Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Natural Sciences
Department of Biology

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In situ biomass estimation of cultivated kelp using RGB imagery

Master's thesis in Ocean Resources
Supervisor: Glaucia Moreira Fragoso
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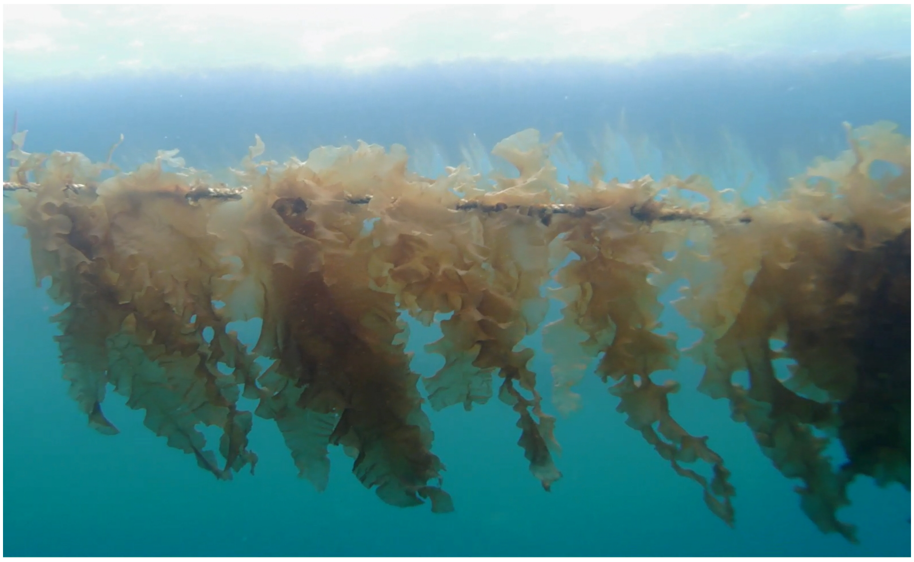
May 2023



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Abstract

Global seaweed aquaculture production makes up over one quarter of the total aquaculture production, with a production volume up to 35.1 million tons in 2020. In Norway, there is an increasing effort towards developing seaweed aquaculture as a new bioeconomy. Production is based on two kelp species, *Saccharina latissima* and *Alaria esculenta*, due to their high growth rates. However, Norwegian seaweed aquaculture is not profitable and is a small-scale industry. Biomass monitoring is one of the processes that today is inaccurate, time-consuming, labor-intensive and destructive. Hence, automated biomass monitoring is identified as one of the principainnovation needs.

Parallelly, there has been in a rapid development in recent years related to the use of underwater robotics and image processing techniques. State-of-the-art technology is widely researched and applied in marine operations. Hence, there is potential to apply new methods for monitoring of cultivated kelp.

The aim of this study was to investigate proof of concept for *in situ* biomass estimation of cultivated kelp. The proposed concept was to use underwater RGB imagery and computer vision techniques to estimate area as a proxy for biomass. In order to investigate proof of concept, the main goal was to have a preliminary assessment of: 1) Key environmental factors that might affect the quality of underwater RGB imagery of kelp. 2) The feasibility of deriving quantifiable size information about kelp from underwater RGB imagery. 3) The feasibility of using computer vision-derived area estimation as a robust proxy for kelp biomass.

We found that image quality was highly correlated with phytoplankton biomass in the water, with blooms resulting in lower quality. Our work further indicated that turbidity, possibly in the form of suspended matter (TSM), reinforced the negative effect, albeit appearing to have less importance in the study area. Accuracy of area detection was impacted by image quality. However, factors such as distance between camera and the kelp, and kelp movement due to water movement was of importance. As a result, we propose that kelp farmers should seek to understand and monitor environmental factors.

Our work indicated high feasibility of deriving meaningful size information about kelp from human-supervised annotation, mostly independent of observed image quality. It was also possible to derive computer vision-derived area estimation of high accuracy, albeit the method was somewhat sensitive to image quality. Together, this indicated that underwater RGB imagery is a suitable concept for biomass estimation of kelp.

We found a strong relationship between computer vision-derived area estimates and ground-truth weight measurements, indicating the feasibility of area as robust proxy for kelp biomass. Furthermore, using area estimation as proxy for biomass estimation, had the advantage of simplifying both data collection and processing. Hence, we propose further research based on using area estimation from underwater RGB imagery to build a model for accurate biomass monitoring at farm-scale.

A future scheme for farm-scale monitoring could be based on autonomous collection of imagery and environmental data, and real-time biomass estimation and prediction with machine learning techniques.

Sammendrag (Norwegian abstract)

Global produksjon i makroalgeoppdrett utgjør over en fjerdedel av total oppdrettsproduksjon, med et produksjonsvolum på opptil 35.1 millioner tonn i 2020. I Norge er det stadig økt innsats for å utvikle makroalgeoppdrett til en ny bioøkonomi. Produksjon er basert på to tarearter, *Saccharina latissima* og *Alaria esculenta*, grunnet deres høye vekstrater. Dog, norsk makroalgeoppdrett er ikke lønnsomt, og er en små-skala industri. Overvåking av biomasse er en av prosessene som i dag er unøyaktig, tidkrevende, arbeidskrevende og destruktivt. Dermed er automatisert overvåking av biomasse identifisert som en av de viktigste innovasjonsbehovene.

Parallelt har det vært en rask utvikling de siste årene relatert til bruk av undervannsrobotikk og bildeprosesseringsteknikker. Toppmoderne teknologi er bredt utforsket og anvendt i marine operasjoner. Dermed er det et potensial i å anvende nye metoder for overvåking av kultivert tare.

Målet med denne studien var å undersøke konseptbevis for *in situ* biomasseestimering av kultivert tare. The foreslåtte konseptet var å bruke undervanns RGB-bilder og datasynteknikker for å estimere areal som en proxy for biomasse. For å undersøke konseptbevis, var hovedmålet å ha en innledende vurdering av: 1) Sentrale miljøfaktorer som kan påvirke kvaliteten på undervanns RGB-bilder av tare. 2) Gjennomførbarheten til å utlede kvantifiserbar størrelsesinformasjon om tare fra undervanns RGB-bilder. 3) Gjennomførbarheten til å bruke datasynutledede arealestimat som en robust proxy for tarebiomasse.

Vi fant at bildekvalitet var i stor grad korrelert med fytoplanktonbiomasse i vannet, og at oppblomstringer resulterte i lavere kvalitet. Vårt arbeid indikerte videre at turbiditet, muligens i form av oppløst materiale (TSM), forsterker den negative effekten. Riktignok ser den ut til å ha mindre viktighet i studieområdet. Nøyaktigheten på arealdeteksjon var påvirket av bildekvalitet. Imidlertid var faktorer som distanse mellom kamera og taren, og tarebevegelse grunnet vannbevegelse, av betydning. Som et resultat foreslår vi at tareoppdrettere bør søke å forstå og overvåke miljøfaktorer.

Vårt arbeid indikerte høy gjennomførbarhet til p utlede meningsfull størrelsesinformasjon om tare fra menneskeovervåket annotering, stor sett uavhengig av observert bildekvalitet. Det var også mulig å utlede datasynutledet arealestimat av høy nøyaktighet. Riktignok var metoden noe sensitiv for bildekvalitet. Samlet indikerte dette at undervanns RGB-bilder er et passende konsept for biomasseestimering av tare.

Vi fant et sterkt forhold mellom datasynutledet arealestimat og reelle vektmål, noe som indikerte gjennomførbarheten til areal som robust proxy tarebiomasse. Dessuten, å bruke arealestimering som proxy for biomasseestimering har fordelen av å forenkle både datainnsamling og -prosessering. Derfor foreslår vi videre forskning basert på å bruke arealestimering fra undervanns RGB-bilder for å bygge en modell for nøyaktig biomasseovervåking på lokalitetskala.

En fremtidig ordning for lokalitetsskala overvåking kan være basert på autonom innhenting av bilder og miljødata, og sanntid biomasseestimering og prediksjon med maskinlæringsteknikker.

Acknowledgements

The work on this thesis took place at the Norwegian University of Science and Technology (NTNU), at the Department of Biology, in the period from December 2021 to May 2023. The main portion of the work was conducted at the Trondhjem Biological Station (TBS) and NTNU Centre of Fisheries and Aquaculture (SeaLab). Field work was carried out at Måsskjæra seaweed farm, owned and operated by Seaweed Solutions (SES). The thesis was a part of the NTNU project MoniTARE.

A big thank you to my supervisor Glaucia Moreira Fragoso for letting me embark on this new and exciting project. Your commitment to the project has been essential for setting the direction and for continued progress of the work. Wishing you best of luck with all your research going forward!

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Trondheim, May 2023

Martin Molberg Overrein

Table of Contents

List of Abbreviations (or Symbols)

2D	Two-dimensional
3D	Three-dimensional
AOP	Apparent optical properties
AUV	Autonomous underwater vehicle
cDOM	Colored dissolved organic material
CVA	Computer vision area
FChla	Chlorophyll *a* fluorescence
FHD	Full High-Definition
FOV	Field of view
FTU	Formazine Turbidity Unit
GTL	Ground-truth length
GTW	Ground-truth weight
IOP	Inherent optical properties
MAL	Manual annotation length
ML	Machine learning
NOK	Norwegian krone
NTNU	The Norwegian University of Science and Technology
OOI	Object of interest
PA	Precision Aquaculture
R&D	Research and development
R^2	Coefficient of determination
RGB	Red, green, blue
ROI	Region of interest
ROV	Remotely operated vehicle
SES	Seaweed Solutions
SR	Squared residual
TBS	Trondhjem Biological Station
TSM	Total suspended matter
UN	United Nations
UNSDG	United Nations Sustainable Development Goal

1 Introduction

1.1 Seaweed aquaculture

Seaweed, also known as macroalgae, is a group of photosynthetic multicellular marine algae, traditionally defined into groups based on their pigment composition: green (Chlorophyta), red (Rhodophyta) and brown (Phaeophyta). For most seaweed, their structure consists of a holdfast that anchors the seaweed to a substrate, a stipe and lamina. These multicellular organisms inhabit hard, rocky substrates in the littoral zone down to depths where sufficient light for photosynthesis can penetrate (Hurd et al., 2014). Belonging to the lowest trophic level, seaweed serve as the dominant primary producers in the coastal zone due to its abundance (Krause-Jensen & Duarte, 2016) and high respiratory rates (Middelburg et al., 2005).

Global algae aquaculture production, dominated by seaweed, has exponentially increased for decades (Cai et al., 2021b), with a production volume up to 35.1 million tons, wet weight, in 2020. This accounts for 97 percent of total algae production, including wild harvest, and more than one quarter of the total aquaculture production (FAO, 2022a). Red and brown seaweed are the primary target groups in seaweed aquaculture, as well as the second and third-largest group, respectively, in aquaculture in general (FAO, 2022b). Despite the large production, only 5.4 percent (in 2019) of the total aquaculture value comes from seaweed (Cai et al., 2021b). The large volume-low value correlation can be explained by the fact that 99.5 percent of the global seaweed production can be attributed to Southeast Asia, with China and Indonesia making up the bulk of it (FAO, 2022a). The region has longstanding traditions for using a majority of production for direct human consumption and processed food components, traditionally yielding a lower price. Only a small percentage of biomass is used in non-food applications, such as feed, pharmaceuticals, cosmetics and fertilizers (Lange et al., 2020; Stévant et al., 2017).

For seaweed cultivation, there is no need for input factors such as feed, fertilizers or freshwater, so-called extensive aquaculture (Padam & Chye, 2020). Consequently, the production costs are low compared to intensive aquaculture. This, fueled by a growth rate far exceeding that of terrestrial crops and plants (Kraan, 2020), enable seaweed aquaculture to be profitable despite traditionally low product value (Neori & Nobre, 2012). A growing seaweed cultivation industry can replace or become additive to current wild harvesting, supplying the hydrocolloid industry with biomass. Moreover, seaweed cultivation supplies a growing opportunity for biorefinery industry by utilizing seaweed as a source of food, feed additive, pharmaceuticals, cosmetics, biomaterials and bioenergy (Kraan, 2020). Additionally, seaweed aquaculture has value related to climate change mitigation and adaptation. This includes the ability to sequester carbon, mitigate ocean acidification and eutrophication (Lange et al., 2020), and protect coastal areas against flooding and erosion. Furthermore, seaweed can be utilized for biofuels and other products, representing a carbon neutral alternative to traditional fossil fuels and raw materials such as soy and palm oil (Duarte et al., 2013; Krause-Jensen et al., 2018; Sondak et al., 2017). Also, by moving production from terrestrial fields and wild harvest to coastal regions, conflict regarding land overexploitation and dispute can be avoided. In summary, seaweed aquaculture can provide a significant contribution to reaching the United Nations Sustainable Development Goals (UNSDGs).

