable of distinguishing between specific vegetation types. Moreover, first results show that the technique is able to provide SAV depth limits, but this needs further tests and validation/intercalibration against existing methods before any conclusions can be made. On the other hand, the *in situ* drone approach only provides discontinuous measurements (points) and is not feasible for large area national monitoring.
- Among the different RS techniques investigated in this report, the *in situ* application of drones provides the most obvious and easiest technology to implement into the current vegetation monitoring in the coastal zone.
- Overall, each of the presented techniques – S2, SOP, drones – has its advantages and disadvantages and the way forward is a smart combination of the RS techniques into an efficient monitoring framework to enhance the benefits of SAV monitoring, in particular, if SAV areal cover will be used as a supplementing indicator of ecological status.

Part II: Chl monitoring with S2 and S3 satellites:

- The Sentinel satellites provide unprecedented free data in terms of spatial, spectral and temporal resolutions. Never before has satellite imagery for Denmark been available on a daily basis and consequently collecting great amounts of data which among other use can be used to estimate Chl in water bodies. However, the satellites are relatively new (launched between 2015-2018) and method development for the processing of the data is continuously improving. The results presented in this report should therefore be seen as a snapshot.
- Two different Sentinel satellites were investigated: S2 mainly designed for land applications providing imagery at 10 metre pixel resolution but only every 3-5 days, while S3 specifically designed for water applications providing imagery on a daily basis but only at 300 metre pixel resolution. The three main advantages of using satellite imagery are 1) to get frequently insights into the spatial distribution of Chl for the entire water body and large areas, 2) to get information for water bodies not included in the ground surveys at all and 3) to get data in between *in situ* sampling.
- In general, the analyses revealed a higher variability in satellite-derived Chl than *in situ* data, with S2-derived Chl particularly noisy. The results from S3 turned out to be smoother and generally closer to the NOVANA data. Despite the coarser pixels of S3, even for small water bodies, we achieved good results, most likely due to the water-specific sensor design of the S3 satellite. In order to get the most comprehensive GES assessment, the combination of S2 and S3 seems like a cost-effective way to supplement *in situ* monitoring, in particular in the currently non-monitored water areas.
- Temporally aggregated Chl (monthly means) showed good agreement between all three approaches, still with S2 having the highest variability.
- In order to get a quality estimate of the satellite-derived Chl concentrations, they are usually compared with *in situ* measurements, like NOVANA. These comparisons bring together very different spatial scales, with ground surveys providing point information and the satellites providing spatially aggregated information per pixel, like 300 × 300 metres for S3. Moreover, it is often forgotten that also *in situ* measurements can be erroneous. A thorough quantitative statistical analysis is mostly not feasible because of the time difference between ground sampling and satellite overpass. A proper match-up useful for statistics should optimally fall within a 30 minutes to 2 hours window from the satellite overpass to avoid moving of water masses. Still it is useful to contrast Chl from different sources by looking into time series and their seasonality and how well and when they compare.
- As the S2 and S3 satellites only retrieve information on water surface properties, they cannot replace *in situ* sampling in deeper stratified waters where important Chl peaks often occur. In general, *in situ* observations are always needed for comparison purposes as mentioned above.
- Proper validation of S2 and S3 Chl estimates has not been possible under this activity due to lack of suitable match-up data. For both S2 and S3, the inclusion of a longer time series and expansion of the geographic scope – e.g. entire Denmark – would expand the validation data basis significantly. As a supplement to NOVANA activities, we recommend that the EPA invest in the AERONET system where one or more stations could contribute with important data for an optimization of the Chl retrieval algorithms to Danish coastal conditions and contribute to a proper validation.

Overall, for both Chl and eelgrass monitoring it must be stressed that collection of *in situ* data should continue to be an important part of the national assessments, as these data are essential for evaluating RS data and information on e.g. eelgrass depth limits is an important part of existing monitoring of marine vegetation.

Sammenfatning

I dette projekt har vi undersøgt anvendeligheden af forskellige remote sensing (RS) teknikker i overvågningen (~monitering) af miljøtilstanden i det kystnære danske havmiljø. Vores analyser omfattede to miljøtilstandsparametre: 1) monitering af udbredelse af undervandsvegetationen (SAV: bestående af ålegræs, andre marine blomsterplanter og makroalger) og 2) monitering af vandkvalitetsparameteren klorofyl-a (Chl). Projektets overordnede formål var at vurdere potentialet for anvendelse af forskellige RS-teknologier som afløsning, eller supplement, til dele af det traditionelle Nationale Overvågningsprogram for Vandmiljø og Natur (NOVANA) med henblik på at opnå en bedre vurdering af miljøtilstanden (~Good Ecological Status, GES), i de 119 danske vandområder, som er omfattet af EU's vandrammedirektiv. De undersøgte RS-datakilder inkluderede Sentinel 2 og 3 satellitterne (S2, S3), sommer orthofotos (SOP) og luftbårne droner. Styrker, svagheder og videnshuller blev vurderet ud fra undersøgelser i ni kystnære lavvandede marine systemer, omfattende 17 vandområder i perioden 2016 til 2018. I alle de undersøgte områder blev data indsamlet med RS-teknikker sammenholdt med data indsamlet via traditionelle *in situ* metoder. Baseret på de indsamlede erfaringer, præsenterer vi et økonomisk overblik over udgifter ved RS-baseret monitering og kommer med anbefalinger til, hvorledes RS-monitering af det kystnære vandmiljø kan gøres operationelt. Endeligt skitserer vi, hvilket fremtidigt arbejde som det vil være oplagt at forfølge, såfremt de forskellige RS-teknikker skal integreres i den danske miljømonitering i marine områder. I det følgende præsenterer vi vores væsentligste konklusioner.

Del I: SAV monitering med S2, SOP og droner:

- S2 tilbyder den mest realistiske tilgang til at levere storskala (national) årlig kortlægning af SAV i kystzonen. SOP er et godt supplement, som bidrager med værdifulde, detaljerede informationer om udviklingen af lokale bestande. SOP kortlægningen er dog mere specifik i forhold til ålegræs end S2, som p.t. har sværere ved at skelne ålegræs fra anden vegetation. Den lange SOP tidsserie (data fra 1950erne) gør det endvidere muligt at analysere udviklingstendenser, såfremt arealudbredelse benyttes som en GES indikator.
- Fælles for alle RS-teknikkerne er deres styrke i estimeringen af arealudbredelsen af SAV på lavt vand, og deres begrænsning i forhold til at estimere ålegræs dybdegrænsen, som p.t. er en nøgleparameter i miljøtilstandsvurderingen.
- *In situ* målinger med droner er p.t. den eneste RS-teknologi, som kan differentiere mellem vegetationstyper samt bestemme dybdegrænser. Opfølgende tests og validering/interkalibrering i forhold til eksisterende metoder er dog nødvendige, før der kan drages endelige konklusioner i forhold til potentialet for at bestemme dybdegrænse. Ydermere giver *in situ* dronemetoden diskontinuerlige, punktvise målinger og vil være omkostningsfuld i forbindelse med overvågning af større områder.
- Generelt set har alle tre teknikker – S2, SOP, droner - hver deres fordele og ulemper, og vejen fremad i form af en smart kombination af alle RS-teknikker viser et stort potentiale som supplement og understøttelse af den nuværende monitering. Især hvis SAV-arealudbredelse benyttes som en supplerende indikator for økologisk tilstand.

Del II. Klorofylmonitering med S2 og S3:

- Sentinel satellitter bidrager med en hidtil uset mængde af gratis data af høj rumlig, spektral og tidslig opløsning. Aldrig før har så detaljerede satellitdata over Danmark været frit tilgængeligt på daglig/nærdaglig basis, og det har bidraget til indsamlingen af enorme mængder af data, som bl.a. kan bruges til at estimere Chl i vandområder. Satellitterne er dog relativt nye (opsendt mellem 2015-2018), hvilket betyder at processeringsmetoderne for datakomponenterne stadig er under konstant forbedring. Resultaterne, som præsenteres i denne rapport, skal derfor betragtes som et snapshot af mulighederne i sidste halvdel af 2018.
- To forskellige Sentinel satellitter blev undersøgt i denne analyse: S2, som hovedsageligt er designet til landapplikationer og tilbyder data med en pixelopløsning på 10 meter, dog kun hver 3.-5. dag. S3 er specielt designet til applikationer over vand og tilbyder data hver dag men med en pixelopløsning på 300 meter. De tre primære årsager til at bruge satellitdata er 1) for at få et indblik i den rumlige fordeling af Chl over hele vandområder og over større områder, 2) for at få information over vandområder, som ikke afdækkes af *in situ* målinger, og 3) for at opnå dataindsamling i de mellemliggende perioder mellem *in situ* målinger.
- Generelt set viste analyserne en større variabilitet i satellit-estimeret Chl-værdier fremfor *in situ* data, og S2 data varierede i særlig høj grad. Resultaterne fra S3 data var generelt mere jævne og lå tættere på NOVANA data. På trods af den grovere opløsning på S3 opnåede vi gode resultater, selv over mindre vandområder, formentligt grundet sensorens konfiguration, som er optimeret til marin monitering. Dog giver S2, grundet den højere pixelopløsning, et vigtigt indblik i Chl-distributioner på mindre områder, om end ikke i absolutte tal, i hvert fald kvalitativt. I forhold til at opnå den mest dækkende GES monitering vurderes det, at kombinationen af S2 og S3 er den mest omkostningseffektive måde at supplere de eksisterende *in situ* målinger, især over de områder som endnu ikke bliver moniteret.
- Temporal aggregering af Chl (månedlige gennemsnitsværdier) viste god overensstemmelse mellem alle tre metoder, dog havde S2 til stadighed den største variabilitet.
- For at vurdere kvaliteten af de satellitafledte Chl-koncentrationer, sammenlignes de normalt med *in situ* målinger som NOVANA. Disse sammenligninger sammenholder meget forskellige rumlige opløsninger med *in situ*, der giver punktinformation, og satellitterne som giver et rumligt aggregeret billede per pixel, som 300 × 300 meter for S3. Begge datakilder kommer desuden med hver deres usikkerheder i koncentrationsbestemmelsen. En grundig kvantitativ, statistisk analyse er for det meste ikke mulig på grund af tidsforskellen mellem jordprøvetagning og satellitovergangen. En passende match-up, brugbar for statistiske vurderinger, bør optimalt falde inden for 30-120 minutters forskel mellem satellitpassagen og *in situ* målingen for at sikre sammenlignelige forhold i det dynamiske marine miljø. Det er dog stadig yderst brugbart at sammenholde Chl fra forskellige kilder ved at se på tidsserier og årstider for at vurdere, hvor godt og hvornår de kan sammenholdes.
- Eftersom S2 og S3 satellitterne kun indsamler information fra den øverste del af vandsøjlen, kan de ikke erstatte *in situ* målinger i dybere stratificerede vande, hvor et Chl-maksimum kan forekomme. I forhold til vurdering af værdierne - og evt. decideret kalibrering – er *in situ* observationer altid nødvendige til sammenligning, som nævnt ovenfor.

- En decideret validering af S2 og S3 Chl-estimaterne har ikke været mulig under denne aktivitet grundet mangel på egnet sammenligningsmateriale. For både S2 og S3 kan inddragelse af en længere tidsserie samt fokus på fx hele Danmark udvide datagrundlaget betydeligt. Som supplement til de nuværende NOVANA-aktiviteter anbefaler vi desuden, at MST investerer i en eller flere valideringsstationer (AERONET-systemer) som vil kunne bidrage med vigtige data til at optimere Chl-algoritmerne til danske kystnære farvande samt bidrage til en ægte validering.

Overordnet set skal det for både Chl og ålegræs understreges, at indsamling af *in situ* data fortsat bør være en vigtig del af den nationale overvågning, da disse data er essentielle i forhold til at evaluere RS-data og information, for eksempel i forhold til dybdegrænser for ålegræs, som udgør en vigtig del at den eksisterende monitering af marin vegetation.

1. Introduction

The Danish coastal waters cover more than 7,000 km of shoreline in predominantly shallow (<10 m depth), productive waters including several fjords. Danish estuaries and coastal waters were markedly affected by eutrophication during the twentieth century. To mitigate these problems, national action plans have been enacted since the 1980s to reduce nutrient loadings and improve the quality of the coastal waters. In agreement with the EU Water Framework Directive (WFD) (European Commission 2000), systematic monitoring and regular reporting of the assessments of the ecosystem or environmental health of the national coastal waters are required. The WFD is implemented in Denmark through the Danish River Basin Management Plans (vandområdeplaner). In Denmark, the National Monitoring and Assessment Programme for the Aquatic and Terrestrial Environments (NOVANA) provides the data needed for the assessments. Two of the most important NOVANA parameters, which are currently used to assess the ecological state of Danish coastal waters, are 1) the depth limit of eelgrass and 2) the summer mean (May to September) surface (1 m depth) chlorophyll a (Chl) concentrations. For each parameter, the average level over a 6-year period are compared with target values, to assess if good ecological status (GES) is achieved. Assessments are made for a network of 119 individual water bodies representing different typologies with different target values. Hence, the Danish River Basin Management Plans rely on high-quality monitoring data with good spatial coverage. Although most water bodies are currently monitored, some are not, and it is also of interest if new technologies can improve the spatial coverage of the existing monitoring programme.

The NOVANA monitoring of Chl and eelgrass depth limits relies on a combination of ship-based periodic samplings (Chl) and *in situ* transect investigations (eelgrass depth limits). Both approaches are geographically fixed and follow specific sampling intervals. Coastal zones are, however, highly variable, and water samples taken for Chl measurements during one day may not represent the following day, week, month or season and may not represent the nearby areas (Carstensen & Lindegarth 2016). Similarly, even though the current annual vegetation surveys provide detailed information on eelgrass depth limits along specific transect lines, it does not allow the assessment of the overall vegetation coverage of whole water bodies or seasonal variations in vegetation coverage. Even though the NOVANA programme has been developed to detect the spatial and temporal variability, resources are restricted. It would therefore be a tremendous benefit to the environmental monitoring programme if new technologies such as satellites and drones could provide additional data that can help uncover the dynamic changes in time and space, and additionally provide information for non-monitored water bodies.

1.1 Aims and deliverables

The overall aim of this project has been to investigate and assess the potential use of a range of remote sensing (hereafter RS) technologies for monitoring of water quality parameters in the nearshore coastal zone of Danish waters.

<u>Part 1</u> relates to monitoring of submerged aquatic vegetation (SAV). This part focuses on mapping the distribution of eelgrass meadows, which dominate

the vegetation cover in the shallow zone. The RS methods applied for mapping SAV are satellite data (Sentinel 2, or S2), summer orthophotos (SOP) collected by planes and drone data. Also included in this part is an assessment of the ability of drones to monitor the macroalgal distribution and use of drones to collect *in situ* data for ground truth observations.

Part 2 investigates the use of Sentinel 2 and 3 (hereafter S2 and S3) for monitoring of surface Chl.

For both parts, we compare the remotely sensed data with available *in situ* data in selected test areas, to evaluate the accuracy of the RS estimates. Based on these analyses, we evaluate the potential for improving the current monitoring approaches that constitute the foundation for WFD assessment of ecological status. We provide an analysis of the costs and evaluate the benefits of the different RS techniques and their applicability to a future national monitoring programme. We conclude the report with considerations on how data collection by RS technologies can be operationalized.

2. Materials and methods

2.1 Test areas and data sources

Nine coastal areas comprising 17 water bodies were included in our analysis (*Table 2.1*). The areas were selected to represent the diversity of the 119 shallow nearshore coastal water bodies for which Denmark has to assess the ecological quality, according to the WFD.

Table 2.1. Overview of test areas and data types used for assessment of the applicability of different remote sensing (RS) techniques for monitoring of submerged aquatic vegetation (SAV) and surface chlorophyll (Chl). RS technologies included Sentinel 2 (S2) and 3 (S3), summer orthophotos (SOP) and drone data. *In situ* data types for SAV included transect data from the NOVANA monitoring programme, data from underwater (UW) photos and sampling cores. For chlorophyll (Chl) all *in situ* data were 1 m samples collected as part of the national ship-based NOVANA programme. Comparisons between different RS techniques and *in situ* data are shown in green for chlorophyll (Chl) and yellow for SAV. The Sydfyynske Øhav (area 2) is further divided into smaller water bodies for comparison of Chl with S2 and *in situ* Chl data.

Name (abbreviation)	**Characteristics**	**Water bodies**	**Parameter**	**S3**	**S2**	**SOP**	**Drone**	***In situ***	**Year**	**Season**
1. Nibe-Gjøl (NG)	A shallow area with abundant eelgrass	156	SAV					Transect	2016	May/Jun
			Chl					None	2017	All year
2. Sydfynske Øhav (SF) (incl subareas)	Many islands and abundant eelgrass	214 (63,64,65, 68,72,89)	SAV					Transect	2016	May/Jun
			Chl					Ship	2017	All year
3. Roskilde Fjord (RF) inner & outer	A shallow, narrow system, with high Chl and some eelgrass	2, 1	SAV					Transect	2016	May/Jun
			Chl					Ship	2017 2018	All year Jan-Nov
4. Isefjord (IF) inner & outer	A shallow system, with high Chl and some eelgrass	165, 24	Chl					Ship	2017 2018	All year Jan-Nov
5. Flensborg Fjord (FF)	A narrow, deep system	113	SAV (eelgrass)					UW photo	2018	Aug
6. Rødsand Lagune (RL)	A protected eelgrass-dominated system	209	SAV (eelgrass)					UW photo	2018	Aug
7. Wadden Sea (Vadehavet, VH)	A tidal system with exposed seagrass banks	121	SAV (eelgrass)					Transect	2018	Aug
8. Seden Strand (SS)	Inner eutrophic part of Odense Fjord	93	SAV (macroalgae)					Cores	2017	Aug
9. Begtrup Vig (BV)	Shallow part of Aarhus Bay	145	SAV (macroalgae)					Harvest	2018	Sep

In Danish waters SAV includes both seagrasses and macroalgae. The composition and abundance of SAV are largely determined by sediment characteristics, water clarity and salinity. In coastal turbid waters such as the Danish, application of RS techniques for mapping of SAV is restricted to SAV in the shallow sublittoral coastal zone (see Harvey et al. 2018). Here, SAV mostly consists of seagrasses, which in Danish waters are dominated by eelgrass (*Zostera marina*).

Due to the processing of the RS data, the S2 mapping of SAV covers both seagrasses (dominated by eelgrass) and macroalgae, whereas the SOP mapping is calibrated directly against eelgrass cover data from available monitoring transects (See Ørberg et al. 2018 for more details). In the case of drones, we calibrated the red-green-blue (RGB) images against different sources of *in situ* data, and applied algorithms to make maps aiming to differentiate between eelgrass and macroalgae.

While our investigations focused on eelgrass and Chl monitoring, the Danish Environmental Protection Agency (MST) also wanted to obtain experiences and advice of using RS techniques for mapping of macroalgae. Accordingly, we have included Seden Strand and Begtrup Vig in our analysis. The test areas used in our investigations are shown in *Figure 2.1*.

