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Autonomous quantification of kelp biomass on offshore aquaculture installations using side scan sonar

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In recent years, global demand for macroalgae has grown as a sustainable food resource, potential tool for marine carbon dioxide removal (mCDR), and various pharmaceutical and cosmetic applications. Traditional commercial macroalgae monitoring is time-, labor-, and cost-intensive, with manual inspection limited to surveying small areas and shallow depth ranges. While advanced acoustic technologies such as side scan sonar (SSS) have long been established as a tool within the fishing industry, sonar use in commercial macroalgae aquaculture has been limited. Sonar allows for broad scales of qualitative and quantitative measurement and thus will be an important component in autonomous monitoring of offshore aquaculture installations to assess infrastructure integrity and crop growth. Here, we present a method for the analysis of side scan sonar observations on a commercial macroalgae installation. We utilize geometric principles to estimate kelp height on each farm line and approximate standing biomass. Our algorithm is applied to a commercial kelp installation offshore of Santa Barbara, California, validated with *in situ* measurements. Our work provides a stepping stone for increasing efficiency and informed decision-making of large-scale kelp installations, decreasing cost and labor for farmers in the face of a higher market demand.

KEYWORDS

aquaculture, giant kelp, macroalgae, side scan sonar, sonar

1 Introduction

Macroalgae aquaculture is expected to grow significantly in the coming decade as technologies for marine carbon dioxide removal and ocean-based biofuel production emerge (World Bank, 2023). Such industries could require aquaculture installations that span hundreds of square kilometers in order to be commercially viable (Bostock et al., 2010). Consequently, new quantitative tools will need to be developed for efficient macroalgae growth and harvest at these scales (e.g., Fischell et al., 2022; Kartveit et al., 2022). And, because farm operations could be situated in offshore waters, autonomous technologies capable of farm surveys will play a significant role in the initial growth and successful maturation of this industry.

There are two closely related tasks that a robotic platform can accomplish on a macroalgae farm with present technologies: crop monitoring and infrastructure inspection. Both tasks are related in the sense that a farm operator has a need for regularly surveying the entire farm to determine how well the crop is growing, as well as ensuring that farm infrastructure (consisting of anchors, lines, and floats) is intact. The latter need is also likely

to be a regulatory requirement or liability-mitigation strategy, so that an operator can demonstrate that debris, which could foul other offshore installations (such as wind arrays or oil platforms) or entangle wildlife, has not been released into the ocean. For example, numerical modeling has shown that properly tensioned farm lines reduce the risk of whale entanglement (Gitelman et al., 2024) and so regular surveys to ensure the correction tensioning of a farm could be a monitoring requirement.

Here, we develop a method for assessing infrastructure integrity and quantifying crop growth on a giant kelp (*Macrocystis pyrifera*) farm in the waters of southern California using side scan sonar. The goal of this methodology is to create *in situ* kelp biomass estimates with sufficient spatial resolution and fidelity to enable growth estimates using repeat surveys spaced days to weeks apart. The methods are generalizable to any algal species that will produce an acoustic return. Likewise, the methods are applicable to any offshore installation in deep water, such as wind or hydrocarbon extraction, where infrastructure inspection and monitoring over large areas is needed. While satellite retrievals will play an important part of kelp farm monitoring, remote sensing is unable to observe initial growth stages prior to surface canopy development or provide observations of subsurface farm infrastructure. Additionally, clouds regularly obscure portions of the coastal ocean (regions amenable to kelp growth) for weeks on end, making remote sensing a less effective solution for certain tasks.

We first introduce the principles behind the method in §2. Section 3 revisits this in a specific application at a kelp farm, combing details of the analysis steps and results. A summary and discussion are contained in §4.

2 Method introduction

2.1 Sonar geometry and constraints

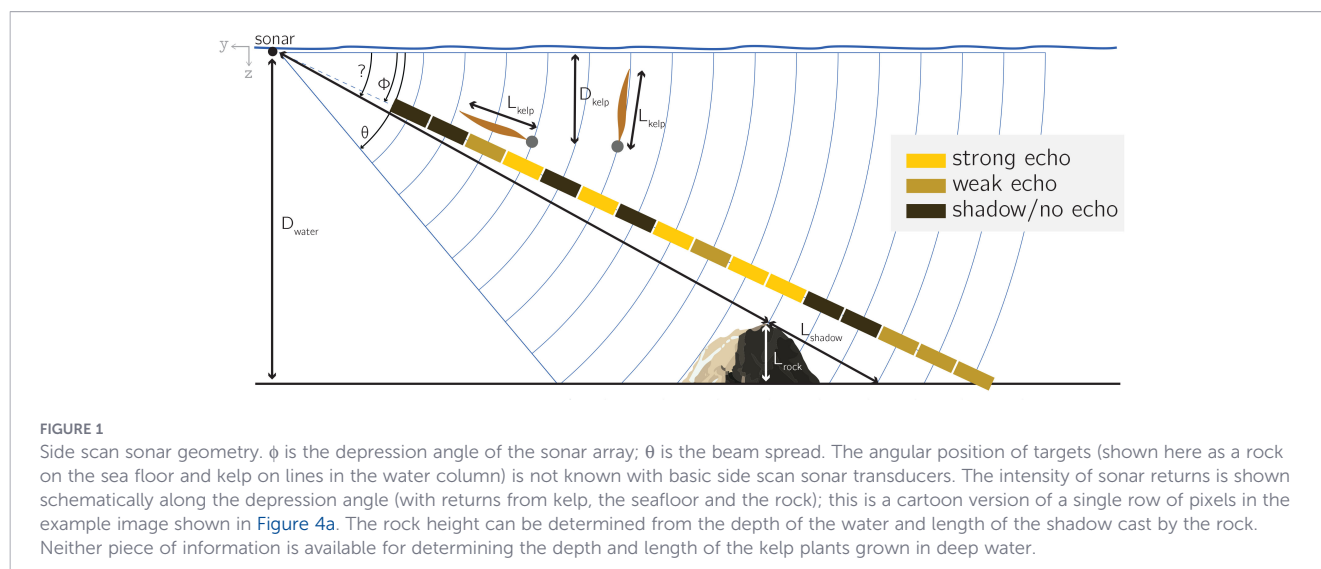
Side scan sonar is ideal for surveying kelp farms because its large swath-width enables rapid coverage of large areas compared to other sonar configurations. Several aspects of the geometry of the sonar

pulse and subsequent return are relevant here (Figure 1) and we will adopt (x, y, z) as orthogonal coordinates aligned with a *forward-port-down* coordinate system relative to the boat. We seek to place sonar returns into a georeferenced east-north-up (E, N, U) coordinate; defining $U = 0$ at the water surface, we report depth $D = -U$ for convenience. A typical commercial-off-the-shelf side scan sonar consists of starboard- and port-facing transducers that are mounted on the keel of a boat or towed body. The leading edge of the transducer is an active transmitter that emits a pulse; timed echo returns are received in the trailing edge of the array. Sonar pulses are emitted in the (y, z) plane as the boat is moved along the x -axis.