Outside of Asia, seaweed production is still incipient, despite the increasing interests in recent years due to the growing awareness of sustainability and wide range of application of this marine resource, fueled by the growing realization that seaweed is a highly sustainable marine resource that can be adapted and utilized in a range of applications, both as food components and in other products. Additionally, it has added environmental, economic and societal benefits (Kraan, 2020). A growing interest is recognized in tropical and sub-tropical waters in Africa, Asia, Chile and the Caribbean, in temperate waters in Morocco, France and Portugal, and in cold waters in the Nordic countries, Canada and Chile (Lange et al., 2020). A rapid growth is predicted, especially in parts of Europe and the Americas, where industry, government and academia are eventually pulling in the same direction (Kraan, 2020). The growing seaweed interest throughout the world, prompted Lloyd’s Register Foundation, with active support of the United Nations (UN) Global Compact, to publish a “Seaweed Manifesto”, envisioning how seaweed can be a part of delivering on the UNSDGs (Lloyd's Register Foundation, 2020). The current optimism is further proved by some of the leading academic, governmental and entrepreneurial institutions on the field envisioning a “Seaweed Revolution” in the making (Financial Times Live, 2023).

1.2 Seaweed aquaculture in Norway

In Norway, seaweed as a food resource can be traced back to the Viking age, where, according to the sagas, seaweed was used as a snack during overseas exploitation, as the high iodine level is preventative against scurvy (Hallsson, 1964; Mouritsen et al., 2013). However, seaweed is not considered an important food ingredient today, as the only significant application is manufacturing of alginate from wild harvested seaweed. Norway is a significant wild harvester of seaweed, second largest in harvested volume after Chile (Cai et al., 2021a). Yet, wild harvest seems to have reached its potential years ago, and production has declined in later years. Hence, it is not equipped to provide the wanted increase in production volume for a developing seaweed industry. Seaweed aquaculture is therefore seen as the way forward (Kraan, 2020).

The total production of cultivated seaweed in Norway was limited to 246 tons at a value of NOK 6.2 million in 2020 (Fiskeridirektoratet, 2023). Seaweed aquaculture in Norway is focused on two brown seaweed, or kelp, species, namely *Saccharina latissima* and *Alaria esculenta*, due to their high growth rates (Cai et al., 2021a; Skjermo et al., 2014). Biomass is primarily used for human consumption, with a broadening range of products, including animal feed, biofuel, pharmaceuticals and bio-packaging, being developed. In recent years, relatively small-size kelp farms have been deployed based mostly on Asian cultivation techniques. This involves seeding the ropes with kelp spores and letting them fertilize and grow into sporophytes in tanks. Further, the ropes are deployed in predetermined patterns, distances and depths at a sea farm, preferably above 10 meters depth (Skjermo et al., 2014). The sea farm itself is typically structured as a square made up of ropes and buoys, held in place by a mooring system (Sulaiman et al., 2015). Alternative techniques include wrapping pre-seeded twine around ropes, or substituting the ropes altogether with nets or flat sheets as growth substrate (Kraan, 2020).

There is a growing interest and effort towards developing seaweed aquaculture as a new Norwegian bioeconomy (Olafsen et al., 2012; Skjermo et al., 2014). Norway is identified as a highly suitable region for productive seaweed cultivation due to the long coastline characterized by nutrient-rich inflow of Atlantic water and favorable climate. Furthermore, Norway is world-leading in marine aquaculture and offshore operations, combined with a strong tradition in marine research. In addition, Norway is actually the ninth largest (and second outside Asia) global seaweed producer (if wild harvest is included), indicating the availability of relevant competence (Cai et al., 2021a). This lays the foundation for a significant development, including offshore seaweed production. Optimistic assessments points towards the fact that seaweed production potential will be as high as 20 million tons by 2050 (Olafsen et al., 2012).

1.3 Needs of the industry

Today, Norwegian seaweed aquaculture is not profitable and is a small-scale industry. This means that cultivation and processing techniques are still at a basic stage, with little to no industry-grade technology. However, recent growing interest in this field of aquaculture on both governmental and industrial level, means that the needs and possibilities for technological advancement is on the rise. Technological advancement is needed to upscale the industry, as ineffective and labor-intensive methods serve as bottlenecks for higher yield and greater biomass quality. The challenges towards upscaling the seaweed cultivation industry is somewhat complex. A primary challenge is the development of cost-effective production techniques for large volumes of seaweed, a prerequisite for reaching profitability (Kraan, 2020). Consequently, there is a pressing need for research and development (R&D) to enable seaweed aquaculture to become a viable industry. A number of fields of R&D has been identified as prerequisites for an industry scale seaweed production. These include cost effective production lines at sea and land, predictable chemical composition and biomass yield, biofouling control, and upscaling strategies from experimental to commercial phase. Towards making the production at sea more cost efficient, automated biomass monitoring is one of the principal technological innovations needed (Skjermo et al., 2014).

1.4 Biomass monitoring

One of the main advantages of seaweed production is the high growth rate of some species (e.g. *S. latissima*). At the same time, this necessitates accurate and effective biomass monitoring to ensure successful deployment and growth development to optimize production (Bell et al., 2020; Skjermo et al., 2014). Kelp farmers today have no accurate and efficient way of monitoring kelp biomass. Traditionally, biomass has been measured manually by visual inspection of a sub-population and extrapolating the results for the whole farm. However, this method can be time-consuming, inaccurate, labor-intensive and destructive. Accurate biomass monitoring is important because the farmers want a predictable control of standing biomass and growth throughout production. Knowledge of growth patterns are key to further optimize conditions and methods for higher yield. Furthermore, it is valuable to know, yearly, how much biomass can be expected to harvest and sell, in order to deliver predictable yield for the processing industry. Implementing non-destructive monitoring is valuable in the sense that harvested kelp for biomass estimation is a direct loss of yield. Automation of farm monitoring can be more efficient timewise, reduce the costs and increase health and safety. These are important factors towards building a profitable production. Development towards an offshore-based seaweed industry amplifies the need for remote monitoring. The share scale of envisioned seaweed cultivation (Olafsen et al., 2012) itself requires that automated monitoring is available, accurate and effective (Skjermo et al., 2014). A monitoring method that can provide relevant and objective information for farm management and operation would serve as a step towards more knowledge-based and automated practices (Føre & Alver, 2022).

The first part of the challenge of monitoring kelp biomass is to collect data about the kelp. One possible method is to use an underwater robot mounted with a camera that can capture imagery of the kelp (Bell et al., 2020). This can streamline the data collection, as one no longer is dependent on going by boat to physically lift up the lines for visual inspection or harvesting samples, and thus making monitoring more effective. The second part of the problem is to extract information from the collected data. By applying computer processing to the image data collected by the underwater vehicle, it is possible to extract numerical information about the size of the kelp (Jin et al., 2023). Additionally, it can increase the accuracy of the extracted information compared to visual inspection, as one no longer is dependent on a pair of eyes, thus making monitoring more accurate.

1.5 Underwater robotics

Robotic systems designed for underwater use include a range of technologies, such as submarines, submersibles, remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) (Sørensen et al., 2020). ROVs are underwater vehicles that are operated by an operator on the surface using a remote-control system. They are typically tethered to the surface by a cable that provides power and communication between the vehicle and the operator. Typically, ROVs can be used in underwater environments where it is difficult or impossible for humans to access, such as underwater inspection, maintenance, and repair, as well as scientific research, data collection and exploration. For this purpose, they can be equipped with a variety of payload sensors, including optical, acoustic and environmental sensors that allows for data collection by either remote sensing or direct measurements in field (*in situ*). In addition, navigation sensors can be equipped for control of positioning, depth, heading and velocity (Sørensen et al., 2020). ROVs come in a range of sizes, from small handheld devices to large vehicles capable of carrying heavy equipment and conducting complex operations (Ludvigsen & Sørensen, 2016). AUVs are advanced underwater vehicles that can operate at different levels of autonomy, meaning they can perform pre-programmed tasks with minimal, too no, human intervention (Ludvigsen & Sørensen, 2016; Sørensen et al., 2020). Both ROVs and AUVs represent sensor-carrying platforms that is extensively used in collection of underwater imagery by utilizing optical sensors (Johnsen et al., 2020b).

1.6 Underwater imagery

Underwater imagery refers to the use of optical sensors to capture images or videos underwater. Optical sensors can collect high-resolution qualitative data about underwater objects of interest (OOIs). Water visibility is a constraint to the possibility for quantitative data collection with optical sensors (Ludvigsen & Sørensen, 2016), a constraint that can be summarized as the apparent optical properties (AOP) of the water. Photons that travel through water can either be scattered or absorbed by water molecules, and by compounds such as phytoplankton, colored dissolved organic material (cDOM) and total suspended matter (TSM). These properties are the inherent optical properties (IOP) of water, and will not change based on the light conditions (IOCCG, 2000; Johnsen et al., 2009). On the other hand, the apparent optical properties (AOP) of water depend on both IOPs and light conditions. This means that the AOPs are altered and regulated by light condition-affecting factors such as sun angle, albedo, surface waves, changes in cloud cover, rain, snow and air humidity (Sakshaug et al., 2009). The AOPs alter the spectral light absorption and backscatter, negatively affecting the range of which optical sensors can detect and measure OOIs (Sørensen et al., 2020). As a result, the range must be adjusted according to the size and complexity of the OOI, as well as the required resolution, to obtain data of satisfactory quality (Johnsen et al., 2020b).

RGB (red, green, blue) imagery with digital cameras constitutes the most available and simple method for optical underwater data collection. Digital cameras capture imagery that produce images by assigning each pixel with an intensity value for red, green and blue. The color channels largely correspond to the three wave bands the human eye is sensitive to, and when combining the intensity of each, the result is the color the human eye perceive (Johnsen et al., 2020b). Underwater imagery can with these properties be relevant in applications such as measuring of geological conditions, archaeological features and biological identification and attributes (Sørensen et al., 2020). As RGB imagery can only render information about three wave bands, it has constraints compared to other multispectral and hyperspectral optical sensors. However, the combination of availability, simplicity and affordability makes RGB imagery an important method in, for example, biomass estimations of both terrestrial crops (Wang et al., 2021) and cultured fish (Saberioon et al., 2017).

Two digital cameras can be combined into a stereo camera by mounting them in a setup next to each other. They need to be aligned at a known, fixed distance and be synchronized by cable or other connection. The stereo setup will function similar to the human eyes by giving a binocular (two-eyed) vision that can render estimations about depth to objects through use of point triangulation (Johnsen et al., 2020b). Consequently, stereo imagery can allow for three-dimensional (3D) modelling of a number of different OOIs, with some of the most groundbreaking underwater applications being modelling of ship wreck sites (Diamanti et al., 2021) and complex benthic habitats (Nevstad, 2022). There has been remarkable advancements in the usage of underwater imagery in later years due to the occurrence of new processing techniques, driven by developments in computer capacity and computer vision software (Sørensen et al., 2020).

1.7 Computer vision

Computer vision is a field of science that enables computers to interpret and understand visual information, such as images or videos. The technology uses advanced algorithms and mathematical models to analyze and collect meaningful information from visual data, for example, detecting objects and their attributes, identifying patterns or tracking movement (Yan, 2022). Computer vision algorithms have greatly increased the ability to non-invasively measure organisms through image analysis (Weinstein, 2018). Possible applications of computer vision techniques are numerous and ever increasing. Furthermore, with the recent exponential advancements of artificial intelligence, including the vast sub-field of machine learning, computer vision is destined to become an increasingly important field of R&D (Yan, 2022). As in-depth reviewed by Zion (2012) and Saberioon et al. (2017), computer vision application in aquaculture has been in the R&D stage for more than 30 years already. Yet, only recently have some concepts taken the step into commercially viable products (Føre & Alver, 2022).

1.8 Underwater operations in aquaculture

Underwater operations have become an increasingly important tool in aquaculture (Føre & Alver, 2022). In aquaculture farms, ROVs can be used for inspection of nets and structures for early detection of damage or wear (Kelasidi et al., 2020). In combination with optical sensors and computer vision techniques, underwater robotics have several usages (Zion, 2012). This includes, for example, real-time detection and monitoring of welfare indicators such as lice, disease, injury and deformity, and monitoring of individual feed pellets or the feeding behavior of fish (Føre et al., 2018). Biomass monitoring of fish is another application already in extensive use in fish aquaculture (Saberioon et al., 2017). Size is estimated based on parameters such as area, length, width and pose, and can provide high accuracy estimates of biomass (Coro & Walsh, 2021; de Verdal et al., 2014; Viazzi et al., 2015; Zion et al., 1999). Optical sensors and computer vision techniques enable development of more accurate, effective and remote monitoring of kelp biomass. The potential is constantly increasing on account of the rapid development in camera technology and speed of computer processing (Saberioon et al., 2017). Overall, do the implementation of underwater robotics and imagery in combination with computer vision techniques in aquaculture, have the potential to drastically improve the efficiency and sustainability of aquaculture (Føre & Alver, 2022).