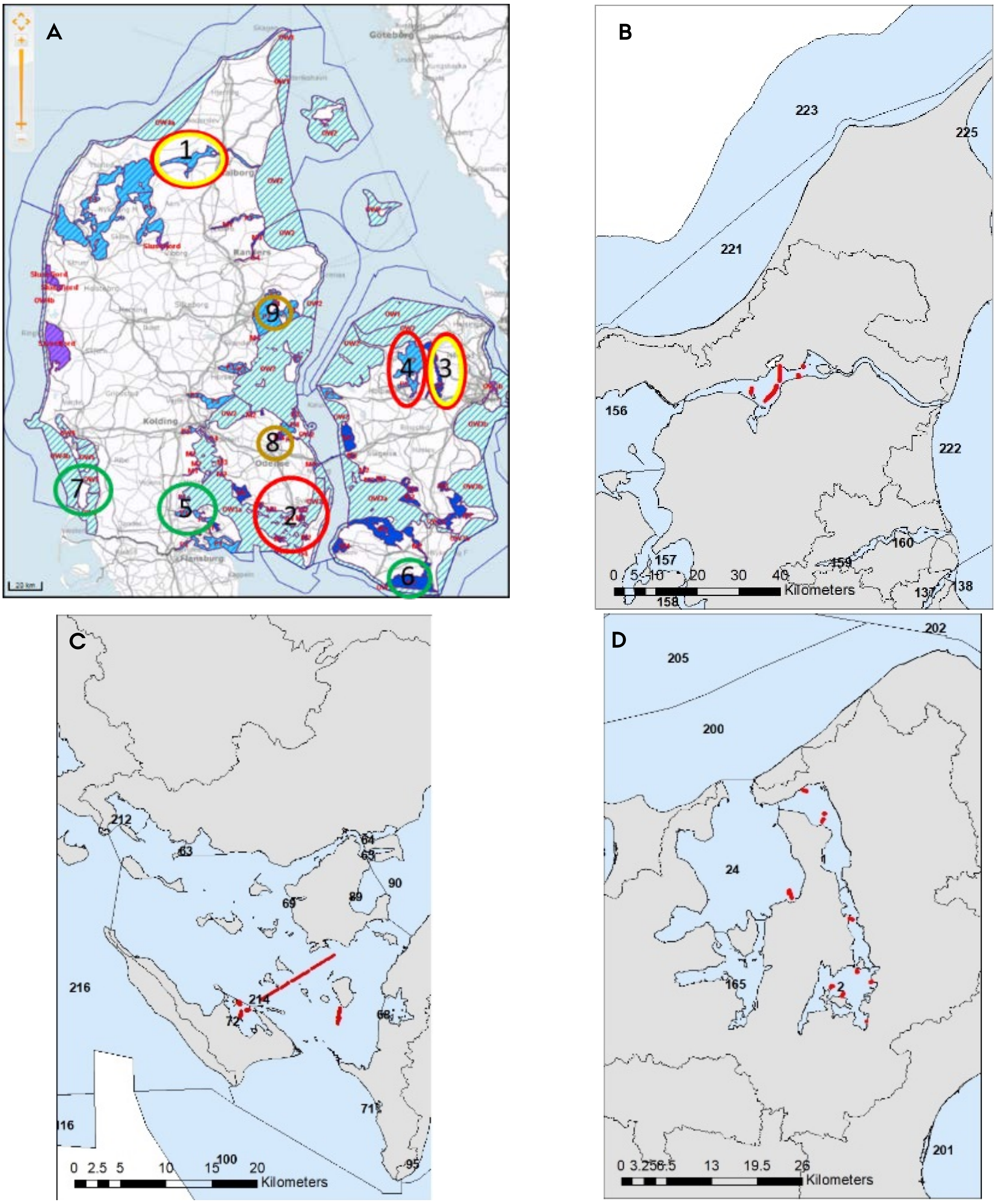


Figure 2.1. A) Overview of the 9 test areas described in *Table 2.1*. Green circles represent the drone sites for eelgrass monitoring; brown circles are drone sites for macroalgae mapping; red circles show areas analyzed by S2 for Chl and SAV. Chl was also examined in area 3 and 4 by S3. Yellow circles show areas where SOP data were analyzed for eelgrass. B) The Nibe-Gjøl area; C) Det Sydfynske Øhav and D) Roskilde Fjord and the Isefjord. Red dots in B, C and D represent *in situ* transect for SAV and numbers identify the water bodies as listed in *Table 2.1*.

Table 2.2 provides further information on the remote sensing and *in situ* data used in our investigation.

Table 2.2. Overview of data types, their spatial and temporal and resolution, the area covered and application in this project. *For SAV the S2 data were processed at 10 m, for Chl at 20 m. It should be noted that it is now possible to work with 10 m Chl resolution.

Data type	Platform	Resolution	Temporal coverage	Coverage	Application
Satellite	S2	10-20 m *	2-3 days	National	Chl, SAV
	S3	300 m	1-2 days	National	Chl
SOP	Fixed wing piloted plane	16, 25 cm (2008-2016, see details in Ørberg et al. 2018.)	Once every second summer, see details in Ørberg et al. 2018.	National	SAV
Drone		0.5-5 cm	Once during investigation	Local to regional	SAV
In situ	Ship	Point (metres)	Every 2 weeks	Local	Chl
	Transect (diver or video)	Metres	Once every summer	Local	SAV, species
	Video drop	Point (<metres)	Once every summer	Local	SAV, species
	Core	Point (metres)	Once during investigation	Local	SAV, species

2.2 Processing of remote sensing data

Our analysis of RS data involved a series of steps from the initial download of raw satellite data to the final estimation of water quality parameters – SAV and Chl. Subsequently, we briefly explain the steps undertaken to derive SAV and Chl from remote sensing data. For further details we refer to Harvey et al. (2018).

2.2.1 Quantifying SAV coverage from S2 imagery

1. SAV coverage at Roskilde Fjord was quantified based on a cloud-free S2 image from spring 2016, using an object-based image analysis. In an object-based image analysis, an image is segmented into separate groups of pixels with similar properties. Together these segments, composed from multiple pixels, form distinct objects. In contrast to an object-based analysis, classes (e.g. SAV coverage) are defined pixel-by-pixel, with all pixels having the same size, same shape and no connection with their neighbours in a traditional pixel-based analysis. Before the classification, all external factors influencing the satellite signal were corrected, like changes in the atmosphere.
2. The satellite image was classified into sand and SAV objects with training data (visually identified points/areas with SAV which are used to train the algorithm) created from high-resolution satellite imagery and SOP. Classification was then undertaken on the derived image objects using spectral image bands from the visible spectra, up to the near-infrared band (not including).
3. All deeper values were filtered out with a depth raster to a depth of 4 m, which was selected based on the observed and reported water visibility of Roskilde Fjord on the day of the satellite image acquisition.

2.2.2 Retrieval of Chl concentrations from S2 and S3 imagery

1. After the raw S2/S3 imagery was downloaded, a standard software (Case-2 Regional CoastColour processor – C2RCC)) was used for the retrieval of Chl concentrations (Brockmann et al. 2016; Harvey et al. 2018). C2RCC provides Chl maps for each satellite image feeding into the processor. For

a more detailed description of satellite RS-reflectance processing, we refer to chapter 3 in Harvey et al. (2018). Note that no local tuning with NOVANA was applied and the results presented are derived with the standard C2RCC approach.

2. The S2 satellite does not provide one complete image for the entire Denmark at once. Instead several so-called *tiles* are provided, each covering a part of Denmark. These tiles have to be united with a process called "mosaicking", in order to get one complete image per date. This step is done with the output of the C2RCC processor.
3. We only used satellite imagery covering in the period between 1 March and 31 October to exclude darker autumn/winter months where Chl estimates are more uncertain because less light is reaching the satellite sensors (Harvey et al. 2018). The reference year of the analysis was set to 2017, but since 2017 was exceptionally cloudy, providing a low number of usable images, we also processed imagery from 2018 for Roskilde Fjord and Isefjord (see *Table 2.1*).
4. For further analysis of the Chl data, we masked out the sublittoral zone up to a depth of 3 metres for all the water bodies, to minimize the effect of sea floor reflectance on the Chl retrieval. In coastal waters, the signal measured by the satellite in the sublittoral zone is a convolution (~cross correlation) of all that is found at the seabed and in the water column. Since we cannot separate the two, the entire area with a mixed signal is masked out and not used for calculations. The 3-metre threshold was selected based on visual inspection of satellite imagery and bathymetry contours.
5. Finally, we calculated surface summer mean Chl maps from S2 and S3, respectively, by averaging all available images between 1 March and 30 September for 2017 and 2018, respectively.

2.2.3 Estimation of SAV coverage using SOP

The following is a condensed version of the steps involved in the analysis of SOP data. For a more thorough description, we refer to Ørberg et al. (2018).

1. Retrieval of raw data: The national coverage of SOP image data, with 4 channels (RGB + NIR) are delivered for analysis (as opposed to mere viewing) as 2 × 2 km tiles in ECW (lossy compressed) format. The tiles are cut out from a national mosaic of the overlapping original photo frames, with frame-to-frame colour matching applied to reduce mosaic image differences over land.
2. Atmospheric correction: To the best of our knowledge, no systematic adjustments are made by the data supplier with respect to correction of atmospheric noise. Frame-by-frame colour matching is applied by the supplier to reduce mosaic image differences over land. No specific atmospheric correction was therefore applied (or would be possible to apply) to the image data provided for analytical use, as part of the SAV mapping.
3. Processing: The SOP image data of open water surfaces are affected by sunglints, which are seen as localized (1-10 pixels) extremely bright image data created by specular reflectances of sunlight from water surface facets. These can occur with densities that will affect mapping results. An object-based method was developed and applied to (a) map sunglint pixels and (b) reduce the sunglint effect. This was achieved by local averaging with none sunglint image data. SAV was mapped from the SOP image data using two alternative, supervised methods. Both methods were supervised in that they used reference data (the NOVANA transect monitoring

data values of eelgrass and of sand percent cover) to develop (train) statistical models that were then applied to map SAV for the full extents of the image data. The reference data were also applied for model cross-validation. The two applied methods are two commonly applied statistical models for image-based mapping: the linear discriminant analysis model (LDA) and the maximum likelihood classification (Mahalanbonis distance) (MLC) model. The LDA model equates the mapping variable (eelgrass presence) as a linear function of input image data channel (R,G,B) pixel values, each modulated by a coefficient (weight); the functions product is then cut by an empirically determined threshold to form the discriminant map. The MLC model describes a set of target classes (eelgrass, sand) in terms of correlation and covariance matrices of the image data channel pixel values; pixel class is then determined as the class with the maximum likelihood as represented by the Mahalanbonis distance derived from the matrices. Both methods were applied as per pixel image classifications. As analysis indicated a decreasing correlation of image pixel values to eelgrass coverage with increasing water depth (related to the short wavelength light penetration extinction function of water), depth thresholds were applied to the LDA and MLC maps, using a coarse (50 m) national bathymetry raster dataset; for the less turbid, open sea area of South Fyn the applied depth threshold was -5 m, for the more closed fjord areas (with more influence of land run-off) of Nibe-Gjøl and Roskilde Fjord, the applied depth threshold was -2.5 m. As far as possible, models were evaluated based on 75 % of the pooled, randomly selected, reference data points for all study areas for three years (2012, 2014, 2016), cross-validated with the remaining 25 %. An exception to that was that the MLC model for 2016, which was evaluated on data for just Nibe-Gjøl. Due to lack of image data coverage and poor image data quality for the other study areas, LDA and LMC SOP SAV mappings for 2016 were made for just Nibe-Gjøl and Roskilde Fjord.

2.2.4 Mapping of eelgrass and macroalgae with drones

Our drone investigations covered five different areas (*Figure 2.1*, *Table 2.1*) and examined the use of drones for mapping of submerged eelgrass (Flensborg Fjord-area 5; Rødsand Lagune-area 6) and emergent eelgrass (Vadehavet-area 7 during low tide). Furthermore, we investigated use of drones for mapping of macroalgae (*Ulva lactuca* in Seden Strand-area 8 and *Fucus vesiculosus* in Begtrup Vig-area 9). The mapping and *in situ* sampling procedures differed slightly between the five areas as explained below.

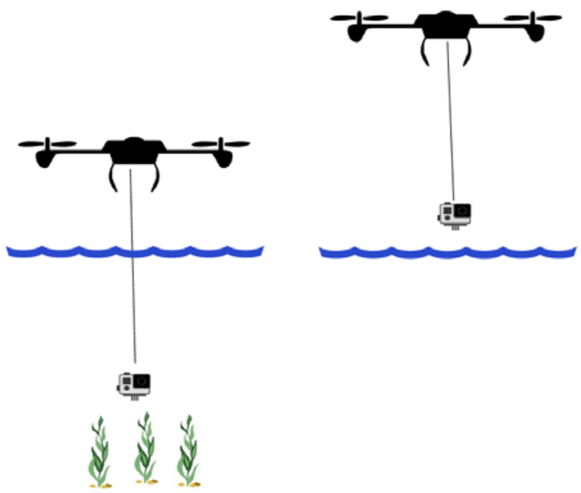
Flensborg Fjord

The aim of the drone investigation in Flensborg Fjord in August 2018 was to gain experience on the use of different types of drones for mapping of submerged eelgrass meadows. Specifically, we evaluated the importance of flight line overlap, uncertainties associated with number of key points for stitching, disturbances from sunglints and weather conditions. Four types of drones were initially tested. Results presented in this report focus on acquisition by the DJI Inspire 1. The software Agisoft PhotoScan was used to stitch the pictures together.

Rødsand Lagune

Here we investigated the use of drones for both areal and ground truth mapping of eelgrass. In October 2018 we deployed an Inspire 1 drone equipped with a Zenmuse X3 camera for above ground imagery. The ground truth part was in both areas conducted along previously established NOVANA monitoring transects. A GoPro Hero 5 camera, programmed to take a photo every 10 seconds, was hanging 7 metres below the drone in a wire. The drone was programmed to lower the camera to 1 m above the seafloor for 15 stations along the transect, where the benthic conditions were recorded (*Figure 2.2*). Water depth at a given point was obtained from a bathymetric map. Between stations the drone was set to a flight speed of approximately 7 km/h to avoid fluctuations of the wire and GoPro camera. Areal cover mapping was performed using one battery over 20 minutes, along a predetermined grid at 23 metres above sea surface providing an overlap of 75 % between pictures. Agisoft PhotoScan, a photogrammetry software, was later used to stitch the pictures together. Analysis of the vegetation was done using the red, green and blue spectral bands of the image and a maximum likelihood algorithm where the ground truth data were included in ArcMap.

Figure 2.2. Illustration of the drone technique used for ground truth observations of eelgrass in Rødsand Lagune.



Wadden Sea

The Wadden Sea is a tidal area where different species of eelgrass (mostly *Zostera noltii*) become fully exposed at low tide. Monitoring of eelgrass in these areas traditionally consists of interpretation of photographs taken manually from a plane flying at approximately a height of 600 metres. Observations from these photos are then compared with a number of sample points collected by walking along a predefined transect. These ground observations are finally used to estimate the area covered by more than 20 % eelgrass. Here MST (Lasse Ø. Jensen) assessed the application of drones for i*n situ* determination of eelgrass cover for a number of sample points next to the conventionally sampled ground truth transect. The study area was located in the northern part of the Wadden Sea, east of the island Fanø. The drone video were obtained during August 2018 using a Phantom 4 drone equipped with a 20 MP RGB camera. The software Universal ground Control Station (UgCS) was used to plan and execute a preprogrammed route. One transect of approximately 250 metres took about 14 minutes to fly, using only a single battery. Drone video was taken 2 metres above the ground with a flight speed of 1.5 km/h. The camera was oriented due north and in a 70-degree angle from the horizontal plane to minimize sun glare. The drone recorded video with a resolution of 2720 × 1530 at 29 frames per second. Eelgrass percent cover was registered manually by pausing the video every 10 seconds (approximately every 10 metres). Delineation and calculation of the areal extent of the eelgrass and comparison with ground truth observations were not done as part of this exercise. Finally, ortho-mosaics were also created in the Wadden Sea using a Phantom 4 as above, or an Ebee+, both equipped with a 20 MP RGB camera. At a height of 100 metres, we could identify patches of eelgrass, but not the different species within the meadows.

Seden Strand

Seden Strand is a shallow highly eutrophic brackish part of Odense Fjord with reoccurring blooms of the green macroalgae, *Ulva lactuca*. A project was conducted to estimate the cover and biomass of the plant in order to assess the amount of carbon, nitrogen and phosphorus that accumulate is this system. The study utilized data from the national SOP mapping (see earlier description) in 2012, 2014 and 2016, and compared these with drone recordings from September 2017. Drone recordings were made with an Inspire 2 drone along a grid with a flight height of 30 to 45 metres providing a pixel resolution of 2 to 3 cm compared to SOP data with a resolution of 12 to 16 cm. The software Agisoft PhotoScan Professional was used to stitch a map together, covering a total of 32 hectares. Analyses of the RGB signals in the SOP and drone maps were done with ArcMap software. We used a maximum likelihood classification to determine the cover of *Ulva lactuca*. For the drone image, the MLC was calibrated against 10 *in situ* observations. These were taken manually using a core sampler with a diameter of 56 cm (*Figure 2.3*).

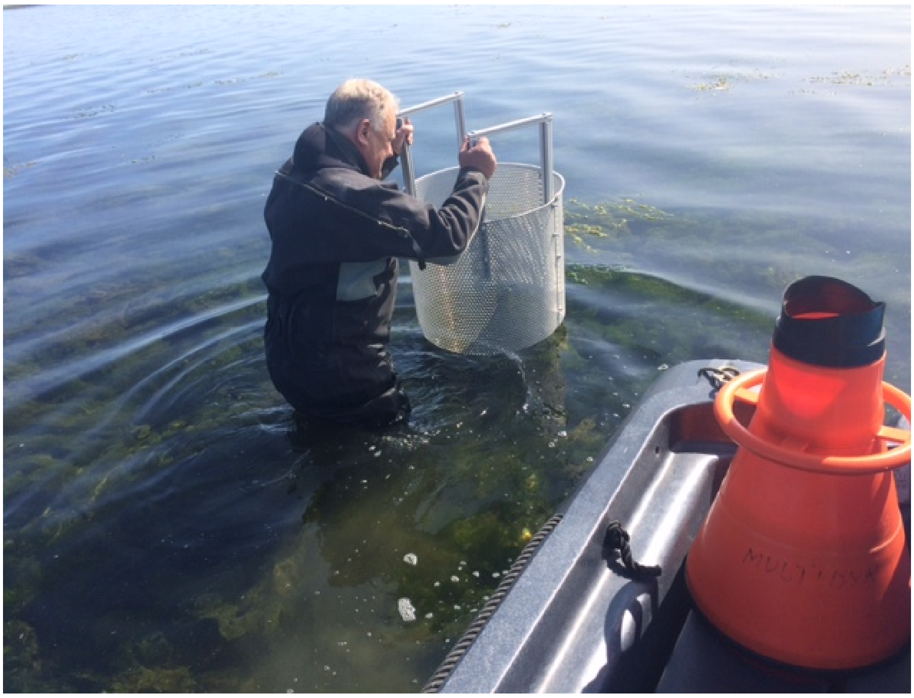


Figure 2.3. *In situ* sampling of *Ulva lactuca*. At 10 points, percent of cover was determined, and samples were taken for analysis of biomass (carbon, nitrogen and phosphorus).

Biomass samples taken with the core sampler were freeze-dried, dry weight was measured and analysis was done to obtain content of Carbon (C), nitrogen (N), and phosphorous (P).

Begtrup Vig

Begtrup Vig is a shallow microtidal area in the northern part of Aarhus Bay. The area has a dense coverage of the perennial *Fucus vesiculosus* (Bladder wrack) which has a commercial value. Here we applied a drone to map the efficiency by which different methods removed *Fucus vesiculosus* by harvesting at different intensities. This approach makes it possible to test the sensitivity of drone-based observations of macroalgal cover in the shallow sublittoral zone. Our investigation was conducted in September 2018 and covered five transects running 35 metres perpendicular to the coast line. Each transect was 2 metres wide and separated into 5 metre intervals. A drone was applied to map the area before and after harvest of *Fucus vesiculosus*. Harvesting was done using five different methods, varying from 100 % removal to no removal (control). We used a Mavic 2 Pro drone, programmed to fly at 20 metres altitude and with a picture overlap of 80 %. The total area was mapped over 10 minutes. The picture mosaic was stitched together using the software Agisoft Photoscan Professional, which also enabled us to produce a digital elevation model (DEM) with Argisoft Photoscan of the area covering 12 ha in total. The orthophoto mosaic was analysed in ArcMap and classified against a series of ground truth observations, using a maximum likelihood procedure.

2.3 Comparison with *in situ* data

In the following, we describe the procedures to compare remotely sensed SAV and Chl with *in situ* data.

2.3.1 Submerged aquatic vegetation

Sentinel 2 and SOP

S2- and SOP-derived maps of SAV/eelgrass were compared with *in situ* monitoring transect data for 2016. For 2016, S2 and SOP image data were available for Nibe-Gjøl, Roskilde Fjord, and South Funen (except for SOP where low quality disabled analysis – see *Figure 3.6*).

The comparison between the SAV maps and *in situ* data was conducted at two scales:

(a) In each of the three study areas, we compared similarities and differences in the areal extent covered by the two mapping methods (SOP and S2).

(b) In subareas within study areas corresponding to positioning of the NOVANA transect data, the S2 (10 × 10 m) pixels and SOP (0.2 × 0.2 m) pixels were compared with *in situ* coverage of eelgrass.

At these two scales we investigated:

1) The degree of agreement between *in situ* and S2, in relation to NOVANA eelgrass coverage categories and depth categories. Thus NOVANA data were used for validation – not for calibration.

2) The degree of agreement between SOP and S2 SAV mappings

3) The sensitivity of the S2 SAV mapping to different thresholds of eelgrass coverage. This analysis addresses the ability of S2 to assess eelgrass depth limits.

Data preparation:

The SOP SAV mappings are essentially presence absence data sets with pixels classified as either SAV or sand (see Ørberg et al. 2018). The S2 SAV mappings are multiclass, with pixels classified as SAV, sand, or deep (water). For comparison purposes, the S2 maps were recoded to presence/absence categories combining sand and deep, making them equivalent to the SOP maps.

For the entire study area comparisons, it was necessary to base analysis on equivalent study area definitions as SAV/eelgrass mapping extents differed between the SOP and S2 mappings. Differences were mostly caused by partial absences of SOP image data (e.g. an area of ca. 10 km^2 in the central part of the Nibe-Gjøl study area and a large area in the northern part of Roskilde Fjord), and the depth threshold applied to the SOP eelgrass mappings (see section 2.2). The Roskilde Fjord mappings included the north-eastern part of the neighbouring Isefjord; to derive SAV mapping just for Roskilde Fjord, the Isefjord parts were excluded from the analyses.