The sonar transducer array has a fixed depression angle ϕ from level (which is nominally parallel with the y -axis). The acoustic pulse is very narrow in the x -direction, but spreads radially in the y - z plane with spread angle θ , which is typically 40° – 50° . The acoustic echoes of targets within this spread angle, however, are only known in a radial coordinate system based on the distance to the transducer and the sum of ϕ and the instantaneous roll of the boat. (For simplicity, we ignore pitch and yaw in this discussion).

To convert sonar returns from the radial distance along the depression angle into a (y, z) position, traditional analysis of side scan sonar relies on knowing the distance from the transducer to the sea floor, combined with the length of the shadow created by a sonar target. The ambiguity of the target's angular position within the beam is resolved through trigonometric identities. At issue for deepwater applications, however, is that there are no bottom signal or shadows with which to constrain the geometry. And, even in situations where the bottom is present, shadows from kelp and farm lines may be too fine for accurate calculations. A major challenge to the accurate quantification of kelp biomass is that plants of identical length that lay in the radial and angular directions will appear to be different lengths in the subsequent sonar image, as illustrated in the colored bars in Figure 1.

We present here a method for resolving this geometric ambiguity through the combination of specific survey routes and image processing techniques. The result is a three-dimensional reconstruction of the farm and its crop that can be obtained with a single platform using commercially-available sonar.



Methods have been developed for three-dimensional reconstruction of targets using sonar returns but they rely on using multiple sensors or receivers. For example, [Hunt and Kirmani \(2019\)](#) suggest solving this problem by using two side-by-side transducer elements to find the z-coordinate or using three two-dimensional representations (of which two must know the z-coordinate) to constrain the three-dimensional position. Problematic to this approach is that the true angle to the target is not known from a single-transducer sonar array. [Donly and Trantham \(2022\)](#) suggest creating stereoscopic images using two separate sensors on two platforms. This approach is operationally challenging and more expensive owing to the need to acquire and maintain two platforms. Notably, neither of these references present proof-of-concept data or specifically address challenges of biomass estimation.

Side-scan sonar (SSS) has proven to be an effective tool for estimating biomass in coastal marine environments, particularly in areas that are challenging to sample using traditional methods. For example, [Degraer et al. \(2008\)](#) demonstrated the utility of high-resolution SSS to quantify the growth and distribution of *Lanice conchilega*, a tube-building polychaete, to overcome limitation of point sampling of the species' patchy spatial distribution. SSS is widely recognized within fisheries science as a valuable technique (cf. [Ridgway et al., 2024](#)). As we envision for its applications in aquaculture, it has also been used effectively for gear detection ([Fulton et al., 2023](#)) and for monitoring the health of artificial reefs ([Ali et al., 2022](#)). SSS also proves useful when waters are murky and visibility is low, creating high resolution images similar in quality to optical images ([Li et al., 2024](#)).

Extracting relevant information from sonar datasets, however, remains a significant challenge. Manual data review is time-consuming and labor-intensive, leading to increased interest in automated analysis methods. In particular, artificial intelligence (AI) and machine learning (ML) techniques are being developed to support automated feature extraction ([Fulton et al., 2023](#); [Ridgway et al., 2024](#)); [Vatnehol et al. \(2018\)](#) illustrate the adaptation of SSS for fisheries management by developing an algorithm to detect patterns in fish schools. As these technologies advance in fisheries applications, there is a growing opportunity for aquaculture

installations to adopt and benefit from similar sonar-based methods and analytical efficiencies.

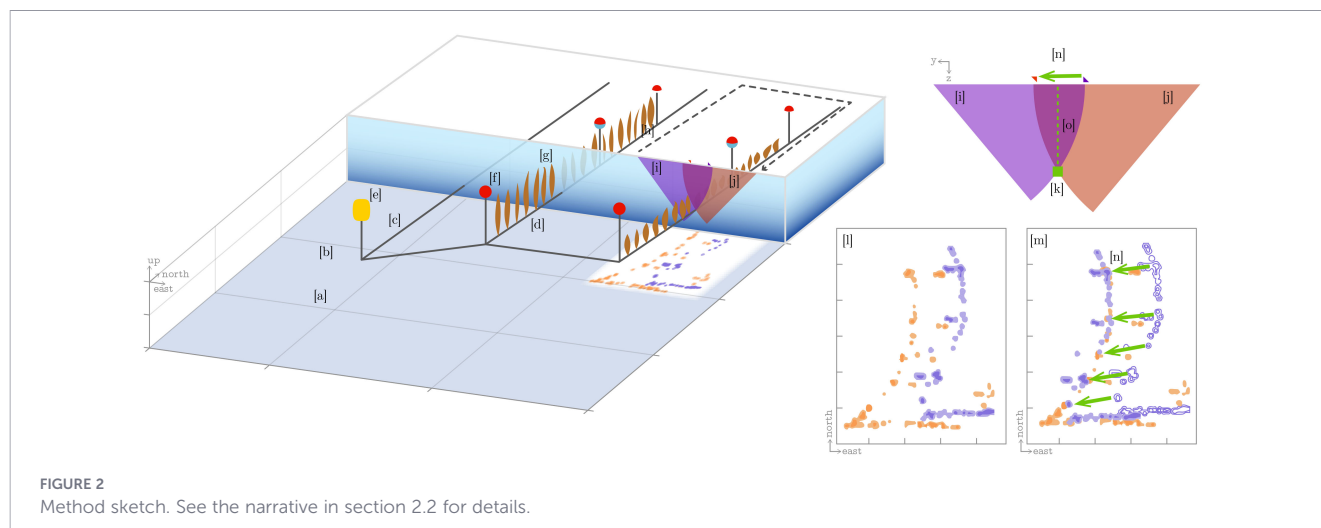
The method we describe herein uses a single-element side scan sonar transducer, requires no careful syncing between multiple sensors, and operates independently of the bottom. The key technological advance is the procedure by which we find the depth by aligning two horizontal images of kelp farm locations. It is a flexible method for three-dimensional assessment of underwater environments and is particularly well-suited to the survey needs of the large areas typified by commercial-scale aquaculture installations.

In the next section, we describe the image processing technique used to determine the ($E, N, U = -D$) position of objects in the farm. The next section provides methods and results from a kelp farm. Analysis methods specific to this farm configuration and *Macrocystis* crop show how resolving the crop geometry yields biomass estimates.

2.2 Method of three-dimensional reconstruction via image rectification

Lettering in square brackets in this section refers to annotations in [Figure 2](#). The goal is to determine the three-dimensional structure of the farm [a-f] and its crop [g]. The farm consists of lines [a-d] and floats [e-f]. In this sketch, anchor lines [a] descend to the seafloor at the perimeter of the farm structure, with perpendicular lines [b-c] forming a subsurface lattice that is supported by large floats [e]. Cultivation lines [d] are strung between this outer tensioning structure, supported by multiple smaller floats [f]. Clearly other farm configurations are possible; the basic feature of interest in this installation is a cultivation line that is suspended at a constant depth. For *Macrocystis* in Southern California waters, this depth is roughly 10 m.

