ASSESSMENT OF THE AREAL DISTRIBUTION OF SUBMERGED AQUATIC VEGETATION USING REMOTE SENSING IN DANISH COASTAL WATERS

Integrated Marine Monitoring – analytical phase

Scientific Report from DCE – Danish Centre for Environment and Energy No. 596 2024

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Peter A.U. Stæhr[1]
Lisbeth Tangaa Nielsen[2]
Mihailo Azhar1, Cordula Göke[1]
Silvia Huber[2]
Jesper P.A. Christensen[1]
Lars B. Hansen[2]
Sanjina U. Stæhr[1]
Dorte Krause-Jensen[1]

[1]Aarhus University, Department of Ecoscience
[2]DHI

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Author(s): Peter A.U. Stæhr[1], Lisbeth Tangaa Nielsen[2], Mihailo Azhar[1], Cordula Göke[1], Silvia Huber[2], Jesper P.A. Christensen[1], Lars B. Hansen[2], Sanjina U. Stæhr[1] & Dorte Krause-Jensen[1]

Institution(s): [1]Aarhus University, Department of Ecoscience, [2]DHI

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Abstract: The use of different types of remote sensing data to acquire information on the distribution and cover of marine underwater vegetation was examined in two Danish fjord systems for the period 2017-2023. Promising results including high resolution vegetation mapping, differentiation of vegetation types as well as different algorithms for improved cover and area classification were investigated. Results from classifications and estimates of areal coverage were combined with modelling to develop novel eelgrass indicators of ecological status, which were evaluated against existing indicators. Recommendations for large-scale implementation of remote sensing as a promising tool to map and monitor marine vegetation are provided.

Keywords: Remote sensing, submerged aquatic vegetation, eelgrass, macroalgae, good ecological status, indicator, areal coverage

Front page photo: Ortho photo from summer 2022 covering Strynø in the South Fynen archipelago. Obtained by Mihailo Azhar

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LTN		x	x	x	x	x		x	x	x	x			
MA		x	x	x	x				x	x	x			
CG		x	x	x	x				x	x	x	x		
SH	x	x				x	x		x	x	x	x		
JPAC	x	x						x		x				
LBH	x						x			X		x	x	x
SUS										x				
DKJ	x									x				

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Contents

Preface

This report presents results from a sub-project of the 4-year Integrated Marine Environmental Monitoring (in Danish "Integreret Marin Miljøovervågning ~ IMM) project, which is a transversal project under the Danish Environmental Protection Agency (EPA). The IMM project includes both monitoring technologies, IT architecture and environmental modeling with the main aim of integrating and modernizing the marine monitoring program. Furthermore, all the IMM sub-projects are divided into separate projects for the analysis and the implementation phase. This subproject focuses on the use of remote sensing technologies for improved mapping of submerged aquatic vegetation and assessment of ecological status in Danish coastal waters as described in the Water Framework Directive (WFD). The subproject is done as a collaboration between Aarhus University, DCE and DHI A/S, with Aarhus University in charge of the assessment of ecological status and DHI A/S in charge of the remote sensing-based analysis. The report has been read and commented on by the Danish EPA.

Sammenfatning

Danmark er via vandrammedirektivet forpligtet til at vurdere miljøtilstanden af vores kystnære havmiljø. Dette omfatter bl.a. analyser af den marine undervandsvegetation, som i mere end 30 år har været overvåget som en del af det nationale marine overvågningsprogram, NOVANA. Overvågningen omfatter flere hundrede transekter, hvor blomsterplanter (primært ålegræs) og makroalgers forekomst, dækningsgrad, og dybdeudbredelse kortlægges og afrapporteres årligt. Særligt ålegræs er en nøgle parameter i NOVANA programmet, da der er udviklet en robust indikator for miljøtilstanden baseret på dybden af hovedudbredelsen af ålegræs. For makroalger er der udviklet en ny indikator, som baserer sig på ændringer i den akkumulerede dækning med dybden. Miljøindikatorerne anvendes til at vurdere den økologiske tilstand, med særligt fokus på at vurdere om God Økologisk Tilstand (GØT) er opnået, som vandrammedirektivet kræver. Denne rapport analyserer mulighederne ved at anvende forskellige typer remote sensing (RS) -teknologier til at kortlægge undervandsvegetationen (ålegræs og makroalger/submers aquatic vegetation (SAV)), og baseret på disse data at udvikle en ny indikator til at vurdere den økologiske tilstand af de danske farvande.

Rapporten omfatter detaljerede studier i to vandområder, hhv. Odense fjord, ydre del og Nibe Bredning (del af Limfjorden) og data fra perioden 2017 til 2023. Vi har anvendt Remote Sensing (RS) data fra Sentinel-2 satellitterne (S2), ortho photos (OP), og en kommerciel satellit (Airbus Pléiades Neo) med høj rumlig opløsning / Very High Resolution (VHR). Analyserne havde til formål at 1) videreudvikle metoder til at kortlægge arealudbredelse af SAV vha. forskellige typer RS-data, 2) teste muligheden for at skelne mellem ålegræs og makroalger og, baseret på RS-data, at 3) udvikle en ny økologisk tilstandsindikator for vandkvalitet.

Klassificering af SAV baseret på S2, VHR og OP data blev foretaget ved hjælp af en deep learning metode, fremfor den tidligere anvendte pixel-baserede random forest metode. Den nye metode blev valgt ud fra et ønske om at etablere en mere robust model, som også er fleksibel med hensyn til hvilke billeddata, der anvendes som inputdata. Analyserne viste, at metoden virker, ikke kun på S2-data, men også på OP- og VHR-data. Skaleringspotentialet er også tydeligt; i løbet af projektet har det været muligt at udføre længere tidsserieanalyser for to vandområder uden at generere store mængder nye træningsdata til klassifikationen. Vores analyser bekræfter også, at deep learning metoden kan effektivisere den nuværende klassifikation og kortlægning af undervandsvegetationen, der er indbygget i SAV Denmark App'en udviklet af DHI, samt bidrage til mere ensartede resultater, der er mindre afhængig af hvem der anvender af App'en.

For at udvikle en økologisk tilstandsindikator baseret på SAV-arealudbredelse blev de samme principper anvendt, som den eksisterende indikator for ålegræssets hovedudbredelsesdybde (Zmax) er baseret på. Arealindikatoren blev således baseret på en sammenligning af nye observationer (her SAV-arealet i 1 til 5 m dybdeintervallet, baseret på henholdsvis S2 og OP) i forhold til SAV arealet ved en god referencetilstand, hvor sidstnævnte blev estimeret ved hjælp af en model udviklet for ålegræs. Sammenligning af den nye arealindikator med den eksisterende Zmax-indikator viste generelt god overensstemmelse og gav sammenlignelige vurderinger af

den økologiske tilstand i Odense Fjord og Limfjorden, dog med afvigelser i nogle år. Begge indikatorer viste en begrænset sammenhæng med målte vandkvalitetsparametre (klorofyl og lysdæmpning, Kd) i de to vandområder. Da arealindikatoren anvender reference-værdier for ålegræs, men nye RS-observationer for SAV, kan indikatoren kun anvendes i områder hvor SAV er domineret af ålegræs, som i Nibe Bredning og til dels i Odense fjord.

Endelig testede vi muligheden for at estimere Zmax ud fra RS-data ved at modellere dybdeafhængigheden af den RS-baserede dækningsgrad af SAV. Dette blev gjort på både transekt- og systemniveau for de to områder. De estimerede Zmax værdier viste god overensstemmelse med de traditionelle opgørelser udført af MST, særligt for modeller baseret på data for hele vandområdet og bedst for vandområdet i Limfjorden, hvor udbredelsen af ålegræs er mere homogen end i Odense Fjord.

På baggrund af de indhøstede erfaringer har vi en række anbefalinger til yderligere undersøgelser i en eventuel implementeringsfase af IMM-projektet:

1. Implementering af den testede deep learning metode til SAV klassificering, og mulighed for multitemporal SAV kortlægning baseret på S2, OP og satellit VHR-data. Det vil markant forbedre den rumlige information og give indsigt i vegetationens dynamik og udbredelse gennem hele vækstsæsonen, men også mellem år. Deep learning metoden er baseret på - og afhængig af mange annoterede træningsdata, og derfor vil inddragelse af flere træningsdata løbende forbedre billedtolkningen. Udvikling af en national/regional database af billedtræningsdata vil derfor forbedre metodens anvendelighed markant. Storskala kortlægning bliver derved væsentligt mere effektiv og sammenlignelig i tid og rum uden krav for billede specifikt trænings- og *in situ* data.

2. Betydningen af sæsonvariationer i SAV udbredelsen bør undersøges nærmere for den udviklede areal-baserede indikator.

3. Muligheder for at klassificere %dækning af SAV i de enkelte pixels ved hjælp af S2-data for herved at forbedre areal-SAV-kortlægningen samt data til den areal-baserede indikator.

4. Mulighed for at forbedre arts-separation i SAV kortlægningen med brug af VHR og/eller OP og deep learning modellen.

5. Videreudvikling af den anvendte ålegræs GIS model til at forbedre kortlægningen af reference ålegræsarealet i vandområderne.

6. Vurdering af arealindikatorens anvendelighed på lokal skala (omkring transekter) og national målestok (alle relevante vandområder).

7. Udvikling og vurdering af en økologisk tilstandsindikator baseret på tætheden (patchiness) af SAV.

8. Videre test af modellering af Zmax ud fra RS-baseret SAV dækning i dybdeintervaller.

Summary

Denmark is obliged via the water framework directive (WFD) to assess the ecological status of our coastal marine waters. This includes, among other, analysis of the marine submerged aquatic vegetation (SAV), which has been monitored for more than 30 years as part of the national marine monitoring program, NOVANA. The monitoring includes several hundred transects where the occurrence, cover, and depth distribution of flowering plants (primarily eelgrass) and macroalgae are quantified and reported annually. Eelgrass is a key parameter in the NOVANA program, as the main depth distribution (Zmax) of eelgrass is a primary indicator of the ecological status for the Danish Sea. For macroalgae, the indicator is based on changes in the accumulated cover with depth. The vegetation indicators are used, together with other indicators, to assess the ecological status and specifically, whether good ecological status (GES) is achieved, as required by the WFD. This report analyzes the possibilities of using different types of remote sensing (RS) technologies for mapping the areal coverage of SAV and from this develop a new indicator for GES assessment.

The report includes detailed studies in two water areas, outer Odense Fjord and Nibe Bredning (part of the Limfjord) respectively, and data from the period 2017 to 2023. Here data from the Sentinel-2 satellites (S2), ortho photos (OP) and a commercial satellite (Airbus Pléiades Neo) with high spatial resolution / Very High Resolution (VHR) were used. The purpose of the analyzes was to 1) further develop methods to map the area distribution of SAV, 2) test the possibility of distinguishing between eelgrass and macroalgae and, 3) based on SAV area data, to develop a new environmental indicator for assessment of the ecological status.

Classification of SAV based on S2, VHR and OP data was done using a deep learning method as opposed to the previously used pixel-based random forest method. The new method was chosen based on a desire to establish a more robust model, which is also flexible regarding which image data is used as input data. The analyzes documented the usefulness of the deep learning method, not only on S2 data, but also on OP and VHR data. A clear scaling potential was also made evident; during the project, it was possible to carry out longer time series analyzes for two water areas without generating large amounts of new training data for the classifier. The evaluation also confirms that the method can streamline the current method that is built into the DHI-developed SAV Denmark App, as well as contribute to more uniform results that are less dependent on the person operating the App.

To develop an ecological status indicator based on SAV distribution area ("SAV area indicator"), the same principles were used as for the existing indicator for the main distribution depth (Zmax) of eelgrass. The area indicator was thus based on a comparison of observed status (here the SAV area in 1 to 5 m depth interval, based on S2 and OP respectively) in relation to the area of SAV at a reference state, where the latter was estimated using a model developed for eelgrass. Comparison of the new SAV area indicator with the Zmax indicator showed overall good agreement and provided similar assessment of ecological status in the two test areas, although with some differences. Both the new area-based and the existing Zmax indicator, however, showed a limited relationship with measured water quality parameters (Chlorophyll and

light attenuation, Kd). Since the area indicator uses reference values for eelgrass, but new observations obtained with RS-data provides SAV values, the indicator can only be used in areas where SAV is dominated by eelgrass, such as in Nibe Bredning but less so in Odense fjord. Thus, the new area-based indicator represent eelgrass and not SAV.

Finally, we tested the possibility of estimating Zmax by modeling the depth dependence of the RS-derived SAV coverage. This was done at both the transect-level, and at water area level for the two test areas, where SAV is dominated by eelgrass. The estimated Zmax showed good agreement with the traditional calculations carried out as part of the national monitoring program, especially for models based on data for the entire water area and best for the water area in Nibe Bredning, in the Limfjord, where the distribution of eelgrass is more homogeneous.

Based on the experience gained for both RS-analysis and development of new indicators, we have several recommendations for further studies in a possible implementation phase of the IMM project:

1. Implementation of the tested deep learning method for SAV classification, and the possibility of multitemporal SAV mapping based on S2 and VHR data. It will significantly improve the spatial information and provide insight into the vegetation dynamics and distribution, throughout the growing season, but also between years. The deep learning method is based on and dependent on many annotated training data. Inclusion of more training data will therefore continuously improve the image interpretation Development of a national/regional database of image training data will accordingly significantly improve the method's usability. Large-scale mapping thereby becomes significantly more efficient and comparable in time and space without requirements for image-specific training and in situ data.

2. Further assessment of the importance of seasonality in SAV cover for the responsiveness of the new areal-based indicator.

3. Possibilities of specifying the density of SAV using S2 data, to improve estimates of observed areal SAV cover.

4. Possibility of better species separation in the SAV mapping using VHR and/or OP and the deep learning model

5. Further development of the eelgrass GIS model applied to accurately model local conditions and estimate the SAV areal under reference conditions.

6. Assessment of the performance of the areal indicator at local scale (around transects) and national scale (all relevant water areas).

7. Development and assessment of a RS status indicator based on densities and patchiness of SAV.

8. Further test of modelling Zmax from analysis of RS-based SAV cover along depth gradients.

1 Introduction

Peter A.U. Stæhr, Lisbeth Tangaa Nielsen, Mihailo Azhar, Cordula Göke, Silvia Huber, Jesper P.A. Christensen, Lars B. Hansen, Sanjina U. Stæhr and Dorte Krause-Jensen

The underwater marine vegetation or the submerged aquatic vegetation (SAV) along Denmark's coastline has been monitored for more than 30 years as part of the national marine monitoring program, NOVANA. The monitoring includes several hundred transects where the occurrence, density, and depth distribution of flowering plants (primarily eelgrass) and macroalgae are mapped and reported annually. Especially eelgrass is a key parameter in the NOVANA program, as the depth of the main distribution of eelgrass (Zmax, defined as the maximum depth of 10% eelgrass cover) is a primary indicator of ecological status. For macroalgae, new indicators reflecting macroalgal species richness and changes in the accumulated macroalgal coverage with depth have been developed and are in the process for approval at the EU level. The environmental indicators are used to assess the ecological status of marine flora under the water framework directive (WFD) in Denmark's 109 coastal water bodies. Currently, data for determining the main distribution depth of eelgrass is based on a manual visual review of video recordings along depth gradients. Macroalgal cover estimates are based on diving. However, these in situ collection methods are both costly and time consuming, and "only" provide data / information on the selected locations/transects, and not for the entire water body.

The Danish Environmental Protection Agency (EPA) has therefore previously supported DCE-led projects (RESTEK project) to develop effective supplementary methods to monitor the large-scale area distribution and coverage of eelgrass in Danish waters via Remote Sensing (RS) (Rasmussen et al. 2020, Ørberg et al. 2018, Stæhr et al. 2019a; Boderskov et al. 2022). In addition, DHI has developed a satellite-based classification system for the EPA – currently implemented with Copernicus Sentinel-2 data - for mapping marine vegetation distribution. This system constitutes a digital platform with a mapping tool (SAV Denmark App) which enables the Danish EPA employees to train a classification model in predefined calculation areas and create submerged aquatic vegetation (SAV) maps based on any Sentinel-2 (S2) image accessible via the App.

Different studies have documented the usefulness of RS technologies for mapping marine vegetation (eelgrass and macroalgae) in shallow coastal waters (e.g., Stæhr et al. 2019a, Lønborg et al. 2022, Huber et al., 2022). Mounted with the right camera and/or measuring equipment, drones, airplanes, and satellites can also be used to record many important supporting parameters in water, such as water temperature, light attenuation/visibility depth, chlorophyll content, turbidity. The conclusion from the RESTEK project (Stæhr et al. 2019a), and other later publications (Mederos Barrera et al. 2022, Lønborg et al. 2022) is that RS technologies have a great potential to map SAV. However, the conclusions also highlight that there is not one perfect RS technology to map SAV, and that the inclusion of RS technologies should be carefully considered with validation e.g. based on the existing conventional *in situ* observation/monitoring program. Furthermore, differences in spatial, spectral, and temporal resolutions as well as area coverage give rise to different strengths and weaknesses of the individual RS technologies in terms of mapping SAV. Drones, for instance, provide data with very high spatial resolution (VHR) that can enable differentiation between marine vegetation types, but the data only covers small areas and the operating cost for drones (price per km^2) is relatively high (Stæhr et al. 2019a). In comparison, satellites (e.g., Copernicus Sentinel-2) provide systematic data at 10m spatial resolution, covering a larger spectral range (visible-shortwave infrared) and a large spatial coverage, but the lower spatial resolution makes it difficult to distinguish between vegetation types, e.g., eelgrass from macroalgae. However, for SAV mapping at large scale, analyzing free satellite S2 imagery is currently the only cost-efficient method that can facilitate operational and consistent monitoring of SAV. Continuously operating satellite sensors can cover large areas quickly and repeatedly. This enables assessment of different vegetation stages during the growing season in optically shallow waters that are sufficiently clear to retrieve significant reflectance signals from the seafloor habitats. A common challenge for almost all the RS technologies is also to detect bottom vegetation at depths where limited light reduces the contrast between the vegetation and the surrounding seafloor, in Danish coastal water roughly greater than 4-5 meters (Stæhr et al. 2019a), or in the presence of turbid or choppy waters. This limits the potential of RS-methods to assess the full areal distribution of eelgrass, and coverage of macroalgae all the way to their depth limits as well as to monitor changes in these variables over time. Nevertheless, RS-techniques have the potential to supplement existing information with estimates of area cover at shallow and intermediate water depths where the issue related to limited light is not prominent such as in systems characterized by very shallow water.

1.1 Project aims

The project "Assessment of the areal distribution of marine vegetation using remote sensing" is a sub-project under the 4-year IMM (Integrated Marine Environmental Monitoring, in Danish 'Integreret Marin Miljøovervågning') project. This IMM project is further divided into an analysis phase (2023) and an implementation phase (2024-2026). For the analysis phase, the Danish EPA has asked for a description of how DCE and DHI can deliver research and development around the following:

1. Develop tools to map the marine underwater vegetation in all Danish coastal waters using cost-efficient RS technologies, building on existing mapping tools (SAV Denmark App - https://sav-denmark.dhigroup.com).

2. Develop a new environmental indicator of ecological status based on the areal extent of marine underwater vegetation. The indicator should eventually, in an implementation phase, make it possible to assess ecological status in all coastal water areas with eelgrass using an Ecological Quality Ratio (EQR) scale. The EQR scale should be intercalibrated with the existing eelgrass depth limit (Zmax) indicator to reach consistency between the two indicators.

1.2 Expected outcomes

1.2.1 Remote Sensing of underwater vegetation

1. Further method development of a satellite-based classification system

2. Test methods to integrate different RS data (Orthophotos (spring and summer), Sentinel-2 and VHR commercial satellites to determine areal cover of SAV and assess the ability to distinguish vegetation types.

3. Test the value of supplementing information layers (e.g., bathymetry, Kd/light, eelgrass habitat suitability model) for mapping vegetation coverage.

1.2.2 Marine vegetation status indicators based on RS data

1. Develop and test a new environmental ecological indicator based on RS-based data on areal SAV coverage. This should focus on the 1-to-5-meter depth interval to avoid bias from physical exposure (shallow depths) and uncertainties with RS classification of SAV at greater depths associated with low signal to noise ratio here.

2. Define reference conditions for areal coverage of eelgrass dominated SAV based on modelling and historical knowledge. And use this to define EQR values representing different environmental status conditions.

3. Compare the resulting new area-based indicator against the existing Zmax-based indicator and assess the importance and links to key environmental conditions obtained through the NOVANA program (light attenuation (Kd) and Chlorophyll).

4. Evaluate the possibility of estimating the maximum distribution depth limit (Zmax) of eelgrass from RS-based coverage along depth gradients and assess the robustness of the estimated Zmax-indicator.

2 Methods

Peter A.U. Stæhr, Lisbeth Tangaa Nielsen, Mihailo Azhar, Cordula Göke, Silvia Huber, Jesper P.A. Christensen, Lars B. Hansen, Sanjina U. Stæhr and Dorte Krause-Jensen

The analysis focuses on two test areas 1) outer Odense fjord and 2) Nibe Bredning in the Limfjord (see Figure 2.1).