For comparison of remotely sensed data with the NOVANA monitoring data, the following data sets were produced:

(a) The NOVANA point eelgrass coverage, the NOVANA point depth and the S2 SAV presence or absence, and

(b) The NOVANA point eelgrass coverage, the national bathymetry data set depth, the S2 SAV presence or absence and, for the corresponding S2 (10 × 10 m) pixel, the SOP SAV percent coverage and number of SAV patches.

To study the sensitivity/threshold of the S2 SAV mapping, we prepared three reclassifications of the *in situ* (NOVANA) data:

1) if *in situ* cover >= 10 % then presence, else absence
2) if *in situ* cover >= 50 % then presence, else absence
3) if *in situ* cover = 100 % then presence, else absence

For each of these three *in situ* absence/presence sensitivity/threshold classifications, we compared with the S2 SAV absence/presence classification. Basically, we calculated the percentage of pixels in a map classified correctly (where S2 and *in situ* agree on presence or absence) or incorrectly (where S2 and *in situ* disagree). This simple analysis enabled us to determine how sensitive the S2 SAV classification was in the different study areas.

Drone

The aim of these case studies was to test whether it was possible to obtain reasonable estimates of eelgrass and macroalgal cover in nearshore Danish waters. We evaluated the performance of drones for mapping eelgrass and macroalgae, by simple comparisons with the available *in situ* data, either obtained via the NOVAVA programme or via designated ground truth observations. Detailed analyses of depth distribution of eelgrass and species composition were not part of these studies.

2.3.2 Chlorophyll

In order to get a quality estimate of the satellite-derived Chl concentrations, they are usually compared with *in situ* measurements, like NOVANA. A thorough statistical analysis is often not feasible because of the time difference between ground sampling and satellite overpass. A proper match-up useful for statistics would fall in ±2 hours window between the two measurements and this is hardly the case. For more details we refer to section 3.4 Validation and match-up in Harvey et al. 2018. Below we describe the approach we have chosen for the comparison in the light of the challenges described above.

The comparison between satellite-derived and *in situ* Chl was threefold:

1) Pixel-based comparison with NOVANA Chl

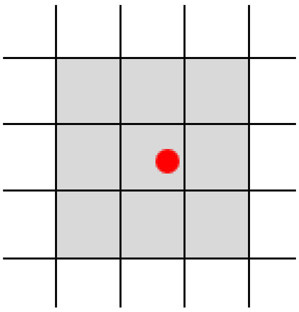
2) Area-based comparison using mean values per water body with NOVANA Chl

3) Summer mean comparison between satellite and NOVANA Chl

Pixel-based comparison

Once the S2 and S3 satellite data were processed and Chl calculated, we used the geographic coordinates of the NOVANA stations to extract pixel values from the satellite-derived Chl products. For S2, besides the pixel values corresponding to the NOVANA station coordinates, we also extracted the values of all neighbouring pixels, resulting in 9 pixels in total (3 × 3 pixels of 60 × 60 m, 1 pixel = 20 m; *Figure 2.4*). For the stations in Roskilde Fjord and Isefjord we additionally extracted values for 15 ×15 pixels which represent one S3 pixel (300 × 300 m). This allowed us to compare Chl from the two satellites by accounting for the same area. For S3, we only extracted the value of one pixel corresponding to the NOVANA station location, because of the coarse spatial resolution of S3 (1 pixel = 300 × 300 m). Finally, all extreme S2 and S3 Chl values (Chl < 0.5 µg/L and > 50.0 µg/L) were assumed to be outliers and dismissed from our analysis.

Figure 2.4. Schematic representation of the pixel extraction, with the red dot representing a NOVANA station and the grey coloured pixels the 3 × 3 satellite pixels.



For the comparisons, we only used NOVANA Chl data taken in the upper one metre of the water column. Previous experiences have shown that this depth agrees well with satellite-derived Chl estimates. Also one metre depth corresponds to the sampling depth used for GES assessments using Chl.

Area-based comparison

For the area-based comparison we aggregated Chl per water body area and calculated mean values from all the pixels for the S2 and S3 products, respectively. From this we got a time series with one mean value per water body and point in time. For the averaging we excluded all shallow areas less than three metres deep, which were influenced by vegetation and seafloor signals. These mean values were then compared to the NOVANA point measurements to see how well the NOVANA location in fact represents the entire water body.

Summer mean comparison

To evaluate the possible use of S2/S3 for the estimation of GES, we calculated the Chl summer means for the period 1 May to 30 September for both 2017 and 2018 in each water body. The summer means were calculated for both the different pixel aggregated values, for S2 (1 × 1, 3 × 3, 15 × 15 pixels) and S3 (1 × 1 pixel) as well as the area-per area-based per water area. This analysis was done to assess the influence of spatial scales on the Chl values. Student's t test pairwise comparison was used to test for differences in Chl mean values between these spatial scales and results are presented in x-y scatterplots based on model 2 type regression analysis. Finally, to further evaluate the usefulness of S2 for mapping water body integrated Chl, we obtained S2 data for seven small water bodies within the Sydfynske Øhav (*Figure 2.1A* and *Table 2.1*).

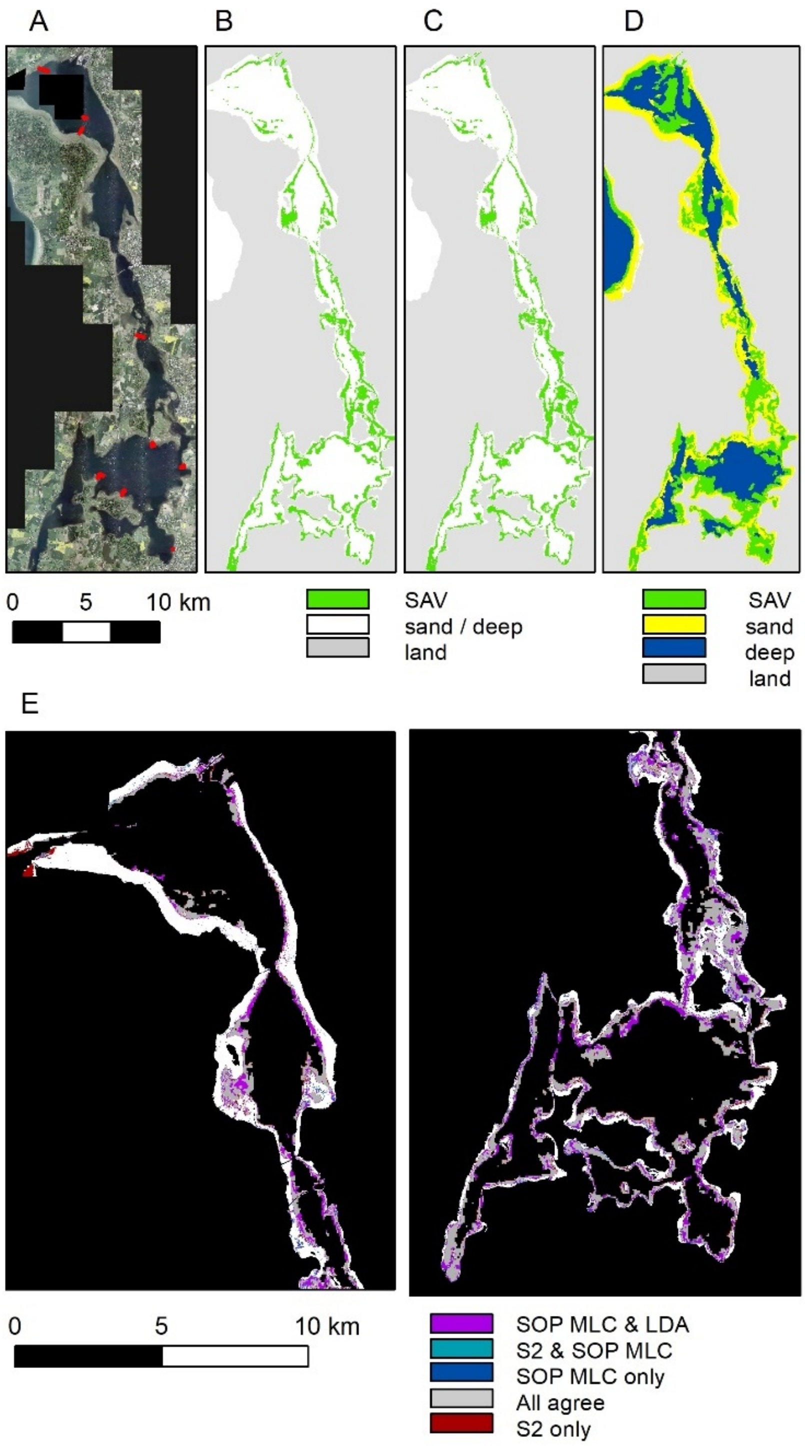
3. Results and discussion

3.1 Part I: Submerged aquatic vegetation

3.1.1 Roskilde Fjord

In Roskilde Fjord we had access to both SOP, S2 and *in situ* data (*Figure 3.1*).

Figure 3.1. Results for SAV mapping in Roskilde Fjord. A) 2016 SOP image data with *in situ* monitoring transects points (red); eelgrass classified from SOP using the B) LDA method and C) MLC method; D) SAV derived from S2 and E) comparison of S2 and SOP-MLC and SOP-LDA derived SAV/eelgrass, excluding (black) parts in 4A not included in all three mappings.



Using SOPs, we determined the SAV distribution in Roskilde Fjord using both an LDA and an MLC method (see Ørberg et al. 2018). The SOP LDA method mapped 1.5 million patches of eelgrass with a total area of 2,465 ha and the MLC method mapped 2.6 million patches of eelgrass with a total area of 2,560 ha. For the same extent the S2 map identified 649 patches of SAV, totalling 1,774 ha or 25.4 % of the fjord. The distribution of patches between different size classes are shown in *Table 3.1*.

Table 3.1. Number of SAV patches within different size classes for S2 and SOP derived for two different classifications, for example S2 mapped 112 patches of SAV with a size > 1 m and <=10 m^2.

Size class (km^2)	0.00001	0.0001	0.001	0.01	0.1	1	10	100	Total (km^2)
S2	1	0	236	261	112	37	2	0	71.1
SOP-LDA	1506452	7384	716	134	46	25	6	0	107.5
SOP-MLC	2594795	10735	978	163	52	28	5	0	112.8

While the two SOP methods map similar total extents of eelgrass (difference < 5 %), the eelgrass patches are distributed slightly different among size classes with the main difference being in the small size group (*Table 3.1*). These differences are very hard to tell from *Figures 3.1B* and *3.1C*. The S2 mapping differed (lower) from the SOP LDA and MLC mappings by 34 % and 37 %, respectively (relative to S2 total) with more than half of the underestimation falling in the 0.00001 ~10 × 10 m group. This suggests that SOP is more optimal for small patch detection. Differences between the S2 and SOP mappings are particularly noticeable in the central and southern parts of Roskilde Fjord, but are spatially uneven (*Figure 3.1E*). Also, from *Figure 3.1D* it is clear that the S2 mapping suggests that SAV is absent along many continuous parts of the nearshore zone where the SOP method indicates presence of eelgrass. Part of the differences between SOP and S2 derived SAV relates to differences in the depth zone masks used (SOP 2.5 metre compared to 4 metre for S2).

We assessed the accuracy of the S2 and the SOP-based SAV maps by comparison with *in situ* transect observations on eelgrass cover in Roskilde Fjord (*Table 3.2* and *3.3*). To assess the sensitivity of the S2 and SOP determinations, we chose to compare results for three different threshold levels (10, 50 and 100 % eelgrass cover).

Table 3.2. Roskilde Fjord confusion matrices comparing classification results of the Sentinel 2 image analysis with i*n situ* monitoring data of eelgrass coverage. For each pixel, data were categorized into presence or absence of eelgrass, and compared with *in situ* presence/absence using of 10 %, 50 % and 100 % cover of eelgrass as thresholds. Correct classification gives the % of pixels classified correctly to each category and in total.

Cover threshold	*In situ*		Sentinel 2		% *in situ* classified correctly
			Absence	Presence	
10 %	Absence	168	140	28	
	Presence	80	39	41	
	Total	248			**73.0**
50 %	Absence	225	168	57	
	Presence	23	11	12	
	Total	248			**72.6**
100 %	Absence	248	179	69	
	Presence	0	0	0	
	Total	248			**72.2**

The S2 SAV map had a high level of agreement (72 to 73 %) with *in situ* eelgrass presence and absence (*Table 3.2*). While overall agreement was similar for the different eelgrass cover thresholds, disagreement was highest in the near-shore shallow zone (*Figure 3.2*). Agreement was very high (90 to 100 %) for the two deepest depth categories, as both *in situ* and S2 predict very low SAV cover near the eelgrass depth limits.

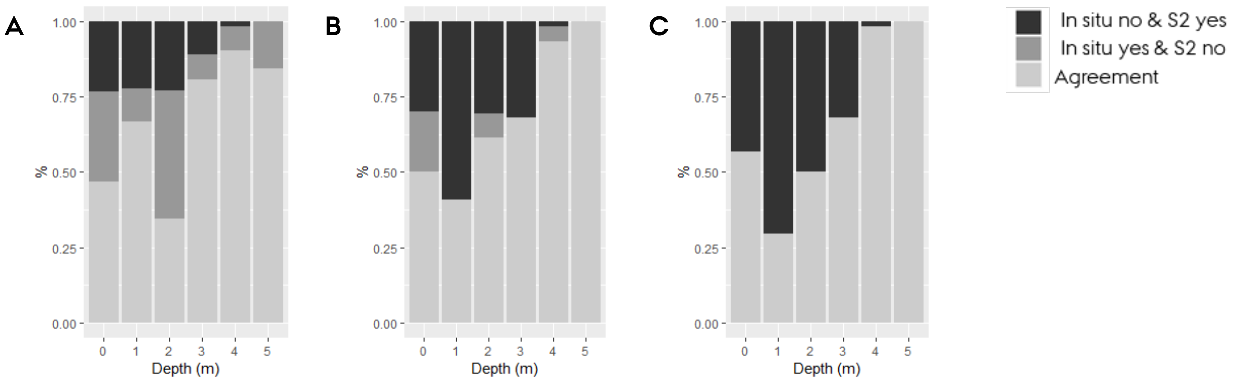


Figure 3.2. Roskilde Fjord comparison of agreement between i*n situ* monitoring data (eelgrass) with S2 (SAV) at different depth intervals. Figures show results for different thresholds of eelgrass cover A) 10 %; B) 50 % and C) 100 % cover and for different depth zones.

The SOP SAV map also had a high level of agreement (63 to 79 %) with *in situ* eelgrass presence and absence. Agreement was lowest for the 10 % eelgrass cover thresholds (*Table 3.3*).

Table 3.3. Roskilde Fjord confusion matrices comparing classification results of the SOP LDA image analysis with *in situ* monitoring data of eelgrass coverage. For each pixel, data were categorized into presence or absence of eelgrass and compared with *in situ* presence/absence using of 10 %, 50 % and 100 % cover of eelgrass as thresholds. Correct classification gives the % of pixels classified correctly to each category and in total.

Cover threshold	***In situ***		**SOP LDA**		**% *in situ* classified correctly**
			Absence	**Presence**	
10 %	Absence	81	72	9	
	Presence	70	47	23	
	Total	151			**62.9**
50 %	Absence	130	108	22	
	Presence	21	11	10	
	Total	151			**78.2**
100 %	Absence	151	119	32	
	Presence	0	0	0	
	Total	151			**78.8**

Agreement levels for the SOP mapping in Roskilde Fjord were between 50 % and 75 % for all threshold levels and depths down to 3 m (*Figure 3.3*). This is very similar to those seen for the S2 (*Figure 3.3*).

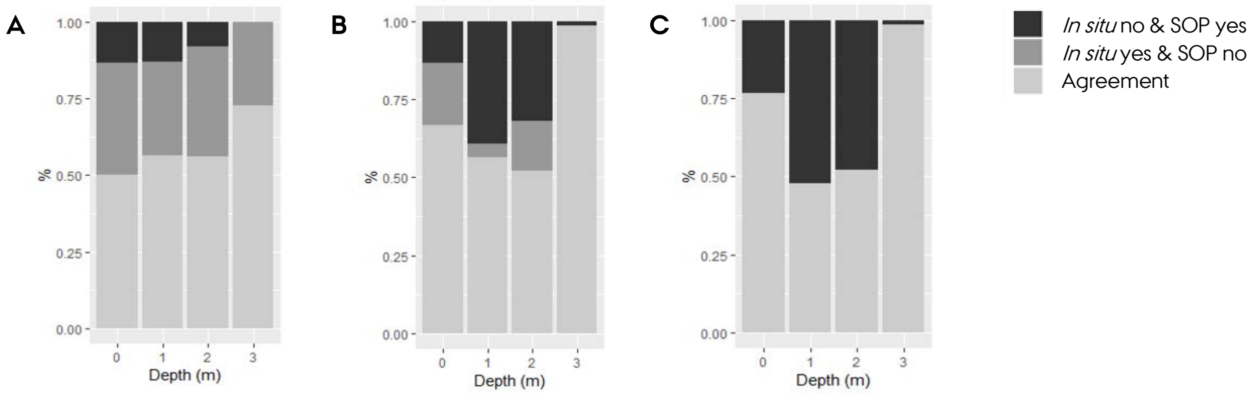


Figure 3.3. Roskilde Fjord comparison of agreement between *in situ* monitoring data (eelgrass) with SOP (LDA) at different depth intervals. Figures show results for different thresholds of eelgrass cover A) 10 %; B) 50 % and C) 100 % cover and for different depth zones.

Similar to S2, disagreement was highest in the near-shore shallow zone. For the deepest depth category, the agreement rose 100 % except for the 100 % eelgrass threshold, for which it was 75 %. In our analysis of SOP data, we applied a depth threshold of 2.5 metres. Consequently, agreement with *in situ* data at the 3 to 4 metre depth interval stems from absence of eelgrass here.

3.1.2 Nibe-Gjøl Bredning

In Nibe-Gjøl Bredning, we had access to SOP, S2 and *in situ* data (*Figure 3.4*).

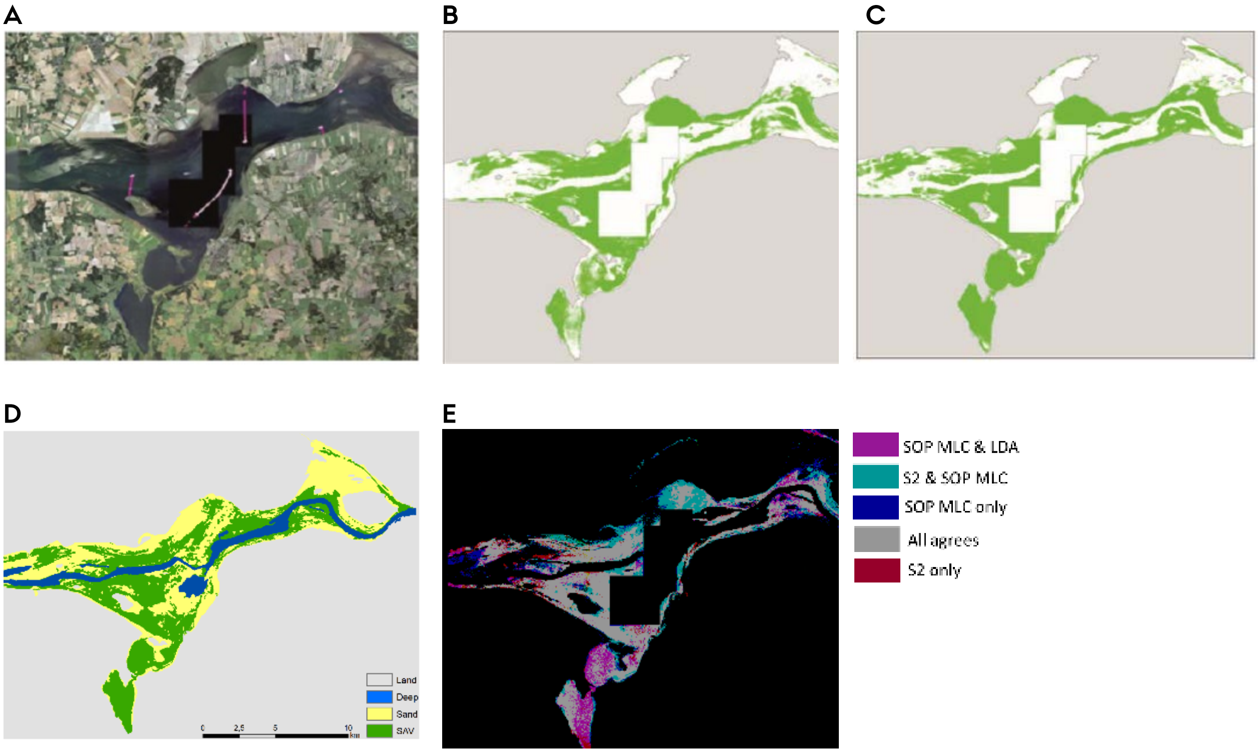


Figure 3.4. Results for SAV mapping in Nibe-Gjøl Bredning. A) The rectified SOP image with indications of *in situ* transects; B) SAV derived from SOP LDA; C) SAV derived from SOP MLC; D) SAV derived from S2; E) Comparison of agreement between SOP and S2 SAV maps. Empty squares in A, B, C and E are areas with no SOP data.