Each line is surveyed twice using a side scan sonar mounted to a GPS-equipped surface vessel, once each from alternate sides, in a path [h] nominally parallel to the cultivation line. This method results in alternate views [i-j] of the same target [k]. As outlined in the preceding section, the z-position of a target appearing in the sonar return is not known.



The solution is to first produce two images in the (E, N) plane, shown overlaid on one another as purple and orange in [1]. The images are produced by plotting the upper $\sim 0.1\%$ of returns in their (E, N) position, projected from the radial distance from the boat, corrected for the global position and orientation (including yaw and pitch) of the sonar to a flat surface on $z = U = 0$. By taking the most significant returns, we allow the image rectification process to ignore transient artifacts, such as fish, in the subsequent steps. Note that the orange and purple positions in [1] are not true locations owing to the uncertainty of the position of the return within the spread angle.

These two images, which share a common resolution and geographic bound, are then aligned [m] using image processing techniques to find the non-uniform displacement matrix [n] between the two images (the shift in the (E, N) plane necessary to align common features). This displacement matrix provides the missing information that allows the depth [o] of the target to be determined via the intersection of two circles. The non-uniform displacement aids in removing potential artifacts from differential farm motion between the two images.

The equations for the intersection of two circles in the (y, z) plane are

$$y_1 = (Y^2 + R_B^2 - R_O^2)/2Y \quad (1a)$$

$$z_1 = [4Y^2 R_B^2 - (Y^2 + R_B^2 - R_O^2)^2]^{1/2}/2Y. \quad (1b)$$

The origin of circle O , with radius R_O , is at $(0, 0)$; the origin of circle B , with radius R_B , is at $(Y, 0)$. The position of their intersection for $z > 0$ is located at (y_1, z_1) and the distance between the two origins is $Y = y_1 + y_2$.

Equations (1) are used to find the depth of a sonar target by plotting sonar returns O and B on a line $y, z = 0$. The sonar sources are located at $S_O = (0, 0)$ and $S_B = (Y, 0)$. Because only the radial distance to the target is known, the points O and B are plotted at $(R_O, 0)$ and $(R_B, 0)$, respectively. In this representation, the distance Δy between O and B is known only because we have stipulated here that these two sonar returns are from the same target. The image registration process serves to link points in Figure 2[i] such that $Y = R_O + R_B - \Delta y$ can be found. With Y known, Equation 1b can be evaluated to find the depth. Though described here along a line y for

clarity, Equation 1a can be used to correct the position of the point in the (E, N) plane.

Conceptually, the approach to finding the unknown distance between the opposing sonar scans is straightforward. The plotted positions $O = (E_i, N_i)$ and $B = (E_j, N_j)$ are always at the maximum horizontal distance from their respective sonar sources; deeper returns should be plotted closer to the sonar (but of course this information is not known *a priori*). In the uncorrected plot [1], orange will always be plotted west of blue (in our chosen coordinate system) and the distance between point pairs can be interpreted visually as the depth of the target. The quality of the solution, then, is dependent upon correctly matching up pairs of points.

In the following section we present results from a field trial testing this method. Although other image registration functions exist, we focus here on evaluating the tunable parameters of a single method in order to illustrate the general approach.

3 Demonstration of method

3.1 Farm configuration

Data were collected on an offshore mooring installation (hereinafter, “the farm”) operated by Ocean Rainforest Inc. in 2024. The farm was located ~ 3 nm south of Santa Barbara, CA (34.334°N , 119.707°W) on the continental shelf with a water depth of 75 m over a gently sloping, sandy bottom (Figure 4). The long axis of the farm consisted of two ~ 1 -km-long east-west lines running parallel to one another, separated by ~ 150 m (Figure 4). Each backbone line was anchored at the ends of the line and suspended in the water column at a target depth of 10 m by 12 large surface floats spaced ~ 60 m apart. North-south backbone lines connected each pair of floats; these lines also extended out of the farm to anchors at the sea floor. Each rectangle section between the east-west and north-south lines supported two cultivation lines. The nominal spacing between cultivation lines and the parallel north/south backbone lines was 20 m. Each cultivation line was approximately 110 m long. At this installation there were 22 cultivation lines, providing ~ 2400 m of cultivatable line. This installation is similar to the farm configurations described in Bak et al. (2018) and St-Gelais et al. (2022).

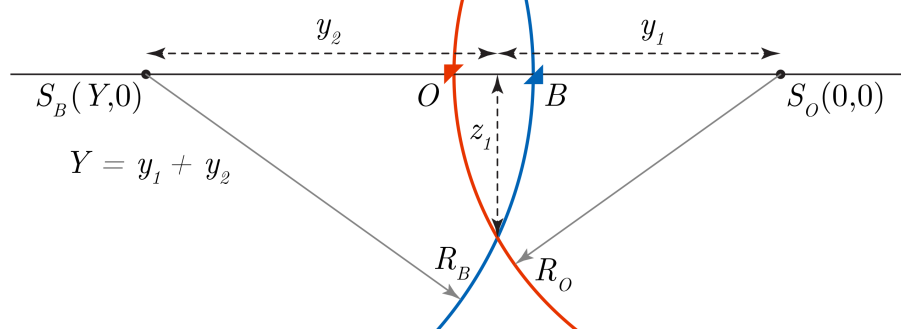
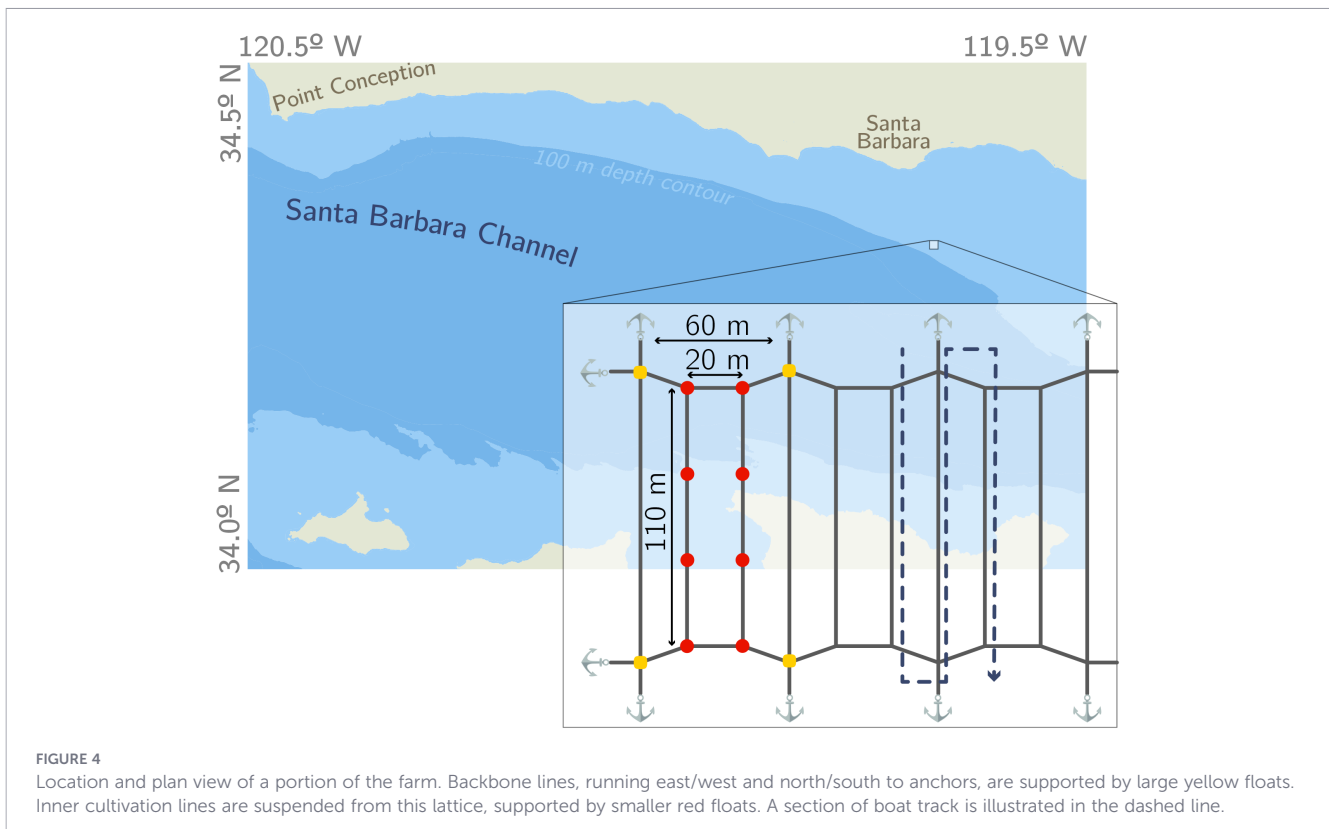