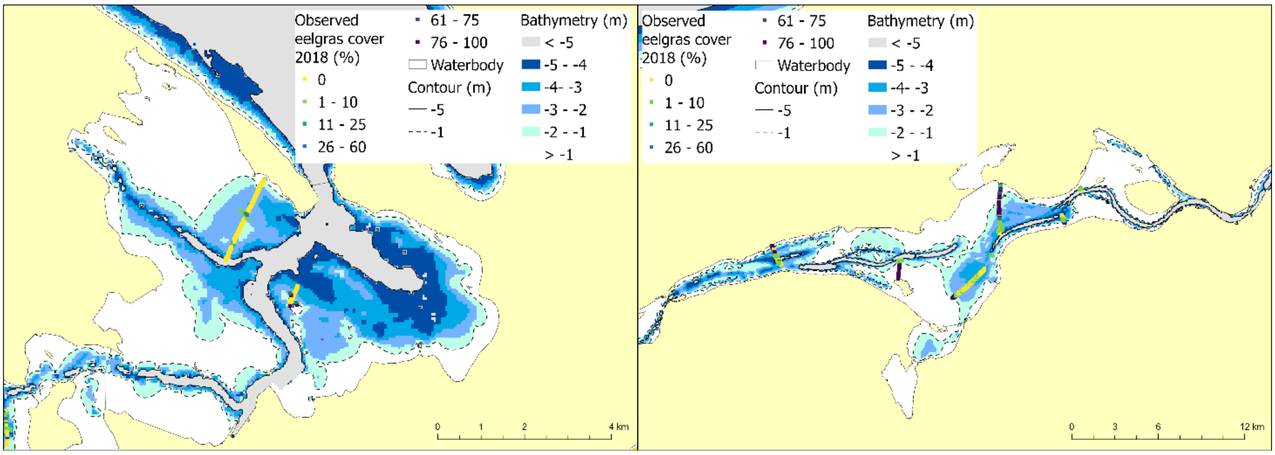


Figure 2.1. Test areas used for comparison of remotely sensed vegetation coverage. Left) outer Odense fjord; Right) Nibe Bredning in the Limfjord. Maps indicate the 1 to 5 m depth interval and observed eelgrass cover along NOVANA transects.

2.1 Remote Sensing products

2.1.1 Further development of a satellite-based classification system

The method currently implemented in the Backend of the SAV Denmark App (SAV Denmark App - https://sav-denmark.dhigroup.com) is based on a light gradient boosting machine (LGBM) which is a freely distributed, open-source gradient boosting framework for ML originally developed by Microsoft (Meng et al. 2017). The LGBM was chosen because it is a powerful and efficient technique for building predictive models; the training process is fast, additional training polygons can be added easily at any stage, and the model can be applied to very large datasets. A more detailed description of the implementation and application at large scale is described in Huber et al. (2021). The drawback of the LGBM implementation is that the model needs to be trained each time a new SAV map is created using the SAV Denmark App. In this task (this report) DHI investigated how the satellite-based classification system can be further developed and optimized by using Deep learning methodologies and explore ML model architectures developed for computer vision tasks that would allow to reuse pretrained models and apply them on new satellite imagery without retraining them. Such a transfer learning-based approach would reduce manual input considerably in the App and reduce objectivity of an operator providing training data via the SAV Denmark App.

For the transfer learning-based approach, DHI tested a convolutional neural network (CNN) specifically developed for semantic segmentation and improved prediction performance as compared to other well-known CNNs (Yi et al. 2019). The CNN learns to perform the SAV classification based on image annotations. The annotations contain representative characteristics (spectral and contextual) of the relevant habitat classes (i.e., submerged aquatic vegetation, soft bottom and/or hard bottom, vegetation types etc.) extracted from satellite imagery. To get a robust model for classifying SAV in Sentinel-2 imagery, the CNN was trained using image annotations from four different water bodies in Denmark (parts of Odense Fjord, The Limfjord, Sydfynske Øhav and Lille Bælt), and S2 imagery from mid-April to late August between 2017 and 2023, but without 2018 and 2022 which were only used as independent test data for model performance validation. As a general principle, the greater the amount of training data the more accurate the final map will be, assuming the input quality of the training data is good and represents the diversity of features of each habitat class seen in the input imagery. An independent dataset to that used for training, the validation data, is then used to tune the classification model to improve its performance. These two steps may be iterative to progressively improve model performance. The outcome of the training is a robust SAV classification model (prototype), termed Base Model hereafter.

The Base Model's performance is tested with available S2 images of 2018 and 2022 (= test data). By using data from a different year, we avoid spatial correlation between our training dataset and the actual test dataset used for evaluating final model performance. In addition, data from a different year, rather than a different water body, was chosen to evaluate the model performance in the more relevant use case of application to future years, as the model can be trained on past years for data from all coastal waters in Denmark if needed. When benchmarking different models for a classification problem, several metrics can be used to evaluate their performance and determine which model performs better. Usually, it is best to consider multiple metrics and not rely solely on one, as different metrics may give different insights into the model's performance. We use accuracy, F1 score and recall in the benchmarking to report the predictive performance of the models. Accuracy (acc) is a metric that quantifies the proportion of correct predictions out of all predictions made, and it is most effective when used with balanced datasets. On the other hand, recall is a measure that calculates the ratio of correctly predicted positive instances to all actual positive instances in the data. The F1 score is a metric that integrates precision and recall, making it suitable for datasets that are not balanced. Where feasible and meaningful, NOVANA data is used to assess the quality of the SAV maps.

The main satellite input data for mapping SAV distribution remains unchanged in the SAV Denmark App. The mapping relies on atmospherically corrected imagery since 2016 acquired by the Copernicus S2 mission. The S2 mission is a land monitoring mission with a constellation of two satellites (S2A and S2B), allowing a revisit time of 3 days in the northern regions. As the S2 satellites also observe the land-water surface it can be used for marine observations as well. S2 satellites cover 13 spectral bands out of which three optical bands (red, green, blue) are mainly used for the benthic habitat mapping due to the lower absorption of light by water in this part of the spectrum. All these bands have a spatial resolution of 10x10 m. Before training the CNN on the data, the imagery is normalized and scaled by a non-linear transform to enhance contrast in marine areas.

2.1.2 Integration of different RS data for areal cover of SAV

Given that various RS data sources each possess their unique advantages and disadvantages associated with their respective specification such as spatial, spectral, and temporal resolutions, the combination and integration of different RS data can be advantageous and lead to more robust and comprehensive results beyond using one data source alone. For instance, one of the advantages of S2 is the regular, systematic image capturing, allowing for multi-temporal analysis, both between years and within the growing season of individual years, as well as the potential for consistent SAV mapping on a national scale. Air- and spaceborne VHR data, on the other hand, captures spatial details that remain unseen within the 10 x 10 m pixels of S2, allowing mapping of different SAV types and potentially extraction of more precise areal coverage estimates. The annual OP campaigns in Denmark therefore offer a valuable data source to examine selected areas in detail. However, the VHR satellite and OP data typically covers smaller areas, with the OP campaigns primarily focused on land areas, resulting in suboptimal spatial coverage. The VHR data is furthermore susceptible to noise from surface waves as well as image artifacts in OP (e.g., seamlines). A combination of the different RS data sources is therefore required to leverage their full potential for mapping shallow coastal habitats.

DHI evaluated how SAV maps derived using CNNs and S2 imagery can be made more "robust" by integrating multitemporal imagery and how the mapping process with multi-temporal data can be made more efficient by using pre-trained models. The results are compared to NOVANA transect data. The model architecture was additionally tested on VHR satellite imagery and spring orthophotos, to explore the performance on imagery containing a higher level of spatial details. All the various RS imagery tested in this study are listed in Table 2.1.

Table 2.1. Information on RS imagery used in this project. Odense fjord covers the outer fjord, and Nibe Bredning is part of the Limfjord.

RS type	Data period used	Test areas	Specifications
Copernicus Sentinel-2 satellites	2017-2023	Odense fjord Nibe bredning, Lillebælt and Sydfynske Øhav	RGB, 10x10 m pixels
Airbus Pléiades Neo VHR satellites	Spring 2023	Odense fjord	RGB, 0.3x0.3 m pixels (pansharpened)
Orthophotos	Spring 2022 Spring 2023	Odense fjord Odense fjord	RGB, 0.125x0.125 m pixels "
	Summer 2018	Odense fjord and Nibe bredning	RGB, 0.2x0.2 m pixels

AU investigated summer OPs from 2018 using NOVANA ground truth locations as training points using the XGBOOST pixel-based model (Chen & Guestrin 2016). The NOVANA ground truth points presented a challenge as these *in situ* observations and their associated data points sometimes did not align with the OP imagery. Despite this uncertainty of the exact spatial reference of NOVANA observations, AU wanted to investigate utilizing these in situ ground truthing without needing to create new labels for the pixel classification.

For each NOVANA datapoint a window of neighboring pixels was analyzed. An initial preprocessing of OP images was conducted to remove pixels that had an abundance of high reflectance values in the NIR band. This threshold was developed by analyzing OP regions that had wave and glint artifacts.

Secondly, because the NOVANA datapoints include a coverage percentage we filtered datapoints that had a less than 10% coverage as SAV absence. This would ensure that remaining neighboring pixels were more likely to contain seagrass pixels. The remaining data points were then used in the training of the model.

2.1.3 Value of supplementing information layers for SAV mapping

Usually, the information contained in optical RS data is sufficient for mapping SAV in Danish coastal waters with S2 data. However, the mapping can be supported with supplementing information such as bathymetry. For Odense Fjord, DHI tested if adding bathymetry could improve the performance of the CNN classification model applied on atmospherically corrected S2 data (Figure 2.2). The bathymetry layer was derived from S2 data and merged with survey data. Basically, the CNN model was trained with image annotations from multiple S2 images and bathymetry from Odense Fjord and the result compared to the SAV output of the same model but without using bathymetry. The models were compared in terms of accuracy, F1 metrics and recall.

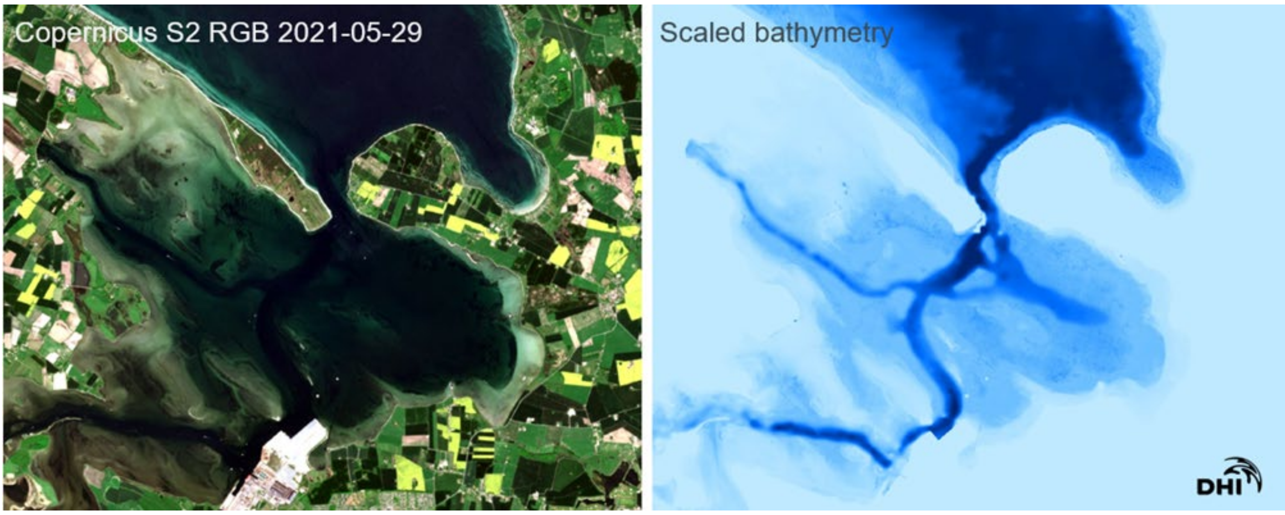


Figure 2.2. Data from Odense Fjord used to test the use of bathymetry data to improve performance of the SAV CNN-based classification.

Similarly, for the XGBOOST OP model, AU investigated the use of supplementary information layers on improving the detection performance of the model. Here we introduced ratios between the RGB-bands, a sediment raster layer and a 50 x 50 m resolution bathymetry raster derived from acoustic side scan sonar mapping (Danmarks Dybdemodel, 50 m opløsning (gst.dk). To prevent ordinality in the model's interpretation of the sediment raster layer, a one hot encoding transform was used. The models were compared using standard accuracy, F1 and recall metrics. By systematically introducing the different layers we measured the contribution of each information layer. Model evaluation was conducted with an 80-10-10 random split on the NOVANA *in situ* ground truth data. Here 80% of the data was used for training the model, 10% was reserved for testing and a final 10% for validation. The validation split was unseen by the model during training and only used as validation.

Evaluation of the model variants was conducted with stratified five-fold cross validation where the dataset was partitioned into training-test-validation subsets five times, while an even distribution of classes was maintained. The repeated cross-validation ensures results were not dependent on the partitioning process and were thus more robust.

2.1.4 Distinguishing vegetation types using RS data

Directly distinguishing marine vegetation types in S2 data is a difficult task without inclusion of supplementary data. An alternative could be to use VHR data from OPs and satellites to map different SAV species in single images and combine the results with multi-temporal S2 SAV maps. In this task, the capability of differentiating SAV types using VHR RS imagery was tested using commercial Pléiades Neo VHR satellite data from May 2023 and a spring OP from 2022 for Odense Fjord (cf. specifications table 2.1). It was assumed that since different SAV types can be visually distinguished in both image sources, the CNN model should be able to classify them as well. Eelgrass meadows can exhibit quite unique patch patterns. In some instances, they grow in a circular formation that evolves over the course of a season. As the season progresses, the center of these circles is thinning out and tend to become less dense, which is usually also visible in VHR RS data. Moreover, in spring imagery, eelgrass tends to be lighter green as compared to macroalgae. DHI tested if this distinctive pattern can also be traced in VHR RS data and be used to distinguish different vegetation types.

For the test, two SAV types were identified – eelgrass and non-eelgrass type of SAV - based on visual characteristics using image interpretation and aligned with the presence of eelgrass from NOVANA *in situ* observations.

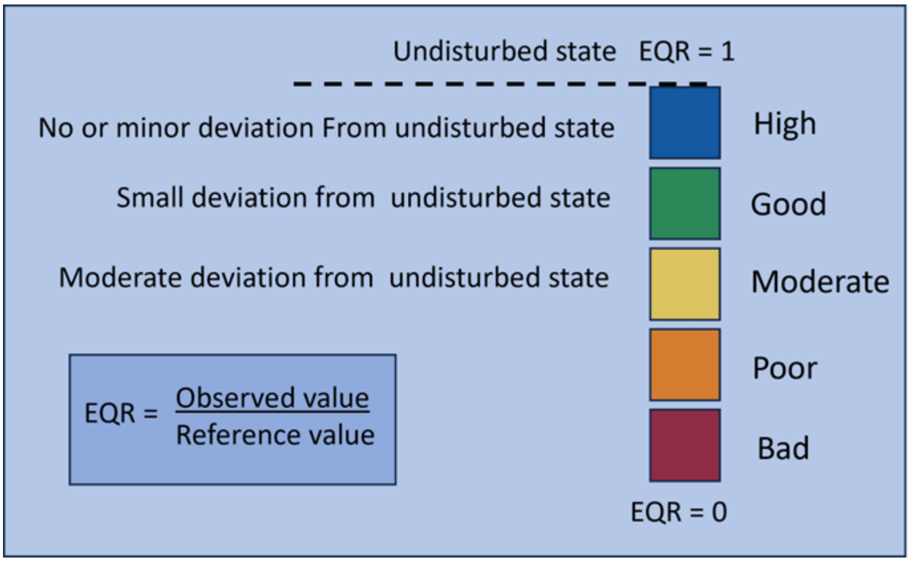
Using a similar model architecture as for the S2 analysis described earlier, a CNN OP model was trained on a small set of annotations from the 2022 spring OP and another model with annotations extracted from the VHR satellite data. The spring OP from 2022 was taken under near ideal conditions for SAV mapping with excellent water clarity and no or very limited noise from surface waves. Despite relatively good water clarity conditions, the VHR satellite imagery was affected by noise from surface waves in most of the covered area and some areas were also impacted by light cloud cover. Accordingly some of the affected pixels were masked out.

Successful testing with VHR data (airborne and spaceborne) using the same CNN architecture as with S2 would greatly facilitate the implementation of VHR data analysis into the SAV Denmark App to enhance the S2-based mapping and support SAV type separation and refine SAV areal estimates.

2.2 Development of an ecological status indicator based on RS data

For the development and test of a biological indicator based on RS-based areal extent of SAV, we applied the commonly applied WFD ecological status assessment approach, where ecological status classes are defined by comparing a reference condition with the observed condition for a given area to calculate an ecological quality ratio (EQR). Five ecological status classes are used for the WFD classification system: high, good, moderate, poor, and bad. These are determined using an EQR scale ranging from 0 (bad) to high (1), see figure 2.3.

Figure 2.3. Overview of the five ecological classes used in the water framework directive. The EQR is the ratio between the present (observed) condition and the reference condition in a particular water area. The EQR value can range between 0 and 1.



Reference conditions and EQR values have previously been defined for eelgrass depth limits using the maximum depth of the main distribution of eelgrass distribution (Zmax), as a water quality descriptor (Timmermann et al. 2020). Zmax is here defined as the depth where the main distribution (>10% coverage) ends.

The application of Zmax to assess the ecological status of our coastal waters, is based on the establishment of statistically strong relationships between Zmax and water clarity (Nielsen et al. 2002, Markager et al. 2010, Christensen et al. 2021) and between water clarity and longer-term changes in loadings of total nitrogen (TN) (Nielsen et al. 2002, Duarte 1991, 1995, Krause-Jensen et al. 2005, Christensen et al. 2021, Krause-Jensen et al. 2021). In addition, availability of historical observations of eelgrass distribution (from around year 1900, Krause-Jensen & Rasmussen 2009) has made it possible to determine so called reference conditions for eelgrass maximum depth limits (Zmax), representing undisturbed natural distributions. Using modelled relationships between Zmax, Kd and TN-loadings, it has then been possible to infer summer average values for water clarity, Chlorophyll-a concentrations, and annual TN-loadings in different water areas around Denmark in reference (pristine) condition (Timmermann et al 2020 and Timmermann et al 2021). For most of the 109 water bodies under the WFD in Denmark, there is accordingly defined a historical eelgrass Zmax and water clarity (Kd) value which represents the reference condition for each water body. In addition, EQR threshold values have been defined representing the transition from high to good (HG), good to moderate (GM), moderate to poor (MP) and poor to bad (PB) (Timmermann et al. 2020). These are shown in Table 2.2.

Table 2.2. EQR values separating the five ecological status classes for eelgrass depth limit. From Timmermann et al. (2020).

Class	EQR
Reference	1.00
High to Good	0.90
Good to Moderate	0,74
Moderate to Poor	0.50
Poor to Bad	0.25
Bad	0.00

2.2.1 Ecological status based on areal extent

To develop reference conditions for an indicator based on the areal extent of SAV, we take advantage of an existing spatial GIS model which based on available environmental data layers calculates suitability for potential eelgrass cover (scale 0 to 100% potential cover) for all the Danish coastal waters (Staehr et al. 2019b, Timmermann et al. 2021). The eelgrass habitat suitability model (HSM) utilizes light conditions at bottom based on Kd and depth, sediment classes, bottom shear stress, relative exposure related to waves, salinity, water temperature and low oxygen (Timmermann et al. 2021). The model operates at a 100x100 m pixel resolution and has previously been calibrated and validated using a data set covering environmental data for all Danish coastal waters during a 2012-2016 period. Given the time constraints of this project, we applied the HSM model without further local re-calibration or re-validation to improve local accuracy.

To determine the reference Kd value needed for the model to estimate reference eelgrass areas, we calculated the mean light attenuation (Kd) from the eelgrass depths limit (>10% eelgrass coverage) under reference conditions, the status determined for the Danish River Basin Management Plan 3 (hereafter referred to as VP3) (Timmermann et al. 2020) and from the eelgrass depths limits representing the HG, GM, MP and PB transitions.

For all model scenarios, we calculated the eelgrass probability (0 to 100%) in each 100x100 m pixel using the new reference-Kd data, while keeping the other environmental variables unchanged. The assumption is that the main driver of change from e.g. a poor to a moderate status in each water body, are changes in benthic light availability, as indicated in several studies investigating long-term changes in eelgrass (e.g. Nielsen et al. 2002). The nationally calibrated model is used to showcase the application possibilities. In future, the model needs to be recalibrated and validated to local and updated conditions, and further developed with better data layers on eg. sediment suitability.

As the areal indicator should optimally represent responses in eelgrass areal cover related to changes in water quality (Kd, Chlorophyll-a and TN-loadings) we decided to restrict the analysis area to a depth range of 1 to 5 meters. Above 1 meter, presence and density of eelgrass is expected to be strongly sensitive to physical exposure from wave action. And at greater depth (here set to below 5 meters depth), detection of eelgrass using either S2 or OP becomes very challenging in many of our turbid waters (Staehr et al. 2019a). Although underwater vegetation can be detected with RS at greater depth under clear water conditions, Danish coastal waters are generally turbid, thus limiting the depth range that can be used for RS detection. In this study comparing several RS approaches, a mask was created to restrict the assessment area provided by the model, S2 and OP data.

For the comparison between the RS results and the model, the RS data was aggregated on the same resolution as the eelgrass model. While we expect that the orthophotos have an adequately high resolution, SAV detection from RS data with lower resolution can mean that the cell is only partly covered with vegetation. As a first estimate, we therefore applied a factor of 0.5 on the S2 gating them to 100m x100m resolution (Figure 2.4). This assumption will be discussed later. The results are either used as area covered or cover percentage within one grid cell (Figure 2.4).