For Nibe-Gjøl, the SOP-LDA method mapped 4.3 million patches of eelgrass with a total area of 4,700 ha and the MLC method mapped 3.0 million patches of eelgrass with a total area of 5,984 ha. For the same extent (i.e. excluding parts where SOP data were not available), S2 mapped 133 patches of SAV, totalling 4,900 ha. The distribution of patches between different size classes are shown in *Table 3.4*. For S2 we only used the area where SOP data were available.

Table 3.4. Number of SAV patches in Nibe-Gjøl within different size classes for S2 and SOP derived for two different classifications. Areas where SOP data were not available were excluded from the S2 analysis.

Size class (km^2)	**0.00001**	**0.0001**	**0.001**	**0.01**	**0.1**	**1**	**10**	**100**	**Total (km^2)**
S2	0	1	19	60	34	11	7	1	18.5
SOP-LDA	4324065	41052	2332	153	23	7	4	1	20.1
SOP-MLC	3006287	24734	1545	136	21	8	3	2	27.6

Similar to Roskilde Fjord, the SOP-LDA and SOP-MLC mappings provided very similar estimates of eelgrass cover in the different size classes, except for the largest group, where classification of two patches caused the MLC classification to estimate overall 37 % higher total cover than the LDA classification. The LDA classification provided a total cover estimate very close (7 % difference) to the S2 estimate, although the methods differed in the distribution between patch sizes. The three mappings only showed agreement for a relatively small portion of Nibe-Gjøl (grey in *Figure 3.4E*). The major differences between the results of the three methods occurred in the northern and southern parts of the area.

Along the transect lines, the S2 SAV had between 65 to 67 % agreement with *in situ* eelgrass presence and absence (*Table 3.5*).

Table 3.5. Nibe-Gjøl confusion matrices comparing classification results of the Sentinel 2 image analysis with *in situ* monitoring data of eelgrass coverage. For each pixel, data were categorized into presence or absence of eelgrass, using of 10 %, 50 % and 100 % cover of eelgrass as thresholds. Correct classification gives the % of pixels classified correctly to each category and in total.

Cover threshold	*In situ*		Sentinel 2		% *in situ* classified correctly
			Absence	Presence	
10 %	Absence	582	463	119	
	Presence	510	235	275	
	Total	1092			**67.6**
50 %	Absence	664	504	160	
	Presence	428	194	234	
	Total	1092			**67.6**
100 %	Absence	732	526	206	
	Presence	360	173	188	
	Total	1092			**65.4**

While overall agreement was similar for the different eelgrass cover thresholds (*Table 3.5*), disagreement was highest in the near-shore shallow zone (*Figure 3.5*). Similar to Roskilde Fjord, agreement increased with depth, supporting evidence of low SAV cover near the eelgrass depth limits.

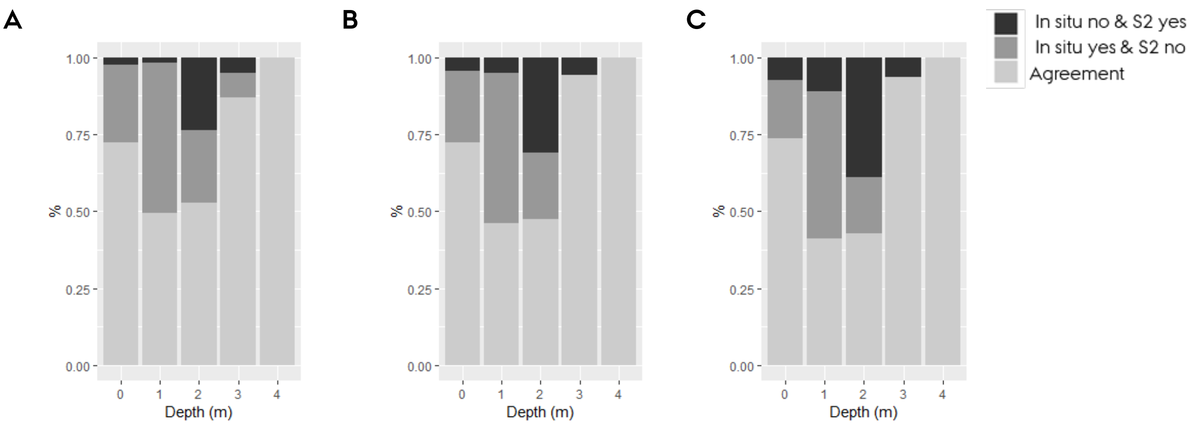


Figure 3.5. Nibe-Gjøl comparison of agreement between *in situ* monitoring data (eelgrass) with S2 (SAV) at different depth intervals. Figures show results for different threshold of eelgrass cover A) 10 %; B) 50 % and C) 100 % cover.

Due to time requirements for the logistics of completing the project within the required deadline, we were unfortunately not able to present a confusion matrix to compare classification results of SOP with the *in situ* NOVANA monitoring data. Unfortunately, this makes it difficult to compare the accuracy of SOP vs S2 for SAV mapping in this area.

3.1.3 Sydfynske Øhav

In the Sydfynske Øhav we only had access to S2 and *in situ* data (*Figure 3.6*).

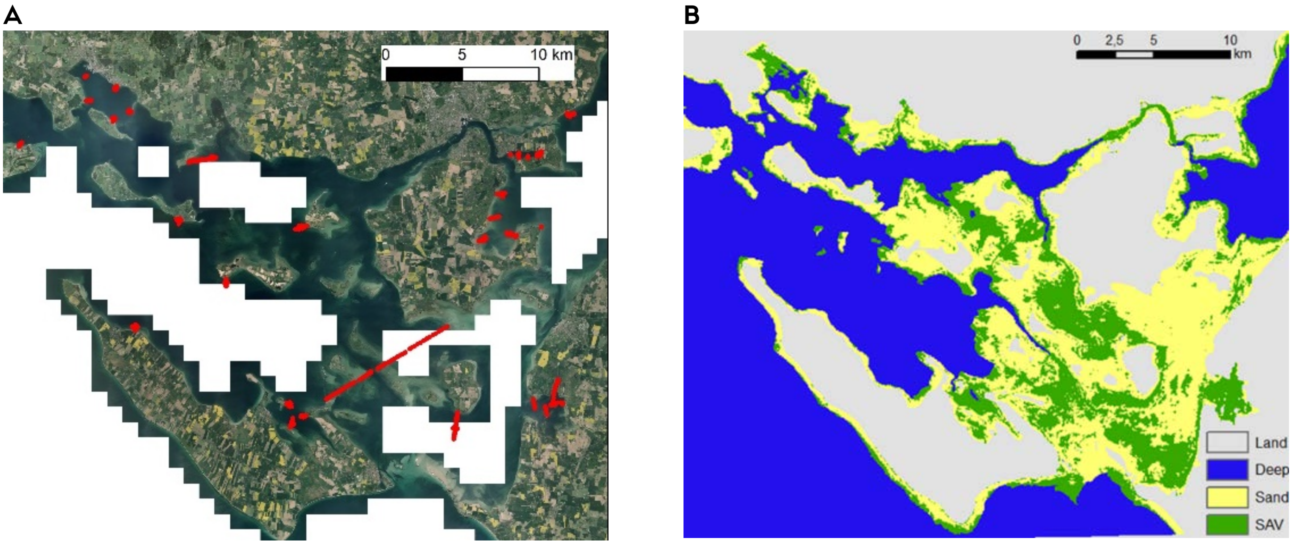


Figure 3.6. Results for SAV mapping in the Sydfynske Øhav. A) 2016 SOP image data with *in situ* monitoring transect points (red); B) SAV derived from S2.

The area had lower (51 to 58 %) agreement with *in situ* eelgrass presence and absence along the transect lines (*Table 3.6*) compared to Roskilde Fjord (*Table 3.2*) and Nibe-Gjøl (*Table 3.5*). Also, there was a tendency towards better agreement for the 50 and 100 % eelgrass threshold, suggesting that the S2 map did not capture low density (10 % cover) areas quite as well. Looking at the level of agreement at different depths (*Figure 3.7*), it appears, however, that the level of agreement had a similar pattern for the three eelgrass thresholds, with agreements of 60-80 % at shallow water, decreasing to 25-50 % agreement at deeper water. The analysis based on the 10 % threshold shows a similar pattern, except for lower agreement levels, of just 50-75 %, also for the shallow water areas. The pattern with depth seen here contrasts with that seen for the equivalent Roskilde Fjord and Nibe-Gjøl analyses, where agreement levels were highest (over 75 %) for the deeper water areas. Given that water depth is associated with light extinction, and thereby weaker reflectance signals, the pattern seen here for Sydfynske Øhav is closer to the expected pattern than that seen for Nibe-Gjøl and Roskilde Fjord.

Table 3.6. Sydfynske Øhav confusion matrices comparing classification results of the Sentinel 2 image analysis with *in situ* monitoring data of eelgrass coverage. For each pixel, data were categorized into presence or absence of eelgrass, using of 10 %, 50 % and 100 % cover of eelgrass as thresholds. Correct classification gives the % of pixels classified correctly to each category and in total.

Cover threshold	***In situ***		**Sentinel 2**		**% *in situ* classified correctly**
			Absence	**Presence**	
10 %	Absence	1114	644	470	
	Presence	683	405	278	
	Total	1797			**51.3**
50 %	Absence	1484	891	593	
	Presence	313	158	155	
	Total	1797			**58.2**
100 %	Absence	1780	1044	736	
	Presence	17	5	12	
	Total	1797			**58.8**

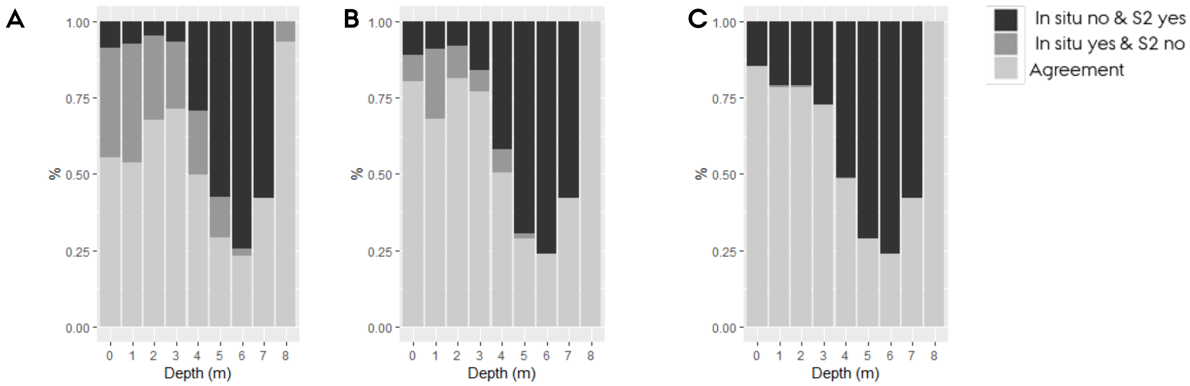


Figure 3.7. Sydfynske Øhav comparison of agreement between *in situ* monitoring data (eelgrass) with S2 (SAV) at different depth intervals. Figures show results for different threshold of eelgrass cover A) 10 %; B) 50 % and C) 100 % cover.

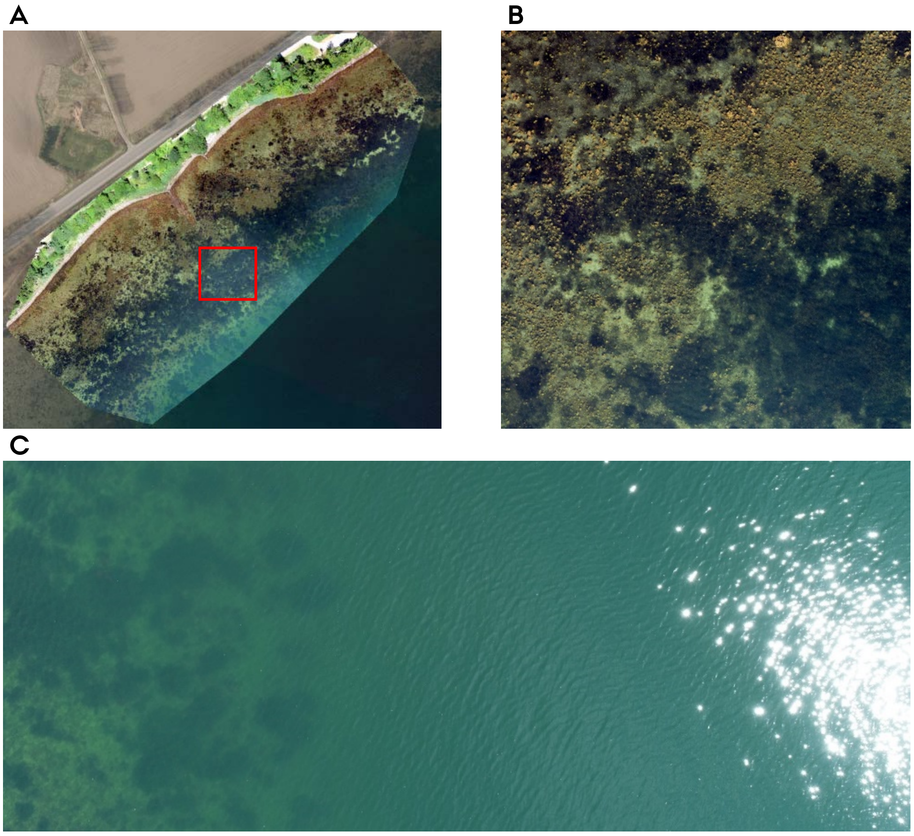
3.1.4 Drones

In the following we present the most interesting results from the many drone investigations performed during this project. Further details are, however, available for each of the studied areas upon request.

Eelgrass

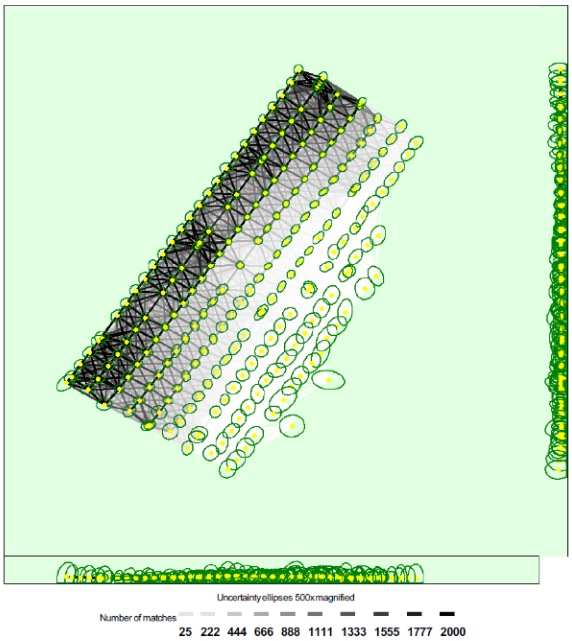
In Flensborg Fjord the drone was deployed from a boat (Quicksilver 550 pilothouse). While departure was easy, landing on the boat's roof was not possible due to excessive boat movement. The drone was therefore retrieved manually from the air. The drone was programmed to 75 metres altitude, which is less than the maximum 100 metre allowed altitude. Recordings were made with different overlaps between pictures. To illustrate issues related to stitching of images and sunglint, we produced a mosaic image of a small section of the northern part of the fjord (*Figure 3.8*).

Figure 3.8. Test of drone sampling for mapping of eelgrass in a small coastal section of Flensborg Fjord. A) The entire RGB mosaic; B) an enhanced section showing details of mixed vegetation and sediments; C) example of problems with sunglint.



The processing of the mosaic image showed that the uncertainty associated with stitching of image points (using an overlap of 75-80 %) increases with water depth and distance from the shoreline, as fewer key points are available for stitching (*Figure 3.9*).

Figure 3.9. Computed image positions with links between matched images. The darkness of the links indicates the number of matched 2D key points between the images. Bright links indicate weak links and require manual tie points or more images. Dark green ellipses indicate the relative camera position uncertainty of the bundle block adjustment result.



The uncertainty (size of green circles) of the position of the individual pictures therefore increases with depth as the benthic key points get blurred. The mapping exercise in Flensborg Fjord provided a number of valuable recommendations:

1. An overlap of 90 % forward and 75-80 % to the sides should be applied for optimal stitching of the image mosaic.
2. Spatial accuracy of the mosaic image decreases with increasing depth.
3. Detailed mapping of the submerged vegetation is difficult when there are ripples on the sea surface.
4. Problems associated with sunglint can be reduced by using a polarized filter on the camera. It seems possible to further reduce sunglint problems by recording pictures away from the sun.
5. Based on #2 and #3, optimal weather conditions are no/little wind and a diffuse cloudiness at high altitude.
6. While mapping of eelgrass meadows is relatively easy at shallow water, the maximum depth distribution is difficult to evaluate. Partly because of the increased spatial inaccuracy with depth, and due to a weaker benthic signal. Other issues such as accuracy of water depth at the site of observation need to be resolved.

In Rødsand Lagune we mapped the coastal vegetation and classified this using a maximum likelihood classification. Also, we investigated a novel approach to obtain ground truth data by lowering a camera into the water column. This was done at 15 points from shoreline corresponding to a NOVANA eelgrass transect (*Figure 3.10*).

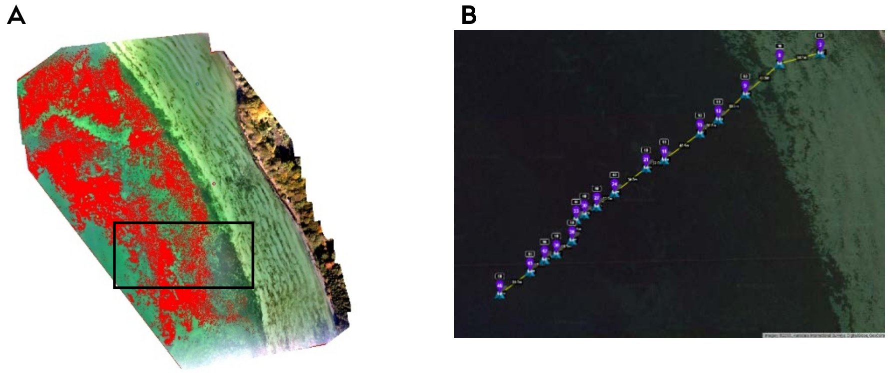
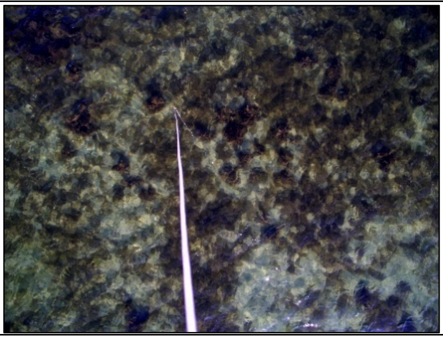
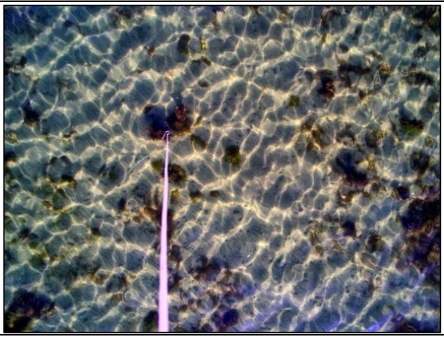
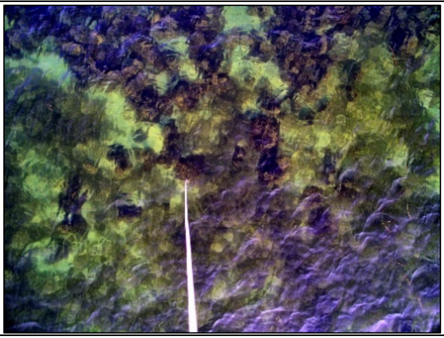
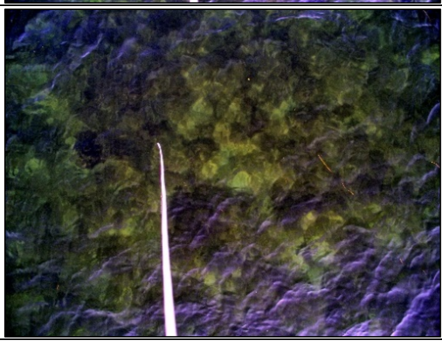
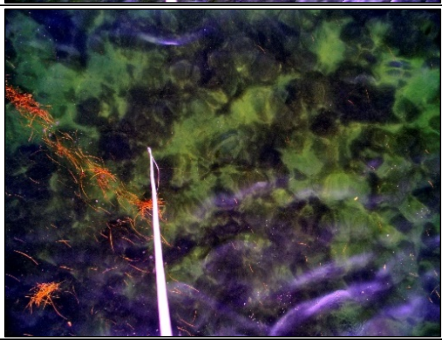
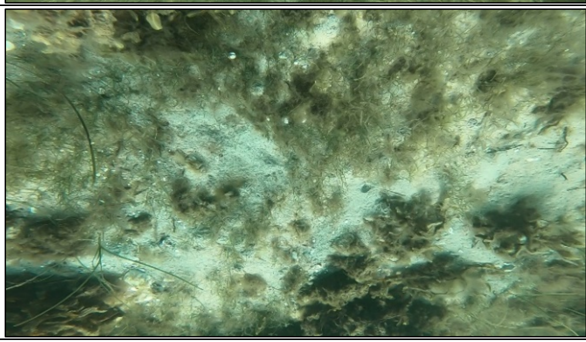


Figure 3.10. A) Mosaic RGB image of a small section of Rødsand Lagune. Red colours indicate presence of eelgrass based on a maximum likelihood classification; B) ground truth points sampled with the drone. The area of the transect is shown as the black square in A.