FIGURE 3

Intersection of two circles. Positions S_i represent two sonars; an object is detected at the intersection of the two circles. The distances from the sonars to the object are the radii R_i . O and B show the position of the object inferred from each sonar without knowledge of the object depth, z_1 .



3.2 Side scan sonar data collection

Farm survey routes were planned using a Python script that optimized a sequence of mow-the-lawn waypoints based on the configuration of the farm. The mow-the-lawn spacing provides for each line to be imaged twice, once from each side. The sonar swath width was set such that the distance to a line is roughly similar in each image/alternate direction (i.e. we used a narrow swath so that both images are produced from similar geometries). The four bounding corners of the farm backbone lines were determined manually via ship-mounted GPS. The nominal spacing of the farm grow lines was $\Delta x = 20\text{ m}$ and so the east-west distance was divided into $N = L/\Delta x + 2$ survey segments, where L is the average distance between the eastern and western floats. (This description refers to cardinal directions owing to the east-west orientation of the farm; it is trivial to determine the spacing and survey orientation for any rectangular region.) The additional two segments are to ensure that the survey starts outside of the farm bounding box, so that the eastern and western-most edges are imaged. Likewise, the along-cultivation-line segments (oriented north-south) were started one line spacing Δx prior to the line and concluded one line spacing past the end; this ensures that the entire grow line is imaged and also allows for the junctions of the floats and lines to be imaged.

We used a Blue Robotics BlueBoat for surveying the farm. The boat was tasked to work up-current, traversing the line at the down-current end of the farm first. (Though not absolutely critical for BlueBoat's electric motor, this choice is deliberate so that bubbles created by the boat do not appear in subsequent neighboring surveys, which is a major issue for gas-powered where the exhaust creates a curtain of tiny bubbles that can contaminate the image.) A

pair of Cerulean Omniscan 450 kHz sonars were mounted on either side of the boat. The sonars were mounted nominally 15 cm below the water surface, with a 25° depression angle and 50° beam spread. Surveys were conducted at a speed of 1.0 m/s. Collecting data at 5 Hz, this produced an along-track resolution of 20 cm. The horizontal beam spread is 0.5°, resulting in an along-track pixel size of 8.7 cm at 10 m range and 26 cm at 30 m range. The swath range was set to 35 m; the Omniscan 450 allocates 1200 bins for memory, yielding a cross-track resolution of 2.5 cm.

3.3 *In situ* biomass observations

In-situ measurements of kelp stock were taken by Ocean Rainforest, Inc. (ORI), on roughly two-week intervals from late June through September 2024. Each line was sampled in three 1-meter sections, each representing 1/3rd of the line. Within each sampled section the individuals were counted and the three longest individuals were measured. Once plants reached over 50-cm length in the sampled 1-meter section, all plants in the one-meter section were removed in order to measure biomass weight. Weight was taken as both wet and dry. To be consistent with other reports on kelp length-to-biomass ratios (Rassweiler et al., 2018; Reed et al., 2009), we use the wet weight when comparing biomass.

3.4 Sonar observations

For narrative purposes we will refer to the process of collecting sonar data as “imaging”, as the acoustic returns are used to create visual images of the farm. A representative “raw” image of a section of the farm is shown in Figure 5b. This is a traditional waterfall

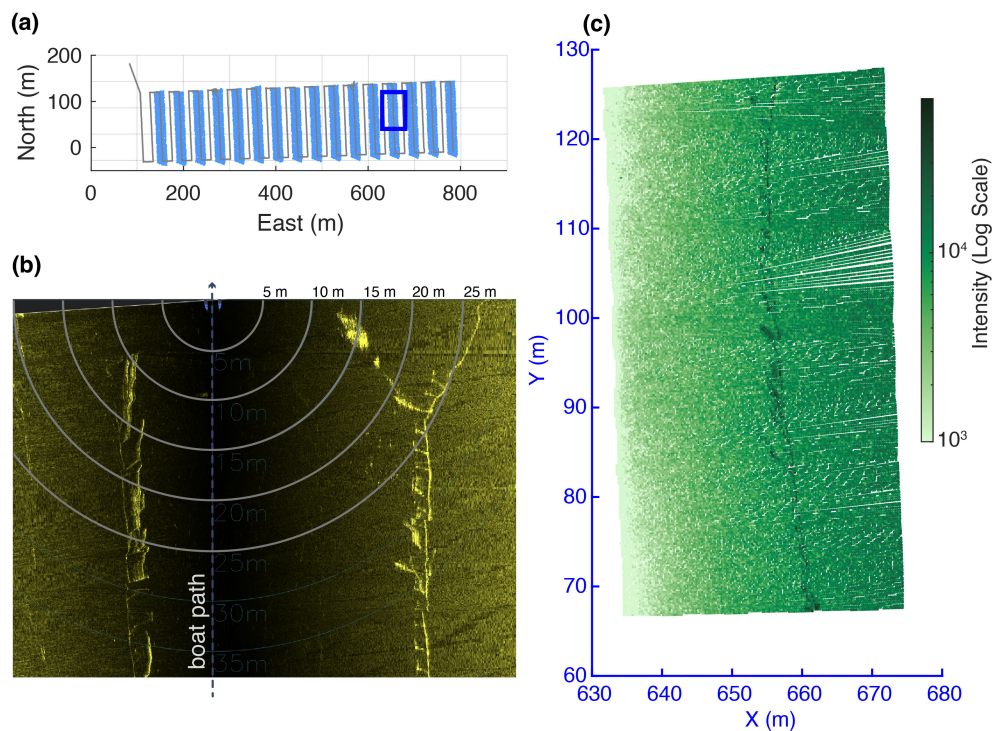


FIGURE 5

Example of sonar return geo-registration. **(a)** The boat track across the farm, showing location of all east-looking sonar pings. **(b)** The native sonar view display, with kelp evident in the sonar imagery. Range circles have been augmented for clarity. **(c)** Georeferenced sonar pings, as a function of the local farm coordinates. The section of line to the east side of the boat in **(b)** is shown in **(c)**, with the general location denoted by the blue box in **(a)**.