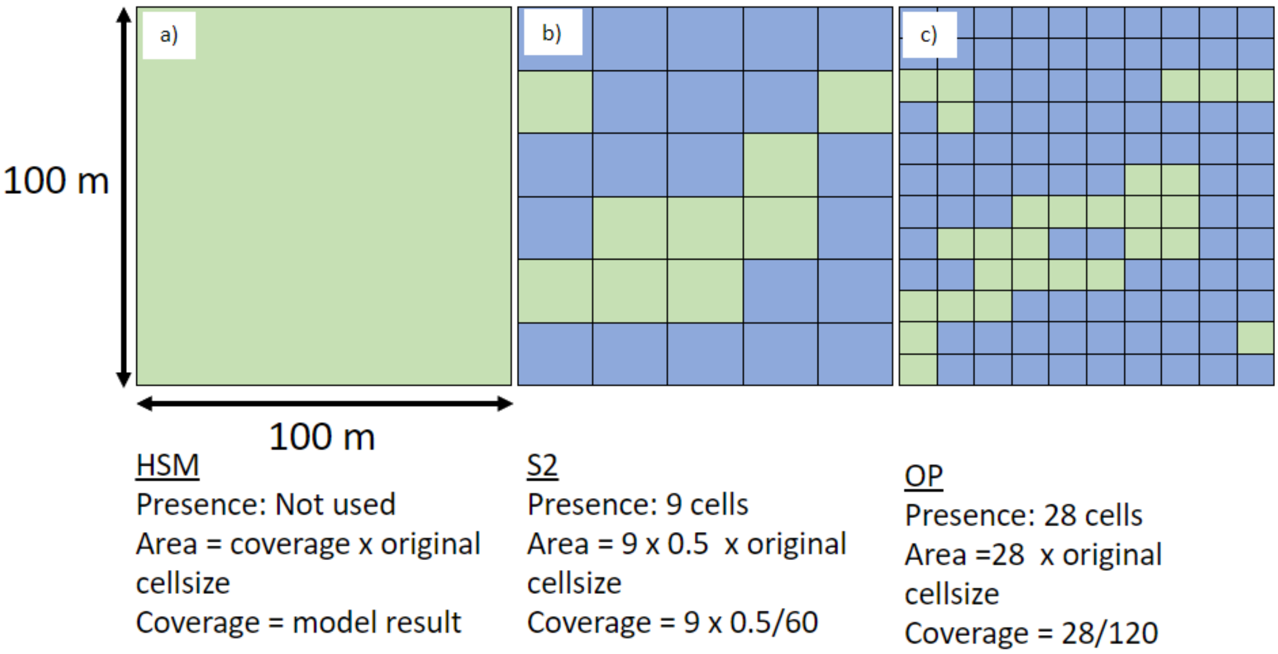


Figure 2.4. Diagram showing how we aggregate estimates of SAV cover for comparison of the different types of areal data (S2, OP and HSM derived).

We calculated the modelled areas within the selected depth range by multiplying the probability value per grid cell by the size of the grid cell. First, we use the HSM to calculate the eelgrass area (ha) per water area under reference water clarity (kd) conditions, and EQR ratios representing HG, GM, MP and PB transition values based on the corresponding Kd-threshold values from the eelgrass depth limit EQR-thresholds. The reference area is then used to calculate the EQR value for a given water area: EQR = modelled VP3 status and observed area/reference area. The variation between modelled and observed data can be used to describe the reliability and limitations of the respective outputs. To define which ecological status group the observation corresponds to, the calculated EQR-value is now compared with the EQR values representing H, G, M, P or B conditions. The process is shown in figure 2.5.

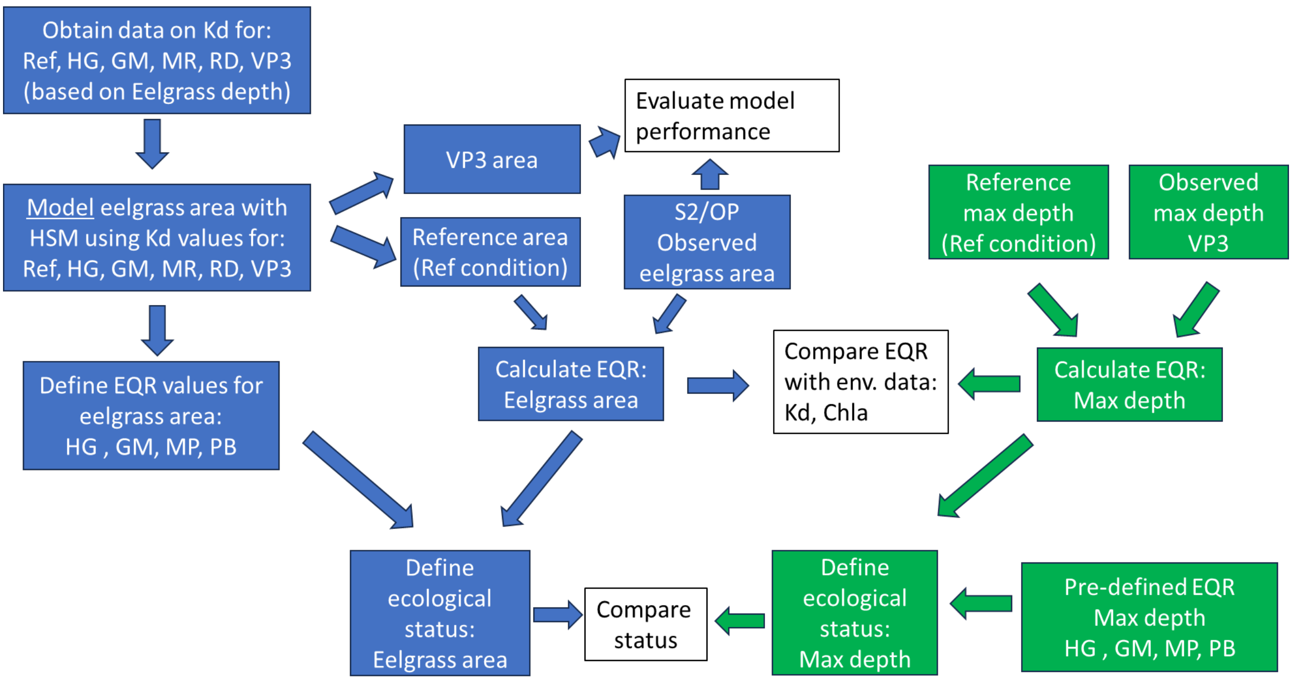


Figure 2.5. Process flow diagram. Blue boxes represent data and analysis involved in determining ecological status for eelgrass area. Green boxes represent data and analysis involved in determining ecological status for eelgrass depth limits. White boxes represent comparisons between the two approaches and an evaluation of the performance of the model used to predict eelgrass area. VP3 is the River Basin Management Plan 3, from which light attenuation (Kd) values have been determined for each water body.

To assess the usefulness of the proposed areal indicator, we applied area information on eelgrass for the two water bodies, outer Odense fjord and Nibe Bredning in the Limfjord. The SAV area was determined from classification of S2 and from OPs as described in section 6.2.1.

It is important to note that because the RS method assesses the distribution area of SAV, whereas the model assesses the reference conditions for eelgrass, the comparison between the current distribution area and reference distribution area is only relevant for areas where eelgrass dominates SAV. This is the case Nibe Bredning in the Limfjord). In outer Odense fjord, fucoid macroalgae have likely contributed to the S2 estimated SAV cover, and this is also a relevant issue in other Danish coastal waters.

2.2.2 Intercalibration with eelgrass depth limit indicator

To evaluate the usefulness of remotely sensed data on SAV area as a measure of water quality, we investigated relations between the calculated EQR values for the areal indicator with water quality conditions (Kd and Chlorophyll-a). For comparison we make a similar investigation for the EQR values obtained using the Zmax indicator.

Specifically, for S2 derived areal SAV data, we investigate the importance of temporal (annual) changes in eelgrass area for the determination of EQR-values and associated ecological status assessment.

2.2.3 Estimating the depth distribution limit Zmax from RS-data

In areas where the SAV is dominated by eelgrass, it is potentially possible to assess the maximum depth limit of the main distribution limit of eelgrass (Zmax) based on RS classification of SAV. To estimate Zmax from RS data, we collated SAV absence and presence from the CNN-based S2 and XGBoost-based summer OP prediction map for the two study areas. We first created a 100 m buffer region around existing NOVANA transects programmatically by finding centroids of the transect over the recorded sampling locations (see figure 2.6 below). The Euclidean distance from each sampling point to the centroid was then calculated and outliers are handled for distances beyond the 5th and 95th percentile. A convex hull was then used over the remaining points to generate the 100 m buffer zone, as illustrated in figure 2.6.

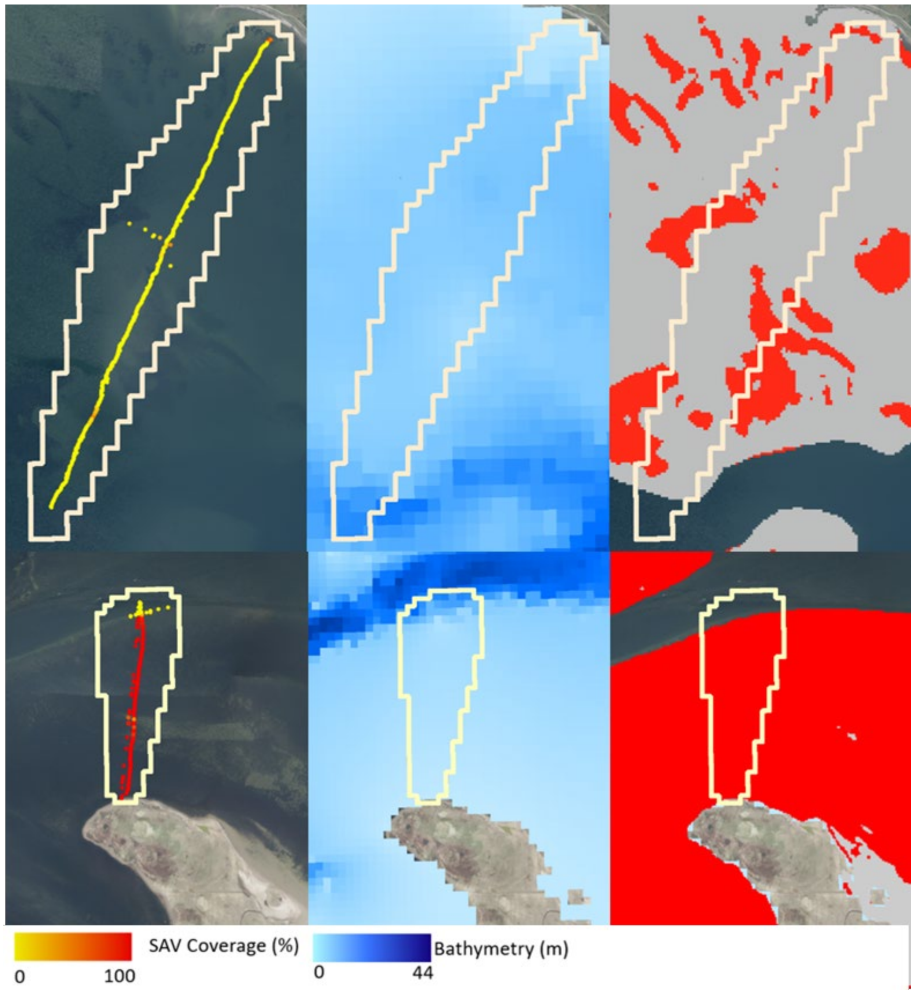


Figure 2.6. An example transect buffer from Odense fjord (top row) and Nibe Bredning, the Limfjord (bottom row). The buffer zone is delineated by the pale-yellow outline in all images. Left column: Transect buffer overlayed onto OP RGB raster with NOVANA observations depicted by points. Yellow points represent low and red points high SAV coverage; Middle column: Underlying bathymetry raster; Right column: S2 SAV predictions overlayed onto OP RGB raster; SAV presence is depicted in red and SAV absence in grey colour.

For 2018 there are three NOVANA transects in Nibe Bredning, the Limfjord, and two in Odense fjord. With the transect buffer we then aggregated the SAV presence/absence predictions by their associated depth. The aggregation was done over a 100 x 100 m region and a SAV coverage percentage was then calculated. For every aggregated SAV coverage cell, we queried the underlying bathymetry raster to bin the coverage into a depth gradient, see figure. 6.7. For S2 SAV predictions each cell size was 10 x 10 m before aggregation, and for summer OP each cell size was 0.2 x 0.2 m.

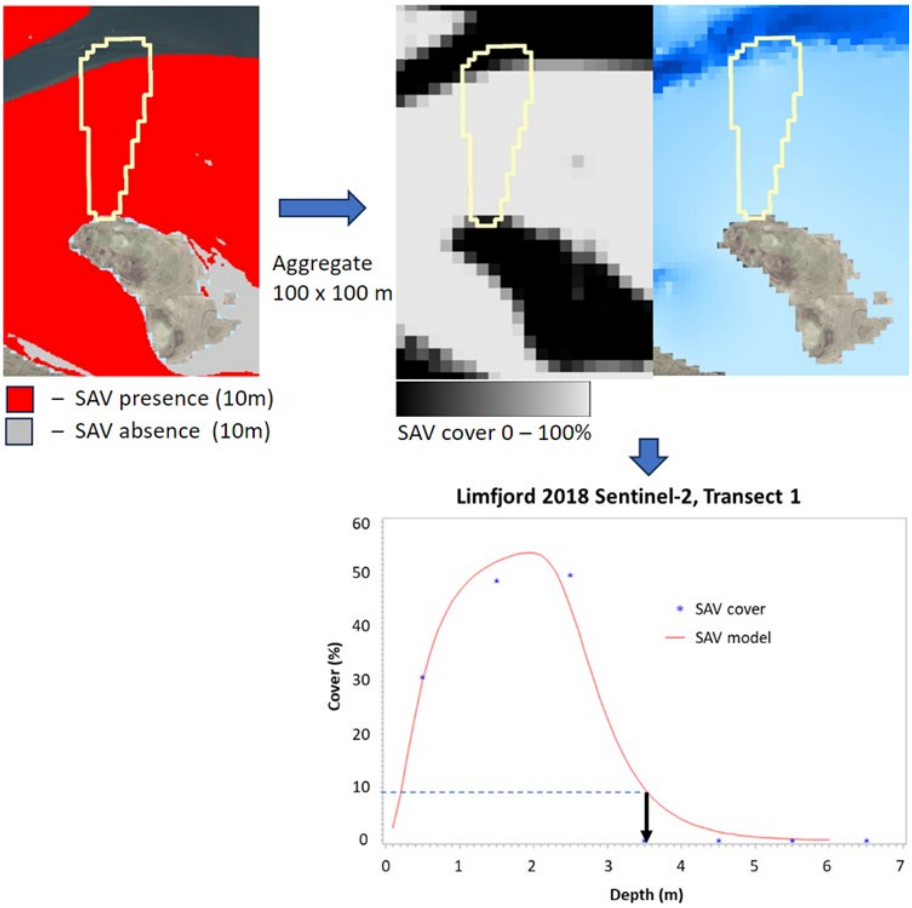


Figure 2.7. Diagram illustrating how SAV (here eelgrass) coverage (%) is calculated from SAV presence and absence, in this case by Sentinel-2. SAV coverage was calculated per pixel (100 x 100 m) and combined with the bathymetry map. From this we then binned cover estimates into different depth intervals and applied a non-linear model to estimate Zmax at 10% cover (black arrow).

To estimate Zmax from the cover distribution along the depth gradient, we applied a non-linear model which previously has been used successfully to model the cover of macroalgae along a depth gradient. (Carstensen 2020).

Modelled %cover =(max*tanh(I_{sat}*exp(-k_{bio}*z)))/(1+($phys_{exp}$*(z**-2)))

Where max is the maximum %cover, I_{sat} a light saturation term, k_{bio} is the attenuation coefficient of the eelgrass index/cover, z is the depth and $phys_{exp}$ represents the level of physical exposure from waves. The physical exposure term is included to model changes in cover at shallow depth, followed by an optimum defined by maximum cover, and then a decrease defined by the light dependent variables. The parameters of the model were determined simultaneously by nonlinear regression using the Gauss iterative method in SAS/STAT software package (SAS Institute Inc. 1994).

In addition to estimating Zmax from cover around individual transects, we aggregated SAV cover for the entire fjord systems, and binned cover into depth intervals. This enabled us to provide an overall estimate Zmax for each of the two coastal areas and investigate trends in Zmax over the 2018 to 2022 period.

Results from the estimated Zmax values were compared with the Zmax values derived from analysis of the NOVANA transect observations. The latter is derived from detailed analysis of the so-called T-shaped vegetation transects, where Zmax is defined as the greatest depth where 10% coverage of eelgrass is reached. The procedure is described in appendix 2 in a recent publication from Miljøministeriet (2023).

3 Results

3.1 Remote Sensing products

Lisbeth Tangaa Nielsen, Silvia Huber, Lars B. Hansen, Mihailo Azhar

3.1.1 Further development of a satellite-based classification system

The main goal of this task was to investigate deep learning approaches to improve the satellite-based classification system currently implemented in the SAV App and hence reduce manual work in the mapping process. This was done by implementing and training deep learning CNN models developed for computer vision tasks, such as semantic segmentation tasks.

DHI developed a robust CNN Base model (prototype) for SAV predictions using S2 imagery. This part of the analysis did accordingly not include separation of SAV types (i.e. seagrasses and macroalgae) but see later analysis on this. To get a robust SAV classifier, the Base model was trained using image annotations from four different water bodies in Denmark (Odense outer fjord, the Limfjord, Sydfynske Øhav and Lille Bælt), and S2 imagery from mid-April to late August between 2017 and 2023. The image annotation was distributed across the entire water bodies for multiple images covering both spring and summer conditions. The training data is a sparse set, consisting of labeled polygons of relevant classes, thus not all pixels in an image is labeled and used for training. With this database of heterogeneous S2 annotations, different configurations of regions and seasons for model training could easily be tested. The trained Base model was applied on new S2 images, which were not used for the training (= transfer learning), to test its predictive power. To improve the model's ability to generalize features from multiple images, the preprocessing scheme was optimized for S2 imagery as compared to the existing approach in the App. The Base model was tested for Odense Fjord (Figure 3.1) and the area of Nibe Bredning in the Limfjord.

Figure 3.1. S2-based SAV classification based on a S2 optimized preprocessing scheme. S2 imagery (left) for 20 April 2019 in Odense fjord. The S2 classification (right) used a CNN model architecture where light green colors represent SAV, light yellow represents non vegetated areas

To assess the accuracy of the model, a set of annual SAV maps was created for each of the two test sites to get more robust estimates. The annual SAV maps represent aggregates of all the individual SAV maps created from cloud free S2 imagery acquired between April and September per year. Pixels classified as SAV in the annual maps had to be assigned the SAV class in at least 1/3rds of all the individual SAV maps. The predicted SAV areas in the annual maps were compared with available NOVANA data on the presence of eelgrass and floating macroalgae, using threshold value of 10% cover ration to convert to a binary SAV presence for comparison to the SAV maps. The S2 images listed in Table 3.1 were evaluated for Odense Fjord. Results show accuracies ranging from 0.70 to 0.88 when compared to independent NOVANA data and highest f1 score for 2019 (f1 = 0.71).

Table 3.1. Assessment of SAV classifications using the prototyped Base model applied on S2 data compared to NOVANA transect surveys (combined cover ratio of eelgrass and floating macroalgae, where available) for Odense Fjord; image annotation from years in bold are used for model training.

Year	Accuracy	f1	recall
2018	0.88	0.38	0.29
2019	0.82	0.71	0.60
2020	0.70	0.63	0.40
2021	0.79	0.63	0.56
2022	0.70	0.45	0.74
2023	Data used for training but no NOVANA data available for validation		

A similar analysis was conducted for Nibe Bredning in the Limfjord (Table 3.2). Again, imagery from 2018 and 2022 were not used for training the deep learning model. The accuracies range from 0.66 to 0.87, like the ones achieved for Odense fjord, but f1 and recall achieved higher maximum scores (max f1 = 0.91 and max recall = 0.86). Interestingly, highest assessment metrics were achieved for 2018, the year not used for training the model. This demonstrates the potential of the predictive capabilities and robustness of the pre-trained *Base model* using CNN architecture.

Table 3.2. Assessment of SAV classifications using the prototyped Base model applied on S2 data compared to NOVANA transect surveys (combined cover ratio of eelgrass and floating macroalgae (where available) from Nibe Bredning, the Limfjord; image annotation from years in bold are used for model training.

Year	Accuracy	f1	recall
2018	0.86	0.91	0.86
2019	0.87	0.9	0.84
2020	0.66	0.53	0.39
2021	0.73	0.66	0.53
2022	No NOVANA data available for validation		
2023	Data used for training but no NOVANA data available for validation		

To assess the S2 SAV maps spatially, the annual SAV data was com-pared along NOVANA transects in the investigated areas. In figure 3.2 the observed eelgrass cover was qualitatively compared (overall patterns and trends) to S2 SAV frequency for 2018 and 2021 based on the analysis of 5 images from 2018 and 4 images from 2021 (see also Figure 3.4). The comparisons show good agreement, with differences mostly observed for transitions between unvegetated and vegetated sections and sometimes for areas with low eelgrass cover, where the area of sparse SAV is not detected in all images. This is not surprising as the scale between the two datasets differs considerably (point data versus 10x10 m pixels), and the potential issues with spatial alignment of ground survey data add uncertainty.