At each of the 15 ground truth positions, an underwater (UW) photo was taken simultaneously by the drone just above the water surface, and by a GoPro camera approximately 1 metre above the seabed (*Table 3.7*). From the UW photos we made a visual analysis to distinguish vegetation from sediment, and between different vegetation types and finally determined the % cover of eelgrass. Comparing with the NOVANA transect data on eelgrass cover, the analysis showed a good agreement (*Table 3.8* and *Figure 3.11*).

Table 3.7. Examples of drone and underwater photos used for eelgrass cover estimations along 15 sample points in Rødsand Lagune.

Station # / eelgrass % cover	Drone pictures	Underwater pictures
#1 2 %		
#2 2 %		
#3 30 %		
#4 40 %		
#5 10 %		

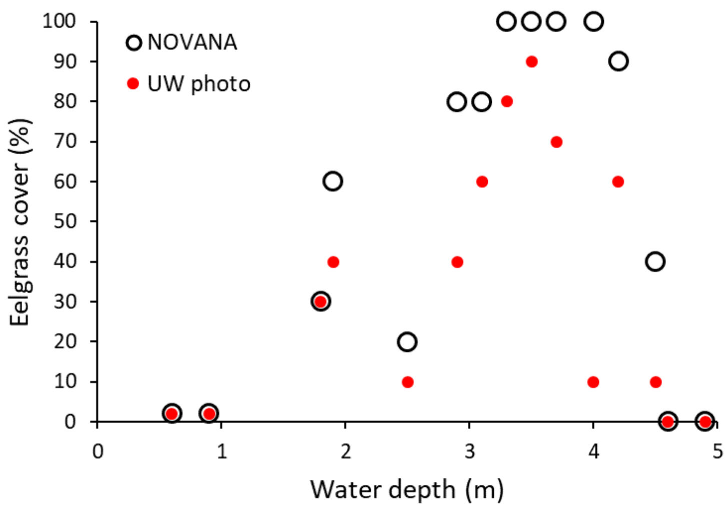
Results for the 15 sample points are shown in *Table 3.8*.

Table 3.8. Comparison of eelgrass cover along 15 sample stations in Rødsand Lagune. NOVANA represents data collected using an underwater video system during August 2016. UW estimates are based on underwater drone-based photos in October 2018. The sample depth and drone altitude are also shown.

Station #	Latitude N	Longitude E	Depth (m)	% eelgrass NOVANA	% eelgrass UW photo	Drone altitude (m)
1	54.65767	11.70488	0.6	2	2	6.5
2	54.65759	11.70431	0.9	2	2	6
3	54.65734	11.70382	1.8	30	30	6.2
4	54.65714	11.70344	1.9	60	40	6.1
5	54.65703	11.70319	2.5	20	10	5.5
6	54.65681	11.70268	2.9	80	40	5.1
7	54.65674	11.70243	3.1	80	60	4.9
8	54.65654	11.70199	3.3	100	80	4.7
9	54.65644	11.70173	3.5	100	90	4.5
10	54.65637	11.70156	3.7	100	70	4.3
11	54.65633	11.70145	4	100	10	4
12	54.65616	11.70139	4.2	90	60	3.8
13	54.65605	11.70116	4.5	40	10	3.5
14	54.65601	11.701	4.6	0	0	3.4
15	54.65591	11.70079	4.9	0	0	3.1

The precision of the preprogrammed drone altitude has previously been estimated to lie between 0.15 and 0.21 m for a DJI Phantom drone (Kulhavy et al. 2017). Water depth was estimated by comparing information extracted from the NOVANA transect observations with the drone height. Estimates of eelgrass cover based on the UW photos followed the same pattern with depth as NOVANA observations (*Figure 3.11*).

Figure 3.11. Comparison of eelgrass cover estimated using the conventional video transect method (NOVANA) and from UW photos taken with a drone.



UW photo estimates were on average 20 % lower than the NOVANA estimates (33 vs 53 %). This is likely because of eelgrass senescence at the later UW photo sampling (October vs August for NOVANA). Also, there may have been a decrease in eelgrass during the two years since NOVANA (2016) and UW photo (2018) estimations. Nevertheless, there was an overall good correspondence between the two methods for estimating eelgrass cover which both indicated a lower depth limit of 4.5 metres. Future evaluations of the UW photos should make sure to compare it with simultaneous video transects. Also, efforts should be made to thoroughly evaluate the use of drone-based UW documentation of the depth limits of eelgrass.

In the Wadden Sea the test of drones for obtaining ground truth data was made along a 250 metre transect line in the south eastern part of Fanø (*Figure 3.12*).

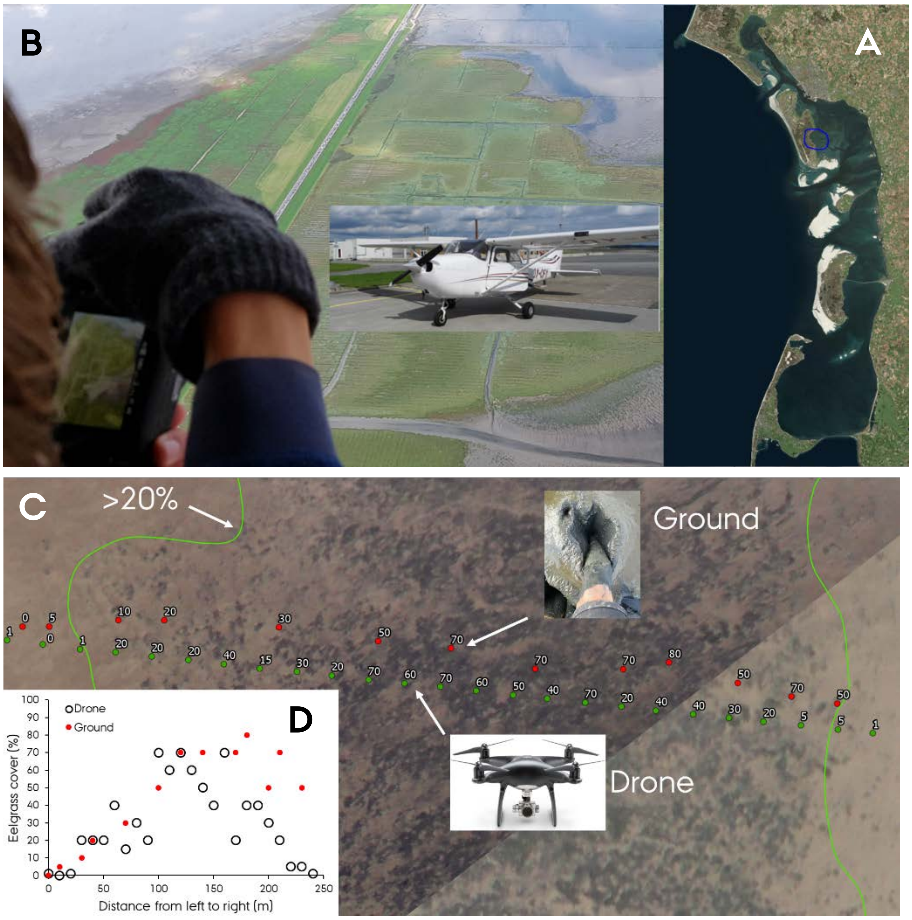


Figure 3.12. Mapping of eelgrass (*Zostera noltii*) during low tide in the Wadden Sea. A) the Danish part of the Wadden Sea with a blue ring around the test area near Fanø; B) Air photography used to estimate the areal extent of eelgrass; C) Close-up of the airplane photo with inserted in situ observations estimated from a drone and from ground observations. The green line delineates the area estimated to have more than 20 % cover of *Zostera noltii*; D) comparison of eelgrass cover based on high resolution drone RGB images and manual *in situ* (ground) observations.

The drone- and ground-based *in situ* observations showed the same trends with higher cover at the centre of the patch. Differences in overall levels (30 vs 44 % cover drone and ground, respectively) were caused by higher ground levels near the right hand side of the patch. It seems likely that these differences were caused by small-scale heterogeneity in patch distribution. More samples were provided by the drone, giving a more detailed description of the eelgrass gradient than the time-consuming ground sampling. It therefore seems that drones are well suited to support eelgrass mapping in the Wadden Sea as they provide a more detailed and thus representative coverage of eelgrass distribution. Furthermore, colour-based recognition of eelgrass based on classifications such as MLC and LDA might be a useful approach to automate drone-based *in situ* estimations of eelgrass cover and for differentiation between seagrass species such as *Z. marina* and *Z. noltii*.

Macroalgae

In the inner part of Odense Fjord, in an area named Seden Strand, we applied a combination of SOP and drone data to map recurent blooms of the macroalgae *Ulva lactuca,* during a series of summers (*Figure 3.13*).

Figure 3.13. Result of a SOP- and drone-based mapping of the cover of *Ulva lactuca* in Seden Strand, the inner, most shallow part of Odense Fjord. Light green colour represents 10-50 % and dark green 51-100 % cover. In 2017, ground truth observations were made at 10 sampling points.

Although the studied area represents a very small area (0.3 km^2) of Odense Fjord, it was of interest to estimate the amount of biomass, carbon (C), nitrogen (N) and phosphorus (P) that could be removed by harvesting *Ulva lactuca* in this confined part of the eutrophic Odense Fjord. The challenge for RS techniques here is that the water is very turbid, reducing the Chl signal. However, due to the shallowness of the area (1 to 2 metres depth) and the density of the macroalgae (typically > 50 % cover), it was possible to classify patches of *Ulva lactuca* well. Based on the 10 *in situ* samples in 2017, the content of C, N and P per unit biomass and a conversion between % cover and biomass was determined. From these measures, we estimated the biomass, C, N and P stored in the algae for the different years (*Table 3.9*).

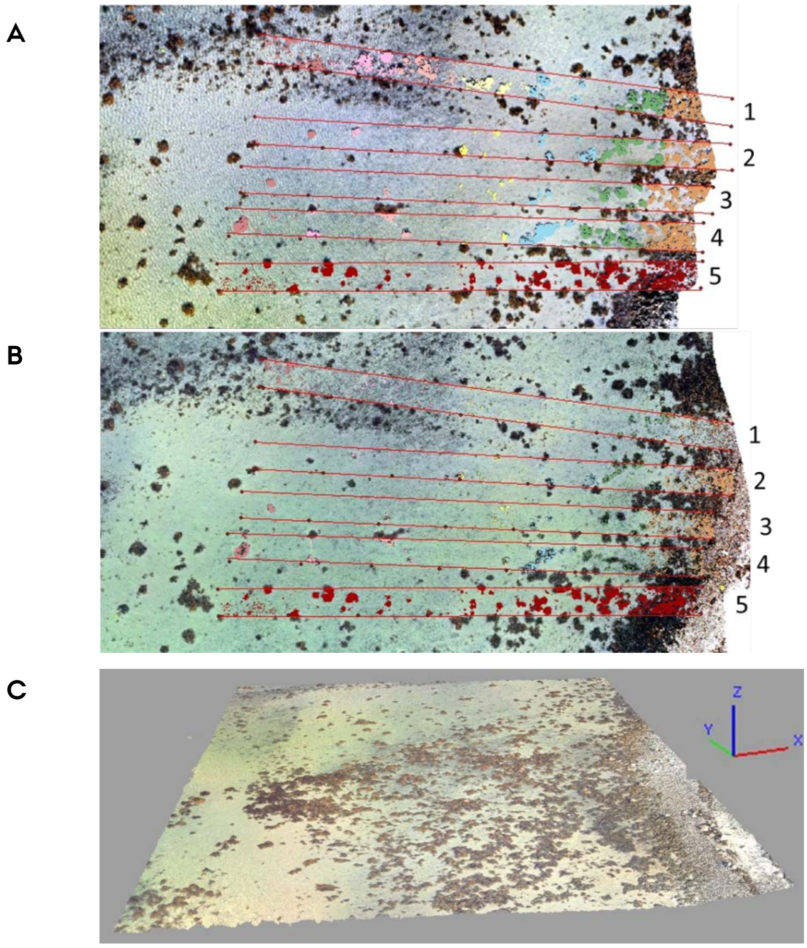
Table 3.9. Calculated areal extent of *Ulva lactuca* in a 320.526 m^2 area of Seden Strand. Based on samples collected in 2017, cover was converted into wet weight (WW) biomass and tons of carbon (C), nitrogen (N) and phosphorus (P).

Year	Platform	10-50 % area (m^2)	51-100 % area (m^2)	Biomass tons W/W	C tons	N tons	P tons
2012	SOP	10.802	81.111	202	14	2	0,17
2014	SOP	7.376	126.609	307	21	3	0,14
2016	SOP	19.780	161.393	400	27	4	0,19
2017	Drone	120.552	172.080	515	35	6	0,24

Comparing the years, cover and biomass of *Ulva lactuca* has almost tripled from 2012 to 2017, with the most obvious change at the 10-50 % cover interval from 2016 to 2017. It is important to note that the drone-based estimates are associated with less uncertainty as the image was calibrated directly against *in situ* samples. In combination with a higher resolution of the drone (1-2 cm vs 12-16 cm for SOP), this may explain the higher cover of *Ulva lactuca* at the 10-50 % cover range.

In Begstrup Vig, we applied a drone to map the efficiency of different methods for harvesting *Fucus vesiculosus*. This analysis provided information on the sensitivity of drone-based image analysis for mapping macroalgae in the shallow sublittoral zone. Also, we wanted to test the ability to make a detailed digital elevation model (DEM) from the drone recordings (*Figure 3.14*).

Figure 3.14. Results from an MLC analysis of drone recordings in Begstrup Vig A) before harvesting and B) after harvesting of *Fucus vesiculosus*. Numbers 1 to 5 refer to different harvest methods, ranging from full removal (1) to partial (5). C) From the drone image, a DEM was furthermore produced, which had been corrected for water.



For each of the 5 harvest methods we compared the areal extent of *Fucus vesiculosus* derived from the MLC classification with the biomass harvested in seveb plots of 2 × 5 metres. Simple linear regression analysis was applied to investigate the strength relationships between harvested biomass (wet weight) and the areal extent (m^2) mapped by the drone using MLC. Regression models were very strong with r^2 values ranging from 0.56 to 0.96. Regression models had quite similar slopes and intercepts close to 0 indicating that the drone-based analysis is sensitive and comparable for mapping of *Fucus vesiculosus* in the shallow, sublittoral zone. The DEM model gave a very detailed and illustrative view on the distribution and biomass of the seaweed. Mapping will be repeated in 2019 and 2020 to monitor the growth and recovery of the seagrass bed.

3.2 Part II: Chlorophyll

3.2.1 Pixel- and area-based comparison

The pixel-based comparison between satellite-derived and *in situ* Chl showed that S3 Chl follows the NOVANA data closer than S2 Chl, even in the narrow, inner Roskilde Fjord (*Figure 3.15*). In general, S2 Chl is noisier during the season with large variability over short time. This difference between the two satellites can be explained with the satellite sensor characteristics of S3, which was specifically designed for water applications, and on the other hand the higher spatial resolution of S2, which is not smoothing out variability on the water surface. Effects on the water surface, such as for instance crests of the waves due to strong winds, have a stronger impact on the reflectance measured by S2 than S3. The latter integrates a much larger area per pixel which makes the signal smoother.

Again, it is important to point out that various scales are involved in the comparison presented, from point measurements (NOVANA) to integrated Chl over 300 × 300 m. In order to evaluate the influence of the integrated area on the Chl, we compared different aggregations by increasing the area (number of pixels) covered by S2 from 1 × 1 pixel (20 × 20 m) to 15 × 15 pixels (equals an area of 300 × 300 m). Logically, we would expect that the S2 Chl 1 × 1 pixel value should be closest to the *in situ* measurement because they are closest in terms of area. However, often this is not the case and a Chl value averaged over 9 or even 225 pixels is closer. Both S2 and S3 detected the blooms, yet the magnitude of the blooms was not always met. Again, one reason might be the different spatial aggregations of the Chl measurements and specific distribution of the bloom.

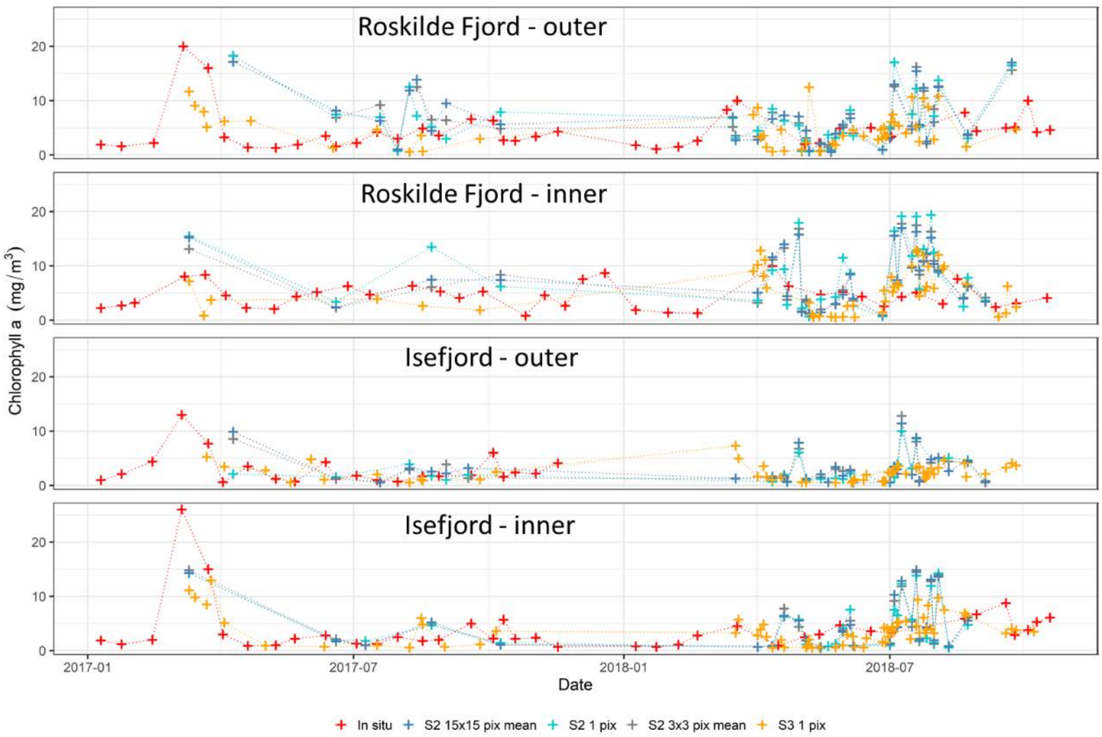


Figure 3.15. Daily match ups of *in situ* Chl samples with sample station specific (local) estimates based on Sentinel 2 and 3 in the inner and outer parts of Roskilde Fjord and Isefjord for 2017 and 2018. For S2, the Chl estimates were derived for 1 × 1, 3 × 3 and 15 × 15 pixels, corresponding to 20 × 20 m, 60 × 60 m and 300 × 300 m pixels. S3 1 × 1 (300 × 300 m pixel) is also shown.

As mentioned earlier, a proper statistical analysis is difficult, because the number of match ups (*in situ* and satellite measurements taken at least on the same day, optimally within a ±2 hours window) is too small. For the monitoring station Ros60, located in the inner Roskilde Fjord, the analysis revealed in fact only two match ups in the period 1 May to 30 September 2017. This strongly limits the applicability of the current monitoring strategy for satellite validation purposes.

Even more so, as true validation requires that water samples are taken within 30 minutes of satellite passing which was not possible with the available NOVANA data which only showed a daily match up on a few occasions. Also, true validation requires that Chl is measured with the HPLC technique which is known to provide lower Chl estimates compared to spectrophotometric analysis (Pinckney et al. 1994) applied in the Danish monitoring programme. Another DCE project is currently investigating if it is possible to apply a simple correction between these methods. While the importance of the Chl measurement technique (HPLC vs spectrophotometric) for the comparison of S2 and S3 Chl with *in situ* is likely to be minor, the expectation would be that given that algorithms used to derived Chl are calibrated against HPLC data, this would result in lower Chl estimates compared to *in situ* samples. In order to improve the validation of Sentinel for Chl monitoring in Danish waters, it is therefore recommendable to consider investment in AERONET validation stations (https://aeronet.gsfc.nasa.gov/). These will also help improve the automated algorithms for screening of clouds at our latitudes.