Significant research has been undertaken related to remote monitoring of both wild and cultivated kelp, although with varying focus and aims. Studies have looked into the use of satellite imagery to detect and quantify kelp (Bell et al., 2015; Bell et al., 2020; Jin et al., 2023), and also with unmanned arial vehicles (UAVs) (Cavanaugh et al., 2021b). These methods show promise towards detecting canopy forming kelps, however they are largely limited to monitoring at large spatial scales, nor do they provide underwater information about kelp not forming canopies. Underwater mapping of wild kelp has been conducted using ROV (Summers et al., 2022) and AUV (Bewley et al., 2012; Mahmood et al., 2020). Bell et al. (2020) applied a ROV in combination with acoustic and optical sensors to gather information about cultivated kelp biomass. With the use of sidescan sonar and RGB camera, imagery of cultivated kelp was collected, and then a machine learning model was trained to automatically detect individual kelp specimens. Similar research was conducted by Stenius et al. (2022), testing an AUV for autonomous image collection at a kelp farm. These studies show the potential that underwater imagery can be used for monitoring of cultivated kelp with high spatial resolution. However, no previous studies, to the authors knowledge, has validated the accuracy of kelp estimation by collecting ground-truth measurements and investigating the relationship.

1.9 Aim of research

The aim of this study was to investigate proof of concept for *in situ* biomass estimation of cultivated kelp. The proposed concept was to use underwater RGB imagery and computer vision techniques to estimate area as a proxy for biomass.

In order to investigate proof of concept, the main goal was to have a preliminary assessment of:

1. Key environmental factors that might affect the quality of underwater RGB imagery of kelp.
2. The feasibility of deriving quantifiable size information about kelp from underwater RGB imagery.
3. The feasibility of using computer vision-derived area estimation as a robust proxy for kelp biomass.

2 Materials and methods

2.1 Study area and design

The study area was located at Frøya island, of the coast off Mid-Norway. Frøya is part of a biodiversity-rich area with significant water mixing due to strong winds and tidal currents (Fragoso et al., 2021). The oceanography is characterized by the Norwegian Coastal Current mixed with freshwater runoffs from Norwegian fjords (Skagseth et al., 2011). Furthermore, the area is exposed to occasional upwelling of warm and nutrient-rich waters of the North Atlantic Current (Sætre, 2007). Consequently, the area is highly productive regarding seafood production, including both wild harvest and aquaculture (Ervik et al., 2018; Tiller et al., 2015).

The field work was conducted at Måsskjæra seaweed farm (63°44.617'N 8°52.756'E) owned and operated by Seaweed Solutions (SES), located close to Sistranda, Frøya (Fig. 1). Sampling occurred seven times from March to June 2022 (Table 1), on kelp that was deployed at sea in November 2021. Selection of sampling days and work schedule was partially dependent on wind and tidal conditions. Data sampling consisted of three individual methods: 1) Continuous measurements of environmental data (temperature, turbidity and phytoplankton) throughout the sampling period. 2) Ground truthing of kelp measurements (wet weight biomass and lamina length and width) was collected by physical harvest after image sampling. 3) Image sampling of kelp performed using RGB cameras on a ROV. Thereafter, image data were processed using computer vision techniques. Finally, statistical analysis was performed on processed image, ground truth and environmental data.

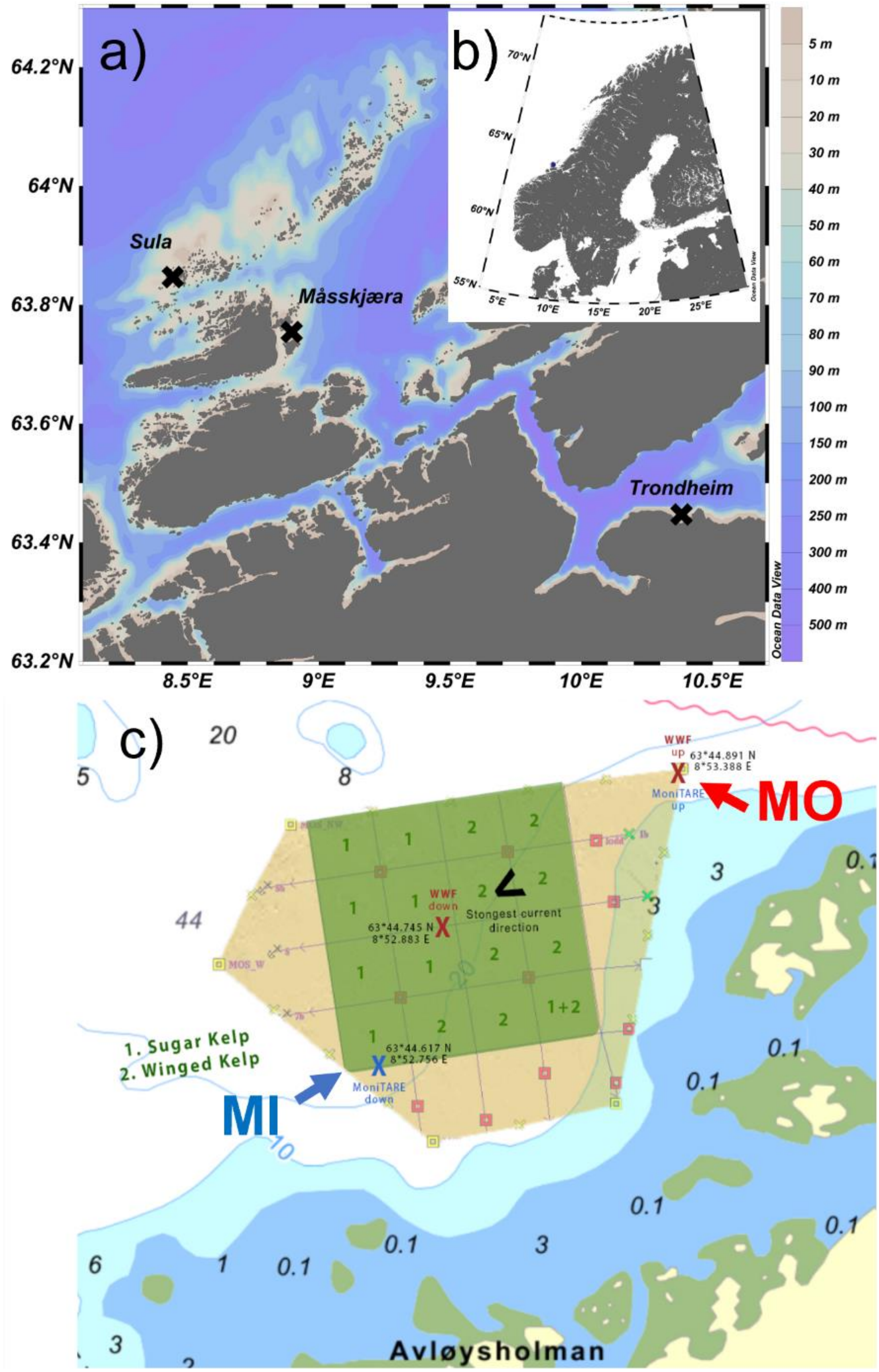

Fig. 1: a) Map showing the location of Måsskjæra seaweed farm, Trondheim city and Sula meteorological station (where wind data were collected) on b) the coast of Trøndelag county (mid-Norway). c) Illustration of the Måsskjæra seaweed farm, showing the collection site (station MI) where the sampling was conducted (blue X).

The field work occurred at the spring, as it is the primary growth-period of the cultivated kelp before biofouling settles (Førde et al., 2016). This enabled us to sample during distinct development stages of the kelp, from young sporophytes in March to 'bushy canopy" in June, to test the method on kelp of different size and growth density. As mentioned, sampling was aimed to be done under as optimal environmental conditions as possible, such as low tides (slack water) and weak wind conditions, as to experience less kelp movement by the currents, where the kelp is kept vertically in the images. However, in practice, several times the tide was turning from low to rising, and the wind was shifting during sampling due of the short time window and the dynamic weather conditions of the study area (Table 1).

Table 1: Field campaign date (2022) and image sampling time. Tidal conditions (Måsskjæra), average and maximum wind speed (Sula metrological station) and cloud cover (Ørland metrological station) for the image sampling time period. Source: www.kartverket.no for tides and www.yr.no for wind and cloud cover conditions.

Field day	**Date**	**Time**	**Tide (cm)**	**Wind (m/s)**	**Wind direction**	**Weather**
1	March 22	10:30-12:00	103-181 (Rising)	5,0 (6,7)		
2	April 5	12:30-14:00	178-232 (Rising)	1,9 (8,7)		
3	April 20	07:50-09:30	37-39 (Low)	2,4 (3,7)		
4	May 4	08:30-09:30	50-63 (Low/rising)	6,1 (8,5)		
5	May 27	10:20-12:10	231-199 (High/receding)	6,7 (8,5)		
6	June 3	08:40-09:20	61-64 (Low)	5,1 (7,9)		
7	June 15	08:40-09:50	84-145 (Rising)	7,9 (11,0)		

2.2 Environmental data

Environmental data was collected in order to investigate whether, and to what extent, they affect observed image quality, and consequently, the possibility for satisfactory area detection yielding meaningful output. We took measurements of three factors affecting the inherent optical properties (IOPs) of the water: 1) Turbidity, a measure of optical clarity of water caused by scattering and absorption of photons. 2) Phytoplankton, measured as chlorophyll *a* fluorescence (*FChla*), with chlorophyll *a* being the main compound of phytoplankton (Fragoso et al., 2021). 3) Temperature. A C3 submersible fluorometer sensor (Turner Designs, USA) was attached to a buoy at Station MI (Fig. 1c), at 3 meters depth. The sensor collected data of *FChla* (calibrated later to concentration in mg m^{-3}), turbidity (FTU) and temperature (°C) every 10 min from February 16 to June 15.

2.3 Sensor-carrying platform and optical sensor

A Blueye X3 (Blueye Robotics, Norway) (Fig. 2) was used as the sensor-carrying platform for the image sampling. It is a mini-ROV which can be carried and operated by one person, with the internal camera providing vision for the operator during dive operations. It can reach great depths, operate for a reasonable amount of time in differing conditions, and light up its own environment. The ROV was chosen for this study due to it being small and maneuverable enough for easy operation in the tight spaces of a kelp farm, while at the same time providing sufficient power to operate in coastal conditions with sensor payloads. It is also relatively easy to operate and affordable, making it an available alternative. The internal camera of the ROV was used as the optical sensor for the image sampling. It is a digital RGB camera equipped with 30° tilt up and down, which can collect imagery with Full High-Definition (FHD) resolution and 115° field of view (FOV).

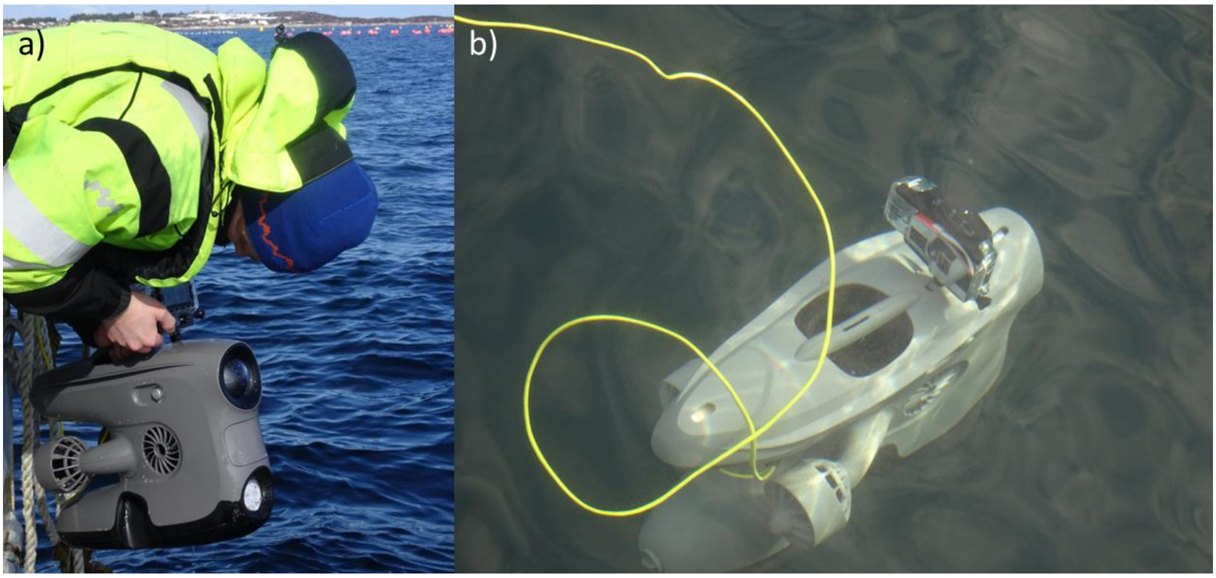

Fig. 2: a) A Blueye X3 ready for deployment, and b) deployed underwater with the tether linking it to the surface unit. Photos: Benjamin Thomason, 2022.

2.4 Image sampling

For image sampling (Fig. 3), a 50-meter-long line of cultivated *S. latissima* at station MI (Fig. 1c) was chosen. A checkerboard, used for size reference, was attached to the start of the cultivation line. Red plastic strips were attached to the line at one-meter intervals, indicating that each meter represents a replicate of the kelp attached to the line. Adjacent triplicates of one-meter kelp replicates were selected for imaging, and image sampling was conducted by maneuvering the ROV sidewards along the cultivation line. For that, the internal camera was pointed in the direction of the kelp and at a sufficient distance to ensure that the whole length of the kelp and width of the one-meter replicate was captured in the frame. The same method was repeated at each field day (Table 1), where adjacent triplicates of one-meter kelp replicates was imaged.