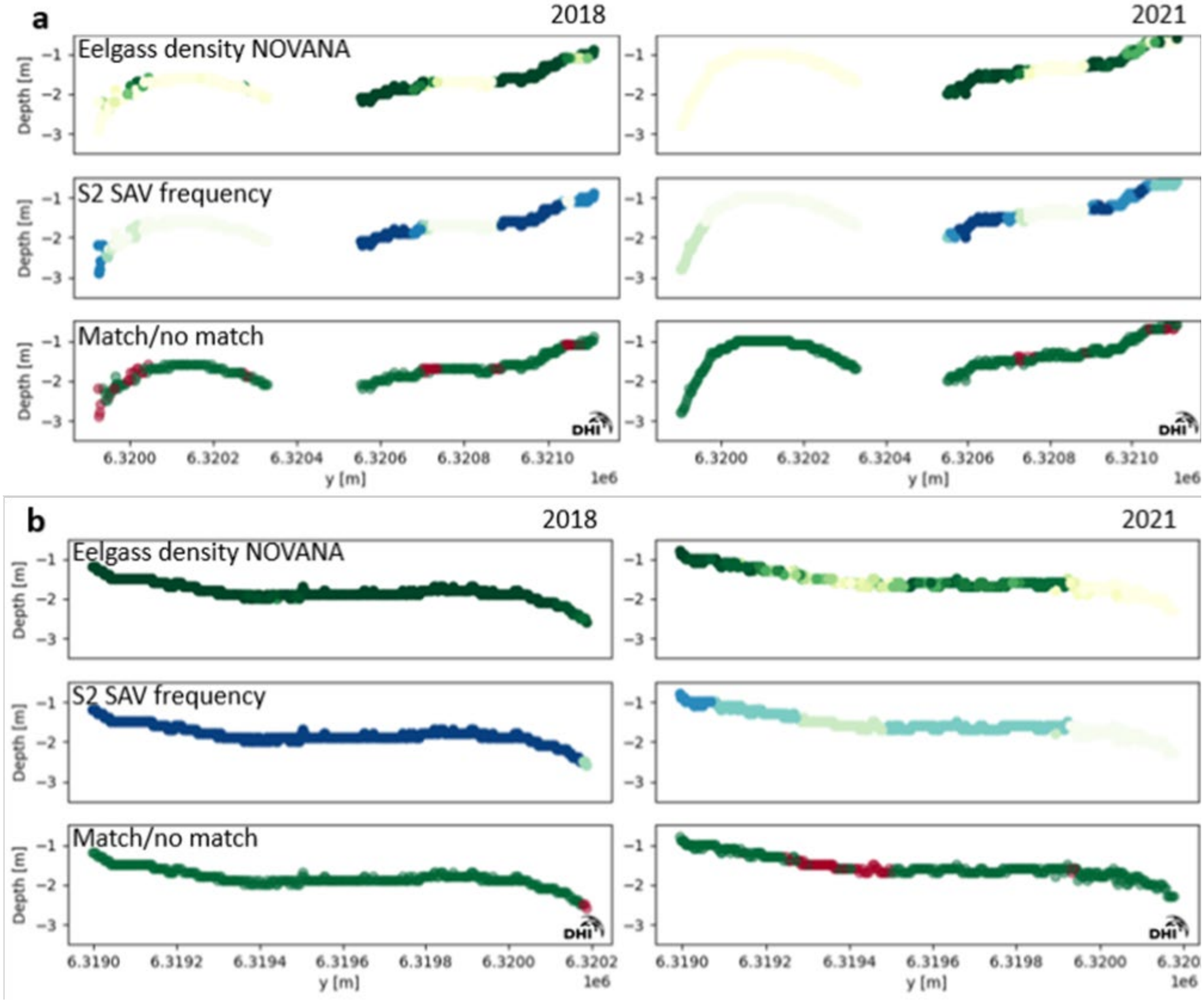


Figure 3.2. Correspondence between eelgrass cover ratio observations in Nibe Bredning, the Limfjord, from NOVANA eelgrass transects (top rows) S2-derived annual SAV frequency (middle) and the match between the two (bottom); green indicates accordance and red disagreement. (a) represents the most western transect compared to (b) the second transect from west (see transects in Figure 2.1). For eelgrass cover, the darker the green colour, the denser the observed eelgrass patch, and for S2 SAV frequency, the darker the blue colour, the more often the pixel was classified as SAV in the multitemporal analysis. The y-axis shows y-coordinates in UTM32N

Comparing the classification accuracy to the eelgrass cover reported in the NOVANA data (see Figure 3.3), the base model in general has a very high accuracy for predicting high cover, whereas for cover in the range 10-50 %, the accuracy is lower. The lower accuracy in areas with lower SAV cover, under suboptimal conditions, reflects that less contrast leads to less accuracy in prediction. Resulting uncertain estimates in low SAV density regions therefore affects spatial distribution maps and assessment of seasonal changes in areas of low contrast.

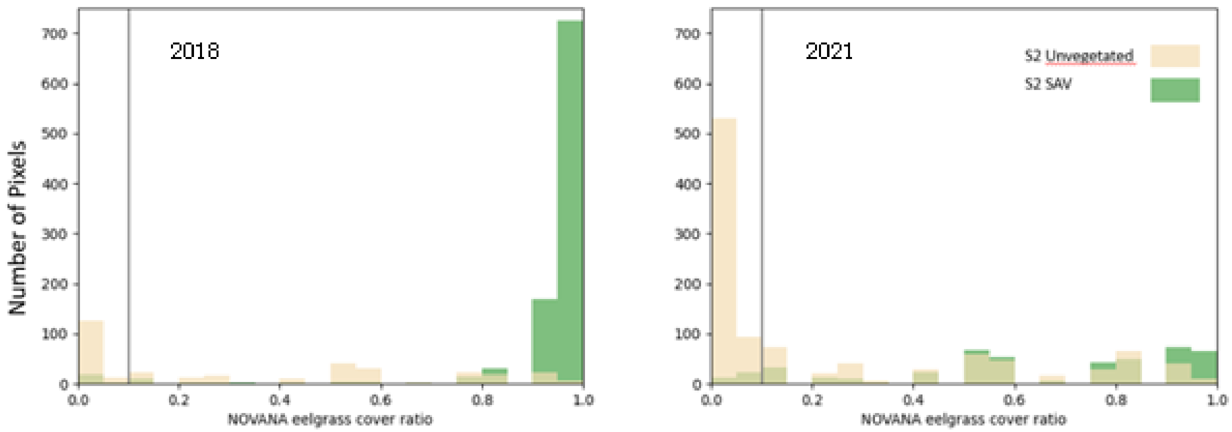


Figure 3.3. Distribution between pixel classification using S2 imagery and eelgrass cover from NOVANA in situ data for Nibe Bredning, the Limfjord for 2018 (left) and 2021 (right). Most pixels classified as SAV (shown in green) falls above the 0.1 cover ratio threshold, and unvegetated below for the 2018 data. For 2021, a larger mixing of the two classes when comparing to the NOVANA data is seen.

The distribution for 2018 was dominated by very high cover ratios, and the S2 model performed well under these conditions. For 2021, the eelgrass cover ratio is more distributed and S2 has more difficulties to capture this pattern, however, the general patterns are well represented.

3.1.2 Integration of different RS data for areal cover of SAV

To achieve robust SAV areal cover estimates, the integration of multitemporal S2 imagery was tested. Seasonal and interannual SAV frequency maps can provide additional insights into distribution changes, growth patterns and SAV types.

The newly developed SAV mapping approach with a robust pre-trained deep learning model (Base model) allows very efficiently to predict SAV across all suitable cloud free S2 images, and even on newly acquired data without providing additional annotations for model training. For Nibe Bredning, DHI applied the model to imagery since 2018 and extracted the SAV area for each prediction. Figure 3.4 clearly shows the seasonal growth of SAV between April and September and a general declining trend from 2018 to 2023 (note that the figure should be interpreted with care as the data can still contain some outliers from artefacts in the SAV maps). Interestingly, interannual variation can be quite significant, in both positive and negative directions and can be associated with eelgrass and/or macroalgae.

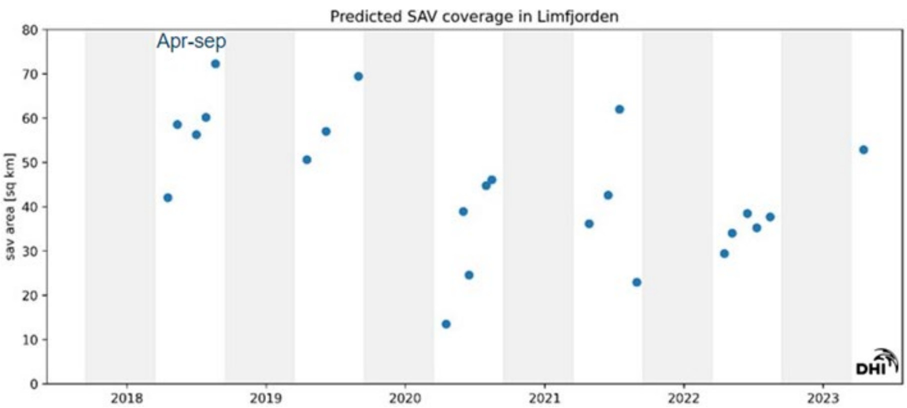


Figure 3.4. Seasonal variation in SAV distribution for Nibe Bredning, the Limfjord for 2018-2023. Sentinel-2 imagery between April and September was used for the analysis. Note that the data is preliminary as the SAV data still may contain artefacts and produce some outliers.

To investigate SAV distribution per depth, the interannual SAV distribution was extracted for different depth intervals for both test sites. As can be seen in Figure 3.5, the largest area covered with SAV is found in the shallow zones and with increasing depth the SAV is decreasing.

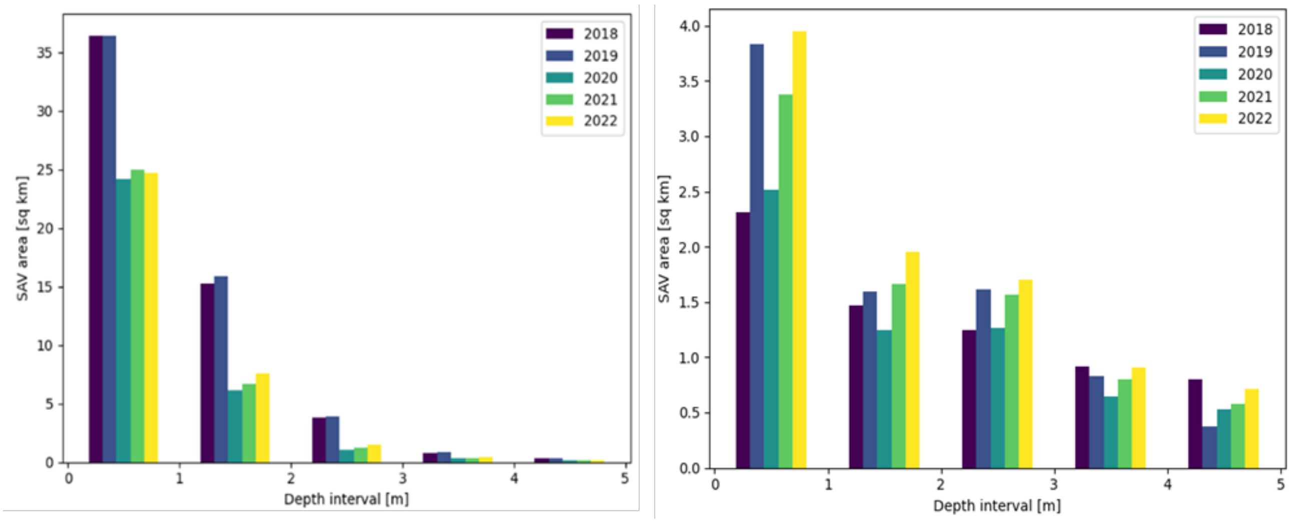


Figure 3.5. Distribution of predicted annual SAV from S2 imagery per depth in the range 0-5m for the years 2018-2022 for Nibe Bredning, the Limfjord (left) and Odense fjord, outer (right), including all areas with a minimum of 10 % coverage. The annual maps represent aggregates of SAV mapped using all available cloud free S2 images between April-September. Note that the depth limit was cut off at 5 meters and the total area compared is 99.7 km2 and 35.6 km2 for Nibe Bredning and Odense fjord, respectively.

For Nibe Bredning, the Limfjord we observed a substantial decrease in vegetation coverage across all depth intervals from 2019 to 2020. This was followed by a minor increase in the subsequent years (2020-2022). Note that the depth limit was cut off at 5 meters as visibility in RS imagery is very limited at depths beyond this limit in the investigated area of interest. The total analyzed area identified in Nibe Bredning is 99.7 km^2.

Compared to Nibe Bredning, the submerged vegetation cover is more stable in Odense fjord, outer. Still there is some interannual difference for the shallowest areas (0-1 m depth). Comparisons to SAV type classifications using VHR data indicate that the majority of the interannual variations can be attributed to differences in macroalgae abundance (cf. section 7.1.4). The total analyzed area identified in Odense fjord is 35.6 km^2.

The corresponding SAV frequency map was produced for Odense fjord using multitemporal S2 imagery from April-September for a 6-year period (Figure 3.6), and for Nibe Bredning, the Limfjord covering the 5-year period 2018-2022 (Figure 3.7). To create the maps the *Base model* was applied on all suitable images in the investigated period. The maps give an indication of how stable SAV patches are across different years.

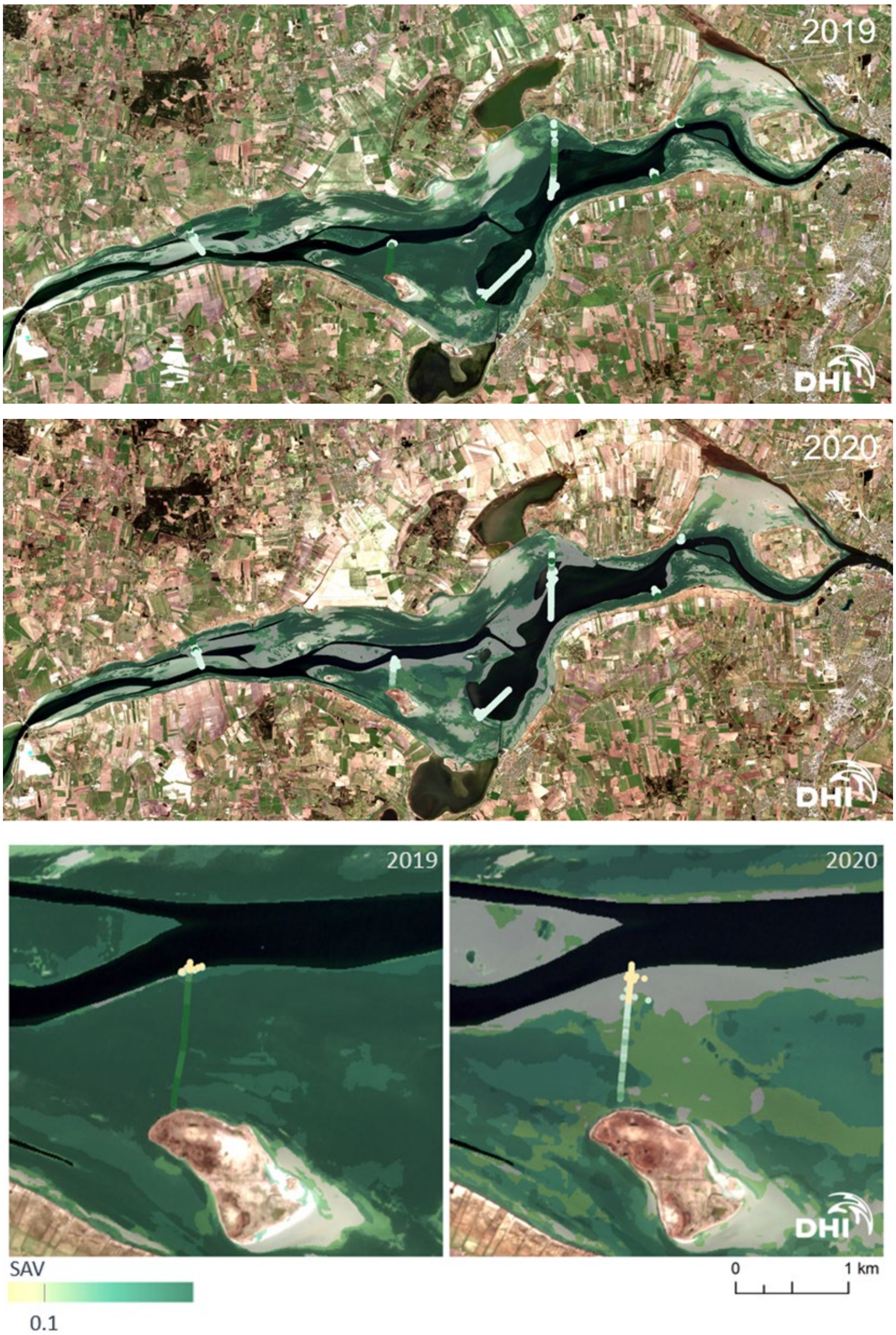
Figure 3.6. SAV frequency map for outer part of Odense fjord derived from S2 data with the prototyped Base model in this study. The darker the green shade, the more often SAV was observed in the 6-year period from 2018-2023.

In Odense fjord, the inter-annual frequency map reveals that some areas exhibit consistent SAV growth, while others display more erratic patterns with high variability suggesting high patch dynamics here. These patterns can potentially be linked to specific SAV types when combined with local knowledge and data with higher spatial resolution, such as OP or VHR data. In Nibe Bredning, similar areas of highly variable SAV cover can be seen, especially in very shallow waters. The reduction in SAV-covered areas between 2019 and 2020 is also seen as larger areas with lower SAV frequency (Figure 3.7).

Figure 3.7. SAV frequency map for Nibe Bredning, the Limfjord derived from S2 data with the prototyped Base model in this study. The darker the green shade, the more often SAV was observed in the 5-year period from 2018-2022.

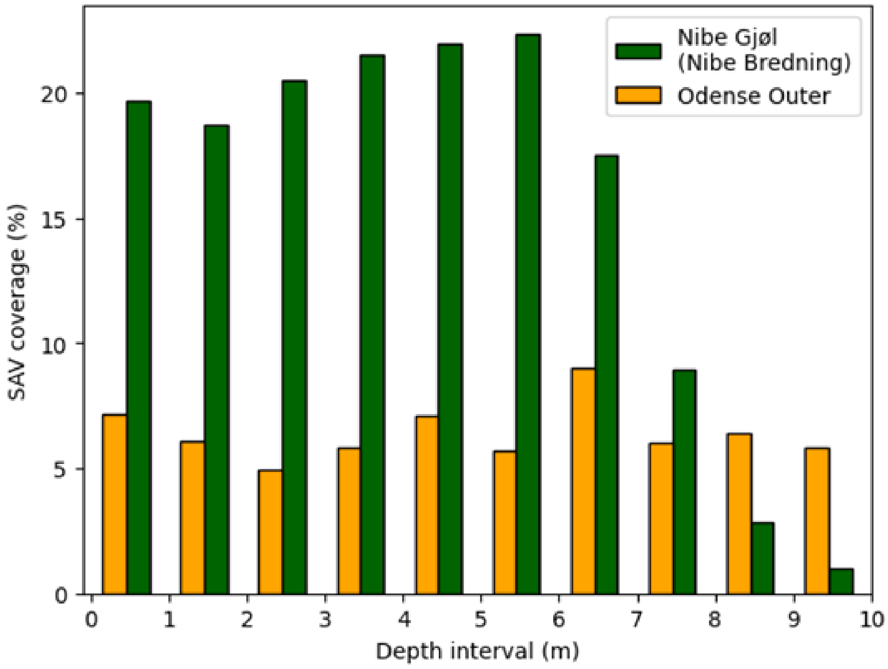
Focusing on the seasonal growth in 2019 and 2020 for Nibe Bredning, the seasonal frequency maps (Figure 3.8) reveal distinctive patterns with constant SAV patches from spring to autumn while for other areas, changes throughout the season can be documented. The interannual comparison shows a distinctive decline in SAV from 2019 to 2020 which is also reflected in the NOVANA observations for the area.

Figure 3.8. SAV seasonal frequency maps for Nibe Bredning, the Limfjord derived from S2 data with the Base model using CNN architecture. The darker the green shade, the more often SAV was observed for 2019 and 2020. The S2 SAV maps are overlaid with NOVANA transect points of the same years (2019 and 2020).



The summer OP 2018 SAV coverage by the XGBoost model (Figure 3.9) revealed an overall higher SAV coverage in Nibe Bredning compared to Odense fjord. In Odense Fjord, eelgrass covered less than ten percent coverage at each depth interval illustrating a patchy but a relatively constant coverage ratio across the depth intervals. In Nibe Bredning steep drops in coverage appeared after the five-meter depth interval, in line with expected lower light levels at deeper depths.

Figure 3.9. Comparison of SAV %coverage over depth, in Nibe Bredning, the Limfjord and outer Odense fjord based on XGBoost classification of summer ortho-photos (OP) 2018.



In terms of distinguishing vegetation types in Nibe Bredning, the Limfjord we compared the relative coverage of eelgrass and SAV for the prediction using summer OP and S2 imagery from 2018 (Figure 3.10). The two predictions largely differ, especially in shallower areas (0-5 m depth). While the CNN-based S2 SAV coverage represents all types of SAV, the XGBoost-based OP coverage reflects eelgrass cover. The model for the OP uses image patches made of pixels with 20x20cm resolution (real ground resolution) and NOVANA ground truth eelgrass observations. NOVANA ground truth observations use coverage between 0 -100% with most observations in either 0% or 100% observations. Due to the high resolution and NOVANA ground truthing, we are confident that the training image patches are highly likely to be eelgrass and not macroalgae. In comparison, the S2 observations are on pixels 10x10m resolution; with this resolution we cannot guarantee with confidence that the 10x10m patches are not just eelgrass.

For the predicted eelgrass coverage using summer OP from 2018, the percent coverage is quite constant for depths down to 6m followed by a decrease in deeper waters, whereas the SAV cover predicted from S2 imagery shows generally higher cover for shallower depth, with a peak in relative coverage at 2-3 m and a decrease towards deeper waters.