representation of side scan sonar data. The boat track during this survey and the location of the representative image is shown in Figure 5a. The cultivation line is evident in Figure 5b, as are backbone lines and kelp plants. The starboard portion of our version of this image (Figure 5c) is plotted in farm-relative coordinates, with an arbitrary origin to the southwest of the farm. The difference between the two visual representations is that our version uses scattered points whereas the SonarView representation interpolates between points and plots newer data over older data.

3.5 Image registration to biomass

As Figures 5c illustrates, the position of any individual data point is the result of the orientation and position of the boat at the time of the sonar ping. We use these positions to index into a two-

dimensional array (which can be displayed and manipulated as an image) of the farm at a desired resolution; in this study we use one-meter bins (or pixels). This binning process is performed separately for eastward- and westward-looking data to produce two arrays (or images). A representative eastward-looking image of the farm is shown in Figure 6a, but only the top 0.1% of pixels based on signal intensity are plotted. (Signal intensity is corrected for acoustic decay with distance before binning.) Figure 6b shows the corresponding westward view of the region. These two sets of data are shown overlaid on one another in Figure 6c, so that the need for the image registration is apparent.

The east and west images can be aligned using image registration tools. In this case, we used `imregdem` (The MathWorks, Inc., 2024). This function is an implementation of the method described in Thirion (1998) which finds the non-uniform displacement field

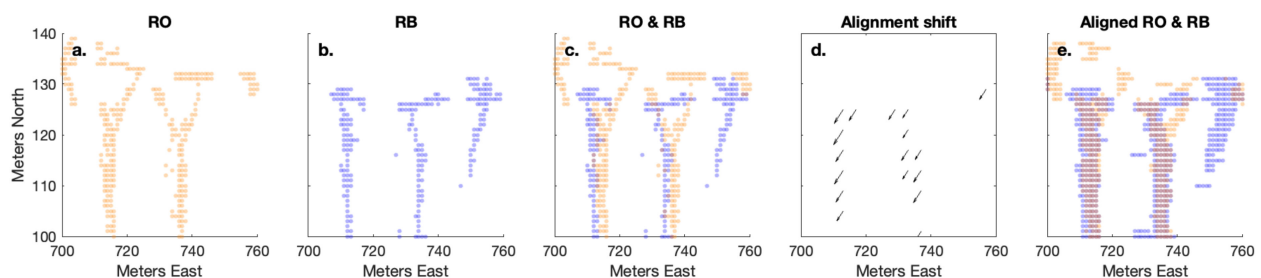


FIGURE 6

Example of the **(a)** east-looking and **(b)** west-looking views of sonar. **(c)** Both views plotted together. **(d)** Quivers illustrating direction of alignment. **(e)** Results after registration and dilation. Though difficult to see in this representation, the pixels still contain intensity information.

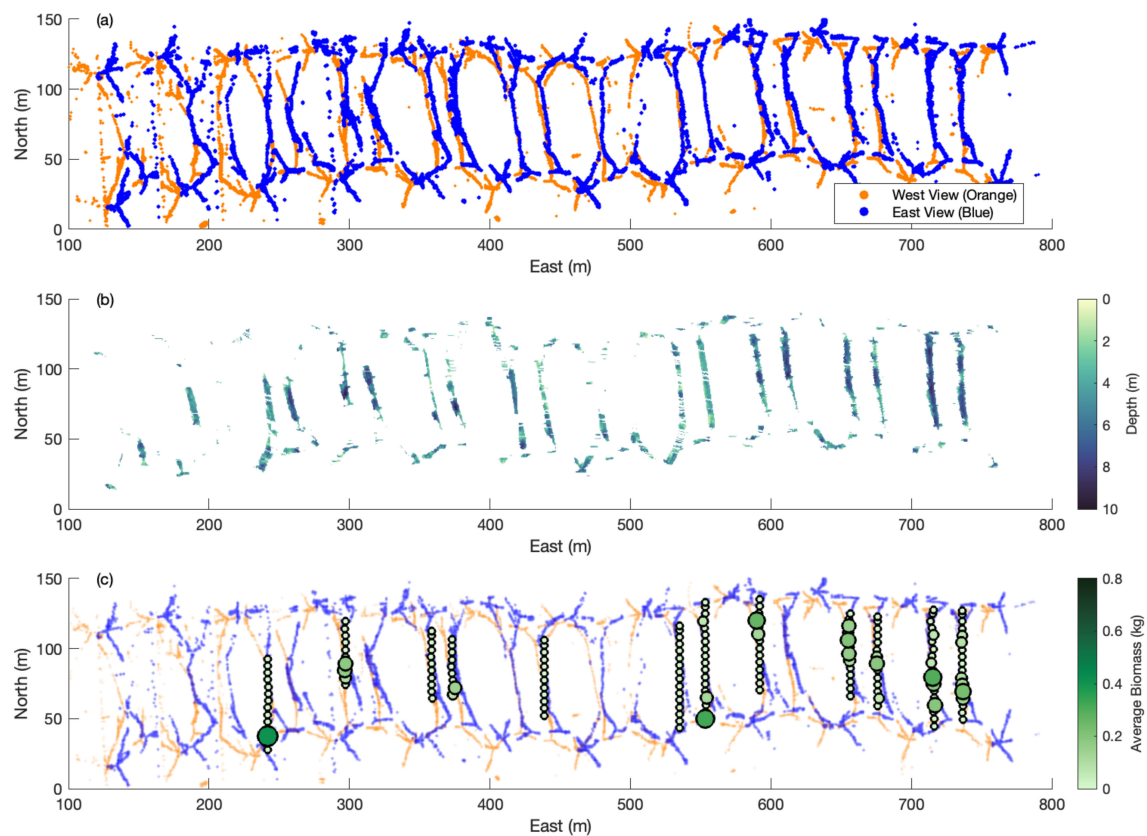


FIGURE 7

Workflow of sonar aggregation to average biomass estimations showing observations from November 2024. (a) East and west views of sonar are first aligned, then combined to find (b) regions of overlap and determine line depths, and (c) calculate biomass. Biomass is estimated in 10-m segments.