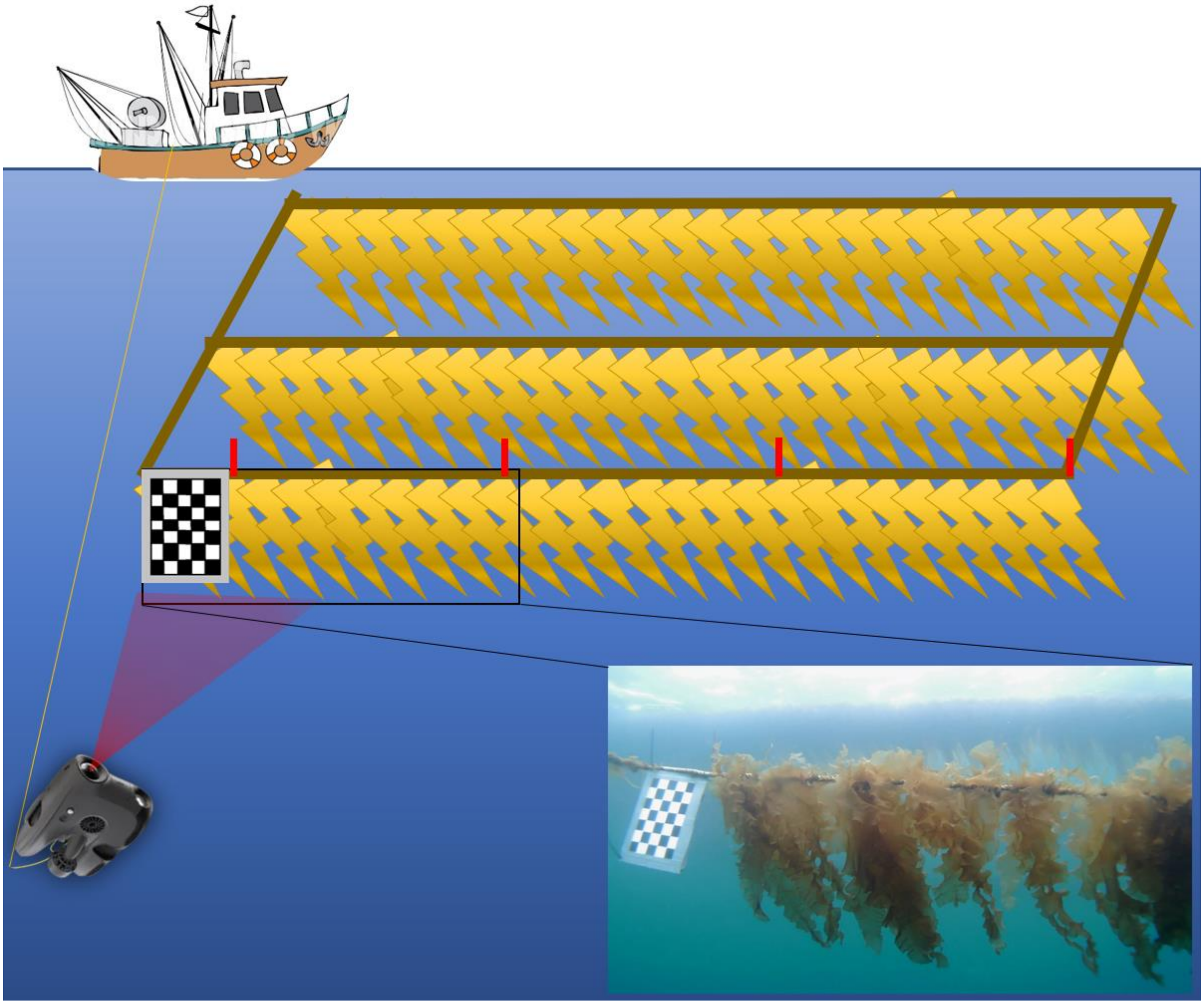

Fig. 3: Illustration of the image sampling method, where a checkerboard is used for size reference, and red strips indicates one-meter replicates of kelp samples. A ROV with internal RGB camera is used to collect triplicate imagery of replicates. Illustration: Martin Molberg Overrein (Adapted from Glaucia M. Fragoso).

2.5 Image processing

Image processing consisted of two different methods: (I) Manual annotation of length performed using a basic image processing program and (II) Area estimation performed using computer vision techniques. After first overview of the sampled image data, it was apparent that the red plastic strips used as one-meter markers was not sufficiently visible to be used as size reference. This meant that image data used in further processing was restricted to the first replicate from each sampling, where strips in combination with the checkerboard could be used as size reference.

2.5.1 Manual annotation of length

Manual annotation, meaning supervised length estimation of the kelp in the image data, was performed using the image processing program ImageJ (Image Processing and Analysis in Java) (Fig. 4). The pipeline started with extraction of six frames of the first kelp replicate from the image data collected by the internal ROV camera (Fig. 4.1). The six frames were selected based on having the checkerboard visible, and with different distances and poses to the kelp, in order to capture some variability in the image data. The selected frames were then uploaded to ImageJ. The checkerboard in the frame was used as size reference to set a scale of pixels per centimeter (pixels/cm) for the corresponding frame (Fig. 4.2). Then, ten kelp specimens in the frame were randomly selected, and length in centimeters (cm) was measured by drawing a line from tip to holdfast of the specimen, using the "line" and "measure" tools in ImageJ (Fig. 4.3). The mean of the measurements is presented as manual annotation length (MAL) hereafter. The pipeline was repeated using image data from each field day.

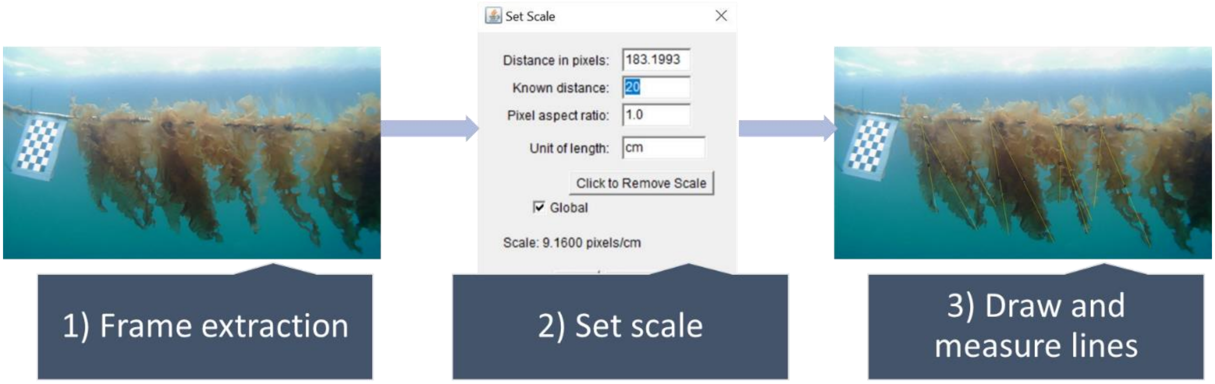

Fig. 4: Pipeline for manual annotation of length performed using ImageJ. 1) Extraction of frames from image data. 2) Using checkerboard to set scale of pixels per centimeter (pixels/cm). 3) Drawing and measuring length from tip to holdfast of ten randomly selected kelp specimens, resulting in manual annotation length (MAL).

2.5.2 Computer vision estimation of area

Computer vision estimation of area was performed using OpenCV (Open Source Computer Vision Library) (Fig. 5), a library of programming functions used for real-time computer vision. Python was the chosen programming language due to its compatibility with OpenCV.

The pipeline started with extraction of six frames of the first kelp replicate from the image data collected by the internal ROV camera (Fig. 5.1). The six frames selected, were the same frames used in manual annotation. The selection was based on having the checkerboard visible, and with different distances and poses to the kelp, in order to capture some variability in the image data. The region of interest (ROI) in the frame was defined as the width of the one-meter replicate and height sufficient to capture the full length of the kelp. ROI was extracted in order to limit area detection to the wanted kelp replicate (Fig. 5.2). Further, clustering of pixel values was applied as a pre-processing step to allow more accurate distinction of color (Fig. 5.3), before color segmentation was applied to distinguish the kelp as the object of interest (OOI) from the surrounding background in the frame (Fig. 5.4). Next, adaptive thresholding was applied to mask out the OOI from the background (Fig. 5.5), allowing detection of the contour of the OOI (Fig. 5.6). Lastly, the number of individual pixels in the contour area was counted. The pixel count was converted to square decimeters (dm^2) by using the known pixel width and real-world width (one meter) of the frame as size reference, presented as computer vision area per meter (CVA) hereafter. The pipeline was repeated using image data from each field day.

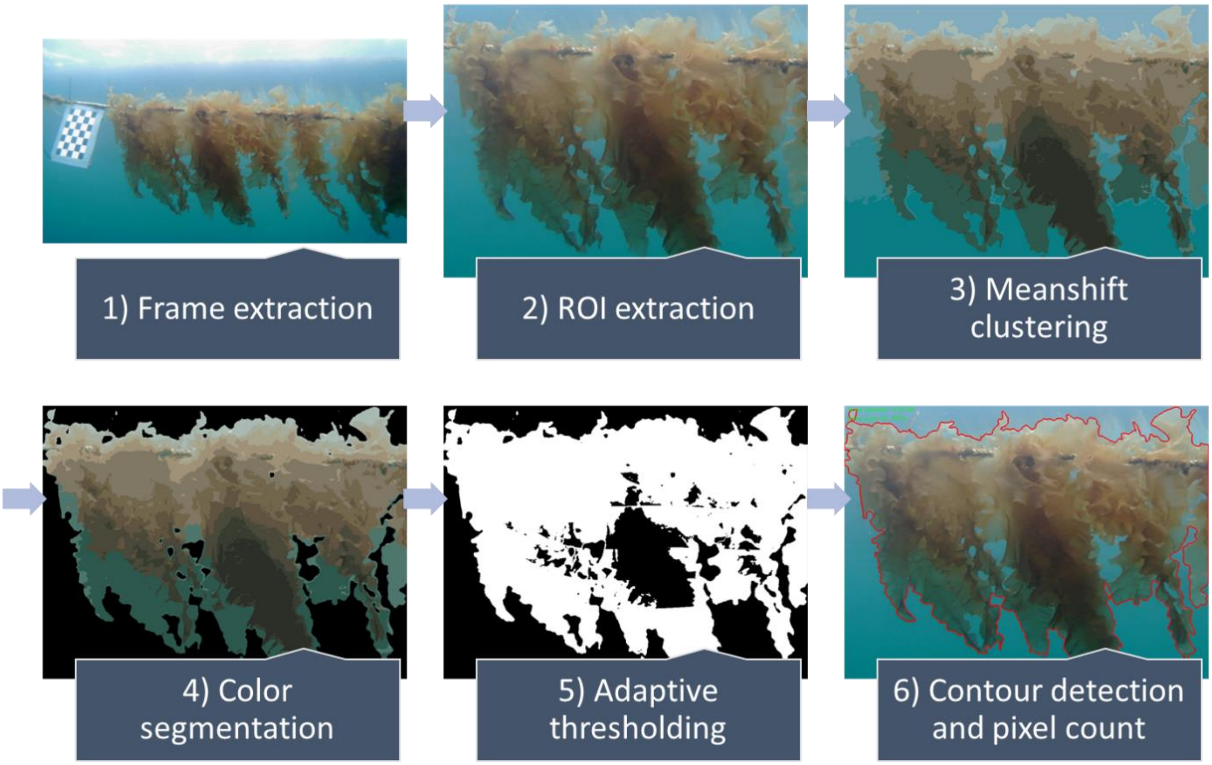

Fig. 5: Pipeline for the computer vision area estimation performed with OpenCV. 1) Extraction of frames from image data. 2) Extraction of region of interest (ROI) from frame. 3) Meanshift clustering of pixel values. 4) Segmentation of object of interest (OOI) based on color. 5) Masking out OOI from the background using adaptive thresholding. 6) Detection of the contour of the OOI and counting of area pixels, converted to square decimeters (dm^2) using known pixel width and real-world width (one meter) of the frame as size reference, resulting in computer vision area(CVA).

2.6 Ground truthing

In order to validate the estimates from the processing of image data and evaluate the accuracy of the method, ground truthing of the same kelp samples was performed. Triplicate ground truthing was conducted by harvesting each replicate separately and measuring wet weight, presented as ground-truth weight per meter (GTW) hereafter. Then, ten kelp specimens from each replicate were measured for lamina and stipe length, as well as lamina width at widest point (Fig. 6). Ground-truth lamina length is presented as GTL hereafter. The same method was repeated at each field day.