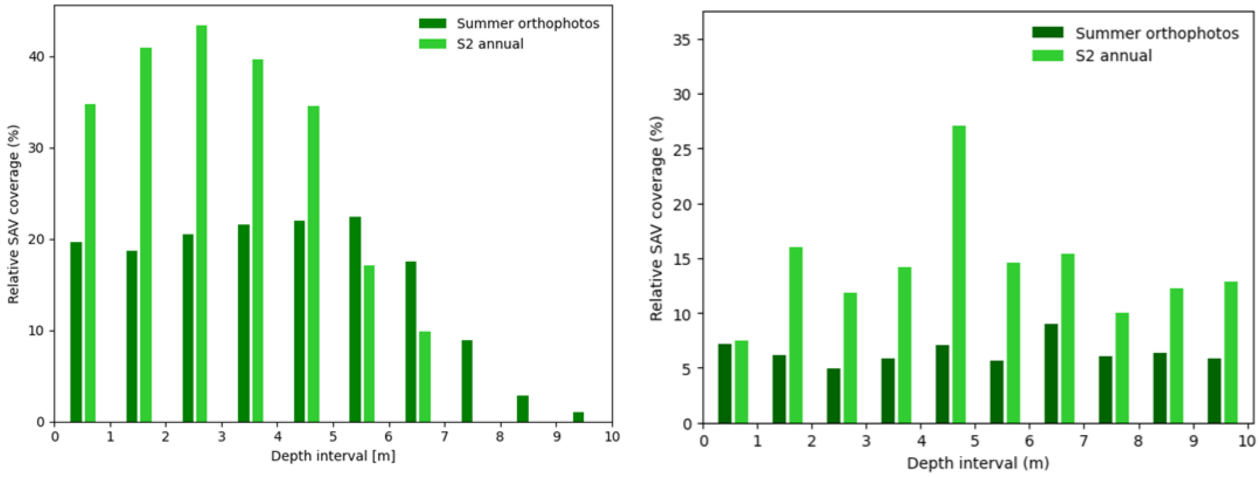


Figure 3.10. Comparison of relative coverage of eelgrass and SAV for the prediction using summer OP from 2018, based on the XGBoost model, and the average SAV prediction from S2 imagery of the same year, using CNN architecture. While annual S2 shows all types of SAV (eelgrass and macroalgae), the results calculated for the OP show eelgrass coverage. Data are from Nibe- Bredning (top) and Odense Fjord (bottom).

3.1.3 Value of supplementing information layers for SAV mapping

The value of using supplementing information (i.e. bathymetry, sediment type and band ratios) for SAV mapping was tested for both CNN-based S2 models and pixel based XGBoost summer OP models.

For the CNN architecture applied on S2 imagery, two different models were tested:

1. A *Site model* which was trained with annotations from S2 imagery only from Odense fjord.
2. A *Site model2* which was trained on annotations from S2 imagery from Odense fjord and a 10m bathymetry layer.

Table 3.3 shows that the model's prediction could not be consistently improved by adding bathymetry information, only the predictions for 19 July better. On the contrary, the model with bathymetry tends to overfit in this test area.

Tests run for Odense fjord using a model supplemented with bathymetric data besides S2 annotations alone showed no improvement in the results (Table 3.3).

Table 3.3. Model performance with and without bathymetry layer for Odense fjord using the CNN architecture

S2 date	Site model			Site model 2 (incl. Bathymetry)		
	acc	*f1*	*recall*	*acc*	*f1*	*recall*
2017-07-19	0.75	0.73	0.71	0.76	0.74	0.72
2018-07-24	0.78	0.37	0.55	0.71	0.31	0.55
2019-07-24	0.80	0.71	0.68	0.79	0.69	0.65
2020-08-17	0.74	0.48	0.51	0.67	0.47	0.61
2021-08-22	0.72	0.60	0.65	0.74	0.63	0.69
2022-08-12	0.78	0.42	0.52	0.73	0.37	0.48

XGBoost model applied on summer OP 2018

Evaluation of the model variants was conducted with stratified five-fold cross validation where the dataset was partitioned into training-test-validation subsets five times, while an even distribution of classes was maintained. The repeated cross-validation ensures results were not dependent on the partitioning process and were thus more robust.

Table 3.4 shows improvement in model performance on validation dataset when including bathymetry, but knowledge of underlying sediment (based on existing classification maps) did not improve the model significantly.

Table 3.4. Model performance using different combinations of inputs: color bands (RGBN), band ratios (between RGBN), sediment type (Sediment) and bathymetry raster (Bathymetry)

Input layers	*acc*	*f1*	*recall*
RGBN	0.81	0.69	0.61
RGBN + Ratios	0.84	0.74	0.67
RGBN + Ratios + Sediment	0.84	0.76	0.70
RGBN + Ratios **+** Bathymetry	0.87	0.80	0.75
RGBN + Ratios + Sediment **+** Bathymetry	0.88	0.82	0.77

The best performing model, the model with all auxiliary information, and the color only model (RBGN) was then applied to the full Odense fjord, outer and Nibe Bredning, the Limfjord (Figure 3.11). In shallower water depths (0-1 m) in both regions, the full auxiliary model tended to overfit to the coarse bathymetry raster. This can be seen for Odense Fjord in figure 3.11b where the underlying bathymetry raster is partially visible as a white square.

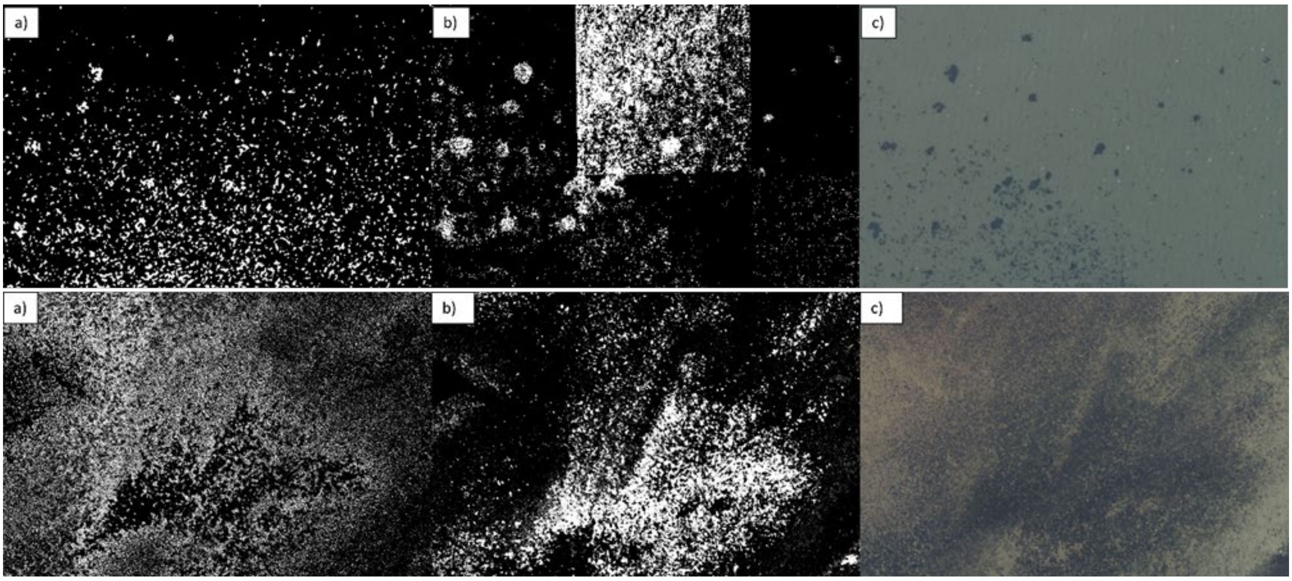


Figure 3.11. Comparison of SAV prediction by the OP-NOVANA model for a) RGBN only, b) RGBN and all auxiliary info, c) Orthophoto; pixels predicted to have SAV are in white. Top panel is for Odense fjord and lower panel is from Nibe Bredning in the Limfjord.

The observed overfitting in shallower areas may be due to the low resolution of the bathymetry raster (50 m). The inclusion of the auxiliary information, however, allowed the model to detect SAV patches in contrast poor areas and with a reduced number of false positive detections. From figure 3.11 it appears that the color information alone is insufficient to detect the large section of eelgrass in the center whereas the inclusion of auxiliary information improves SAV detection, with a stronger detection of the eelgrass pattern. Further investigation using a finer resolution bathymetry map may be fruitful.

3.1.4 Distinguishing vegetation types using RS data

The capability of differentiating SAV types using VHR RS imagery was tested using commercial Pléiades Neo VHR satellite data from May 2023 and a spring OP from 2022 for Odense Fjord (cf. specifications table 2.1). For the OP analysis, initial results are promising with the model predicting the two SAV types reliably (eelgrass and non-eelgrass type of SAV) see Figure 3.12.

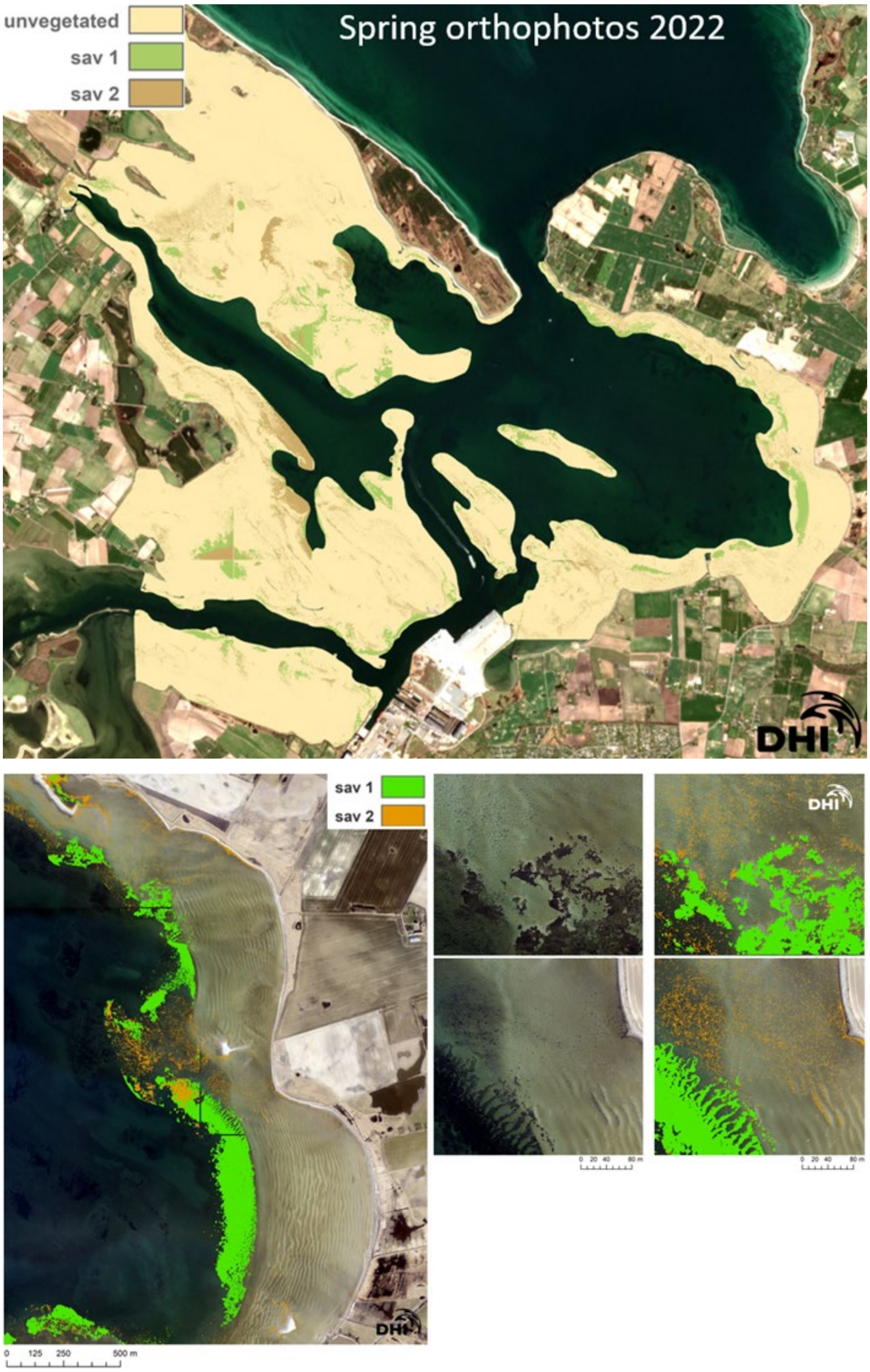


Figure 3.12. SAV type mapping using CNN model and spring OP from Odense fjord in 2022. The top shows the entire mapped area, the bottom row shows the Eastern coast with dense eelgrass beds. SAV type 1 corresponds to habitats with visual characteristics of eelgrass patches and SAV type 2 with macroalgae.

Testing the scaling capability of the approach revealed that a model trained on a subset of the OP could be run successfully on all the imagery of Odense fjord by adding an additional 370 annotated image patches. In total a bit less than 1000 labeled image patches were used to train the OP model. The Odense Fjord-wide OP contained several seamlines and other image artifacts, including visual offsets across seamlines which were complicating the analysis. To mitigate these effects, each 1x1 km tile was preprocessed separately and image annotations were further distributed across various locations to include these data-inherent variations in the model training. The trained model captured the eelgrass patches along the eastern edge of Odense fjord and successfully separated these from other non-eelgrass SAV in the area. Similar results were found in the western part of the fjord, where eelgrass patches along Enebærodde were accurately delineated. Extensive patches of macroalgae were further mapped in the western fjord, though for deeper waters, these were misclassified as eelgrass, suggesting that the model would need further image annotations to improve separation of such extensive areas of SAV other than eelgrass at deeper areas.

Comparing the OP results to the SAV prediction using a S2 image from 17 April 2022, shows consistent overall patterns of SAV, however, when comparing the area estimates from the two predictions, the areal SAV cover is about 30% larger for the S2 prediction than for the OP analysis (Table 3.5).

Table 3.5. Comparison of SAV areas mapped with spring OP, VHR and S2 satellite images

	Area (km^2)			
RS imagery (Date)	**Unvegetated**	**SAV**	**Eelgrass type of SAV (SAV 1)**	**Non-eelgrass type of SAV (SAV 2)**
S2 (8 June 2023)	19.81	5.95	NA	NA
Pléiades Neo VHR (13 May 2023)	22.91	2.85	1.08	1.78
S2 (17 April 2022)	22.33	4.92	NA	NA
OP spring 2022	23.73	3.30	1.53	1.77

The analysis performed with commercial Pléiades Neo VHR data (cf. table 2.1 for specifications) revealed that by only using a small dataset of image annotations, the CNN model could separate the general patterns of the two different vegetation types (Figure 3.13).

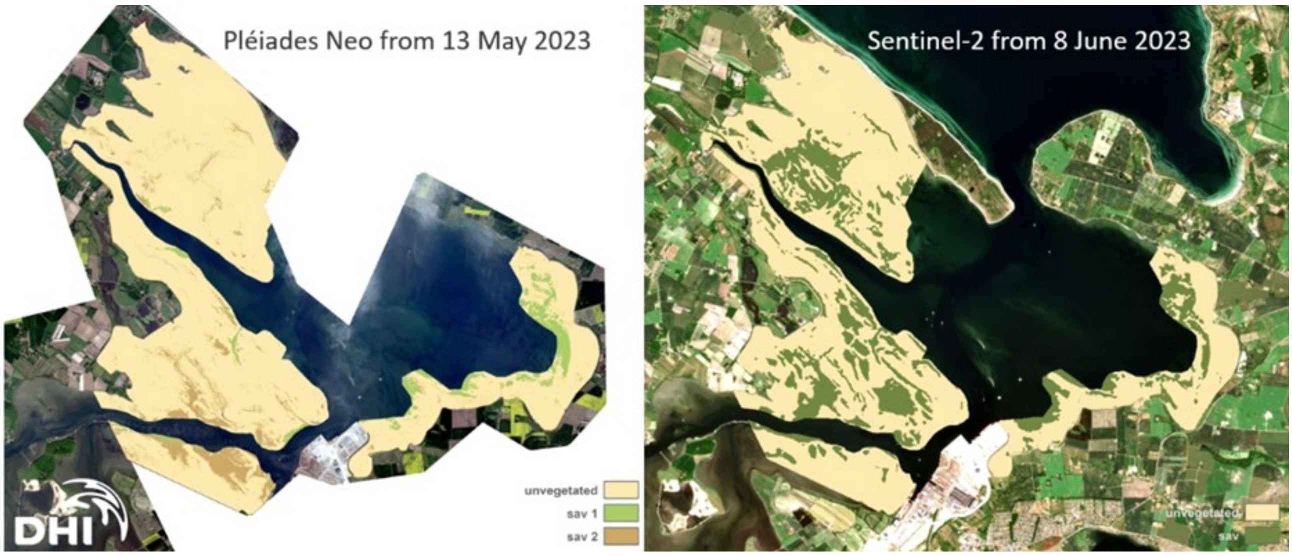
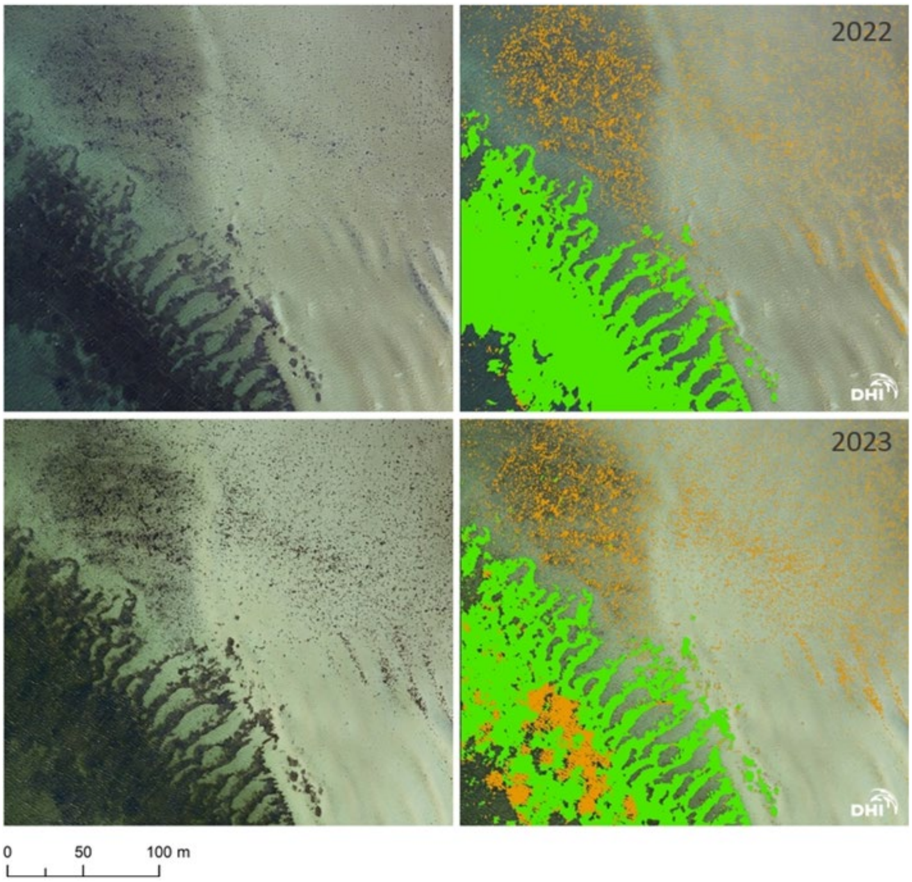


Figure 3.13. SAV mapping using Pléiades Neo VHR imagery (left) and Sentinel-2 (right) for parts of Odense Fjord. For the VHR analysis, SAV was divided into two SAV classes; SAV 1 corresponds to eelgrass and similar species (based on visual appearance in the data) and SAV 2 corresponds to non-eelgrass/macroalgae type of SAV.

When compared to the lower resolution S2 SAV predictions, overall patterns are similar. However, the area predicted to have SAV coverage in the VHR imagery is approximately half of that in the S2 SAV prediction (Table 3.5) as already seen for spring OP data. Again, this difference may be explained by the fact that currently, the S2 model is trained to classify pixels with as little as 10% SAV coverage into the SAV class, while in the VHR image these sparse areas are distinguished into individual scattered patches of SAV and non-SAV pixels. It is encouraging to see that the VHR nicely predicts the distribution of different SAV types, with a higher abundance of eelgrass type of SAV (SAV1) for the eastern side of the fjord, whereas the western fjord is dominated by macroalgae and non-eelgrass type of SAV (SAV2) (Fig. 7.13), in accordance with observations.

The spatial and temporal scaling potential of the CNN-based SAV type mapping model for Odense Fjord trained on spring OP 2022 was tested with OP 2023 data, without additional training of the model (Figure 3.14).

Figure 3.14. SAV mapping result for Odense fjord, using OP's from spring 2022 (top) and 2023 (bottom). The CNN SAV classification model was only trained on annotations from the OP 2022 and then applied on the 2023 data, to test the spatial and temporal scaling potential of the model.



While the spring OP from 2022 is very well suited for marine habitat mapping (i.e., clear water, calm water surface etc.), the imagery from 2023 is influenced by significantly more surface noise and sun glint. However, the model performed well in areas with environmental conditions like those of 2022, especially in terms of mapping the extent of the eelgrass patches. Obviously, the more severe the water surface noise (i.e, waves, glint), the worse the model performed, because the seafloor was no longer visible, and the model was not trained with annotations representing such conditions. Still, the test demonstrated the transferability of the model, by applying the pre-trained OP model from one year to another, completely independent of survey data. This is very promising in terms of large-scale mapping in an efficient and cost-effective manner.