In our further comparison between S2, S3 and *in situ* Chl, we utilized all S2 and S3 data available for 2017 and calculated monthly means (see section 2.3.2 for more details on methodology of calculations) (*Figure 3.16*). On the one hand we calculated pixel-based monthly means for pixels corresponding the locations of the *in situ* samples (for S2 1 × 1, 3 × 3 and 15 × 15 pixels; for S3 1 × 1 pixel), on the other hand we averaged all the pixels of the water area and calculated areal monthly means (*Figure 3.16A*).

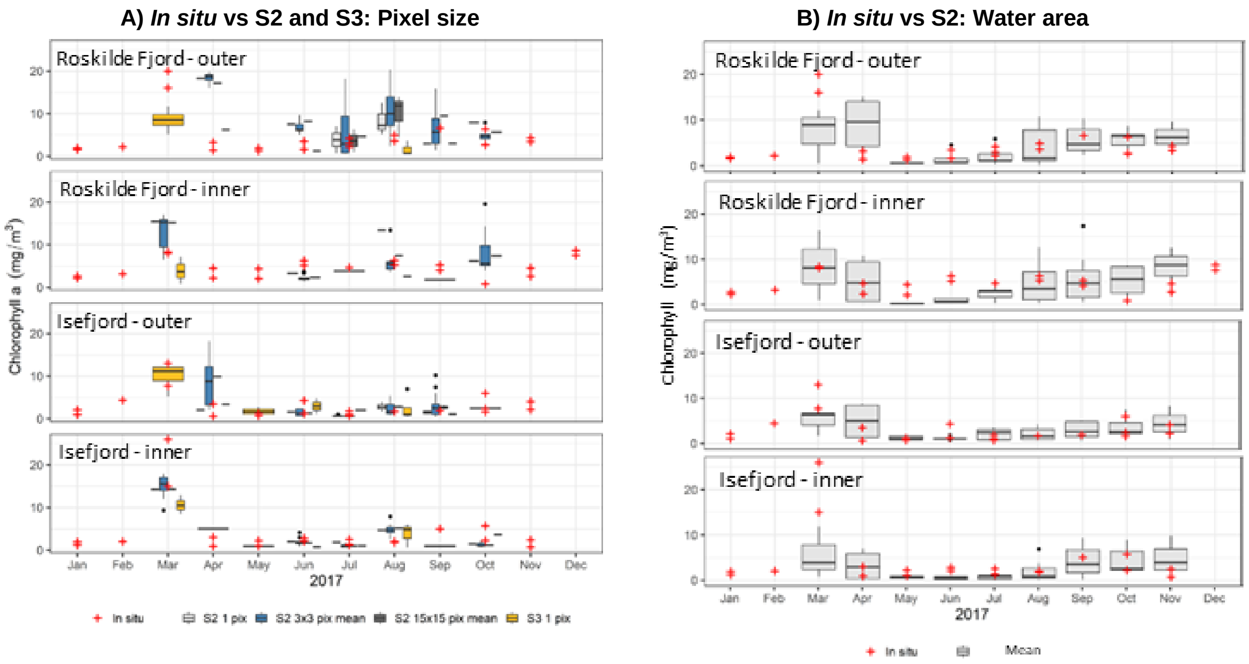


Figure 3.16. Comparison of monthly mean Chl values from S2 and S3 with variations in the *in situ* concentrations. A) Daily *in situ* values are compared with S2 and S3 calculated for different pixel sizes. B) Daily *in situ* values are compared with monthly average Chl representing entire water bodies. The box plots represent the mean, 95 % confidence limits and min-max values.

Satellite-derived Chl concentrations from both S2 and S3 followed the seasonal pattern of the *in situ* measurements reasonably well. A higher variability was apparent for the S2 estimates (1 × 1 pixel) with its higher spatial resolution compared to the S3 estimates. Again, this suggests that S2 estimates for small spatial scales are more sensitive to sub-pixel phenomena such as white crests of waves during windy days or small-scale Chl blooms. S3 covers a much larger area, which might explain the smaller variability and smoother seasonal trends in these estimates in addition to the water-customized sensor design.

Besides the pixel-based comparison, we also compared how well the monthly mean value of the entire water area (excluding the 0-3 m depth zone) matches the *in situ* measurements (*Figure 3.16B*). Interestingly, although there are several differences in the spatial and temporal scales for S2 and *in situ* data, the seasonal trends and levels obtained by S2 resemble that of *in situ* quite well. This could be an interesting approach to retrieve information for an unmonitored water body and to affirm that the location of the NOVANA station effectively represents the entire water body, although this will be challenging during phytoplankton blooms such as the one shown on the cover image of this report.

Since a proper statistical analysis is not feasible with daily data, the performance of S2 and S3 compared to *in situ* Chl was tested quantitatively with monthly aggregated data (both satellite and *in situ* Chl) for three different water bodies (*Figure 3.17*). It should be noted here that no optimization for local conditions has been applied and the results shown are based on the standard C2RCC processor.

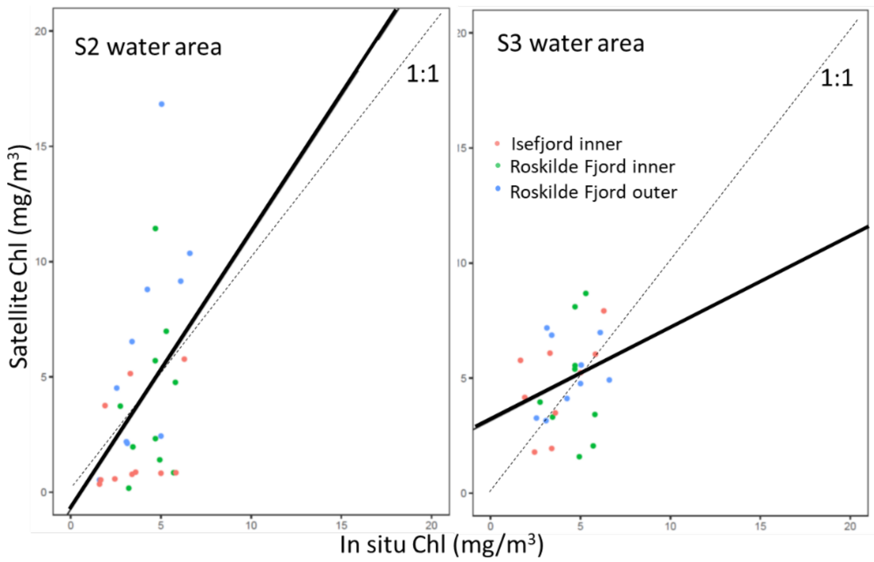


Figure 3.17. Relationships between monthly Chl mean (1 May to 30 September) derived from satellites and *in situ* measurements (1 m depth). Satellite estimates representing entire water areas are shown for S2 and S3. Data cover 2017 and 2018. Full black lines are regression models. For comparison the 1:1 relationship is shown by a dashed line.

For S2 for instance, *Figure 3.17* suggests that using localized scaling parameters in the Chl retrievals could make the EO values much more aligned with the *in situ* values. Model 2 linear regression analysis was done for different spatial scales of the S2 and S3 products (*Table 3.10*). Overall, the level of agreement with satellite and *in situ* data was weak. Comparison of regression models indicates that the water area integrated S2 values aligned better with *in situ* Chl than local higher resolution S2 estimates. For S3, the 1 × 1 pixel (i.e. 300 × 300 m) resolution data at the local scale provided the best comparison.

Table 3.10. Statistics from model 2 type linear regression analysis of relations between satellite-derived Chl and *in situ* Chl. Models were made for S2- and S3-derived Chl for different spatial scales, ranging from 1 × 1 pixel to integration over the entire water area. For the analysis we combined monthly Chl estimates from Roskilde inner and outer Fjord (2017 and 2018) with data from the inner Isefjord (2017).

Sensor	Spatial scale	Intercept	Slope	r^2	*p*	n
S2	1 × 1	1.72	1.04	0.15	0.04	23
	3 × 3	2.04	0.90	0.13	0.08	23
	15 × 15	1.30	1.12	0.18	0.03	23
	Water area	-0.74	1.19	0.20	0.02	30
S3	1 × 1	0.61	0.70	0.18	0.01	26
	Water area	3.15	0.40	0.08	0.07	27

3.2.2 Summer mean comparison

In order to evaluate the possible use of S2 and S3 for the estimation of GES, we calculated the Chl summer means for Roskilde Fjord covering 1 May to 30 September for both 2017 and 2018. The influence of pixel aggregation size for summer mean Chl calculations are presented in *Figure 3.18*.

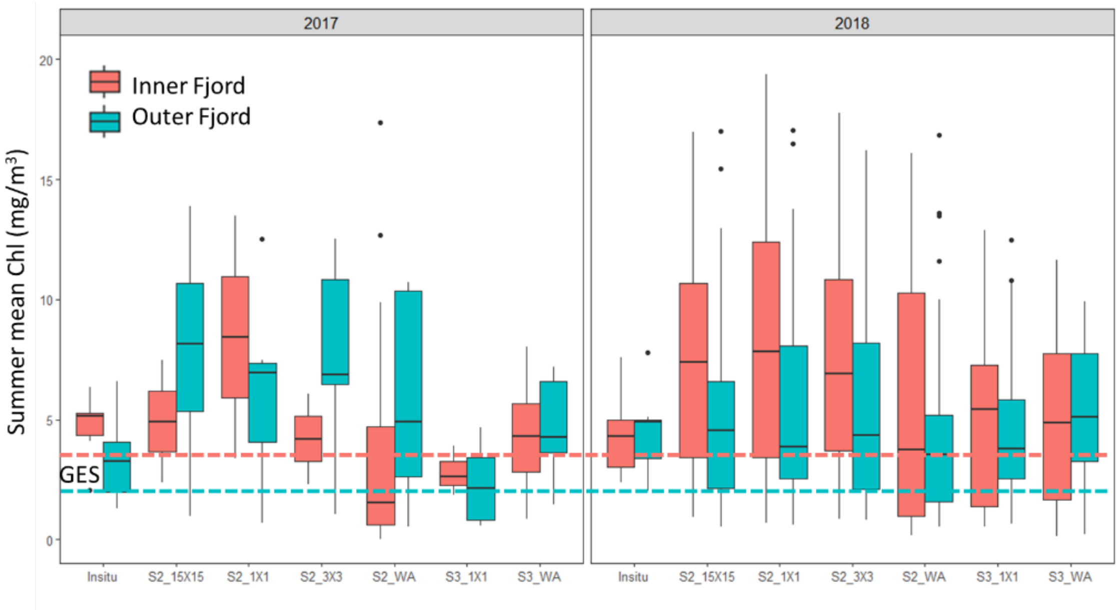


Figure 3.18. Box plots of summer (1 May to 30 Sep.) mean Chl values for inner and outer Roskilde Fjord during 2017 and 2018. *In situ* values are compared with S2 and S3 using different pixel aggregations and values representing the average of the entire water body. The Chl levels required to obtain good ecological status (GES) according to the WFD are shown as dashed lines. Box plots represent the mean, 95 % confidence limits and min-max values.

During 2017 we observed a more random distribution of the different S2 and S3 estimates compared to 2018 which is most likely related to the number of images available in the two years. 2017 was an extremely cloudy year resulting in a small amount of good satellite images. During the sunnier 2018 with optimal conditions for optical satellite monitoring, the result is much more consistent, but with a higher variability due to the inclusion of more images. Interestingly, the variability in the bigger inner part of Roskilde Fjord is larger than in the smaller outer part. As the *in situ* data only represent a single point, the variability here gives a good indication of temporal variability, while S2 and S3 estimates cover both temporal and spatial variability.

To further test for differences between the different estimates of summer mean Chl in Roskilde Fjord, we used a pairwise t-test. While none of the S2 or S3 estimates in the inner Roskilde Fjord were significantly different from the *in situ* measurements in 2017, the estimates from S2 (aggregations of 1 × 1, 3 × 3 and 15 × 15 pixels) were significantly higher than S3 in 2018. For the outer Roskilde Fjord, only the S2 (3 × 3 and 15 × 15) was significantly higher in 2017. The analysis showed that aggregations from S2 Chl over small areas (1 × 1 and 3 × 3 pixels) are more variable than aggregations over larger areas, such as the entire water body. The higher variability in S2 and S3 Chl estimates in 2017, makes the assessment of GES status more uncertain. Overall, this analysis showed that the S2 and S3 Chl estimates are at similar levels as *in situ* measurements, but sensitive to low coverage during years with high cloud cover. Also, S2 and S3 estimates obtained at water body level seem more appropriate as they have less variability embedded.

To further evaluate the use of S2, we compared *in situ* Chl concentrations measured at a central monitoring station with mean values derived by averaging the entire area of 10 different shallow water bodies (without 0-3 m depth areas) (*Figure 3.19*).

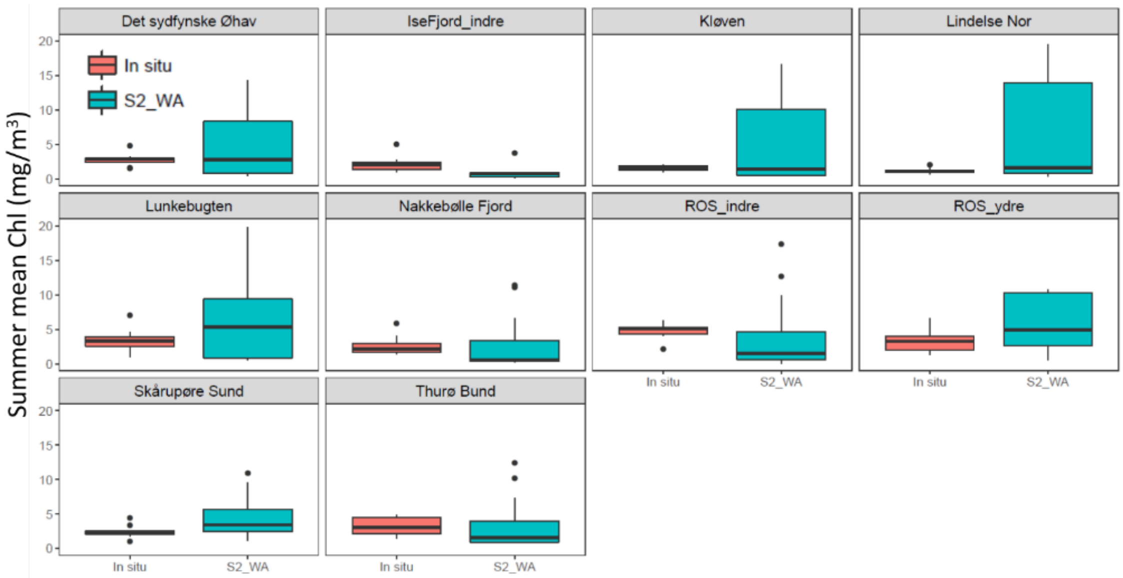


Figure 3.19. Summer (1 May to 30 September 2017) mean Chl values for 10 Danish shallow coastal water areas estimated using Sentinel 2 and from *in situ* water samples (1 m depth).

Except for Thurø and the inner Isefjord, the S2 water area estimates are much more variable than the *in situ* point estimates. Applying a pairwise t-test, we found that in two small areas in The Sydfynske Øhav (Lindelse Nor and Skårupøre Sund) S2 estimates were significantly higher than the *in situ* estimates ($p > 0.05$). Higher S2 Chl estimates here are likely caused by the clear waters in the area and the impact of the seafloor (vegetation and sediment) on the reflectance signal of the satellite sensor which can lead to erroneous Chl retrieval. Besides from these two areas, S2 and *in situ* summer mean values were not significantly different ($p < 0.05$).

Sentinel 2 – summer mean Chl maps

Surface summer mean Chl concentrations were derived from S2 imagery for Roskilde Fjord and the connected Isefjord (*Figure 3.20*). All images between 1 May and 30 September have been used for the mean calculations.

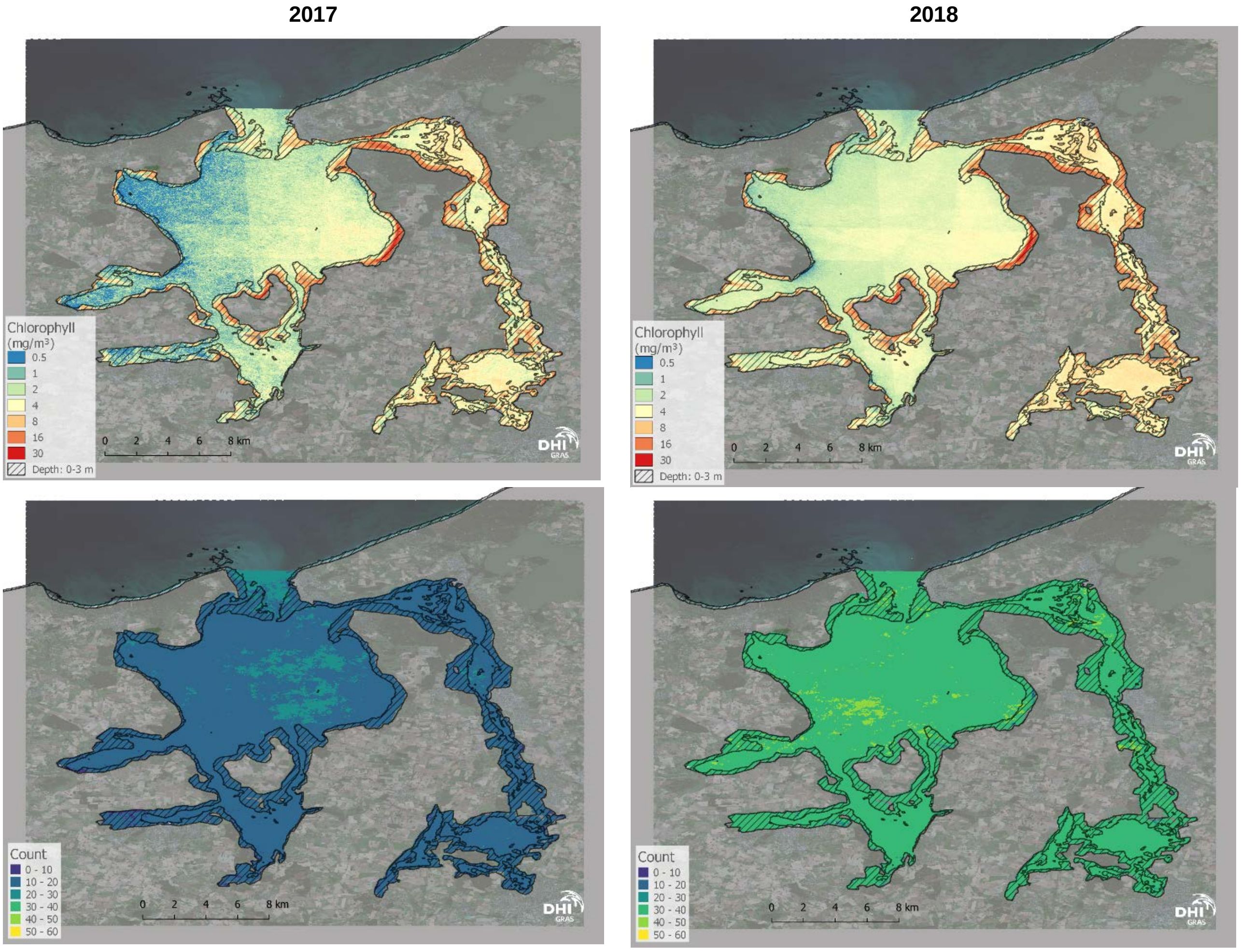


Figure 3.20. Use of Sentinel 2 for Chl mapping in Roskilde Fjord and Isefjord. Upper panel: summer (1 May to 30 September) mean Chl concentration; Lower panel: number of images used for the mean calculations.

In general, the Chl maps show slightly higher concentrations for Roskilde Fjord than Isefjord. For both fjords the values are higher for 2018. The high Chl values (red colours in the Chl maps) along the shallow coastal areas are distorted by signals from vegetation and/or the seabed. The hatched overlay showing the 3 m depth contour agrees with these high values and confirms the selected approach of choosing 3 m as a threshold for Roskilde Fjord and Isefjord, for removal of near shore vegetation/seabed signal.

For the summer mean calculations many more images were available for 2018 than 2017, as illustrated in the "count" maps which show how many images were overall available for each pixel during the entire year (*Figure 3.20* lower panels). For 2017, on average less than 10 images were included into the calculations in Roskilde inner Fjord compared to around 40 in 2018. Nevertheless, using all available S2 data in the inner part of Roskilde Fjord, we were able to retrieve a total of 30 daily values of Chl during this period separated on average by only five days with a variability (standard deviation) of four days. In comparison, the regular NOVANA Chl sampling programme provided nine daily values, on average separated by 18 days with a variability of five days. Used this way, S2 actually provides a better temporal coverage than the traditional sampling, even during a year with many cloudy days. The S2 maps, in particular the one for 2017, show some artefacts (vertical and horizontal lines separating areas with distinctively different Chl values in *Figure 3.20*. These artefacts come from the original S2 tiles and since we only have a small number of images available in 2017, they become distinctively visible.