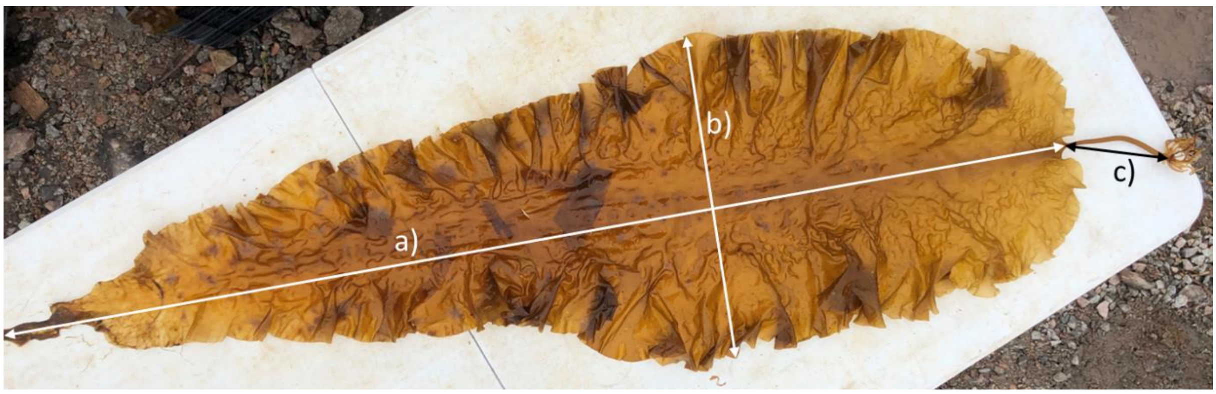

Fig. 6: Ground truthing of Saccharina latissima a) lamina length, b) lamina width at widest point and c) stipe length. Photo: Martin Molberg Overrein.

The image and ground-truth data of the kelp included, initially, only *S. latissima*. However, from visual inspections of the line, settling and growth of *A. esculenta* was observed to occur on the cultivation line around field day 5 (May 27), amounting to around 30 percent towards the end of the field campaign (June 15). Hence, specimens of *A. esculenta* were measured for lamina and stipe length, and lamina width at widest point, on field days 6 (June 3) and 7 (June 15).

On field days 6 (June 3) and 7 (June 15), growth density of the kelp samples was measured to collect additional data for validation. This was done by harvesting the first 25 cm of each replicate separately, counting the number of kelp specimens within that sub-sample and extrapolating the count to get density of the whole one-meter replicate.

2.7 Statistical analysis

Statistical analyses were performed using NumPy, SciPy, scikit-learn and Matplotlib, libraries for data analysis and visualization in Python.

Relationships between MAL versus GTL, and CVA versus GTL, was investigated by applying linear regression and evaluated by their coefficient of determination (R^2). Relationships between CVA versus GTW, and GTL versus GTW, was investigated by applying exponential regression and evaluated by their coefficient of determination (R^2).

Precision of GTL, MAL and CVA was investigated by calculating standard deviation. Accuracy of MAL and CVA was investigated by calculating relative accuracy compared to GTL, and GTL and GTW, respectively.

Relationships between turbidity versus CVA relative accuracy, serving as proxies for water visibility and CVA accuracy, respectively, was investigated by applying linear regression and evaluated by their coefficient of determination (R^2).

3 Results

3.1 Environmental data

Environmental conditions showed significant variation throughout the field period. Average wind speed varied significantly between field days (Fig. 7a). Seawater temperature showed a steady increase throughout the season, varying from 5.6 °C to 9.4 °C (Fig. 7b).

It was observed several peaks in *FChla* throughout the field campaign (Fig. 7c), with a short peak in late March (~2.5 mg m^{-3}), a long peak around mid-April (up to 5.72 mg m^{-3}) and variable values from late May until mid-June (<4mg m^{-3}). The overall trend was towards higher concentrations in the second half of the field campaign. The *FChla* serve as a proxy for phytoplankton biomass and, thus, indicates when phytoplankton blooms took place.

Turbidity showed significant variability throughout the field campaign (Fig. 7c). A relatively similar trend compared to *FChla* concentration up until late May was observed, with a long peak in mid-to-late April (>0.2 FTU). A short peak was observed in mid-June (>0.2 FTU).

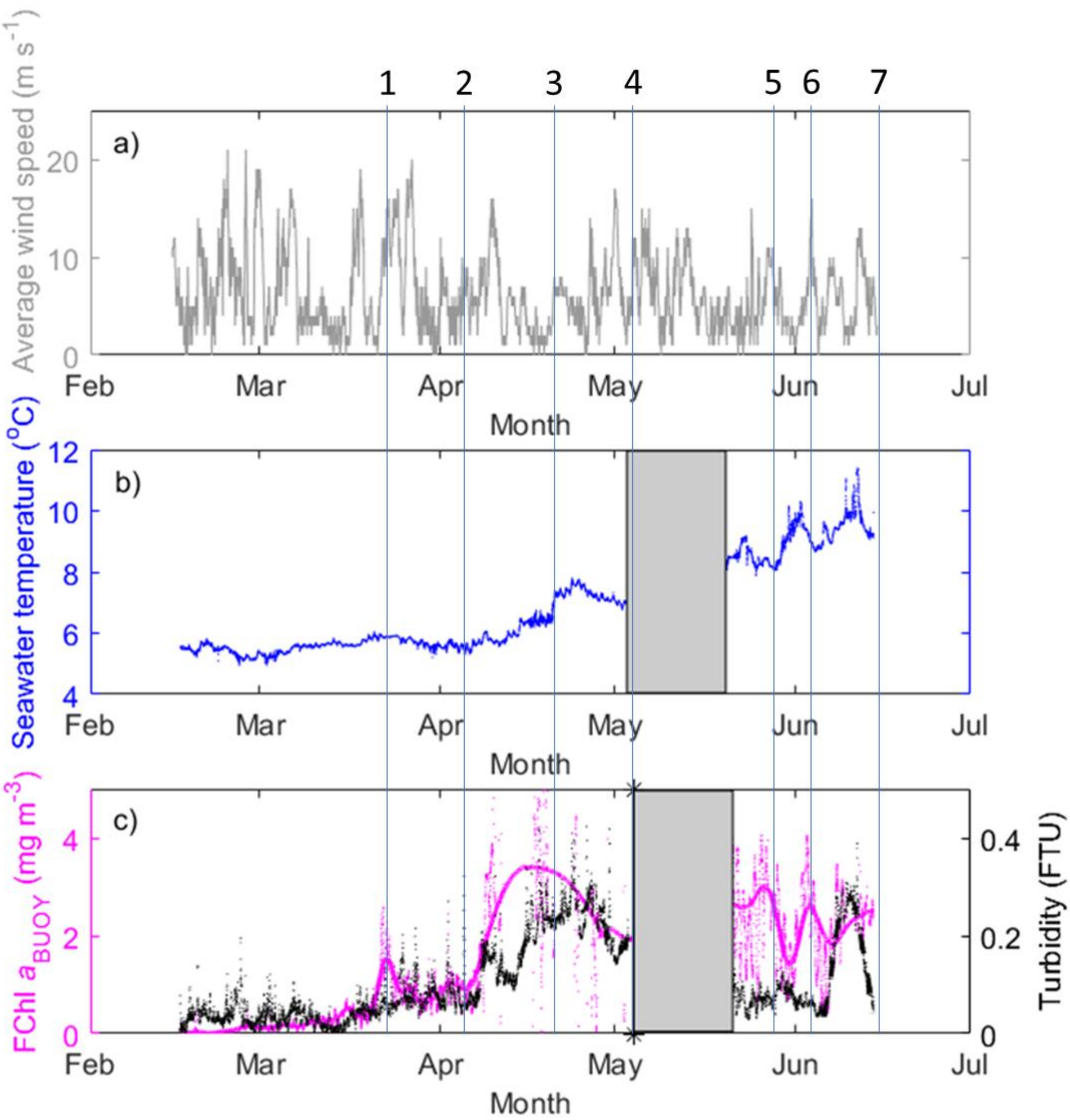

Fig. 7: a) Average wind speed (m s^{-1}) at Sula metrological station, and b) seawater temperature (°C) and c) chlorophyll a *fluorescence* (FChla)*(mg m^{-3}) and turbidity (FTU) at Måsskjæra farm (station MI) from February 16 to June 15. Lines indicate field days. 1: March 22, 2: April 5, 3: April 20, 4: May 4, 5: May 27, 6: June 3, 7: June 15.*

3.2 Image quality and area detection

Notable differences in observed image quality of the frames used in image processing were discovered in the data sampled at different timepoints (Fig. 8) throughout the field campaign. On field days 1 (March 22) and 4 (April 5), the observed image quality was very high, indicating good water visibility. On field day 2 (April 5), it was slightly lower, but still high, indicating relatively good water visibility. On field day 7 (June 15), the observed image quality was low, indicating relatively bad water visibility. On field days 3 (April 20), 5 (May 27) and 6 (June 3), the observed image quality was very low, indicating bad water visibility. Summarized, the trend in observed image quality was towards lower quality in later parts of the field campaign. The observed image qualities are summarized in Table 2.

Fig. 8: Example image frame before computer vision processing, showing observed image quality, from each of the field days.

Notable differences in area detection from the frames used in image processing were discovered in the data sampled at different timepoints (Fig. 9) throughout the field campaign. It is important to note that accuracy of detected area varied in between frames from the same day. The area detection was accurate in all frames on March 22, April 5 and May 4. On April 20, the area detection was moderately partial, but more accurate in other frames from the same day. Area detection was moderately partial in all frames on May 27 and June 3. On June 15, area detection was significantly partial in some frames, while mostly accurate in other frames from the same day.

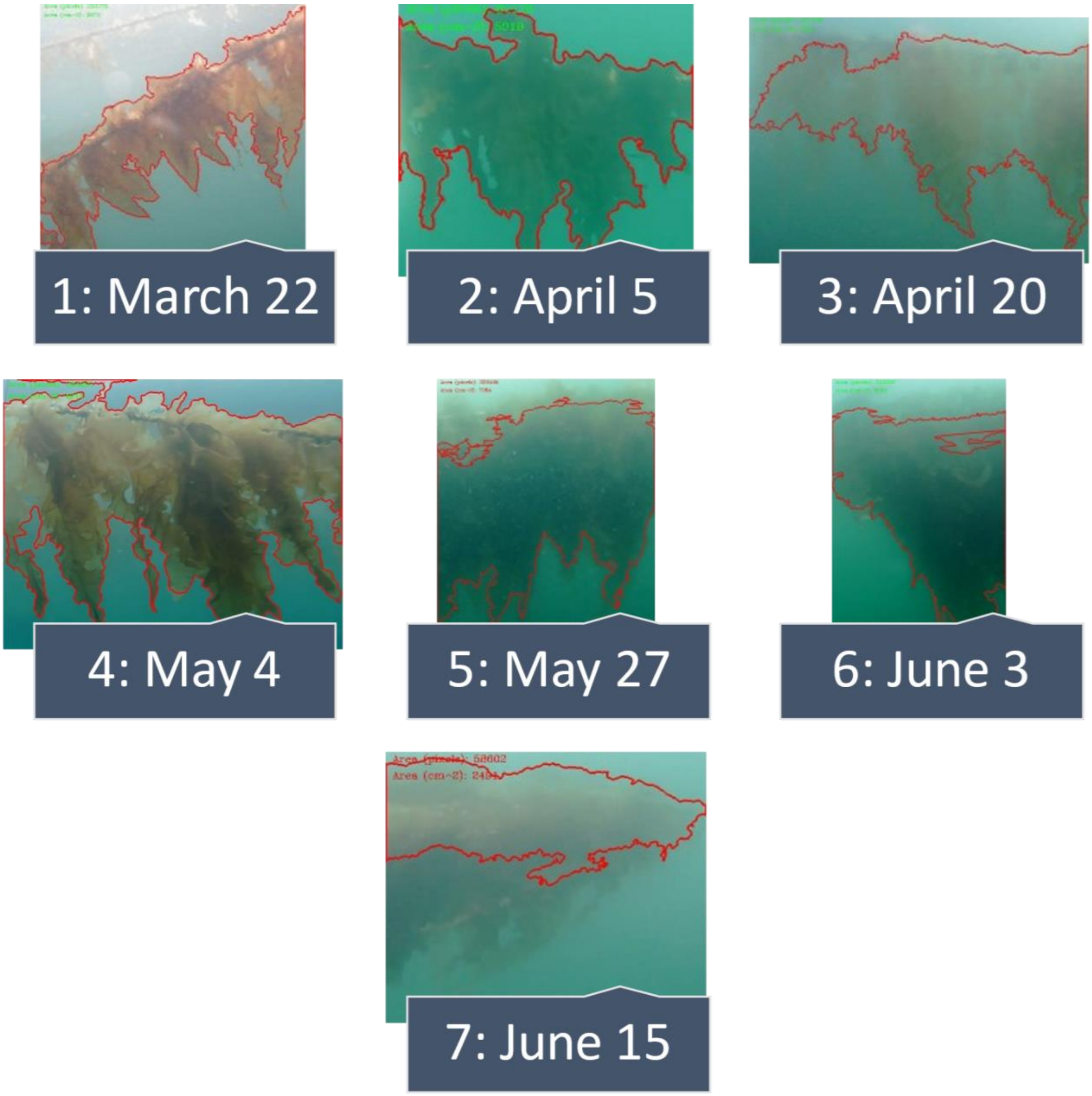

Fig. 9: Example image frame after computer vision processing, showing detected area of the kelp, from each of the field days. Important to note that accuracy of detected area varied in between frames from the same day.