(or matrix) of two images based on diffusion principles. The east and north displacement matrices generated from *imregdemon* are shown in Figure 6d as a combined quiver field, illustrating that the orange image needs to be shifted south and west to align with the blue image. For clarity, quivers are only shown for pixels with non-zero values from Figure 6b, though the displacement matrix contains data everywhere within the image.

After finding the displacement matrix, each image is dilated (compare the width of the blue points in Figures 6c vs. 6e, for example). *Dilation* in an image processing sense refers to the expansion of pixels containing large values into neighboring pixels with zeros. The orientation and size of the dilation kernel can be tuned to select for specific features of interest; in this case we dilate in the east-west direction (perpendicular to the cultivation lines) to retain kelp-containing pixels in the subsequent step, which relies on overlap between the images after displacement. Additionally, the displacement matrix, while non-uniform, does not perfectly align every detail of the two images and so the dilation helps increase the amount of overlap between the two images.

Finally, the dilated and registered images (Figure 6e) are multiplied together to determine the region of overlap. The overlap is interpreted to be the proper alignment between sonar pings. Because the orientation and distance of each pixel relative to the sonar in the original images is known, the depth values are

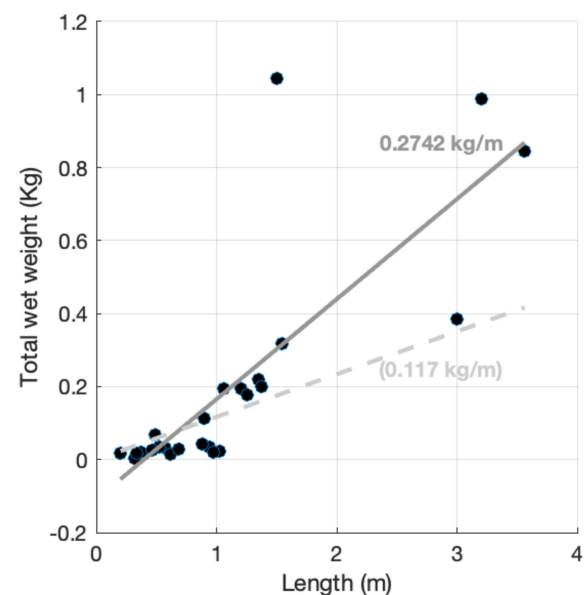


FIGURE 8

Length and weight corresponding to ORI measurements. The linear regression of biomass to length is displayed as a solid line for the ORI data; for reference the reported value for natural kelp forests is included as a dashed line from Rassweiler et al., 2018.

computed geometrically as the intersection of two circular arcs (see [Figure 3](#) and *Methods: Three-Dimensional Reconstruction via Image Rectification*). The result is a fully georeferenced depth matrix that serves as the foundation for estimating kelp length. The pixel size on this matrix sets the lower limit on the plants that can be resolved. In this study we used pixels that were 0.5 m by 0.5 m.

From the georeferenced depth matrix, it is then possible to estimate the length of features within the image by combining their horizontal extent and the difference in depth over that distance (simply via the Pythagorean theorem). As the farm lines run north-south and the current runs roughly east-west, we determined the length of bright pixel features in the east-west direction. Aggregating these results into a larger region accounts for motion of the line and boat. Once lengths along the lines are found, the results must be mapped back to the cultivation lines.

To identify individual cultivation lines, we utilize a Hough transform ([Duda and Hart, 1972](#)) again within the MATLAB Image Processing toolbox ([The MathWorks, Inc., 2024](#)). The Hough transform finds straight lines within an image and we use this tool to find lines meeting a minimum length in order to identify the grow lines. To aid in finding lines that are bowed, we apply a range of parabolic displacements to the middle of the image; unwarped lines become straight within this displacement such that they are identified by the Hough transform. The result of this procedure is that the regions of the depth image that are identified as cultivation lines can be

segmented into smaller regions; the geometry of the imagery within each segment is quantified to determine the length of kelp on the line ([Figure 7c](#)). The estimated length of the kelp can then be converted to biomass using allometric relationships ([Figure 8](#)). For the local Santa Barbara kelp forests, the length-to-biomass ratio is ~ 0.1 kg/m length ([Reed et al., 2009](#); [Rassweiler et al., 2018](#)). The ORI observations yield a relationship that is higher by a factor of ~ 2.5 ; this difference likely attributable to a number of factors. One, farm plant growth was slow and highly variable. And two, the weight measurement is for all of the plants in a one meter section whereas only the three longest plants were measured; the sampling method was not intended to develop a robust allometric relationship. In this paper we use the value of 0.117 kg/m length from [Rassweiler et al. \(2018\)](#).

3.6 Results: maps of farm biomass

The entire farm is shown in [Figure 7a](#); the orange and blue points represent the two opposing views used to determine the farm geometry. Here, we applied the image registration, dilation and depth calculation over subsections of the farm in 70-meter-square regions to produce the larger composite image. Small overlaps between the subsections ensured continuity of the resolved features. Analyzing the farm in subsections allows imregdemon to be slightly more flexible in creating the displacement matrix.