S2 is not specifically designed for water applications, but its higher spatial resolution compared to S3 enables insights into the spatial distribution and small-scale variability of Chl during the growing season.

Sentinel 3 – summer mean Chl maps

We produced maps of surface summer mean Chl concentrations from S3 imagery for Roskilde Fjord and the connected Isefjord (*Figure 3.21*) for the period 1 May to 30 September for both years 2017 and 2018. The summer means calculated from S3 imagery are consistent with S2 in showing higher Chl concentrations for Roskilde Fjord compared to Isefjord. For 2018, the map depicts nicely the spatial variability in Isefjord with generally higher values near the shore. Although S3 passes more frequently than S2 (daily compared to every 2-3 days), the number of useful S3 days was not higher than the S2 owing to data archiving issues at the official data provider's side. (For S2 we counted 30 images in 2017, whereas S3 only provided a total of 10 daily observations to calculate the summer mean Chl in Roskilde inner Fjord). At the time of processing, not all available images for 2017 had been stored in ESA's S3 archive yet and that is why S3 is resulting in a lower number of useful days for Chl calculations. The reasons why the data archiving was incomplete at ESA's side are unknown, but the issue has now been fixed. 2018 is therefore more representative to compare image frequency between the two satellites. An advantage of S3 is its higher overpass frequency and its sensor design, making it more sensitive and useful for Chl mapping in water bodies than S2.

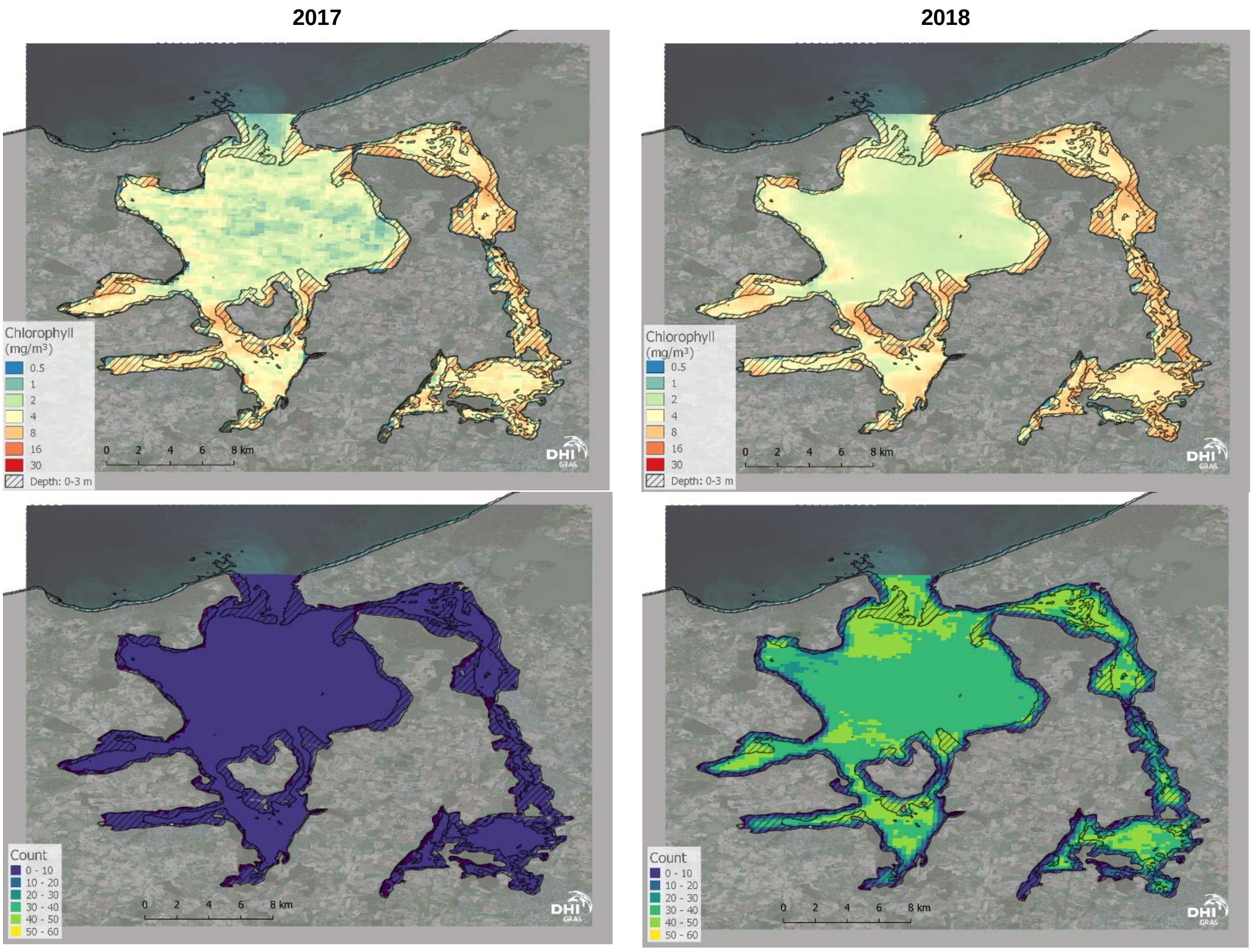


Figure 3.21. Use of Sentinel 3 for Chl mapping in Roskilde Fjord and Isefjord. Upper panel: summer (1 May to 30 September) mean Chl concentration; Lower panel: number of images used for the mean calculations. The low number of images in 2017 is due to bad weather conditions as well as an incomplete data archive at the data provider's side. Therefore, the Chl map appears very pixelated for 2017.

4. Costs and benefits of RS techniques

4.1 Costs

In this study, we chose a top-down approach (Matese et al 2015) to account for the expenses associated with obtaining the final extracted data (maps and derived statistics) from the different remote sensing (RS) technologies. Our analysis covers the activities described in sections 2.2 (Processing of RS data) and 2.3 (Comparison with *in situ* data). To facilitate comparison, we grouped these costs into five categories:

C1 - Data acquisition costs
Include expenses to obtain the raw images and data for *in situ* comparison. While the satellite and aircraft (SOP) data are free, data from drones have costs associated with organizing and conducting the acquisition campaign. *In situ* data obtained via the national monitoring are important for quality assurance. Although they are costly, they are currently freely available and have therefore in this comparison been considered to be free.

C2 - Data handling costs
Include the costs of man-hours to download, store and organize data and perform quality assurance of the formats.

C3 - Processing costs
Include all the costs of man-hours to process the raw RS data into maps of Chl or SAV. The activities depend on the type of RS data, but typically involve geo-referencing and ortho-rectification, atmospheric corrections, application of the relevant algorithms and required manual input. Where the processing is based on data models (the classification schemes), C3 includes man-hour costs for training the models as well.

C4 - Data verification and calibration with NOVANA
Include the costs of man-hours to compare derived Chl or SAV maps with *in situ* Chl or SAV obtained from the national monitoring programme.

C5 – Statistics and reporting
Include the costs of man-hours to provide statistics (mean, range, SD) of Chl (surface concentration) and SAV (total areal coverage, coverage for depth intervals) for the investigated areas. For RS data which provide a nationwide assessment, each of the 119 water bodies will be associated with statistics. For the drone applications, SAV statistics will be provided for the selected area. Reports describing the statistics will finally be produced.

Breaking down the costs for drone mapping of SAV:
The costs associated with data acquisition (C1) concern transportation, salary and maintenance of drone and camera. According to our experience, it is possible to map approximately 100 ha (1 km^2) during a day. One battery life provides approximately 30 ha which are enough to characterize the local SAV distribution pattern. There are no specific costs associated with data handling (C2). Concerning data processing (C3), data verification (C4) and statistics and reporting (C5), it takes around three days to process and analyse a 1 km^2 drone image and write a report.

Breaking down the costs for SOP mapping of SAV:
In the estimates described below, the good case scenario is one where the same, existing, eelgrass classification models can be successfully applied to the new image data. The poor case scenario considered here is one where the existing LDA and/or MLC image data classification models perform badly with new image data and new models need to be made. Gathering of training data to make any new model, making the model and then validating it could involve an additional C3 commitment of 50 hours per model. The poor case scenario considered here is that five new models are needed to obtain a nationwide SAV map for one year totalling 250 hours for nationwide mapping. A poor case scenario might also be one in which, due to marked imaging system-related image data differences, the geographic extents that different models would be applied to, would need to be defined, representing an additional C2 time requirement of possibly 100 hours. While it is possible to imagine the form that the good case scenario will have, it is not possible to define so clearly how the poor case scenario might be, since the SOP data are highly variable in quality from campaign to campaign.

C1: To be part of the SOP state consortium, the partners, which have included both AU and MST, make a certain financial commitment every 2nd year. Being part of this consortium makes data available for unlimited use. Therefore, data acquisition costs for the purpose of SAV mapping could be considered as zero. What might need to be included under C1, is that additional coverage, beyond what the consortium would acquire otherwise, costs extra, with the extra costs to be covered by the consortium partner that requests the additional coverage (but will the additional coverage data be available to all?). That has been the case to get additional extended fjord and marine coverage out to the -6 m contour for SOP 2018, and can be considered as guidance to future situations; however, as each time the SOP consortium arrangements are made afresh, that must be considered as just a rough guide. The extra costs for obtaining SOP data to the -6 m contour were 354,000 DKK in 2018 for the nationwide map.

C2: The SOP are made available for processing and analysis (as opposed to mere viewing) via AU IT disks, without charge for that to institutes or projects. That of course might be different if other organizations undertake the SOP work. Under a best case, least effort, scenario, the SOP tiles would be worked on either one-by-one or as blocks of adjacent tiles, via a script, being a workflow that might need a one-off commitment of about 50 hours to set up. Under a poor-case scenario, to develop the C2 set-up might take 100 hours towards obtaining nationwide SAV coverage.

C3: The SOP are delivered ortho-rectified and geo-coded, without realistic possibilities for atmospheric correction. As a minimum, a one-off commitment of about 100 hours is estimated to get the batch processing script established. Small time commitments would be needed to submit new sets of tiles to the process and undertake housekeeping (estimated at about 1 hour per 1,000 km^2). If, as in the reported work, the software eCognition is used for the sunglint correction, about 5,000 DKK per year should be budgeted towards license maintenance. In total, either 100 or 250 hours are estimated to be required for nationwide maps, under good or poor case scenarios, as described above, respectively.

C4: To cover an entire transect line of NOVANA data, this might require merging of the map results of several SOP image tiles, as well as running a script to extract data and then analyse it, and, if necessary, calibrate the SOP mapping. This would require about 5 hours per transect line, which for a total of 100 transects (approximate number monitored annually) would represent a total of approx. 500 hours. Given that SOP mapping would be implemented to replace eelgrass mapping, a minimum of approx. 75 transects, distributed among the three main water types (clear, turbid, CDOM rich) are considered to be necessary for annual calibration/validation purposes.

C5: A rough estimate is 50 hours per monitoring phase.

Breaking down the costs for Sentinel mapping of SAV and Chl:

The costs associated with nationwide mapping of SAV using S2 and Chl mapping for 119 water areas are based on experiences from DHI GRAS on C1 to C5. These costs do not cover expenses associated with setting up the entire data acquisition and processing system which have been considerable.

Summarizing the costs

The work associated with each process varies greatly for each platform and application due to differences in resolution (and hence computing time) and technical approach (some are more automated than others). The comparison of specific costs is therefore known to be difficult to compare among RS techniques (Valerdi et al. 2005). Given these precautions, we have nevertheless tried to estimate the expected expenses for nationwide mapping of SAV and Chl for the different RS techniques (*Table 4.1*). For the ease of comparison we have applied an hourly salary of 1,000 DKK.

Table 4.1. Estimated costs for different RS platforms. These include drones, summer orthophotos (SOP) from aircrafts, Sentinel 2 and 3 satellites. RS data are used for mapping and extracting statistics of submerged aquatic vegetation (SAV) and surface chlorophyll (Chl). For simplicity, SAV in this table equals eelgrass. The spatial and temporal resolutions of the RS products are indicated. See text above for explanation of costs (C1-5). All costs are in 1,000 DKK. *This SOP estimate is with the extra coverage out to the 6 m depth contour. **This cost depends on the number of eelgrass transects used for calibration which was set to 100.

Type of mapping	RS platform	Spatial resolution	Period covered	Area covered	C1	C2	C3	C4	C5	Total costs
SAV	Drone	1 × 1 cm	Once	1 km^2	8	0	8	8	8	32
	SOP	10 × 10 cm	Once	Nationwide	350*	100	250	500**	50	1250
	Sentinel 2	10 × 10 m	Summer	Nationwide	0	100	530	200	120	950
Chl	Sentinel 2	20 × 20 m	Monthly	Nationwide	0	6	6	9	8	29
		20 × 20 m	Annually	Nationwide	0	50	50	70	60	230
	Sentinel 3	300 × 300 m	Monthly	Nationwide	0	3	3	9	8	23
		300 × 300 m	Annually	Nationwide	0	25	25	70	60	180

4.2 Benefits

Benefits of a given RS technique for monitoring can be evaluated by comparing the knowledge and information obtained as compared to traditional sampling. Benefits may also simply be in terms of the resources (economic costs) associated with the monitoring activity. Although we have rough estimates of the costs associated with the RS monitoring activities (*Table 4.1*), we have chosen not to evaluate the possible financial benefits of implementation of the RS techniques. The main reason being that there are several decisions regarding how and to which degree the RS-based monitoring should be implemented. In addition, larger-scale tests of the RS techniques are needed to fully evaluate their potential and true costs. In the following, we therefore only focus on the possible benefits in terms of the information gathered and how this suits the current management requirements.

A new technique may provide new and interesting data which potentially improve our understanding of changes in the environment. However, if the new information does not match the data currently needed for GES evaluation (currently Chl concentration at 1 m depth, and depth limit of eelgrass), then benefits may be considered small from a management point of view. *Table 4.2* summarizes our results on the information provided by the RS techniques and compares these with the current management needs for Danish coastal waters according to the WFD.

Table 4.2. Comparison of *in situ* and RS techniques for assessment of GES.

Parameter	Method	Data provided	GES indicator	Notes
Chl	*In situ* – Ship-based samples	Every 2-4 weeks [Chl] at several depths at a fixed central station. All year.	Summer mean (min 8 samples) at 1 m depth from the water body during 1 May to 30. September.	Not all water bodies covered.
	Sentinel 2 and 3	Every 1 to 2 weeks [Chl] at near surface somewhere within the water body from March to November. Cover all water bodies.	Seems like S2 and S3 will be able to provide the required GES information.	Seems applicable for GES use. Need some *in situ* data for validation. Uncertain if water area concentrations = fixed central stations.
SAV	*In situ* - Diver / video-based observations	% cover of eelgrass (and other macrophytes) at different depth intervals. Main and max depth limit of eelgrass. Once per year (summer).	Main distribution depth (~depth where eelgrass cover falls below 10 %).	Only once per summer. Not all water bodies covered. No areal information.
	Drone-based	Presence/absence maps of SAV at cm scale. Digital Elevation models. Small areas (< 1 km^2). Sampling on request, typically once per year.		Areal cover currently not a GES indicator.
		Underwater photos along transect lines→ % cover of eelgrass out to depth limit.	Seems like the drone technique will be able to provide the current GES information.	Underwater transect technique needs validation of depth limit detection.
	SOP	Presence/absence maps of SAV at cm scale. Nationwide SAV summer maps every year. Data from 1950s.	Seems unlikely to provide the current GES information.	Detailed patch information. Not able to distinguish species. Unable to determine the depth limit.
	Sentinel 2	Presence/absence of SAV at 10 m scale. Nationwide SAV summer maps every month	May be able to provide the current GES information in clear waters.	Unable to determine the depth limit but better than SOP. Large-scale annual and inter-annual patch dynamics.

Each of the results presented for the different RS techniques in this report show promising possibilities for managers to monitor SAV and Chl, but each of them, if analysed individually, can be incomplete. For SAV the applications of a drone and SOP may be optimal for a fine-scale characterization enabling detailed assessment of intra-area variability, pattern recognition and better substrate separation. However, satellite RS is capable of mapping SAV in the entire Danish coastal zone, potentially several times per year, allowing assessment of different vegetation stages during the growing season. However, if the aim of the SAV mapping is to monitor subtle differences in areal cover (changes in e.g. eelgrass patch size and distribution) in smaller regions (<1 km^2), then higher resolution data provided by drones and SOP are preferable. S2 images do not capture fine-scale heterogeneities and may therefore overestimate SAV coverage. On the other hand, S2 offers a cheap nationwide mapping, and the spectral data acquisition by S2 enables retrieval of information from greater depth than SOP, providing what seems to be a better estimate of the SAV distribution out to the 10 % threshold depth.

Besides the adequacy of the different RS techniques for providing useful data for GES assessment, other conditions are important to consider when choosing the most appropriate monitoring strategy. *Table 4.3* summarizes the overall strengths and weaknesses of the RS platforms used in this study for monitoring SAV and Chl. Our approach follows that of Matese et al. (2015). The mission attributes deal with the planning and execution of the surveys, the ability to reach the site (Range), to deal with weather condition and scheduled practices of data sampler (cloud cover and flexibility), the need of multiple flights to obtain the whole scene (Endurance), and the overall reliability of the platform instalment.

Table 4.3. Comparative platform characteristics for different remote sensing platforms (++ optimal, + good, o average, - poor).

		SAV			Chl	
		Drone	**SOP**	**S2**	**S2**	**S3**
Mission	Range	-	+	++	++	++
	Frequency	-	-	++	++	++
	Repeatability	-	-	++	++	++
	Flexibility	++	+	-	+	++
	Endurance	-	+	++	++	++
	Cloud cover dependency	++	+	-	-	-
	Reliability	o	+	++	+	++
Processing	Payload	o	+	++	++	++
	Resolution	++	+	o	++	+
	Precision	++	+	o	+	++
	Mosaicking and geocoding effort	-	o	++	+	++
	Processing time	o	+	++	+	++

With respect to SOP and satellite, drones can operate closer to the target with more flexibility on scheduling, and its acquisition is non-dependent on cloud cover conditions, but has a much shorter range and endurance and an overall lower reliability, being still in the prototyping phase. Satellite images, on the contrary, cover much larger areas, but they are subject to fixed scheduling and strongly depend on cloud cover. SOP sits in between these two with more flexibility than satellite and better endurance than drones. The image processing attributes deal with the computational chain deployed from the raw images to the final products. It includes the precision and resolution attainable on the maps and the effort and computing time to mosaic, ortho-rectify and produce the outputs. The strengths of drone acquisition are, of course, in higher resolution and precision, but at the cost of a greater effort for mosaicking and geocoding. In principle, images from the national mosaic of aircraft orthophotos require little handling time, with the time cost dependent mainly upon how many separate areas are involved and, to a smaller degree, the mapping area extents. Satellite images, on the contrary, require no mosaicking and geocoding, however, at the price of a much lower spatial resolution. We have summarized the advantages and limitations for the RS techniques investigated in this report in *Table 4.4*.

Table 4.4. Descriptive overview of the different remote sensing techniques included in the report.

Parameter	RS technique	Advantage	Limitation
SAV	Drone	Very detailed. Mostly independent of weather (clouds). Replacement for traditional *in situ* sampling.	Limited to small areas. Limited to determine the SAV depth limit.
	SOP	Detailed patch information at cm scale. Nationwide SAV summer maps every 2nd year. Data from 1950s.	Limited to distinguish between species types. Limited to determine the SAV depth limit. High processing costs. National coverage only every 2nd year. Inconsistent data (e.g. viewing angles, solar zenith angle etc.). Varying data quality. Limited spectral range.
	Sentinel 2	Guaranteed data coverage. Multi-temporal mapping at national scale. Inter-annual patch dynamic. Consistent data. Broad spectral range.	Limited to distinguish between species types. Limited to determine the SAV depth limit. Weather dependent (clouds).
Chl	Sentinel 2	Observations every 3-5 days. Multi-temporal mapping of all water bodies. Inter-annual dynamics. Consistent data.	Weather dependent (clouds). Sensor design optimized for land applications. Absolute accuracy.
	Sentinel 3	Daily observations. Multi-temporal mapping of all water bodies. Inter-annual dynamics. Consistent data. Sensor design optimised for water applications.	Relatively coarse (300 × 300 m pixels). Weather dependent (clouds). Absolute accuracy.

5. Making RS monitoring operational

Previous sections in this report and the review report delivered (Harvey et al. 2018) have described in detail the steps involved in processing and applying the different types of RS data. This section provides recommendations of how RS data can become an integrated part of the national monitoring of chlorophyll and submerged aquatic vegetation. Our recommendations involve considerations on acquisition and processing of RS data, as well as the steps involved in calibration and verification against the traditional *in situ* monitoring data. In addition, the statistical analyses needed, the final reporting and possible roles of the involved institutions are also considered.

5.1 Choice of RS data

As highlighted in our analysis of costs and benefits, there is no right or wrong when it comes to the choice of RS technique. While S3 has better temporal and spectral resolution making it favourable for Chl mapping, many water areas are so small that only S2 will be applicable because the spatial resolution of S3 is too coarse.