The observed image quality and squared residuals (SR) of GTW plotted against CVA, are summarized with mean *FChla* concentration and mean turbidity on individual field days in Table 2. The SRs varied between 0.001 kg/m on April 20, and 2.310 kg/m on June 15, with a clear trend towards higher SRs in later stages of the field campaign (>0.3 kg/m). Both *FChla* concentration and turbidity peaked on April 20, with measurements of 4.485 mg m^{-3} and 0.249 FTU, respectively. High measurements of *FChla* were observed also on May 27 (3.110 kg m^{-3}), June 3 (3.085 kg m^{-3}) and June 15 (2.563 kg m^{-3}). Another peak in turbidity was observed on May 4 (0.184 FTU), while the remaining measurements were similar (~0.060 FTU).

*Table 2: Summary of observed image quality of the frames used in image processing and squared residuals (SR)(kg/m) between computer vision area (CVA)(dm^2/m) and ground-truth weight (GTW)(kg/m). Mean chlorophyll a fluorescence (*FChla*)(mg m-3) and mean turbidity (FTU) at Måsskjæra farm (station MI) on individual field days.*

Field day	**Date**	**Observed image quality**	**Squared residuals (kg/m)**	***FChla* (mg m^{-3})**	**Turbidity (FTU)**
1	March 22	Very high	0.002	1.203	0.051
2	April 5	High	0.005	0.896	0.060
3	April 20	Very low	0.001	4.485	0.249
4	May 4	Very high	0.009	0.679	0.184
5	May 27	Very low	0.426	3.110	0.069
6	June 3	Very low	0.317	3.085	0.064
7	June 15	Low	2.310	2.563	0.063

3.3 Ground-truth length (GTL) versus ground-truth weight (GTW)

The relationship between GTL and GTW was investigated, with GTW being a function of GTL (Fig. 10).

A strong positive exponential relationship ($r^2 = 0.93$) was observed between GTL and GTW, showing statistical significance ($p < 0.05$). Field day 7 (June 15) had a somewhat lower GTL (65.9 cm) than the exponential trend, while field day 5 (May 27) had a somewhat higher GTL (93.5 cm) than the exponential trend.

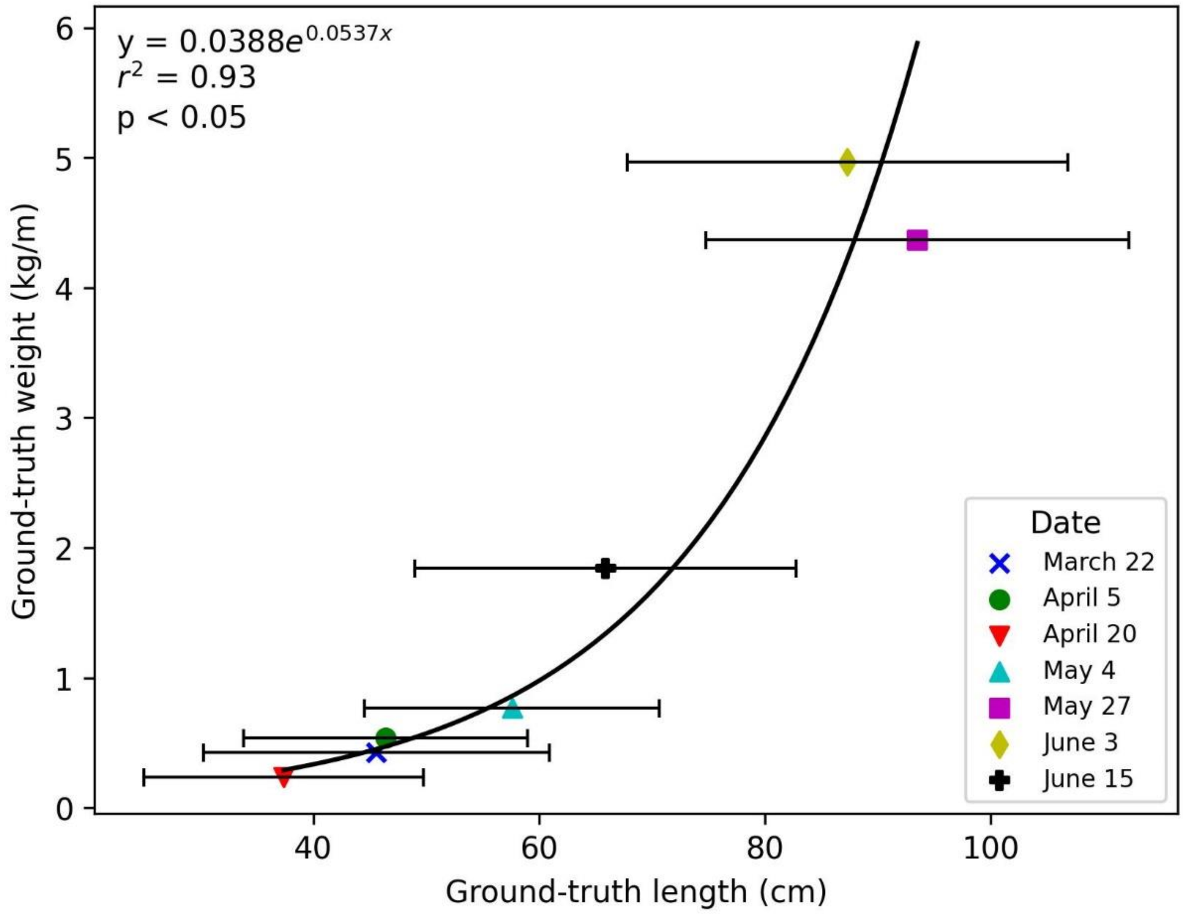

Fig. 10: Exponential relationship between ground-truth length (GTL)(cm) and ground-truth weight (GTW)(kg/m). Error bars show the standard deviation of GTL for each field day (n = 6).

3.4 Manual annotation length (MAL) versus ground-truth length (GTL)

The relationship between MAL and GTL was investigated, with GTL being a function of MAL (Fig. 11). A wide range in lamina length was observed among specimens and sampling timepoints, both for MAL and GTL. MAL ranged from 33.9 cm to 95.7 cm. GTL ranged from 37.4 cm to 93.5 cm.

MAL showed a varying standard deviation between sampling timepoints, ranging from 2.8 cm to 14.0 cm. GTL showed a more similar standard deviation, ranging from 12.4 cm to 19.5 cm.

A strong positive linear relationship ($r^2 = 0.96$) was observed between MAL and GTL. The result was statistically significant ($p < 0.05$).

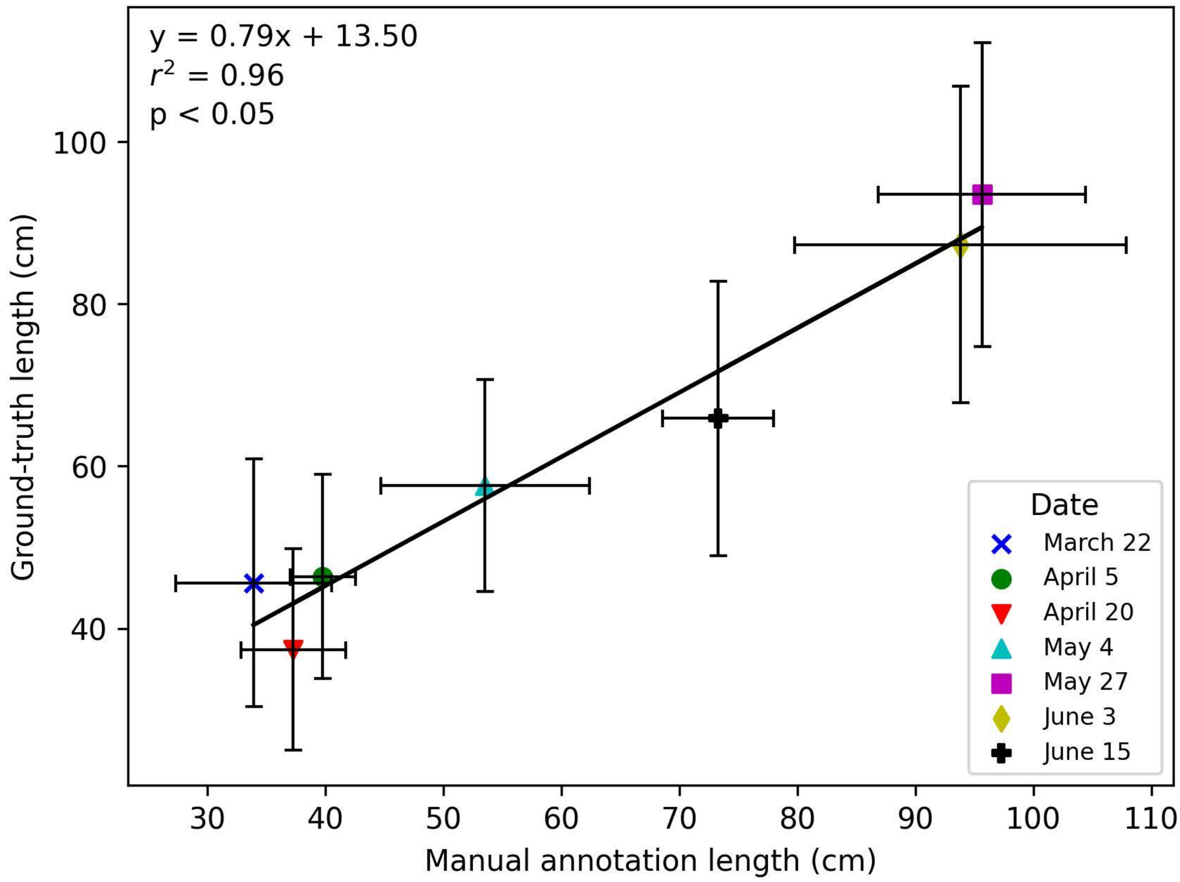

Fig. 11: Linear relationship between manual annotation length (MAL)(cm) and ground-truth length (GTL)(cm). Error bars show the standard deviation of MAL and GTL for each field day (n=6 for MAL and n=10 for GTL).

3.5 Computer vision area (CVA) versus ground-truth length (GTL)

The relationship between CVA and GTL was investigated, with GTL being a function of CVA (Fig. 12). Both CVA and GTL showed a wide range of variation between sampling timepoints. CVA ranged from 32.2 dm^2 to 79.3 dm^2, and GTL ranged, as mentioned above, from 37.4 cm to 93.5 cm.

CVA showed a significant variation in standard deviation among sampling timepoints, ranging from 23.4 dm^2 to 91.7 dm^2. GTL showed a more similar standard deviation, ranging, as mentioned above, from 12.4 cm to 19.5 cm.

A strong positive linear relationship ($r^2 = 0.81$) was observed between CVA and GTL, showing statistical significance ($p < 0.05$) (Fig. 12a). Field day 7 (June 15) had a notably lower CVA (35.6 dm^2) than the linear trend. If data from June 15 was removed from the statistical analysis, an even stronger linear relationship ($r^2 = 0.98$) was observed, showing statistical significance ($p < 0.05$) (Fig. 12b).

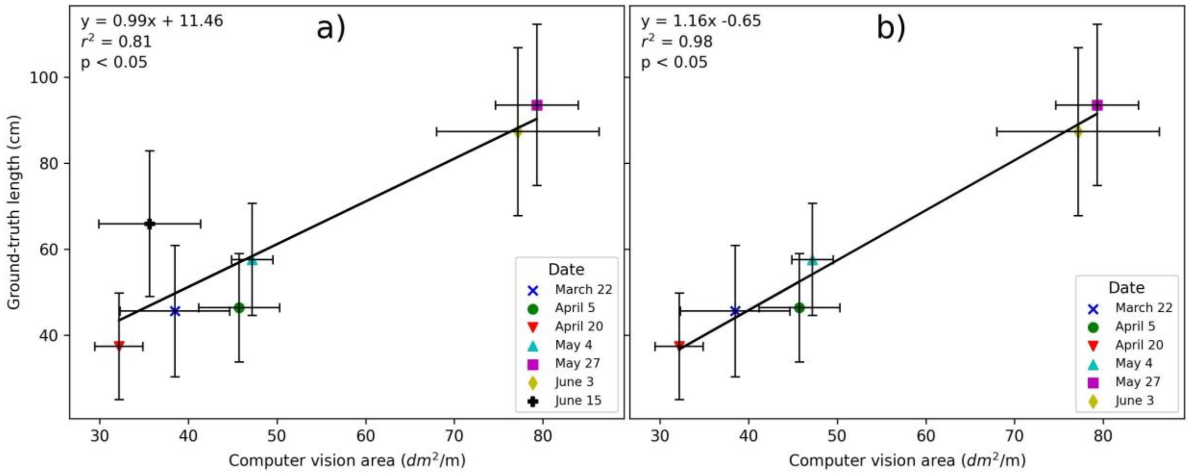

Fig. 12: a) Linear relationship between computer vision area per meter (CVA)(dm^2/m) and ground-truth length (GTL)(cm). b) Linear relationship without data from field day 7 (June 15). Error bars show the standard deviation of CVA and GTL for each field day (n=6 for CVA and n=10 for GTL).