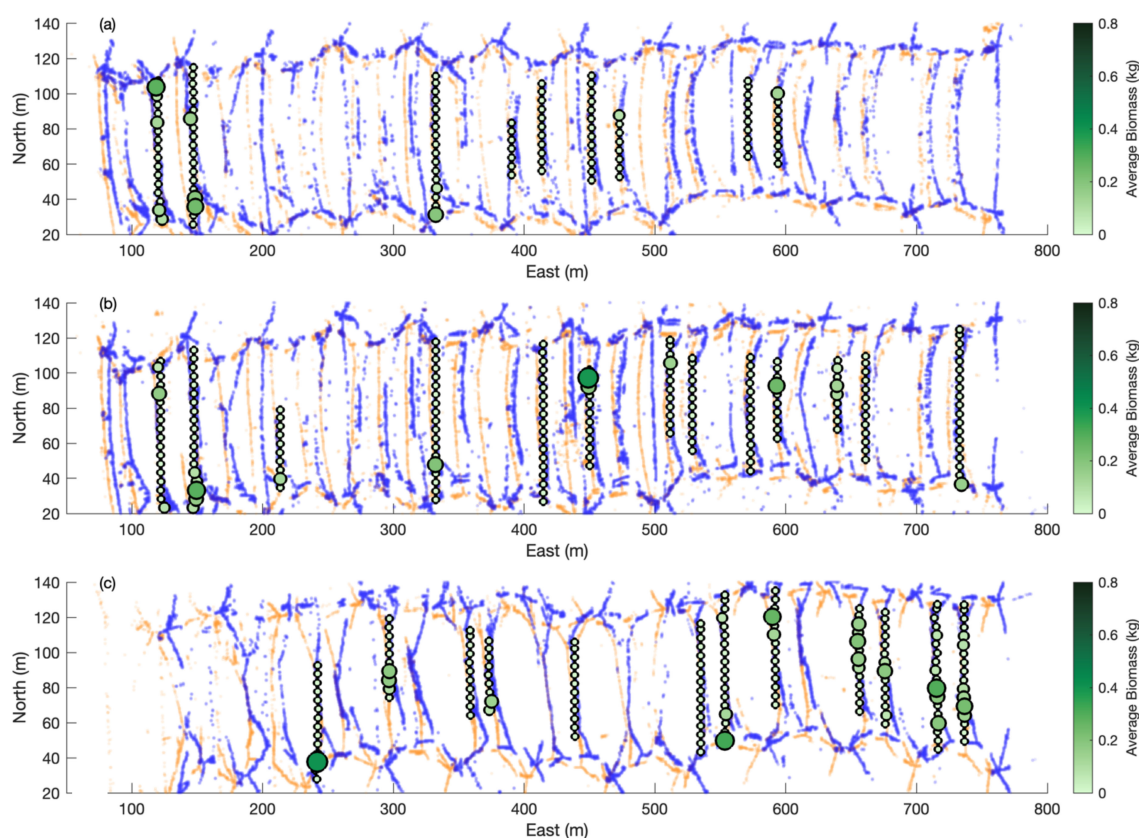


FIGURE 9
Sonar derived biomass estimations for (a) June, (b) July and (c) November. Circle size and color correspond to average biomass per 10m section of line. Sections with no observed biomass are shown as small empty circles.

The registration procedure is effective at aligning many of the cultivation lines, particularly in the eastern end of the farm. The backbone structure of the farm is also evident. Although some of the lines are properly aligned, the limitations of the method are also visible here. In particular, the western end of the farm in Figure 7a shows several straight lines that are the result of surface noise. In general, the areas where the method fails are the locations where lines sag severely. Although we divided the farm into smaller subsections to allow more flexibility in the displacement matrix, the tunable parameters in the image registration and dilation steps were applied uniformly across the farm in this instance; it would be possible to alter these parameters to better adapt to different situations within the farm in an operational setting. Sagging lines can be addressed by warping each image in different directions so that the bowed lines (which are mirrors of each other in the opposing views) are made straight such that the image alignment step is more successful.

From the georeferencing in Figure 7a, the depth of the farm can be determined (Figure 7b). The majority of the farm infrastructure is shown to be around 10 m depth. And, as noted, the western end of the farm is poorly resolved. Within each line, differences in depth in the east-west direction were used to estimate the length of kelp growing on the line.

Estimates of average biomass in each ten-meter-segment are shown in Figure 7c. The results here indicate that eastern end of the farm contained more biomass. Though not immediately obvious, the western end of the farm was not as well tensioned as the eastern end (which is why the method did a poor job of registering lines on

this date); the sagging of the farm line may be one reason that there was better growth in the eastern portion of the farm than the western portion. Additionally, this was an experimental farm installation for ORI in which different methods and outplants dates were used for seeding the lines. Consequently, variations in biomass were expected.

We next present results for three different dates in 2024 (Figure 9). In all of the images, locations where the image alignment has failed to properly align the cultivation lines are evident. Further iteration on subsections of the farm images would improve this, but we used the same options for image registration, dilation, and line identification for all three dates to reduce possible sources of variation. In general, we observe an increase in biomass through time and better growth on the east end of the farm than the west end of the farm (though we note that the west end of the farm is poorly resolved in the November survey, as previously discussed).

Given the uncertainty in the biomass estimates associated with the choice of allometric relationship, we will focus on the validation of our results only in the context of length estimates. In an operational setting, measurements designed to calibrate a sonar length to biomass relationship would be undertaken and such a calibration might even be site dependent.

The sonar results compare favorably with the ORI *in situ* measurements (Figure 10). A rigorous statistical examination of these results is beyond the present scope, however, given the discrepancies in the sampling methods. Nevertheless, there are some general patterns that provide insight into the strengths and weaknesses of the method.

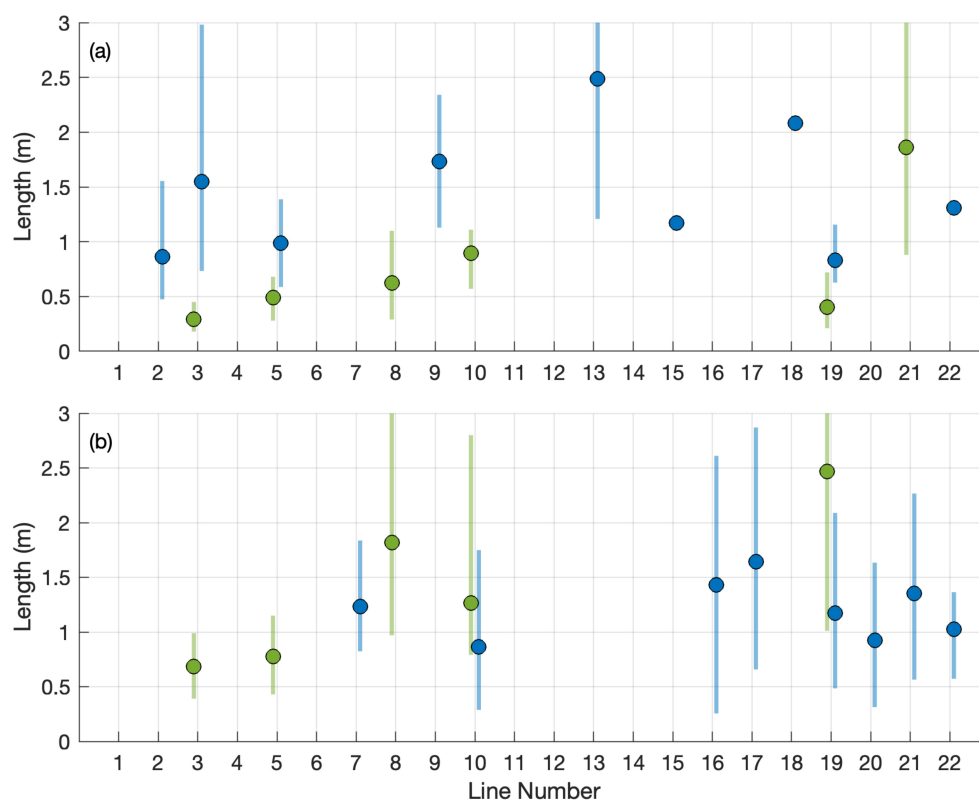


FIGURE 10

Line-by-line comparison of sonar derived estimates of length versus ORI measurements. Circles show mean; bar extends from minimum to maximum. (a) July sonar and July measurement. (b) November sonar and September measurement. Result validation: comparison of sonar to *in situ* length measurements.

Figure 10a shows July, 2024 on a line by line basis (the corresponding map for these data is Figure 9a). At this time, most of the measured plants (in green) were smaller than the 0.5 m pixel resolution and so the sonar data appears to over-estimate the lengths. Many of the longer plants observed in the sonar data, however, are from plants at the north and south ends of the line; the lines were cleared prior to seeding but some year-old

plants remained and there are the source of some of the longer length estimates. There is a better general correspondence between the sonar and measured lengths later in the season (Figure 10b).