Similarly, with SAV, there are obvious limitations and advantages with all three approaches (S2, SOP and drones). Nevertheless, they appear to complement each other very much. Ideally, S2 would be used for nationwide, annual areal coverage at the water body level. The large-scale mapping results can be optimized by integration of relevant, existing, detailed information from SOP, drones, NOVANA, etc. In addition to providing water body SAV coverage percentages in the near-shore zone, a large-scale S2 SAV service could also be used as a screening tool for changes in the SAV abundance. This could again feed into an efficient planning of the more spatially detailed campaigns based on SOP and/or drone (i.e. to be applied where the S2 layers indicate a change).

As mentioned, large-scale S2 SAV should ideally be supplemented with SOP (and/or drone) analysis for local/regional scale studies and S2 evaluation. SOP can be used for a national fine-scale eelgrass map as they since 2018 are available at national scale for most eelgrass areas (i.e. image coverage out to the 6 m depth curve). However, considering that SOPis most suitable for the shallowest parts (0-3 m depth), SOP will not be able to map complete water bodies even with complete SOP coverage. In any case, nationwide use of SOP for SAV mapping would require further development of the image analysis procedure to ease the process and also taking into account separation between eelgrass and other bottom features such as macroalgae and mussel beds (see also Ørberg et al. 2018 section 4.3. and 4.4). This SOP mapping could be used in the following ways:

1. As a fine-scale status assessment of area distribution of eelgrass in Denmark.
2. For comparison with a newly generated national map of potential eelgrass distribution, based on statistical GIS modelling of six important environmental data layers (Staehr et al. 2018 in review). Areas of disagreement between the potential and orthophoto-based eelgrass maps could be explored further in order to identify the reason for the disagreement and thereby help get a step deeper into interpreting the factors regulating large-scale eelgrass distribution.

3. For comparison with earlier SOP in specific areas to address long-term changes over the past decades (since SOP exist back to the 1950s). This will help define area-specific reference conditions for eelgrass (e.g. defined as the sum-area supporting eelgrass in any of the study years, i.e. a "union eelgrass area"). Results from this should be compared with a modelled distribution using the new nationwide GIS approach (Staehr et al 2018 in review).

It would also be relevant to compare national scale SOP eelgrass mapping with satellite mapping. If the correspondence is good, satellite images could gradually substitute SOP as free satellite images at high resolution become available. Satellite images could also be used to address seasonal changes in eelgrass coverage, e.g. in response to summer heatwaves as seen in 2018.

Vegetation transects are required for validation. Here, drone-based observations could supplement transects well. Joining the technologies would accordingly provide a much more complete data set to evaluate the true status of the Danish coastal water quality in terms of Chl and eelgrass/SAV (*Figure 5.1*).

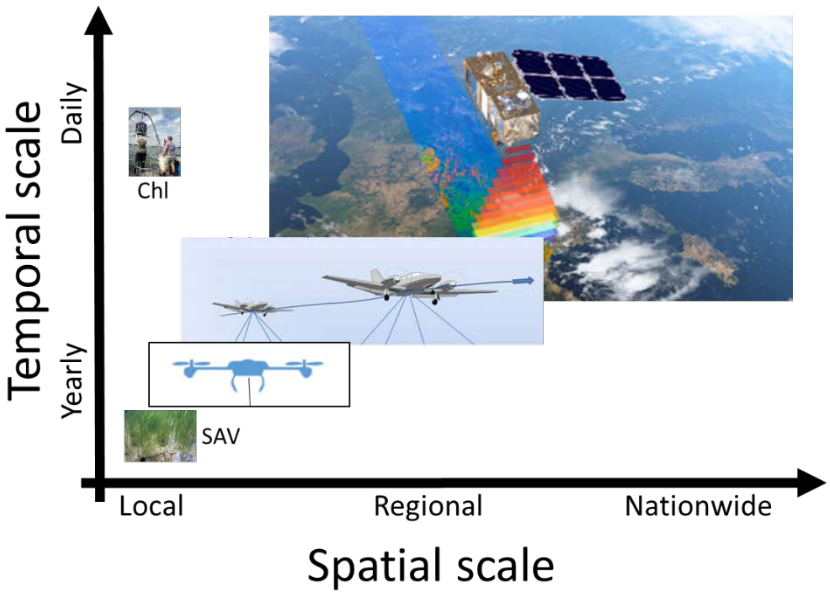


Figure 5.1. The different RS technologies supplement each other with important information on different spatial and temporal scales.

In the following sections, we describe a structure that enables optimal use of the different RS technologies for coastal marine monitoring of vegetation and Chl.

5.2 Data acquisition and storage

Efficient, reliable and safe acquisition and storage of RS data are crucial for its use in long-term monitoring and reporting. For satellite data, data retrieval is possible on a day-to-day basis, requiring a robust and automated data acquisition and storage system such as that currently available at DHI GRAS. As raw data are freely available, issues with data rights are only applicable to processed data payed by the Danish EPA (MST).

For SOP data, the participants of each SOP consortium have data use rights; data derived from the SOP images, e.g. eelgrass maps, would reside with the sponsor (MST). For the SOP images in the method-development project reported here, the ECW 2 ×2 km tile files were combined to raster files for larger test areas before going through each step of the image processing and analysis (see Ørberg et al. 2018 for details). However, for a national scale processing and analysis of SOP data, it is recommended to apply an iterative image processing and analysis procedure directly on the ECW files of the image mosaic and only subsequently combine the analysed images into larger area raster files and/or vector (e.g. ESRI shape polygon) data (see Ørberg et al. 2018, section 3.4 for details).

For drone applications, RS data will be obtained by the drone pilot and should be stored securely at a database in agreement with the Danish EPA. Quality-assured data used for *in situ* verification (NOVANA) are accessible through the national ODA database managed by DCE.

5.3 Data processing

Depending on the RS data type, different processing steps are necessary. These include geo-referencing, image rectification, atmospheric corrections and application of algorithms to derive Chl and SAV estimates. See sections 4.2 and 4.3 for details as well as sections 3.6 and 3.7 in Harvey et al. (2018). In view of recent technical developments and the growing data amounts, data processing needs a highly efficient system optimized for RS data handling which is in the hands of experienced experts. This ensures that new developments are followed and continuously implemented into the processing chain.

5.4 Data verification and calibration (QA/QC)

Comparison with *in situ* data in monitored areas is essential for calibration and verification of RS estimates. This corresponds to a quality assessment and control (QA/QC) of the RS data. The calibration process will be done by the institution responsible for processing RS data. Verification (comparison with NOVANA) of Chl will include time series plots, direct comparison (X-Y scatterplots) of RS vs *in situ* data and associated statistics as shown in section 3.2. Verification of S2, SOP, and drone-derived SAV data will include comparison of presence/absence of SAV with eelgrass data in NOVANA, using different thresholds (10, 50 and 100 %). This will be done for different depth intervals for selected monitored water areas.

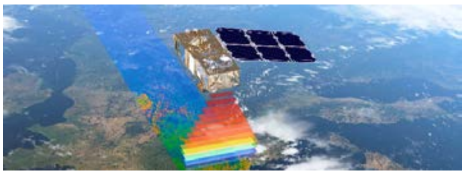
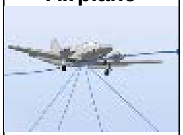
5.5 Statistical analysis and reporting

Once the RS data have been through QA/QC, a number of statistics will be applied for the water areas of interest. For Chl we recommend calculations at each of the 119 water areas using both S3 and S2. In monitored water areas, S3 and S2 values (monthly: March to October) will then be compared. In smaller water areas where S3 is not applicable, only S2-derived Chl estimates will be used. However, in larger water areas S3 estimates will be favoured because of the better spectral and temporal resolution. Finally, summer mean Chl values (1 May to 30 September) will be calculated for each of the 119 water areas and shown together with *in situ* data where possible.

For SAV we recommend using S2 for annual estimation of SAV coverage (e.g. % SAV/WA; km^2 SAV/WA divided into different depth intervals). SOP will be used to estimate SAV (eelgrass cover) in selected water areas with good *in situ* transect data availability. Currently AU obtain SOP data every second year, although yearly data are in principle available.

The recommended procedures and data handling structures are summarized in *Table 5.1*.

Table 5.1. Overview of RS platforms, sensors, spatial and temporal extent along with recommendations for data acquisition, storage, processing, QA/QC, and final products. Responsible institutions in this project are indicated. Abbreviations are for water areas (WA), monthly and summer (1 May to 30 Sep) means (M & S means).

Platform	**Sentinel**			**Airplane**	**Drone**
					
Sensor	S3 OLCI	S2 MSI	S2 MSI	SOP RGB camera	Drone RGB camera
Parameters monitored	Chl	Chl	SAV	SAV (eelgrass, macroalgae)	SAV (eelgrass, macroalgae)
Spatial extent Total area Local area	 Nationwide Larger WA	 Nationwide Smaller WA	 Nationwide All WA	 Nationwide Selected WA	 Small WA Transect/points
Temporal extent Availability Usage	 1-2 days March-Nov	 2-3 days March-Nov	 2-3 days 1 (Jun-Aug)	 Every 2 year 1 (Jun-Aug)	 Once per year 1 (Jun-Aug)
Data acquisition and storage RS data NOVANA (*in situ*) data	 DHI GRAS AU	 DHI GRAS AU	 DHI GRAS AU	 AU AU	 AU AU
Processing Geo-referencing Rectification Atmospheric corrections Application of algorithms	 DHI GRAS	 DHI GRAS	 DHI GRAS	 COWI COWI COWI AU	 AU
Data QA/QC control Calibration with NOVANA Verification with NOVANA	 DHI GRAS AU	 DHI GRAS AU	 DHI GRAS AU	 AU AU	 AU AU
Products - statistics, reporting Chl SAV	AU M & S mean	AU M & S mean	AU Cover per WA and depth	AU Cover per WA and depth	AU Transect and point cover

6. Conclusions

Based on the analysis presented above, some general conclusions can be drawn. The conclusions also follow information provided in *Table 4.2, 4.3* and *4.4*.

6.1 Part I: Submerged aquatic vegetation

All investigated RS techniques have their advantages and limitations for SAV mapping. Common to all techniques is the ability to provide estimates of the areal cover at shallow depth, but also the limitations of estimating the maximum depth limits, which for eelgrass is a key parameter in the assessment of coastal water quality and GES. However, both SOP and S2 allow mapping of the extent of the main depth limits.

SOP or S2 provide presence/absence determination of vegetation as well as discrimination from sediment, but only with data from drones, vegetation can be differentiated into specific species and eelgrass mapped. While SOP and in particular drones provide very detailed information on SAV distribution, including small-scale patches, they lack the large-scale repeated information provided by the S2 satellite. Therefore, for operational monitoring, S2 is the most realistic approach to map large-scale SAV on an annual basis. This is due to:

1. guaranteed data coverage; even in 2017 with extreme cloud cover, good imagery was acquired while SOP do not provide national coverage and moreover 2014 and 2018 were of poor quality. For 2016 large parts of the coastal zones were missing. It is anticipated that SOP images will be available (in relation also to other purposes) to AU every second year and do also exist as available data back in time (from the 1950s), representing a possibility to use SOP for detecting long-term changes in vegetation cover.

2. larger depth retrievals and thereby better areal coverage;

3. cheaper data processing; SOP processing is very time consuming and therefore more costly than S2;

4. assessments of annual and even inter-annual variations in presence and areal cover;

5. consistent data over time guaranteeing consistency in results; this is not the case for SOP with varying viewing geometry, problematic stitching of frames, etc.

As described, all RS techniques have their advantages and limitations (summarized in *Table 4.3* and *4.4*). The smart combination of the RS techniques offers large benefits for eelgrass monitoring and management by providing both small, and large-scale spatial distribution information, such as using S2 for large-scale overviews, SOP for more detailed mapping at specific areas of interest and drones for assessing hotspots and selected sampling. Drones proved very useful for a range of fine-scale applications in the shallow coastal zone for areas covering 20-40 ha. The unique *in situ* monitoring technique using an underwater camera system provides a new way of collecting a larger number of training samples for the algorithms applied on SOP and S2 satellite imagery. Among the different RS techniques investigated in this report, drones seem to provide the most obvious and easiest technology to supplement and possibly replace some of the current vegetation monitoring in the coastal zone. In order to make most use of the different information sources, close coordination between the involved parties is required.

6.2 Part II: Chlorophyll

The Sentinel satellites provide an unprecedented opportunity for environmental monitoring with long-term perspective at least until the end of 2030. Improvements in spectral and spatial resolution combined with the satellites' revisit frequency, have increased the quality and the number of useful acquisitions significantly for Denmark.

The combination of S2 and S3 provides a cost-effective way to supplement national *in situ* monitoring of surface Chl in the shallow Danish coastal waters. In particular, in the currently non-monitored water areas, this is the only way to derive information on environmental status. Despite the rather large pixel resolution of S3 (300 × 300 m), the satellite provided stable, almost daily information on water quality, even in very confined areas such as the outer part of Roskilde Fjord. The comparison between satellite-derived and *in situ* Chl showed in particular good agreement between monthly aggregated values, both for S2 and S3. This approach could be applied for non-monitored water bodies to get a quality estimate filtered for highly variable daily values. Daily Chl values from the satellites have a higher variability than data from *in situ* monitoring, especially the ones from S2 with higher pixel resolution (20 × 20 m) as compared to S3 with coarser pixel resolution (300 × 300 m). The higher variability in satellite data is mainly related to the spatial dimension of the measurement compared to the point measurement of the ground sampling. The difference between S2 and S3 can be explained on the one hand by the sensor design (S3 is particularly built for water applications) and on the other hand by the pixel resolution of S2. More details, such as wave crusts, etc. impact the satellite measurement and lead to higher variability. For S3 these small-scale phenomena are averaged out.

Good results were achieved when comparing averaged Chl per water area (e.g. inner Roskilde Fjord) and *in situ* Chl (single point measurements). This indicates that the *in situ* stations are representing the water bodies well, despite the fact that the satellite-derived Chl includes higher variability in space (area measure versus point measure). Aggregation of S2/S3 for entire water areas seems to provide useful estimates for GES assessment, providing summer mean values similar to *in situ* in most of the studied areas. However, the implications of different sources of variability (temporal, spatial) for satellite and ground measurements for GES assessments need further attention.

The results presented in this report are calculated with a standard approach (C2RCC processor) without local tuning of the algorithm, i.e. calibration with local *in situ* data. With such a calibration, the algorithm can be customized to the water body with enhanced retrieval as a result. However, for this a coordination between ground surveys and satellite overpass would be needed in order to have a high number of concurrent satellite and *in situ* measurements (match-ups), or optimally the deployment of a validation station. The lack of match-ups was also the reason why a thorough statistical analysis was difficult to provide.

RS cannot replace *in situ* sampling, but it can optimize sampling design and fill in gaps, for instance non-sampled water bodies or in between ground monitoring campaigns. Moreover, satellites provide information on water surface conditions and cannot reveal the status in deeper stratified more open waters where important Chl peaks often occur. Instead of excluding certain data sources, data availability should be seen as an asset. By bringing together information from various data sources, the confidence in the data can be enhanced by comparing different data to each other and the assessment of the water quality status becomes more complete.

6.3 Overall conclusion

There is no right or wrong when it comes to application of different RS techniques for water quality monitoring in coastal waters. There are obvious limitations with all approaches compared to traditional *in situ* observations, but also advantages and several ways by which the different RS techniques supplement each other and *in situ* monitoring. Joining the technologies will undoubtedly help provide a much more complete view of the true status of the Danish coastal waters regarding the water quality descriptors, eelgrass and Chl. For both Chl and eelgrass monitoring, it must be stressed that collection of field data will continue to be an important part of the national assessments as these data are essential ground truth data to calibrate and assess the quality of the derived RS products.

7. Future work and recommendations

Based on the analysis presented above and the documentation provided in recent reports by the authors of this report to the Danish EPA (Ørberg et al. 2018; Harvey et al. 2018), some general recommendations and suggestions according to implementation and enhanced use of RS technologies for monitoring chlorophyll a and submerged aquatic vegetation in Danish coastal waters can be made. Incorporation of RS data in aquatic ecological studies is the way forward for improving monitoring and management of aquatic ecosystems.

Through this study we have identified several promising possibilities with the different RS techniques which should be investigated further. Technical advances in the field of RS are fast evolving and methods used to process and analyse the data constantly improved. In the following, we outline the activities we recommend to be investigated further.

7.1 Submerged aquatic vegetation

As a starting point to further explore the benefits of S2, SOP and drone for SAV monitoring, we suggest that transect analyses, during the summer 2019, are supplemented with drone data collection – both for *in situ* comparison, but also for local scale (20-30 ha) mapping of the aquatic vegetation cover. At selected transects thiess analyses should be supplemented with analyses of S2 and SOP data. This would provide an optimal database for calibration and validation of S2 and SOP data and enable larger scale estimates of vegetation cover. Furthermore, these data would make it possible to assess the ability of S2 and SOP to distinguish vegetation types and depth limits.

The frequent overpasses of S2 and its spectral sensor design carry the potential to differentiate species from their seasonal growth pattern. Since completion of the S2 SAV results in this project, DHI GRAS has further developed the analytical approach to include more time steps in the SAV classification. With a machine learning approach, it is now possible to move from a SAV presence/absence approach to a soft classification where the output instead is given as a probability of SAV, allowing for a better representation of the mixed areas. This should further increase the overall accuracy. Future work should look into this approach which would enable a more detailed assessment of both the areal distribution at shallow depth, but potentially also the deeper limits of the vegetation patches.

The high spatial resolution of SOP and drones should similarly be explored further. Especially the ability of drones to supplement or even replace traditional transect determination of eelgrass distribution and depth limits needs attention.

Finally, very high resolution imagery from satellites has not been considered in this report. The commercial data available in sub-meter spatial resolution between the S2 and SOP approaches are thus available. They offer larger regional – local scale coverage at high spatial resolution. With prices down to 15-20 USD per km^2, it can be a good alternative to both S2 and SOP which should be investigated in future assessments.

7.2 Chlorophyll

The extent to which S2 and S3 provide more representative estimates of water area Chl levels should be investigated further in a few selected areas. Routine NOVANA Chl sampling should for a summer period be supplemented with a number of extra sites to provide *in situ* data for the validation of the variability associated with horizontal gradients and patches of Chl derived from S2 and S3 imagery.

In this project we applied a standard processor (C2RCC) to process the S2 and S3 data. While the standard processor provided overall good estimates, we find it very likely that significant improvements can be made to the applied algorithms and derived Chl estimates from the reflectance signal by tuning the algorithm with *in situ* data. Optimization of the processing, however, requires true validation. Given that the Sentinel programme is a long-term investment and that there are several promising possibilities for incorporating Sentinel data in the monitoring of, not only the near coastal zone, but also the more open Danish waters, we highly recommend that Denmark invests in a true validation station such as outlined by the AERONET.

Our recommendations regarding further technical analyses required before implementing RS techniques in marine monitoring of the Danish coastal zone, are summarized in *Table 7.1*.

Table 7.1. Recommendation on further technical analysis required before implementation of RS techniques in Danish near-shore coastal monitoring.

Parameter	RS technique	Application	Recommendation
SAV	Drone	Local presence/absence maps of SAV.	Test of areal cover and patch distribution of SAV as GES indicators.
		Underwater photos along transect lines→ % cover of eelgrass out to depth limit.	Needs validation in selected test areas.
	SOP	Presence/absence maps of SAV at cm scale. Nationwide SAV summer maps every year. Data from 1950s.	Detailed patch information. Not able to distinguish species. Unable to determine the depth limit. Test of areal cover and patch distribution of SAV as GES indicators.
	Sentinel 2	Presence/absence of SAV at 10 m scale Nationwide SAV summer maps every month	Test the ability to detect the depth limit of SAV. Investigate annual and inter-annual patch dynamic. Test areal cover of SAV as a GES indicator.
Chl	Sentinel 2 and 3	Every 1 to 2 weeks [Chl] at near surface somewhere within the water body from March to November Cover all water bodies	Nationwide test is needed of the application for GES assessment. Perform local test to see if WA concentrations = fixed central stations. Invest in AERONET validation station to improve algorithms.

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USE OF REMOTE SENSING TECHNOLOGIES FOR MONITORING CHLOROPHYLL A AND SUBMERGED AQUATIC VEGETATION IN DANISH COASTAL WATERS

Part of the RESTEK project (Brug af remote sensing teknologier til opgørelse af klorofyl-a koncentrationer og vegetationsudbredelse i danske kystvande)

This report investigates the potential of using different remote sensing (RS) technologies to supplement the conventional national NOVANA programme for monitoring of water quality (chlorophyll a) and submerged aquatic vegetation (seagrasses and macroalgae) in Danish coastal waters. The potential of using drones, orthophotos and Sentinel 2+3 satellites are investigated in a number of test sites. From these results, strengths, weaknesses and knowledge gaps are discussed. Recommendations on future steps for integration of RS techniques for monitoring in Danish coastal waters and assessment of good ecological status according to the Water framework directive are also provided.

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