3.2 Ecological status indicators

Peter A.U. Stæhr, Cordula Göke, Mihailo Azhar, Jesper P.A. Christensen, Dorte Krause-Jensen and Sanjina U. Stæhr

3.2.1 Ecological status based on areal extent from RS-data in relation to modelled reference areas

The first step for the development of an indicator based on the areal distribution of eelgrass, was the definition of reference, good, moderate, poor, and bad conditions for areal coverage of eelgrass. For this we applied an existing spatial model (Staehr et al. 2019, Timmerman et al. 2021) which has previously been calibrated and validated against NOVANA data on eelgrass coverage. To model the reference, good, moderate, poor, and bad areas, we modified the original model by varying the light availability at the seafloor (Iz), as determined by the light attenuation coefficient (Kd), the water depth and surface light during summer. Thus, we assumed that the only change between the different conditions (Reference, good, moderate, poor, and bad) was water clarity, and we assumed that changes in water clarity could be represented by a single Kd value for each water area. The modelled reference areas compared well with available historical maps of eelgrass distribution in the two studied fjord systems (Figure 3.15).

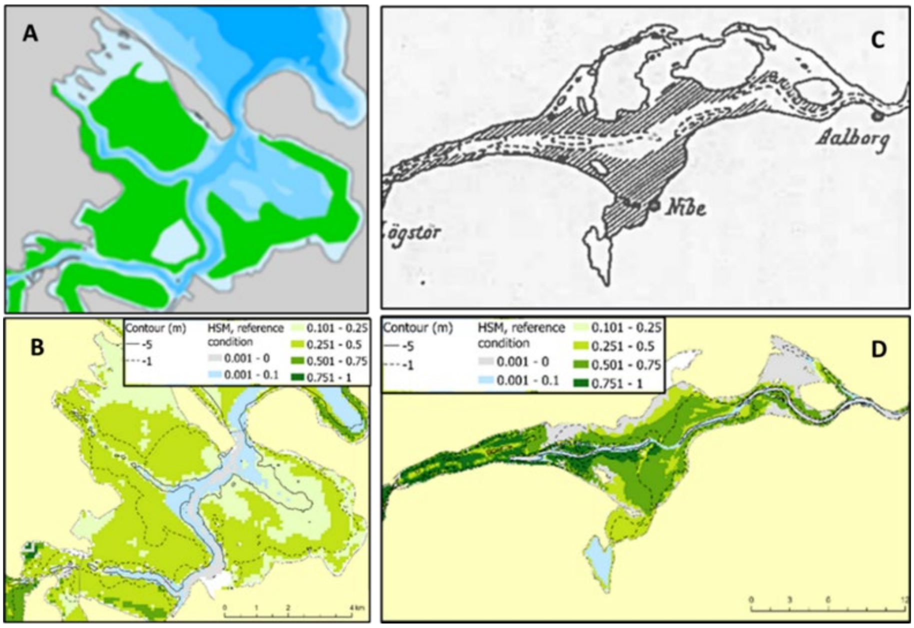


Figure 3.15. Comparing modelled reference areas with eelgrass with historical evidence. For Odense fjord (A and B), the historical map (A) represents observations from 1960 with green color identifying areas with eelgrass (provided by Mogens Flindt). For Nibe-Gjøl Bredning in the Limfjord (C and D), the historical map (C) was obtained from Ostenfeld (1908) where the shaded areas represent areas with eelgrass.

In addition to Kd-values representing the different water quality scenarios, we applied a Kd-value representing water clarity for the depth limits of eelgrass as determined in River Basin Management Plan 3 (VP3), corresponding to status conditions. In addition to Kd-values, we obtained the main distribution depth (Zmax) and from Kd, we modelled the areas covered with eelgrass (presence) for the different scenarios and the VP3 status condition (Table 3.6).

Tabel 3.6. Values of water clarity (Kd), eelgrass main distribution depth (Zmax) and areas of eelgrass under different scenarios of ecological status (Reference, high:good, Good:Moderate, Moderate:Poor, Poor:Bad, and current status). The Kd and Zmax values were obtained from the VP3 analysis (Timmermann et al. 2020), and eelgrass area (presence) were calculated using Kd-values in a habitat suitability model (HSM) by Staehr et al. (2019b). The calculated SAV areas were restricted to cover the 1-to-5-meter depth zonation. Values are shown for the two study areas, Odense Fjord, outer and Nibe- Bredning in the Limfjord.

Area	Condition	VP3 Kd	VP3 Zmax	HSM area (ha)
Odense Fjord, outer	Reference	0.33	5.6	410
	HG	0.37	5	389
	GM	0.45	4.1	341
	MP	0.65	2.8	232
	PB	1.31	1.4	67
	Status	0.74	2.49	205
Nibe Bredning, the Lim-fjord	Reference	0.39	4.7	1005
	HG	0.44	4.2	989
	GM	0.52	3.5	948
	MP	0.78	2.35	772
	PB	1.56	1.175	267
	Status	0.75	2.44	810

In figure 3.16 the modelled reference area of eelgrass is compared to the areal distribution modelled for the status (VP3) conditions.

For Odense fjord, outer the modelled cover is dominantly below 50% except for some small areas in the south of the outer fjord and areas shallower than 1 m. The area with a cover between 25% and 50% for VP3 status condition is above 1 m and moves down into the 1m – 5 m zone for the reference condition.

Nibe Bredning in the Limfjord has generally a higher modelled eelgrass cover, where some areas fall in the class of above 75% potential cover. Similarly, to Odense Fjord, the area most suitable for eelgrass growth lie shallower than 1 m and cover changes little in this depth zone. At greater depths cover increases under reference conditions.

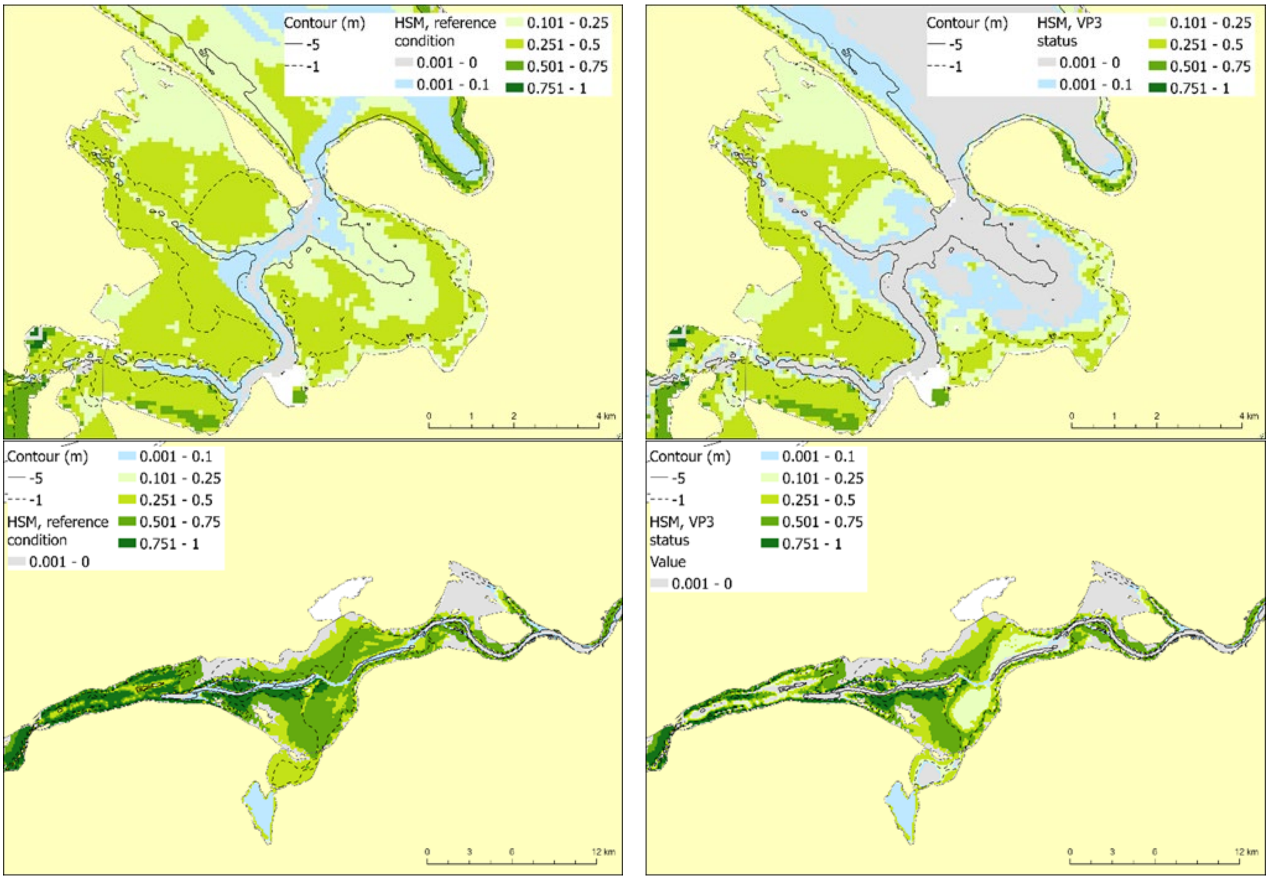


Figure 3.16. HSM modelled areal extent distribution of eelgrass in Odense fjord, outer part (upper figures) and Nibe Bredning, the Limfjord (lower figures). Left figures show the modelled area under reference conditions (high water quality), right: modelled distribution under current ecological status (VP3) conditions. The colors represent the modelled potential cover ranging from unsuitable (0~ 0 %cover) to suitable (1~ 100 %cover).

To develop an area-based ecological status indicator we calculated the EQR values for the status thresholds and compared the mapped areas to these threshold values. We also developed a list of requirements to consider when implementing the area-based approach. While the depth based EQR thresholds for eelgrass (Zmax) are the same for all waterbodies because they are calculated as percentage of the reference condition, the areal EQR depends on the specific delineation of the analyzed area and the water clarity conditions here. Unless the entire waterbody is examined with RS-data, area-specific EQR-values will therefore have to be defined to finally assign the ecological status classes for a given waterbody. The importance of applying a mask for EQR-thresholds are shown in table 3.7.

The analysis shows that reducing the area based EQR calculation to the suggested depths zone of 1 – 5 m, leads to bigger difference between EQR thresholds compared to the thresholds estimated from the whole water body. Thus, limiting the analysis to the depths zone that is strongly influenced by light conditions is recommended based on results from the two sample fjords.

Table 3.7. EQR table to define status groups for the two studied fjords. EQR areas for the area defined by depth limit and RS mask, only limited by depth limits and for the whole fjords.

Area	WFD-status thresholds	EQR depth	EQR area (masked)	EQR area (within 1-5 m depth)	EQR area (complete WB)
Odense fjord, outer	HG	0.89	0.95	0.93	0.96
	GM	0.74	0.83	0.80	0.89
	MP	0.50	0.57	0.51	0.73
	PB	0.25	0.16	0.14	0.52
Nibe Bredning, the Limfjord	HG	0.89	0.98	0.95	0.97
	GM	0.74	0.94	0.84	0.91
	MP	0.50	0.77	0.58	0.75
	PB	0.25	0.27	0.17	0.44

If it is necessary to further limit the analysis area to RS data of adequate quality, the EQR values will thus have to be calculated from the model for the same area. In both sample cases, the EQR values for the masked areas are higher than the EQR values only defined by the depth limits. Since the relevant area can change due to RS data quality, the EQR based on the model must be recalculated for the correct mask. Missing S2 coverage due to cloud cover can be overcome by applying multiple S2-scenes over a growing season should. This will also provide data to determine summer growing season mean cover values.

In figure 3.17, the S2 2018 SAV-presence/absence data is compared with the modelled eelgrass extent under the VP3 status. For the relatively low densities it is possible to visualize where approximately the differences lie. The overlay shows how the model determines low potential cover in areas with patchy distribution determined by S2.

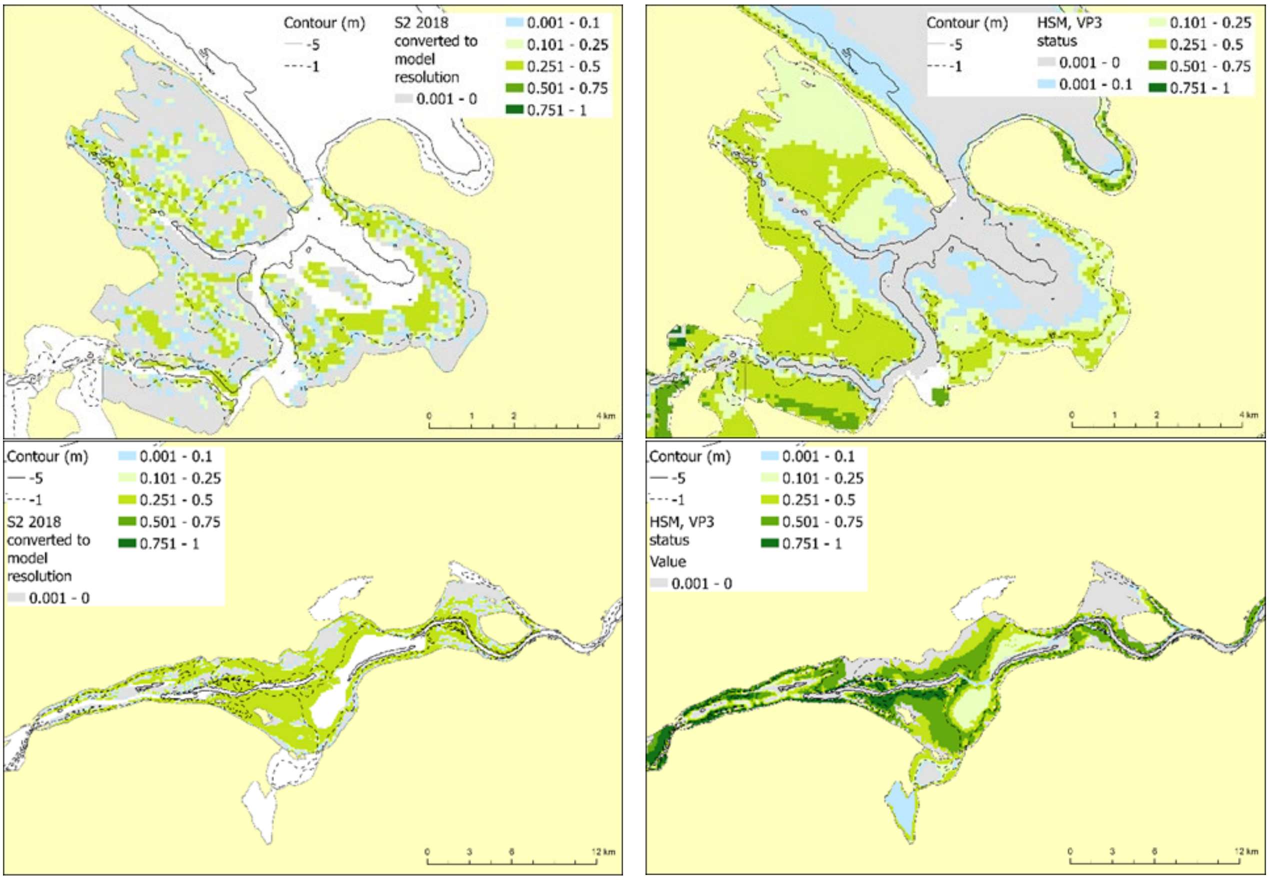
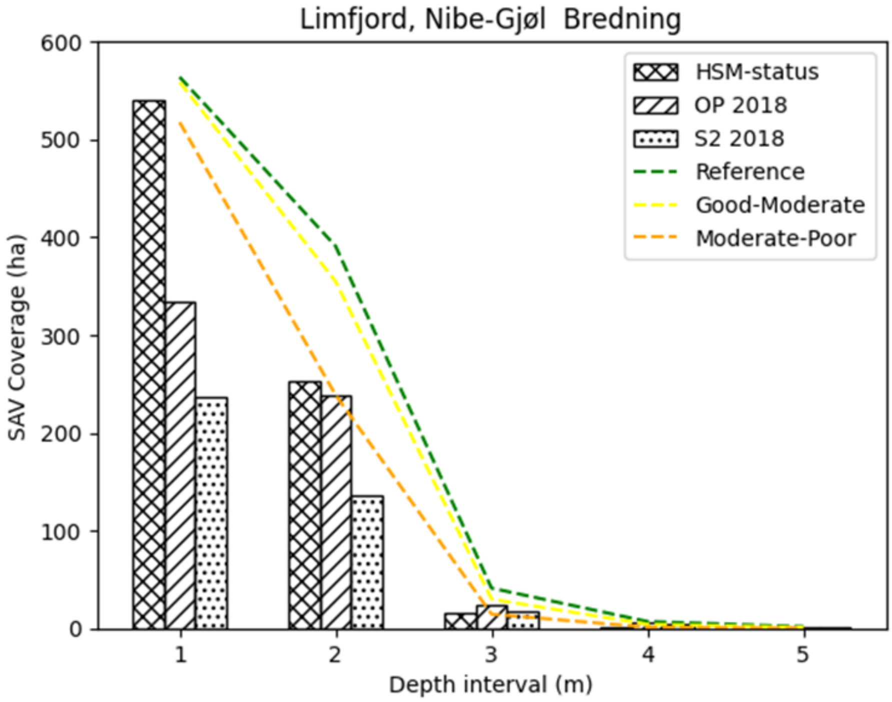


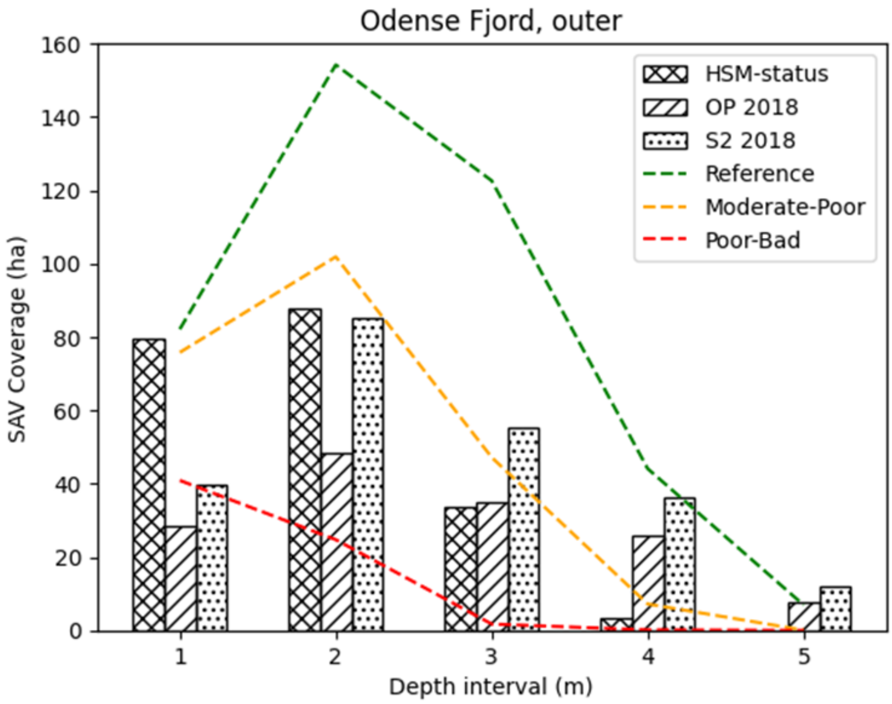
Figure 3.17. SAV coverage in Odense fjord, outer (Top) and Nibe Bredning, the Limfjord (Lower), estimated from Sentinel-2 in 2018 (Left), and compared with the HSM modelled distribution (Right) under the RBMP status conditions (VP3 in figure legends) scenario for 2018. For ease of comparison, we have converted the Sentinel-2 data to same resolution (100 x100 m) as the HSM data.

Just from a visual comparison with the HSM modelled eelgrass extent, it appears that, in Odense fjord, the S2 mapping overestimates SAV close to the optical depth limit, most clearly seen in the eastern part of Odense fjord. There seems to be a good agreement between the HSM modelled and observed (S2) SAV in the Limfjord area.

Based on classifications of SAV by both OP and S2, we calculated the total area covered by SAV in both fjords during 2018 in the 1-to-5-meter depth range and compared with the expected areas estimated under status condition (VP3) with the HSM model (Figure 3.18). The classified SAV data (presence/absence) was converted into SAV cover using the aggregation method outlined in figure 2.4. Similar gradients of SAV with depth were found for S2, the OP and the HMS model although with slightly different patterns in the two fjord systems. While we found a good agreement in the areal extent of SAV with S2 and OP in Nibe Bredning, OP provided much lower SAV estimates in Odense fjord (Figure 3.18, lower graph). According to published data from the Danish EPA, the main depths limit (10% threshold) for Odense fjord, outer and Nibe Bredning was 2.51 m and 3.00 m in 2018 respectively (see table 3.10). In comparison, both S2 and OP mapping suggest relatively high SAV coverage at 3-4 m depths in Odense fjord, whereas the HSM model indicated lower SAV cover here. In Nibe Bredning, the Limfjord, there was a better agreement with expected SAV coverage. below the depth limit for eelgrass.

Figure 3.18. SAV depth dependency in the two studied fjord systems. Here we compare results from RS-mapping with model results for 2018. Inserted colored lines represent thresholds between the ecological status groups. Depth intervals are 1 (0-1m), 2 (1-2m), 3 (2-3m), 4 (3-4m) and 5 (4-5m).





For the year 2018 where both S2 and OP areal data were determined, we assessed the ecological status based on these both data and compared with the status from the eelgrass depth limit. The conversion of EQR values to ecological status classes were made using information from Table 3.7. Odense fjord was assigned poor condition by all available data in 2018. But for Nibe Bredning, the Limfjord the area-based indicators estimated from S2 and OP, indicated a poor condition, compared moderate as determined from Zmax and modelled eelgrass area (Table 3.8). Nibe Bredning, the Limfjord is according to Zmax and modelled SAV area in moderate ecological status, while OP and S2 indicates a poor status. This difference is also seen in figure 3.18, where S2 and OP areas falls below the moderate-to-poor threshold the class boundary. For Odense fjord, the SAV area based on both S2, OP and the HSM model, indicates a system in poor ecological status, which agrees with the status class defined from Zmax (Table 3.8).