A comparison between the sonar and measured lengths is shown in two different histogram representations in Figure 11 and 12. Individual counts on all dates are shown in Figure 11. In June, the inability of the sonar method to resolve the smallest plants is evident

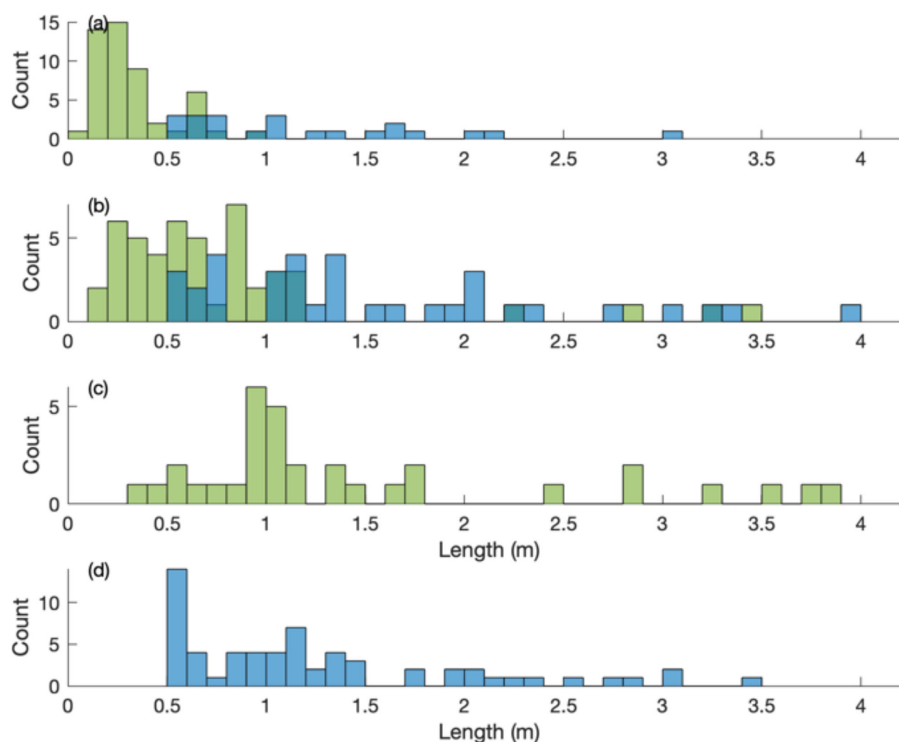


FIGURE 11

Histogram counts of *in situ* measurements (green) and sonar estimates (blue). (a) June, (b) July, (c) September, (d) November.

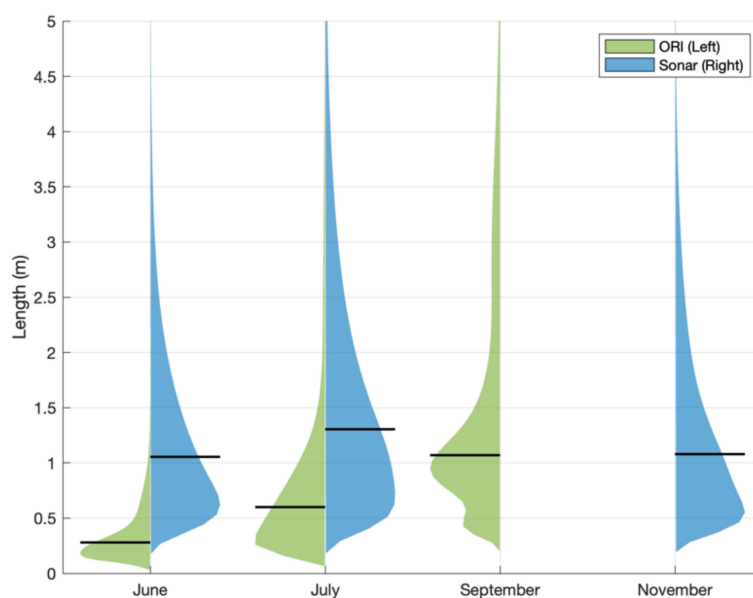


FIGURE 12

Kernel density estimates of *in situ* measurements (green) and sonar estimates (blue). Black bars show the mean value.

(Figure 11a). These counts show that there are very few of the longer plants reported in Figure 10. In July (Figure 11b), the ORI measurements start to include a few longer plants; likewise the number of plants in the tail of the distribution for the sonar observations increases. Sonar estimates are not available again until November (Figure 11d); the closest measurement date is in September (Figure 11c). The two distributions are similar, though it should be expected that senescence has impacted the November distributions.

Figure 12 shows these same observations but presented as a kernel density estimate. The growth in plant length from June to July is evident in both the *in situ* and sonar data; as previously noted, the sonar data contain observations of longer plants at the periphery of the farm that we not sampled by the random spot sampling of the ORI method. The similarity of the distributions associated with the longer plants provides support that the sonar approach could be a viable method for assessing farm biomass with proper calibration data.

4 Summary

Sonar is an effective method for gathering quantitative measurements on kelp health, density, and detection (Bennion et al., 2019). While the utility of side scan sonar has been proven for surveys of fish over large spatial domains (Ridgway et al., 2024), its use in macroalgae farming aquaculture is limited. The method presented above, to our knowledge, provides a first of its kind application of side scan sonar to create a kelp biomass estimation using a single-transducer side scan sonar, independent of multi-instrument calibration. By determining the three-dimensional structure of the farm via image registration, we are able to estimate kelp length and infer biomass along suspended kelp cultivation lines.

Our method provides a means to deal with non-uniformity of farm shape and potential structure by adapting the image registration on a smaller moving window and/or altering the orientation of pixel dilation to isolate features of interest (based on their assumed orientation). We showed that spatial and temporal patterns in kelp biomass could be determined quantitatively, consistent with *in situ* observations (Bell et al. 2020). More detailed and/or site-specific calibration would improve these preliminary results. Similarly, farm-specific pre-processing techniques could be developed. For example, when applying the Hough transform, we currently use the detection to identify north-south farm lines, however this could be first used to identify horizontal backbone lines and remove them from the image, allowing for less noise in the registration step.

There are clearly limitations to the method, as evident in regions of the farm where lines were not resolved. This was a pilot project for both the farm and the sonar method development and so adjustments would need to be made in an operational setting. As noted, proper calibration data would be required. For the sonar data collection, a robotic platform could be tasked with repeat visits of the same region in a day, if desired, to constrain the impact of environmental variables on data collection. Such considerations were beyond the scope of this effort.

Effective monitoring programs are critical to ensure sustainable commercial use of the coastal environment (Ali et al., 2022).

Our approach could be one important tool for quantification of crop status and growth, as well as infrastructure inspection, information that would be useful for both operational decisions and regulatory compliance.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

NN: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. PH: Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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