3.6 Computer vision area (CVA) versus ground-truth weight (GTW)

The relationship between CVA and GTW was investigated, with GTW being a function of CVA (Fig. 13). A wide range in GTW was observed between sampling timepoints, ranging from 0.24 kg to 4.97 kg.

A strong positive exponential relationship ($r^2 = 0.84$) was observed between CVA and GTW, showing statistical significance ($p < 0.05$) (Fig. 13a). Field day 7 (June 15) had a notably lower CVA (35.6 dm^2) than the exponential trend. If data from June 15 was removed from the statistical analysis, an even stronger exponential relationship ($r^2 = 0.95$) was observed, showing statistical significance ($p < 0.05$) (Fig. 13b).

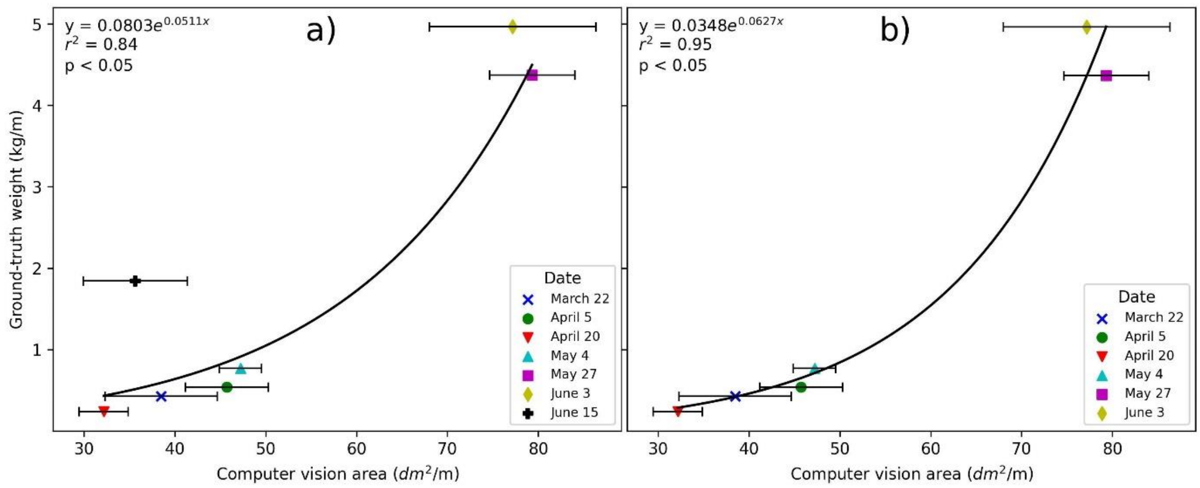

Fig. 13: a) Exponential relationship between computer vision area per meter (CVA)(dm^2/m) and ground-truth weight (GTW)(kg/m). b) Exponential relationship without data from field day 7 (June 15). Error bars show the standard deviation of CVA for each field day (n=6).

4 Discussion

Manual monitoring of kelp biomass is not sufficient to meet the future needs for accuracy and efficiency in upscaled kelp aquaculture. Hence, we aimed to investigate proof of concept for *in situ* biomass estimation of cultivated kelp, towards future automated monitoring of commercial kelp-farms. The concept we investigated was to collect RGB imagery of cultivated kelp, and apply manual annotation and computer vision techniques to detect and derive meaningful size information that could be used as a proxy for biomass. Area was used as proxy, hypothesized to show a strong relationship with biomass. Additionally, we investigated which environmental factors might affect the RGB imagery. Our work indicates that the concept is, in fact, promising as a tool to estimate biomass of cultivated kelp in the future. The concept fits in well with the emerging concept of Precision Aquaculture (PA), which aims to move aquaculture operations from manual and experience-based methods to more automated and knowledge-based methods based on targeted technology and automation principles (Føre & Alver, 2022). Size assessment using computer vision for kelp-farm monitoring is especially mentioned for PA, validating the state-of-the art and relevance of our work.

4.1 Effect of environmental factors on image quality

We measured phytoplankton biomass and turbidity throughout the field campaign to investigate whether they affected observed image quality, and consequently the accuracy of area detection derived from computer vision processing. Our work indicates that phytoplankton can explain, if not all, at least parts of the variation and trend observed in image quality. This is displayed by the fact that we found a significant relationship between the two parameters throughout the field campaign, with higher *FChla* yielding lower observed image quality, and vice versa. We further observed a green hue in the image frames on days with high *FChla* in later stages of the campaign, which, according to existing literature, is a normal result of phytoplankton blooms (IOCCG, 2000; Johnsen et al., 2009; Kjerstad, 2014). The correlation with previous work serves as a validation of our findings. Hence, phytoplankton blooms seem to have an important impact on the ability to collect underwater imagery of satisfactory quality.

Our work further indicate that turbidity might, in combination with phytoplankton blooms, have a negative effect on observed image quality. This is displayed by the exceedingly low image quality observed on April 20, when the turbidity and phytoplankton measurements were both high. Turbidity could not explain the variability, nor trend, in observed image quality the rest of the field campaign. However, this could be explained by the fact that turbidity levels were relatively low on field days, rendering the potential effect of turbidity somewhat inconclusive. Furthermore, we found indication that a notable portion of the high turbidity around April 20 might be attributed to high levels of suspended matter (TSM), indicating that TSM has a significant effect on observed image quality. Imagery from April 20 produced as somewhat more blue hue compared to the green hue observed later in the field campaign, on days with low turbidity and high phytoplankton biomass. These findings coincide well with existing literature, stating that a combination of phytoplankton bloom and high content of TSM result in a dark blue hue (Johnsen et al., 2009; Kjerstad, 2014). Furthermore, TSM represent the most importance substances for underwater scattering of photons, and is highly correlated with turbidity (IOCCG, 2000; Kari et al., 2017).

Therefore, we presume that a combination of phytoplankton blooms and high TSM levels render low observed image quality, but that TSM is of less importance in the studied area. The presumption is backed by literature, stating that the Frøya region, being located of the coast off Mid-Norway, is characterized as a highly productive region. (Fragoso et al., 2019; Fragoso et al., 2021). High primary production means relatively higher levels of phytoplankton. A different situation could possibly be identified in other bodies of waters, such as a more closed fjord system, where different compound composition could alter the underwater conditions (Johnsen et al., 2009). Absorption in general, and phytoplankton especially, seem to be the main driver of light attenuation in the Frøya region during spring. That being said, future research should include measurements of TSM, as well as cDOM, to fully understand the complex optical properties of water.

An interesting aspect in this regard, is that the primary season for phytoplankton blooms coincide with the primary growth season for cultivated kelp, namely the spring. Phytoplankton deplete macronutrients in competition with kelp, inhibiting kelp growth (Johnsen et al., 2020a). Moreover, they likely influence bryozoan settlement on the kelp, which consequently degrade the quality of kelp lamina and reduce the ability to grow (Førde et al., 2016; Njåstad, 2018; Winston, 1977). Considering the impact of phytoplankton on both kelp growth, biofouling and biomass monitoring, it seems apparent that phytoplankton biomass is one of the most important parameters to thoroughly understand and monitor in kelp farming. Furthermore, Frigstad et al. (2020) suggested the implementation of several parameters, including phytoplankton, for a more holistic understanding of light attenuation in the sea. All this points toward phytoplankton being a very important factor for several parts of kelp farming and, thus, representing a factor that is important to understand and monitor.

Measurements of light conditions was not conducted in our study. Yet, by observation of the sampled image data and derived area detections, we can surmise that ambient light did affect image quality. Incident sunlight did, in some cases, seem to help distinguish the kelp from the surrounding water, while in other cases, it seemed to overexpose the images, causing partial area detection. Shadows cast by the kelp from incident light, did in the later stages of the season, hinder or constrain full area detection. This was especially well displayed on June 15, where dark areas of the kelp due to shadowing, rendered significant partial area detection. Weather conditions are the main driver of ambient light variation in shallow waters (Preisendorfer, 1976) and, thus, similar problems have been experienced in other applications (Føre et al., 2018).

Our work indicates that range to the object of interest is important for sufficient image quality and resulting area detection. We observed that detection accuracy was better on imagery at closer range than longer range. On field day 3, area detection was successfully performed with satisfactory accuracy, despite a phytoplankton concentration peak resulting in suboptimal image quality. While on field day 5 and 6, processing rendered partial area detection under similar conditions. One notable difference between the imagery, was that imagery was sampled at longer range on day 5 and 6 due to the longer length of the kelp, indicating that range is a limiting factor to optimal sampling. The literature state that environmental conditions, especially light attenuation, limit the range at which data of satisfactory quality can be obtained (Johnsen et al., 2020b;

Sørensen et al., 2020). Other studies also indicate that quality of RGB imagery is limited by range. Kjerstad (2014) found that range was important for object detection, on account of lowered spatial resolution and light attenuation. Furthermore, this coincides Cavanaugh et al. (2021b), which found that RGB imagery collected with UAV render moderate detection accuracy (67 %). Artificial light might be a solution, although, as our work indicates, light attenuation is a limitation that might reduce the feasibility. Alternatively, choice of camera could be of importance to collect imagery of high quality. Camera type, field of view and spectral resolution are some of the important factors for image collection and should, thus, be considered.

To summarize, our work indicate that one will experience a trend towards lower image quality when sampling throughout the spring season, with variation mostly determined by phytoplankton blooms. High turbidity levels might further reduce observed image quality, although the importance is somewhat ambiguous. These findings are important to consider in future work. One possibility could be to adapt time of monitoring to periods with relative lower turbidity levels and between phytoplankton blooms, in order to collect higher quality imagery. Another possibility could be to understand the relationship between phytoplankton, turbidity and processing, towards developing methods to compensate for it. Similar challenges with image-based underwater monitoring are present for everyone operating in the marine environment. Our findings could therefore prove relevant beyond the scope of kelp farming.

4.2 Size information about kelp from underwater RGB imagery

Our work indicates that it is possible to detect and derive meaningful size information about kelp from RGB imagery. We successfully annotated kelp length from RGB imagery with high accuracy, indicated by the strong relationship between manual annotation and ground-truth measurements (r^2 = 0.96). Hence, our study serves as strong indication that size estimation of kelp from underwater imagery is a feasible method, coinciding with numerous studies applying manual image processing in ecology (Weinstein, 2018). Our study is the first, to our knowledge, to quantify size information of kelp, and comparing it with ground-truth measurements. The fact that we successfully derived accurate size information about kelp from RGB imagery, serves as important complementation to existing research. Previous studies has managed, with the use of machine learning principles, to derive detection of both wild and cultivated kelp from underwater RGB, as well as acoustic, imagery (Bell et al., 2020; Bewley et al., 2012; Stenius et al., 2022). Bell et al. (2020) found relevant results, in the sense that they managed to detect individual kelp juveniles based on underwater RGB imagery. With the use of deep learning models, they detected kelp with 91% accuracy and 7% error compared to human-supervised annotation. Bewley et al. (2012) found similar results, as they detected kelp from RGB imagery of the seafloor using supervised learning, with promising results on detection. Bell et al. (2020), additionally, showed promising first steps towards detection of kelp with acoustic imagery, coinciding with the findings in Stenius et al. (2022). Hence, the potential for kelp detection from underwater RGB and acoustic imagery is apparent, and our findings build on this by indicating that size information can be derived after detecting the kelp. A combination of our findings with the mentioned machine learning-based techniques is therefore an interesting way forward.

The strong relationship was observed between computer vision-derived area estimates and ground-truth length measurements (r^2 = 0.98), indicating that it is possible to derive meaningful size information about kelp by applying computer vision techniques on underwater RGB imagery. This coincides with the fact that underwater RGB imagery has already been successfully applied to estimate size of fish and other organisms in aquaculture (Saberioon et al., 2017; Zion, 2012). However, we found indication that observed image quality had significant importance for the accuracy of area detection. This was displayed by the fact that a relationship between observed image quality and accuracy of area detection was existing, with high accuracy derived from imagery of high observed quality, on March 22 (SR = 0.002 kg/m), April 5 (SR = 0.005 kg/m) and May 4 (SR = 0.009 kg/m). Coinciding, low accuracy was derived from imagery of low observed quality, on May 27 (SR = 0.426 kg/m), June 3 (SR = 0.317 kg/m) and June 15 (SR = 2.310 kg/m). Still, some degree of ambiguity was observed in the relationship, as April 20 yielded high accuracy (SR = 0.001 kg/m) from imagery of very low observed quality. This is an indication that observed image quality do not explain the whole feasibility for accurate area detection. We found indication that area estimates constantly underestimate the length of the kelp. Mathematically, the relationship between area per meter and mean length should be direct in this context. Underestimation can, in the later stages of the field campaign, be explained by partial detection of area due to the effect of environmental factors, as discussed above. This do, however, not explain the trend in earlier stages, which rather is affected by kelp movement due to wave action and currents. This coincides with Summers et al. (2022), as they had water movement introducing error to the results. As a result, this indicate that the investigated concept is not mature enough to estimate length directly without further investigation.