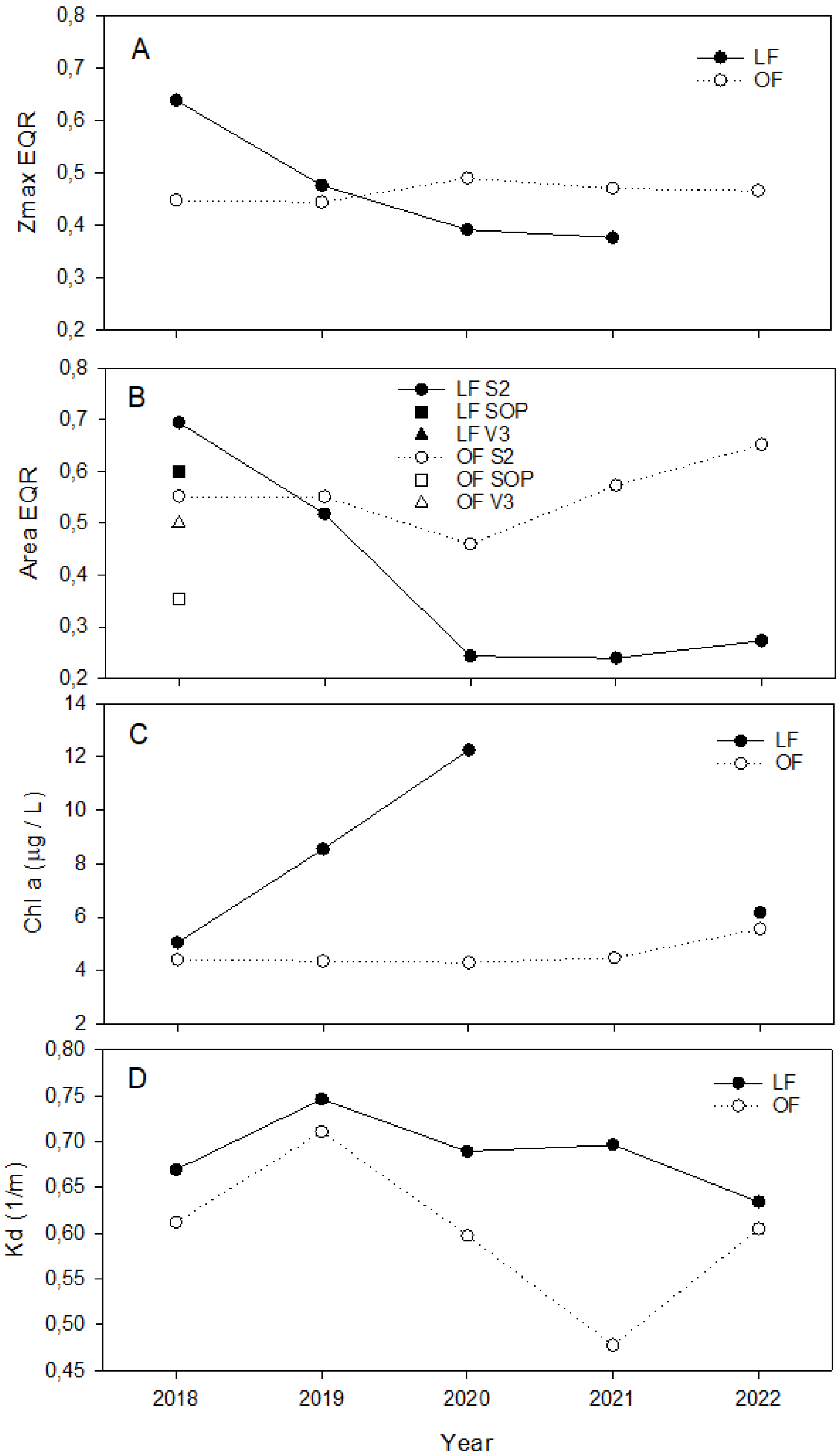
For both fjords, the differences between status class boundaries are small at shallow depth (0-1 m) and increases in deeper areas. This reflects that eelgrass areas in shallow waters are less sensitive to changes in light conditions (which are used for modeling the boundaries of the status classes).

Table 3.8. Ecological status according the WFD classes (here shown Poor (P) and Moderate (M)), as determined with the new area indication using S2, OP and modelled under status conditions (VP3) and compared with status derived from the currently used eelgrass main depth indicator (Zmax).

System	Information type	EQR	Ecological status
Limfjord Fjord (Nibe Bredning, Langerak)	S2 (SAV area)	0,69	P (EQR MP=0.77)
	OP (SAV area)	0,60	P (EQR MP=0.77)
	HSM status VP3 (SAV area)	0,81	M (EQR MP=0.77)
	NOVANA Zmax (depth)	0,64	M (EQR MP=0.50)
Odense Fjord (Outer)	S2 (SAV area)	0,55	P (EQR MP=0.57)
	OP (SAV area)	0,35	P (EQR MP=0.57)
	HSM status VP3 (SAV area)	0,50	P (EQR MP=0.57)
	NOVANA Zmax (depth)	0,45	P (EQR MP=0.50)

Based on the calculated areal coverage under observed (S2 and OP) conditions and the modelled reference areas, we calculated the EQR ratios (observed / reference areas) and compared the ecological status derived from the traditional main distribution depth (Zmax) indicator, with the new area-based indicator, to assess how these changed during the 2018 to 2022 period (Figure 3.19).

Figure 3.19. Comparison of ecological indicators based on A) eelgrass depth limit (Zmax) and B) areal coverage of eelgrass vegetation as estimated for the years 2018 to 2022 in Nibe Bredning, the Limfjord (LF) and Odense fjord, outer (OF) system. Changes in water quality determined as C) Chl a concentration and D) water clarity (Kd light attenuation coefficient) are also shown. For the year 2018, we inserted the area based EQR values determined from orthophotos and modelled status (V3) for comparison.



This preliminary analysis indicates that the area-based eelgrass indicator displays a larger change over time compared with the eelgrass depth-limit indicator. For the Limfjord there was a very significant and positive relationship (r-pearson = 0.97, p=0.03) between the area-based eelgrass indicator and the eelgrass depth limit indicator. In comparison, no significant relationship was observed for the indicators in Odense fjord (p=0.50). Also, it seems that there is no obvious alignment between the temporal changes in the indicators with the water quality parameters shown in figure 3.19. This was investigated further with a simple Pearsons correlation analysis (Table 3.9).

Table 3.9. Pearsons's correlation I and significance level (p) between ecological indicators and water quality parameters – Chlorophyll (Chl) and light attenuation coefficient (Kd). Data used in the analysis are shown in Figure 3.13.

System	Indicator	stats	Chl	Kd
Nibe Bredning	Zmax	r	-0,98	-0,31
The Limfjord		p	0,12	0,69
	Area	r	-0,61	0,2
		p	0,39	0,75
Odense fjord	Zmax	r	0,03	-0,53
Outer		p	0,96	0,36
	Area	r	0,83	-0,09
		p	0,08	0,89

Despite the lack of local calibration of the applied HSM eelgrass model, the applied reduction factor of 0.5 for S2 data and the assumption that SAV identified by RS-data reflects eelgrass, our preliminary results showed an overall good agreement in the status statement for the different types of data, which all categorized Odense fjord as being in poor condition in 2018. For Nibe Bredning, the Limfjord, S2 and OP data indicated a system in Poor condition while Zmax and the HSM model indicated a system in Moderate status.

3.2.2 Estimating the eelgrass depth limit (Zmax) from RS-data

Based on eelgrass cover along individual transects, we estimated the main distribution depth limit (Zmax) from analysis of OP and S2 and compared with cover values and Zmax determined from *in situ* monitoring (NOVANA) data. Examples of results from Odense fjord and Nibe Bredning are shown in figure 3.20.

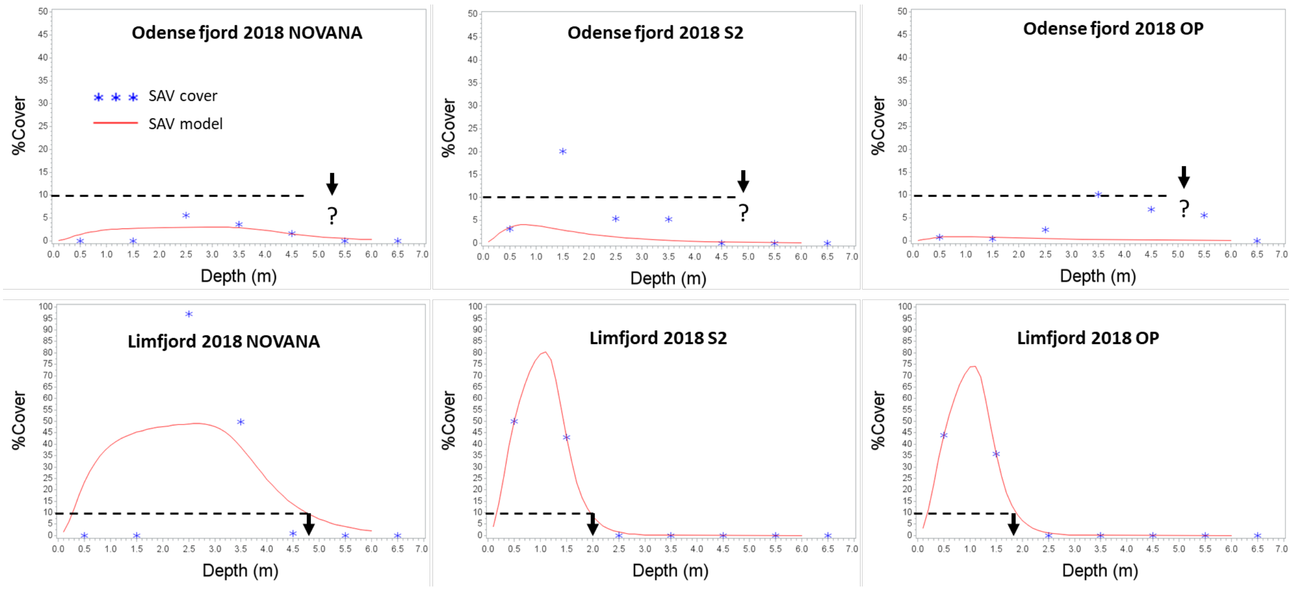


Figure 3.20. Modelling of Zmax for individual transects in Odense fjord, outer (upper) and Nibe Bredning, the Limfjord (lower) using cover data obtained from monitoring (NOVANA), Sentinel-2 (S2) and Orthophotos (OP) during summer 2018. Black arrows indicate the estimated Zmax values at the 10% cover threshold (dashed line).

Similar models were made for each of the NOVANA transects in the two fjords. For most of the transects in Odense fjord, the vegetation cover was below the 10% threshold, and we could therefore not determine Zmax with the modelling approach. This also included the NOVANA stations. For the Limfjord area, we could however, successfully estimate Zmax with the curve fitting approach for all data types. Average estimates of Zmax in the respective fjord based on transect data are shown in Table 3.10.

Table 3.10. Average estimates of Zmax using the curve fitting approach in the two studied areas. For comparison we show the official NOVANA Zmax values provided by the EPA.

Fjord	Data type	Zmax (m)
Odense Fjord (outer)	NOVANA	nd
	NOVANA EPA	2,51
	S2	2,93
	OP	nd
The Limfjord (Nibe-Langerak)	NOVANA	4,42
	NOVANA EPA	3,00
	S2	3,93
	OP	2,25

A similar analysis was made on %coverage estimated using information from S2 and OP of the entire mapped area in each fjord system. Figure 3.21 provides examples of the resulting models for 2018 data.

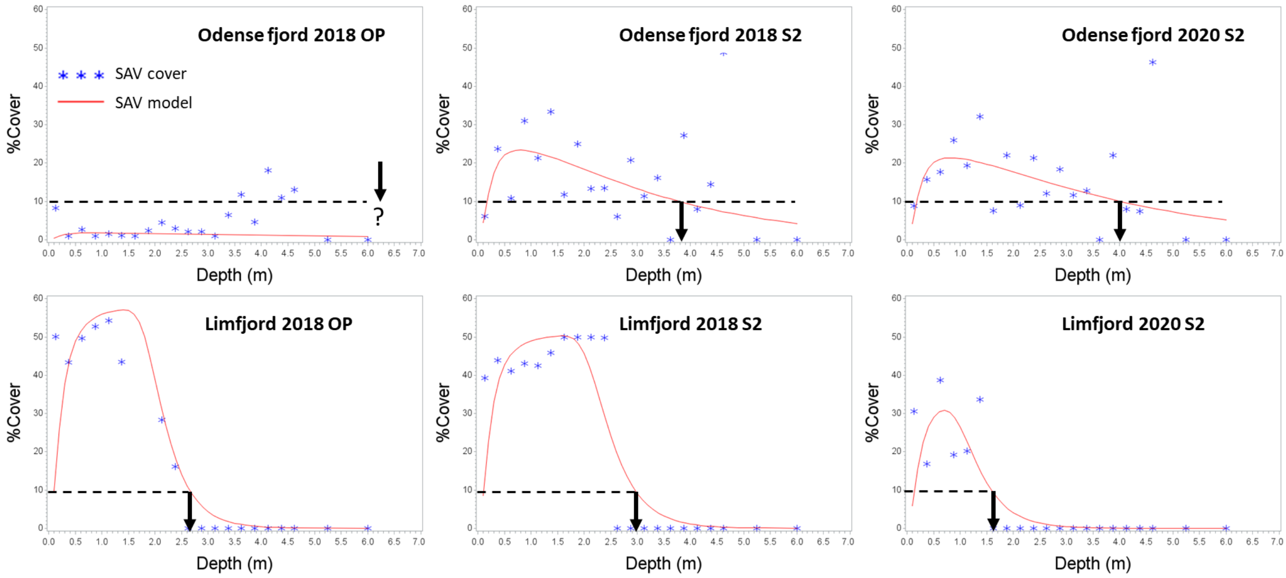


Figure 3.21. Modelling of Zmax using orthophoto (OP) and Sentinel-2 (S2) data from the entire water areas obtained in summer 2018. Odense fjord, outer (upper) and Nibe Bredning, the Limfjord (lower). Black arrows indicate the estimated Zmax values.

Using S2 data we modelled Zmax for the entire period 2018 to 2022 and compared with officially (Danish EPA) published Zmax values for the two fjord systems (Figure 3.22).

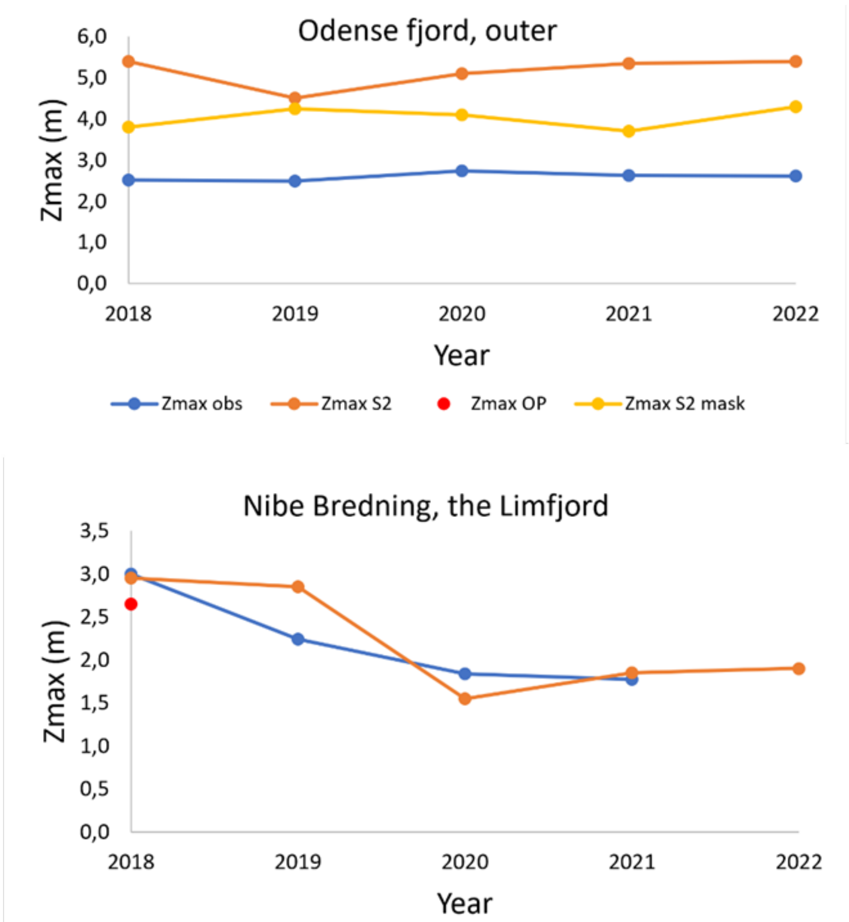


Figure 3.22. Zmax values estimated from modelling of vegetation cover along depth gradients by aggregating cover values across entire water areas in the outer Odense fjord and Nibe Bredning, the Limfjord. Zmax was determined for orthophotos (OP), Sentinel-2 (S2) and compared with Zmax estimated by the Danish EPA from the NOVANA transects. For Odense fjord we show S2 Zmax values with and without an optical depth mask of 3.5 m.

Due to difficulties in classifying benthic vegetation in the deeper parts of Odense fjord, we investigated the usefulness of applying a depth mask of 3.5 meter. This depth corresponds to the depth where < 1% of surface light is available at the seafloor in this system. Regardless of this mask, the estimated Zmax remained much deeper than the Zmax values reported for this system. In comparison, there seemed to be a good agreement between Zmax values from both OP and S2, and Zmax observed, displaying somewhat similar changes in Zmax over time.

We finally calculated the EQR ratios based on the modelled Zmax values and compared the resulting ecological classes defined using EQR criteria developed for the main distribution depth of eelgrass (see Table 2.1). The result is shown in Table 3.11.

Table 3.11. Comparison of Zmax, ecological quality ratios (EQR) and ecological status classes determined for two fjord systems using either traditional *in situ* observations of Zmax, or a modelled Zmax based on RS-cover values.

		Zmax (m)		**EQR**		**Ecological status class**	
Fjord	Year	NOVANA	S2	NOVANA	S2	NOVANA	S2
Odense fjord	2018	2,5	3,8	0,45	0,68	P	M
outer	2019	2,5	4,3	0,44	0,76	P	G
	2020	2,7	4,1	0,49	0,73	P	G
	2021	2,6	3,7	0,47	0,66	P	M
	2022	2,6	4,3	0,47	0,77	P	G
Nibe Bredning	2018	3,0	3,0	0,64	0,63	M	M
the Limfjord	2019	2,2	2,9	0,48	0,61	P	M
	2020	1,8	1,6	0,39	0,33	P	P
	2021	1,8	1,9	0,38	0,39	P	P
	2022	nd	1,9	nd	0,40	nd	P

The ecological status was assessed very similarly when using NOVANA and S2 in Nibe Bredning, the Limfjord but the overestimation of Zmax in Odense fjord by S2 resulted in an overall too positive assessment of the ecological status here.

4 Discussion and conclusions

4.1 Remote sensing products

Lisbeth Tangaa Nielsen, Silvia Huber, Lars B. Hansen, Mihailo Azhar

4.1.1 Further development of a satellite-based classification system

DHI has developed and tested a new deep learning method based on a Convolutional Neural Network (CNN) architecture for the classification of SAV using S2, VHR and OP imagery. The new method was chosen based on a desire to establish a more robust and efficient SAV classification workflow, which is flexible regarding which RS imagery is used as input for the habitat classifications and for which classification models can be trained on image archives and applied to future acquisitions of suitable imagery. This study demonstrated the feasibility of training a base model with annotations from imagery captured at different times and locations, and then applying it to new imagery without additional training. The analysis has shown that the SAV classification workflow using CNN architecture works well, not only on S2 data, but also on OP and VHR satellite imagery. The scaling potential was demonstrated for Odense fjord and Nibe Bredning, the Limfjord, by applying pre-trained SAV models to new data and longer time series without using many efforts on model training. The results confirm that the deep learning-based workflow can streamline the current method that is built into the DHI-developed SAV Denmark App. This also contributed to provide more robust results that are less influenced by the current operator of the App.

This newly developed approach offers several benefits:

- The amount of training data and hence manual input is reduced significantly. The habitat classification thus becomes more efficient (faster and cheaper) and robust by integrating multitemporal data.
- Objectivity of the model training process is increased with reduced manual inputs.
- Without the requirement for 'local' training data, the degree of scaling increases significantly. Large-scale mapping thereby becomes significantly more efficient also with VHR data and ground data can be used for independent validations.
- The data agnostic method enables the integration of other data sources (i.e., air- and spaceborne VHR data) in the SAV Denmark App in an efficient way.
- By using the same method for the analysis of different RS data types, a certain uniformity is ensured in the output, which in turn facilitates comparison of results across data types.
- Models trained per sensor/data source are spatially and temporally scalable for S2 and most likely also for VHR data sources.

4.1.2 Integration of different RS data for areal coverage of SAV

The study confirmed that integrating multiple-temporal S2 imagery increases the robustness of the estimation of SAV coverage and thus the SAV maps. With the new method, multi-temporal S2 imagery can efficiently be processed and by applying a pre-trained *Base model*, seasonal SAV can be predicted to aggregate annual SAV maps and seasonal SAV maps based on frequency of SAV observations over the season. The frequency maps reveal areas with high SAV seasonal variability, and this information can assist in identifying areas with low likelihood of SAV (false positives). However, the frequency maps cannot be used to extract SAV types/species, as not all stable patches represent eelgrass. Other SAV patterns can be rather stable across multiple years, and moreover, eelgrass can also be dynamic (Frederiksen et al. 2004, Balsby et al. 2017).