Our work indicates that RGB cameras mounted on or embedded in underwater vehicles is a suitable method for collecting imagery that can be used to derive meaningful size information about kelp from. By using a small-sized ROV we were able to sample data at close range of the kelp, rendering data with high spatial resolution. Additionally, the platform can be operated by one person, keeping the operational costs low. Our findings coincide with other fields of marine studies employing mini-ROVs with success to accurately collect detailed optical information (Føre et al., 2018; Kelasidi et al., 2020; Nevstad, 2022; Summers et al., 2022). On the other hand, recent studies have shown that kelp can be successfully monitored at larger spatial scales (Cavanaugh et al., 2021a), with the use of available satellite imagery to map and monitor wild (Bell et al., 2020; Tonion & Pirotti, 2022) and cultivated kelp (Jin et al., 2023; Zheng et al., 2019) representing the most widespread and mature methods. Furthermore, automated detection of kelp canopy with UAV has shown that RBG imagery render lower accuracy (67 percent) compared with multispectral imagery (93 percent) (Cavanaugh et al., 2021b). Yet, the sampling methods applied in those studies have been limited to the study of whole farms or canopy-forming kelp from high altitudes, meaning that satellite imagery is highly restricted in temporal and spatial resolution, and AUV imagery is highly restricted in spatial resolution. These methods will have much lower spatial resolution, so maybe not useful for biomass estimation at less than farm scale (or accurate estimation at all). Our concept is consequently an important innovation for continuous and detailed kelp biomass monitoring.

Image sampling with ROV as sensor-carrying platform has considerable constraints, such as the need for human operation, limited battery time and tether length. Consequently, a ROV can usually only collect data at a small spatial scale (Sørensen et al., 2020), as it happened in our study, since we only collected data from small sections of a cultivated kelp line. Thus, extrapolation will be required to estimate biomass for the whole line, or multiple section of the farm. To be able to extrapolate for a whole farm, other types of mobile platforms equipped with cameras should be used on an autonomous mode.

4.3 Computer vision-derived area estimation as a proxy for biomass

In our work, computer vision-derived area estimation was used as proxy to develop a relationship for biomass estimation. This relationship showed considerable promise for robust estimation of cultivated kelp biomass at a broad temporal scale, spanning from mid-March to mid-June. This was displayed by the strong relationship ($r^2 = 0.95$) found between derived area estimates and ground-truth weight measurements, both for kelp of different sizes and under differing conditions. Using area as a proxy for biomass left only 5 percent ($r^2 = 0.95$) of the variation unexplained. There is a number of relevant studies that provides methods for estimation of terrestrial crop biomass using RGB imagery and computer vision techniques. Walter et al. (2018) found a strong relationship ($r^2 = 0.79$) between estimated volume and ground-truth biomass of wheat, using consumer level RGB cameras and processing software. Bendig et al. (2014) reported a strong relationship when using estimated plant height as a proxy for fresh ($r^2 = 0.81$) and dry biomass ($r^2 = 0.82$), using RGB camera on a small UAV. These studies provide indication that our findings are credible, and that the applied method is in fact feasible, using readily available and affordable technology with a number of documented applications, both for terrestrial and marine environment. The fact that area estimates showed a linear relationship with length, and exponential relationship with weight, serve as a validation of the feasibility of using area as a proxy for biomass. This is because our ground truthing, as well as previous studies (Gerard, 1982), show that length and weight of kelp has an exponential relationship. Consequently, our results indicate that a model using area estimates as proxy for biomass can be further developed and eventually applied to accurately predict kelp biomass *in situ* throughout the cultivation season.

We found that using area estimation as proxy for biomass estimation, had the advantage of simplifying both data collection and processing, as imagery is only needed from a single side of the kelp. Volume is often applied as a proxy for biomass, given the close relationship between the two traits. This is especially prominent in terrestrial crop monitoring (Olsoy et al., 2014; Walter et al., 2018). However, significant research is existing with using 2D proxies. Bendig et al. (2014) used plant height for modelling biomass of barley crops, yielding promising results. Our findings also coincide with the findings of Viazzi et al. (2015), de Verdal et al. (2014), Balaban et al. (2010) and Zion et al. (1999), which all used area estimation as proxy for biomass of fish. They found strong relationships ($r^2 = 0.99$), ($r^2 = 0.963$), ($r^2 = 0.987$) and ($r^2 = 0.954$), respectively, when comparing area estimates and ground-truth measurements. Some of the strong relationship might be explained by the fact that shape of individual fish is closely related to biomass. Cultivated kelp hanging along a line has no shape that display apparent relation to the biomass, so the strong relationship identified in our work was somewhat unexpected. Anyway, our findings in comparison with other studies, indicate that area is a promising proxy for biomass estimation of kelp, as it is both robust and easy to collect imagery for. The opportunity to estimate biomass of cultivated kelp based on the investigated concept, is a significant improvement compared to today's manual methods. Therefore, our findings lay the foundation for an initial understanding of the relationship between biomass and possible proxies, indicating the feasibility of a model for biomass estimation without directly estimating the third dimension.

Further developing a model for kelp biomass estimation using area as proxy, seems like a promising path. It simplifies the sampling to use a one-dimensional proxy, as imagery only has to be collected from one side. Statistical uncertainty will be negligible on farm-level, as sampling size will be much larger.

4.4 Future perspectives for biomass estimation of cultivated kelp

The findings in our study can be built upon by quantifying and considering more of the variables affecting the relationship between area and weight. Olsoy et al. (2014) built on their model for estimation of shrub biomass by considering temporal, seasonal change, and spatial, different sites, variables, resulting in marginally stronger models. For a further development of a model based on our preliminary findings, it can be relevant to look at environmental factors, as indications are strong that water current, phytoplankton, turbidity and light conditions greatly impact the robustness of the concept, coinciding with Summers et al. (2022). A possible concept improvement could be to equip relevant sensors on the sensor-carrying platform or in strategic positions around the farm. The collected data could be feed into growth models based on known and presumed properties of the cultivated kelp (Broch & Slagstad, 2012; Peres et al., 2021; Trancoso et al., 2005) and, thus, serve as a tool for indirect calibration and validation of our model. Consequently, potential is existing in combining established and generalized growth models with continuous biomass monitoring, towards gaining holistic control of growth development and. Alternatively, one could use a more direct approach. Kjerstad (2014) suggested that quantification of inherent optical properties (IOPs) of the water where monitoring is conducted, could be applied in pre-processing steps to render image data with more homogenous image values between frames. This could potentially allow for easier object detection and segmentation. However, the discussed aspects will certainly add complexity to the method and, thus, a relevant question is whether data of satisfactory quality can be obtained without adding unnecessary complexity. As stated by Johnsen et al. (2020b), careful consideration of sampling range and choice of sensor can go a long way to compensate for environmental conditions. Hence, going forward, a key consideration is to evaluate the value of increased accuracy and effectiveness, against the drawbacks of adding complexity to monitoring.

The algorithm developed in our study segmented kelp based on color with high accuracy ($r^2 = 0.95$). However, it demanded individual parameter tuning for different conditions and, thus, is still highly dependent on human intervention. The method is therefore readily available, yet currently low throughput. The goal is to enable us to surpass the human intervention, but for that we need to investigate how to apply computer vision, and then build models for automation in the future. Therefore, it seems apparent that a key next step will be to automate the processing stage through machine learning (ML), enabling the creation of algorithms that can learn from data and make predictions based on observed patterns (Yan, 2022). Increasingly advanced ML models are being developed and deployed in a number of applications, also underwater. Saberioon et al. (2017) and Zion (2012) has conducted a thorough mapping of applications of ML models in aquaculture. Promising research has shown that techniques for monitoring of fish is available and robust. In addition, similar techniques can be used in, for example, early detection of net wear and damage in fish aquaculture (Kelasidi et al., 2020). Aforementioned studies (Tonion & Pirotti, 2022) have applied ML techniques for large scale aerial mapping of wild kelp and whole kelp-farms, although higher spatial resolution research is more limited. That being said, preliminary analysis by Bell et al. (2020) were able to detect kelp juveniles underwater with 91% accuracy and only 7% error, using ML techniques on RGB imagery, showcasing the considerable potential of automated processing. Still, restrictions of the method applied in Bell et al. (2020), is that they rendered no quantifiable estimates from the processing or ground-truth measurements. By combining a similar detection algorithm with the area estimation algorithm developed in our study, automated kelp area estimation is feasible. In order to upscale this method, larger sample datasets can be used as calibration and validation data, as to reduce the statistical uncertainty and provide cross- validation of the results (Bendig et al., 2014). As a result, accurate and effective large-scale processing of image data can be developed in the near future.

As RGB imagery seem to have some limitations related to the effect of environmental factors, future research could investigate the use of other sensors, both optical and acoustic. Of them, optical sensors such as multispectral and hyperspectral imagers are of interest. Cavanaugh et al. (2021b) indicated that multispectral imagery might be more robust than RGB imagery. They found higher detection accuracy of canopy forming kelp with multispectral imagery (93 %) versus RGB imagery (67 %). The relevance is that our results using RGB imagery is promising, yet with some limitation in area detection. So, perhaps, multispectral imagery is an aspect to consider in the future. Hyperspectral imagers have been applied vastly and successfully for detection of wild kelp (Johnsen et al., 2016; Mogstad et al., 2019; Summers et al., 2022; Volent et al., 2007). However, when it comes to cultivated kelp, research is more limited.

We tested high spatial resolution sampling of imagery of kelp at a broad temporal scale, as the first study to do so. Our work indicates that underwater methods are necessary to acquire image data of satisfactory quality. Yet, the study was conducted at a small spatial scale. Hence, going forward, we anticipate that our concept can be used as the foundation to upscale image sampling to a large spatial scale using automation, eventually covering whole kelp-farms. For example, (Stenius et al., 2022) developed a methodology where they deployed an AUV to monitor a whole kelp-farm autonomously and continuously. In their small-scale scheme, an AUV followed pre-programmed or self-detected sampling patterns based on the outline of the farm and, thus, enabling sampling of detailed image data of a whole kelp-farm throughout the cultivation season. As the AUV navigates along the cultivation lines with the help of sidescan sonar, using area as a proxy for biomass seems like an apparent option. In addition to being employed as control sensor, the sonar has the ability to collect signals from the kelp, possible to derive size information from (Bell et al., 2020). Still, none of the aforementioned studies, has yet been able to quantify size estimates of the kelp, nor collect ground-truth measurements for validation of the estimates. This indicates that the findings in our study is highly relevant. In the future, upscaling of monitoring can be achieved by combining a refined version of the platform scheme in Stenius et al. (2022), with a refined version of the image sampling and processing in our study. Other possibilities could be moving the cameras along strategically structured cables throughout the farm, removing the need for underwater vehicles. Perhaps the cameras do not need to move around at all, but rather be placed in fixed positions where sufficiently coverage of the kelp can be achieved to obtain accurate estimates. Ultimately, the goal of the technology and method should be to optimize accuracy of biomass estimation, meaning providing sufficiently monitoring, while at the same time minimalize operational costs, risks and complexity.

5 Conclusion

We found that the ability to capture imagery of high quality is significantly related to phytoplankton biomass in the water, with blooms degrading the observed quality. Furthermore, our work indicates that high turbidity levels, possibly caused by suspended matter, further degrade image quality. Still, this effect seems less important in the studied area. Additionally, our work indicates that incident light is of some importance to the image quality. Given the importance of underwater conditions, especially phytoplankton, towards several aspects of kelp farming, we propose that it is of key importance to understand and monitor in the future.

Our work indicate that low image quality can lead to lower accuracy of area detections, through partial detection. The accuracy of area detections is related to the quality of the imagery used in processing. However, detection accuracy is also dependent on factors such as range between camera and the kelp, and kelp movement due to wave action and currents.

Underwater RGB imagery provides the opportunity to derive quantifiable size information of cultivated kelp with high accuracy. Both manual length annotation and computer vision-derived area estimation displayed promising results, indicating that robust biomass estimation is possible. RGB cameras on an underwater vehicle can provide imagery of high spatial resolution, a prerequisite for accurate biomass estimation. Hence, we propose that future biomass monitoring is based on upscaled and automated collection of underwater RGB imagery.

Our work further indicate that computer vision-derived area estimation can serve as a robust proxy for biomass of cultivated kelp. Area and biomass displayed a promising relationship, that can be further validated by upscaled image collection and automated processing.

This novel concept provides important first step findings and estimates towards developing an automated biomass monitoring scheme in kelp aquaculture. Based on our work, we predict a future scheme for farm-scale biomass monitoring based on autonomous data collection and real-time processing. This will be based on state-of-the-art technology and machine learning principles. With new technological advances, a sea of opportunities will be unlocked in the coming years.

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