Compared with NOVANA transects data, good agreement was achieved for Nibe Bredning, the Limfjord. In general, for dense SAV meadows, agreements between S2 based SAV and ground surveys from NOVANA was usually high. For sparse areas, comparisons are more difficult. As the S2 data represent mixed pixels in a 10 x 10 m grid contrasts with surrounding sediments are reduced in low density areas, and estimated cover values will often differ greatly from NOVANA's point observations.

In Odense fjord, SAV habitats seem to be more mixed, some showing high interannual and seasonal variability, while others are rather constant patches of macroalgae (e.g., *Fucus vesiculosus*), which resulted in lower accuracies for SAV estimation than for Nibe Bredning. The RS-based observation of high patch dynamics corroborates with analysis of variability based on NOVANA data (Balsby et al. 2017). With additional ground-truth training data, the model's performance is expected to improve in the future. For the areal coverage statistics, the S2 CNN-based marine habitat predictions present SAV presence/absence per pixel and when extracting statistics basically all pixels having SAV coverage greater or equal than 10 % are summed up, even though they effectively represent mixed pixels. This is clearly visible when comparing S2 SAV coverage estimates to OP or VHR satellite-based estimates. Due to the higher spatial resolution, the data of from OP and VHR these sensors have the capability of separating even small individual patches of macroalgae and eelgrass. In the S2 images, these patches "disappear" in the lower resolution 10x10 m pixels of S2 and appear as more uniform, sparse SAV pixels as shown in Figure 4.1.

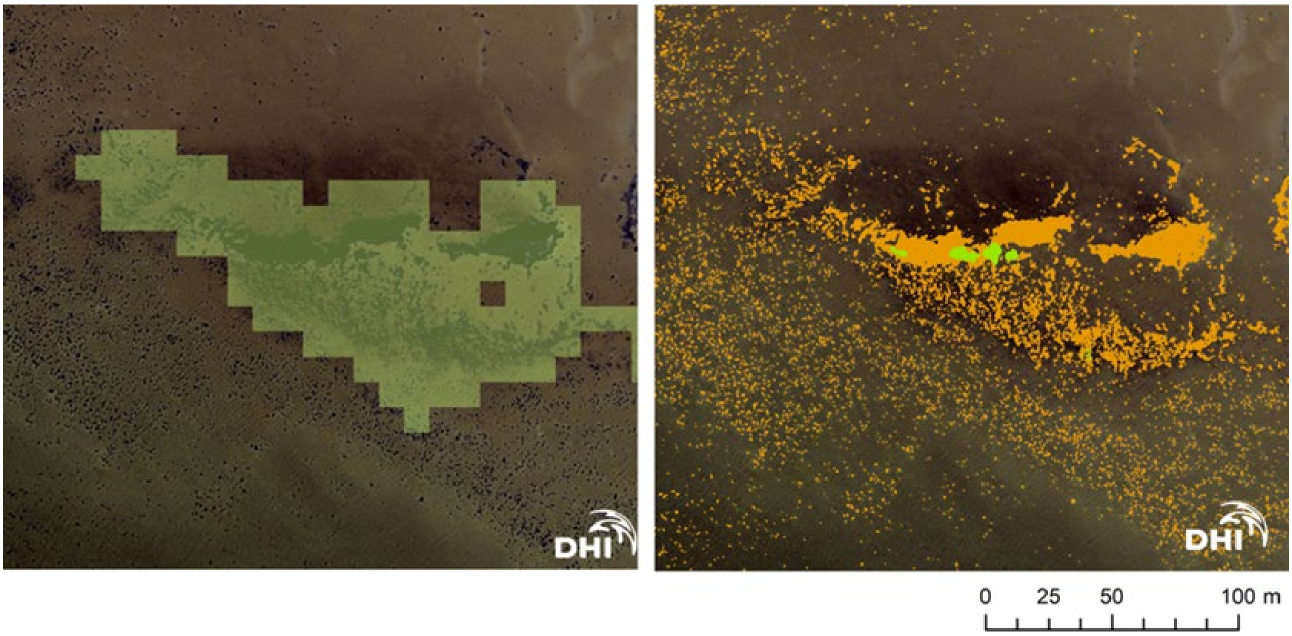


Figure 4.1. Example of spatial resolution impacting SAV areal coverage estimates. Left: SAV mapped using S2; right: SAV mapped with spring OP 2022.

This is due to the S2 Base model's training setting to identify already pixels with as little as 10 percent vegetation coverage as SAV, resulting in a high number of SAV pixels summed up in the end.

The challenges in converting the S2 SAV to a more accurate areal estimate by assigning a common cover is illustrated by comparing the eelgrass cover distribution reported in the NOVANA data (see figure 3.3). The average eelgrass cover ratio in the water body changed considerably between the two years shown. Comparing the area of SAV presence derived from S2 to areas estimates derived from VHR or OP will likely make it possible to refine the areal estimate further or determine the best range of average SAV cover for the area and season.

AU investigated using the existing NOVANA dataset to train a SAV pixel classifier model. Training a robust SAV classifier typically requires a large amount of annotated data, and the labour and time of an expert annotator. The NOVANA datasets include in situ observations of actual SAV distribution, making them a valuable resource that has already been gathered. By focusing on using the available NOVANA ground truth, additional labelling effort can be reduced.

The model's performance on 2018 OP showed that it was possible to train a model that produced adequate output solely on the colour information present in the OP at NOVANA observation locations. However, SAV was often not detected in potential SAV regions with darker pixel values due to the correlation of depth and SAV presence.

4.1.3 Value of supplementing information layers for SAV mapping

In the NOVANA observations, less SAV was observed in deeper areas where pixels in the OP often appeared dark, and therefore, the model learned that dark pixels had a higher chance of SAV absence. Auxiliary information was introduced into the model to handle this. The most significant contributor to improving model performance was bathymetry. Adding depth information enabled the model to have higher confidence of SAV presence in dark pixels for shallower areas and some areas where the contrast between SAV and sediment was poor. The model, however, displayed the potential to overfit to the bathymetric information. This is due to the low 50 x 50 m resolution of the bathymetry raster, where multiple NOVANA observations can be found within a single bathymetry raster cell, thus biasing the model. There is room to improve the model with a finer resolution bathymetry raster and with the inclusion of other spatial information or supplementary information, such as more detailed substrate types.

It should be noted that differences in the effect of bathymetry on model performance for the NOVANA-OP model and the S2 model are expected due to the resolution differences, the underlying model architecture and different data sources applied for model training.

Adding bathymetry as an additional information source to the CNN model did not show any added value for mapping SAV, at least for the Odense Fjord test area. This shows that a robust classification model can be developed on S2 imagery alone, at least for the evaluated test case. A possible explanation for this might be that bathymetric information is already inherent in the satellite imagery with increasingly darker shades for deeper waters and that this relationship is captured by the model.

Still there might be potential to improve the results by adding other supplementing information, for instance related to physical stressors and substrate types at sufficient spatial resolution, but this has not been tested in the frame of this study.

The result with the XTBoost model applied on OP 2018 data, however, showed the opposite. The accuracy of the SAV classification results was in this analysis improved with supplementing information, however, some also created artefacts in the SAV classifications.

This shows that the value of supplementing information depends on the site and the data used for the mapping, and eventually also on the method used. When suitable supplementing information is available it should in any case be tested if it can add to the mapping and help improving results.

4.1.4 Distinguish vegetation types using RS data

DHI has investigated whether the deep learning model can be trained to classify different SAV types using spring OP and VHR satellite imagery. The results confirm the suitability of the model architecture to distinguish between two different SAV types if the habitats appear optically different in the imagery.

Performance of the model highly depends on the input image quality, size and quality of annotations used for the model training and model tuning, as also shown in other studies (e.g., Thomas Berger et al., 2023).

Generally, the higher the spatial resolution, the better the environmental conditions should be under image acquisition for accurate SAV mapping. The classification results are more sensitive to water surface roughness when using VHR data for mapping compared to coarser imagery. This is because the roughness is smoothed out in the 10 by 10 m pixels of S2 imagery, while VHR data can capture each individual wave feature. The study showed that OPs are ideal for species separation mapping using the CNN approach, provided they are acquired under optimal conditions. Alternatively, they can be supplemented with VHR satellite imagery which results in comparable SAV results based on the preliminary models tested in this study. A complicating factor for mapping using OPs are seamlines between tiles. As shown in this study, we could partly mitigate these effects by implementing some extra pre-processing steps and additional image annotations. However, additional model training, especially across different years, is expected to further improve the results. So far, the result presented was only based on a minimally trained model on 2022 OP imagery.

SAV type separation was only tested for two classes, eelgrass versus non-eelgrass type of vegetation. However, other habitat classes should be investigated, such as blue mussel beds that often coexist in the same habitats and are spectrally very similar to SAV. Since the model applied relies very much on structural information, the separation into additional habitats could be tested, provided there is sufficient training data available, for instance from ground or drone surveys.

Based on the results achieved, the CNN model applied on OP and VHR imagery could be a useful element in the SAV Denmark App to supplement the large scale S2 mapping and provide into SAV type separation through the App.

4.2 Ecological status indicators

Peter A.U. Stæhr, Cordula Göke, Mihailo Azhar, Jesper P.A. Christensen, Dorte Krause-Jensen and Sanjina U. Stæhr

4.2.1 Eelgrass ecological status indicator based on areal extent

The investigation of a novel area-based indicator of ecological status, applied remotely sensed (S2 and OP) estimates of SAV (~observed values) and compared these to reference conditions calculated with a GIS model developed for eelgrass (~reference values). As we could not differentiate between SAV types with the applied S2 and OP data, we assumed that SAV in the two studied fjord systems, were dominated by eelgrass. In areas where SAV is dominated by other vegetation types, e.g. macroalgae, the current approach will need to be optimized. As no reference conditions are established for SAV (angiosperms and macroalgae), the best approach would be to apply RS-based observations which discriminate between vegetation types and provide eelgrass cover estimates.

Given this, our study essentially evaluated an area-based eelgrass indicator to assess the ecological status according to existing WFD classes. With this approach, we established EQR-threshold tables for the two studied systems and used these to determine the ecological status using RS observational data. To estimate areas of eelgrass representing reference and WFD class conditions we modelled scenarios with an existing eelgrass model and used information on water clarity (Kd) as the only driver. Other conditions related to climate change, e.g. water temperature and currents related changes in wind conditions, could also have been modified. These climate related conditions were however, investigated with the applied HSM model, and found to be of minor importance for reconstructing eelgrass coverage under historical climate conditions (Timmermann et al. 2021). For the method development, we did not change the model functions even though the Kd input data was replaced by data aggregated on waterbodies instead of spatially interpolated NOVANA data. In support of our modelling approach, we found good resemblance of the modelled reference conditions and historical maps of eelgrass distribution in both studied fjord systems.

To determine EQR-values with the different RS-data types, we developed an aggregation method which enabled comparison of high-resolution OP data (0.2m x 0.2m), with S2 resolution (10m x 10m) and the model resolution (100 x 100 m). As part of this, we made an overall reduction of the S2 estimated %cover by 50%. This was based on the knowledge that a 10m x 10m pixel classified as having SAV, does not have 100% coverage. The 50% reduction made the S2 derived %cover comparable with densities from in situ observations. The %cover in each pixel will likely vary, and it would therefore be optimal if S2 output can be classified to distinguish different SAV densities.

Comparing SAV coverage estimated from both OP and S2 with the modelled areas, made it possible to show the method of calculating area-based EQR-values and assign ecological status classes and comparing with those obtained using eelgrass depth distribution from NOVANA monitoring. Our analysis showed that EQR thresholds defining the ecological status classes, differed between the two study areas, and that the thresholds were affected by the choice of depth interval. This is a result of differences in bathymetry, where Nibe Bredning is dominated by a very shallow and even depth distribution compared to Odense fjord. Nibe Bredning is therefore expected to have a higher areal coverage of eelgrass to obtain good status compared to Odense fjord. In comparison, the EQR thresholds developed for the depth indicator, does not vary among regional water bodies. Future work with the area-based indicator should accordingly evaluate the variability in EQR thresholds between water bodies and consider optimizing the applied depth range to minimize variability, and if possible, apply similar EQR thresholds.

With the developed EQR thresholds, we found that the resulting ecological status assessments (good, moderate etc.) obtained with the area-based and the depth-based indicators were quite comparable for Odense fjord but less so for Nibe Bredning. Part of this could be related to overestimation of the eelgrass area detected by S2 (see previous discussion on this). The reduction of the S2 by a fixed factor (0.5) reduced issues with overestimation of SAV cover but may however, have resulted in underestimation in dense SAV patches.

Mapping of SAV with S2 showed a clear seasonality, with increasing areal cover during the growth season (see figure 3.4). To further reduce uncertainty in the SAV estimated areal coverage, it would be advisable to estimate the areal coverage based on multiple scenes over the growth season. This would furthermore ensure that the entire water body is covered by S2, and thus enable use of constant EQR thresholds (ie. not affected by the area covered by S2).

A simple comparison with other water quality parameters used in assignment of ecological status, showed some alignment with the new area-based indicator, but also discrepancies. This was also found for the traditional Zmax-based indicator, suggesting that at the water body level, it can be difficult to find strong relationships between water quality indicators and year-to-year changes. Thus, while results for the area-based indicator indicate the useability of the approach, there are issues that need to be addressed before implementation of the area-based indicator at larger scale. Importantly, the combination of RS mapping and HSM modelling hinges on the ability of methods to provide comparable results, to ensure that assessments of ecological status is not affected by methodological differences.

For the demonstration purpose, we determined reference and WFD class areas, using a spatial GIS model (HSM) which was originally calibrated using information from all the Danish coastal seas and from a period prior to the 2018-2022 period we examined here. It seems likely that improved data on local conditions, such as wave exposure and bottom shear stress, in combination with sediment characteristics could improve model estimates of eelgrass cover under current and future water quality scenarios.

It is relevant to mention that the applied HSM was originally developed to cover all Danish waters. Some parameters or surrogate layers are known to lack detail both in resolution and data detail, e.g. the sediment classes do not contain organic content and the resolution is not high enough for the resolution of the eelgrass model (Staehr et al 2019b). We have recently developed new approaches to estimate the organic content for which we can test if it improves the eelgrass model. Additional to improving the HSM used in this approach, there are local models available for selected water bodies. While the HSM model is thoroughly calibrated using *in situ* eelgrass transect data, it may be that some local areas are not well represented by transects which may lead to local uncertainties in the local estimations of SAV area. Also, the HSM model was calibrated using eelgrass and environmental data covering a period prior to the investigated period. Ideally, the HSM model should be calibrated with the most recent data available.

Another source of uncertainty relies in the area determined by RS-technologies. For the indicator analysis, we applied S2 and OP classifications which did not distinguish between eelgrass other SAV and other dark elements. As eelgrass and macroalgae co-occur in the two investigated areas, the assumption that the area-based ecological indicator represents eelgrass, is associated some unknown uncertainty. This uncertainty therefore complicates comparisons with existing ecological indicators such as the eelgrass main depth indicator. Future work with the area-based indicator should therefore consider masking out areas where macroalgae and other benthic conditions (eg. mussels and rocks) may significantly bias the RS determined SAV area. For this project we furthermore assumed that the S2 data on presence-absence, represented a threshold of 50% SAV coverage. In future it should be tested, if S2 is capable to estimate the coverage as well, or if there are other approaches to improve the mapping in lower resolutions.

The EQR values are very sensitive both to the quality of the RS-based mapping and the modelling data. Furthermore, the EQR-values are very much dependent on the specific area under investigation. It is therefore essential when comparing areal estimates from a model with those from RS-data of different resolution, that the areas must be clipped by the same mask as the RS data. This is not so trivial as RS-data may vary depending on e.g., cloud cover (for S2) or sun glint and waves (OP). Thus, for every analysis based on RS mapping, an initial step is to identify appropriate model area, and calculate the new EQR thresholds representing these. Optimally the area available for analysis should be representative for the entire water body. Here the advantage of using S2 is that frequent overpasses make it possible to obtain a growing season average map, thus covering the entire area of interest.

4.2.2 Estimating the eelgrass depth distribution limit Zmax from RS-data

Using a simple curve fitting model we were able to estimate the main depth distribution limit of eelgrass from RS-derived SAV cover data along binned depth intervals. Again, we assumed that SAV reflected mostly eelgrass in the studied areas.

The applied curve fitting model approach seemed especially promising when utilizing information on %cover for the entire study areas, which provided Zmax estimates in better agreement with the traditional *in situ*-based determinations. The Zmax estimation procedure worked best in Nibe Bredning, the Limfjord area, where seagrass meadows generally have a higher cover and are more homogeneously distributed. In comparison, the less dense and more fragmented eelgrass patches in Odense fjord, made it difficult to identify the 10% threshold limit from which Zmax is determined. Adding to this, Odense fjord is characterized by more turbid conditions and a quite mixed seagrasses and macroalgae vegetation belt, affecting the delineation of the deeper areas of eelgrass with RS-data. Applying an optical depth mask reduced this problem somewhat, but the ecological status classes were still overestimated. In comparison, the modelled Zmax-values in the Limfjord area, provided very similar assessments of ecological status as compared to the traditional NOVANA approach.

5 Recommendations for the implementation phase

Peter A.U. Stæhr, Lisbeth Tangaa Nielsen, Mihailo Azhar, Cordula Göke, Silvia Huber, Jesper P.A. Christensen, Lars B. Hansen, Sanjina U. Stæhr and Dorte Krause-Jensen

Based on the experience gained from this study, several possibilities should be considered for further investigations in a possible implementation phase of the IMM project.

5.1 Further development of RS products for mapping underwater vegetation

Implementation of the tested deep learning method in the SAV Denmark App for enhancing the current mapping process: With a pre-trained robust deep learning model, the SAV mapping can be based on new S2 images without additional input from the operator leading potentially to an optimization of the resulting SAV maps with limited input.

Implementation of the possibility of multitemporal SAV mapping based on S2 data: It will significantly improve the robustness and quality of the SAV information and provide insight into the vegetation dynamics and distribution, throughout the growing season, but also between years. Furthermore, this will provide better data for assessment of the areal based indicator.

Implementation of OP for mapping SAV in the SAV Denmark App: Already in the current version of the App, OPs can be accessed as a visual aid for S2 image interpretation, but OP data cannot be directly used for mapping. With the new deep learning approach, an implementation of OP classification can be both in the form of a generic SAV model and a model specifically trained to map different SAV classes.

Implementation of NOVANA data into the SAV Denmark App: For both qualitative assessments using visualization and quantitative evaluation of the produced SAV maps, independent field data can be applied directly in the App.

5.2 Development of eelgrass status indicators from RS-data

The assumption that SAV determined from RS is dominated by eelgrass needs to be supported: The developed ecological status indicators (both the area-based and the modelled Zmax-based) currently represent eelgrass indicators and can therefore only be applied in areas where SAV is dominated by eelgrass.

Assessment of the vegetation area based on S2 should be qualified in relation to how close (% coverage) it is assessed to be in each grid cell: In our current analysis, we assumed a mean coverage of 50% in the conversion from the S2 presence/absence cards. The cover is expectedly higher, and if we had used a 60% cover, the area indicator would have also classified Nibe Bredning, the Limfjord to be in a Moderate status. Optimally S2 would be able to distinguish between low, medium, and high cover of underwater vegetation. This, however, requires a lot more accurate training data. Overall, the ability to distinguish sparse from dense vegetation with S2 hinges on clear visible differences between vegetation and bare areas, which can be challenging in areas of mixed vegetation and in waters of high turbidity.

<u>Optimization of the GIS model (HSM) used to determine the area based EQR thresholds should be considered</u>: The HSM model currently used has been calibrated with large-scale national data sets of the driving environmental variables. In the implementation phase, the model should be updated and calibrated in relation to the water areas it will be used for.

<u>It would be obvious to assess the possibility of creating other condition indicators based on data from S2 and OP:</u> For instance, should it be possible to assess changes in the condition based on calculation of densities (% coverage) of underwater vegetation in different depth intervals. The HSM model can easily provide reference states for this parameter.

<u>It is also recommended to further investigate conditions locally around the NOVANA monitoring transects used to estimate Zmax</u>: Here it will be possible to retrieve information about densities and areas and make a more locally well-defined assessment.

<u>Importance of seasonality for the indicator assessment should be investigated:</u> The significance of seasonal changes in the area distribution of underwater vegetation, identified in this study, should be assessed in relation to selecting the optimal S2-based area estimates (is it the summer mean or, for example, spring that responds best to changes in the environmental state).

<u>Overall:</u> Results from this study show that it is possible to create both an area-based condition indicator and to assess the ecological status based on Zmax estimated with RS-data. We therefore recommend continuing with nationwide analysis of these two supplementary RS-based vegetation indicators. Ideally, such an analysis should include both OP and S2 classification and cover a period like this study (e.g. 5 years) to investigate the robustness of the indicators over time in the different water bodies.

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ASSESSMENT OF THE AREAL DISTRIBUTION OF SUBMERGED AQUATIC VEGETATION USING REMOTE SENSING IN DANISH COASTAL WATERS

Integrated Marine Monitoring - analytical phase

The use of different types of remote sensing data to acquire information on the distribution and cover of marine underwater vegetation was examined in two Danish fjord systems for the period 2017-2023. Promising results including high resolution vegetation mapping, differentiation of vegetation types as well as different algorithms for improved cover and area classification were investigated. Results from classifications and estimates of areal coverage were combined with modelling to develop novel eelgrass indicators of ecological status, which were evaluated against existing indicators. Recommendations for large-scale implementation of remote sensing as a promising tool to map and monitor marine vegetation are provided.

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