Mapping the Shallow Water Seabed Habitat With the SHOALS
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Abstract—The Scanning Hydrographic Operational Airborne light detection and ranging (LiDAR) Survey (SHOALS) consists of a bathymetric LiDAR system that provides high-precision measurements of water depth. Although the acquisition is focused on depth accuracy, the return signal, i.e., waveform, contains other relevant information because of integration signatures from the water surface, the water column, and the seabed. This paper highlights the benthic characterization in extracting statistical parameters derived from the bottom backscatter and classifying them. In implementing a specific unsupervised classification, it is significantly proven that the signals derived from habitat, described as statistically homogeneous throughout ground-truth analysis, are similar within an intrahabitat view, whereas they are different between themselves.

Index Terms—Habitat classification, light detection and ranging (LiDAR) bathymetry, multivariate analysis, waveform.

I. INTRODUCTION

ACURATE large-scale remote-sensing surveys have brought many benefits to environmental management in the terrestrial environment. In landscape ecology, satellite imagery, airborne orthophotography, hyperspectral data, passive/active microwaves, radar, light detection and ranging (LiDAR), etc., provide information on habitat distribution, evolution, connectivity, structuring process, and recovery rates, as well as monitoring of ecotones, metapopulations, and even crop physiological status such as water stress level [1]–[6].

Nevertheless, accessing submarine landscapes has never been easy as the sampling equipment is remotely controlled and, consequently, often blind. Considering that more than 70% of the Earth’s surface is covered by water, the lack of efficient seafloor mapping not only constitutes a serious obstacle to understanding the dynamics and structures of assemblages of species at a global scale but also weakens our ability to correctly manage the marine habitat and particularly for sea resources as the exploitation of biological resources increases. Physical, geological, and biological resource maps have proved to be essential aids in sustainable management by allowing the monitoring of environmental fluctuations and the estimation of anthropogenic influence on benthic communities and habitats [7], [8].

Traditionally, many of the earlier mapping studies relied on physical sampling, for example, with grabs, dredges, or both equipment. This approach is not only time consuming and costly but also highly disturbing for the benthic biotopes (i.e., habitats and their associated communities), and only provides scattered discrete data across the study area. Recent improvements in single-beam echosounders, sidescan sonar, and signal processing now provide effective tools to explore the seabed as a complement to the physical sampling methods traditionally used to carry out benthic surveys [9], [10].

Through established methods [11]–[14], commercially available systems, such as BioSonics’ VBT, Echoview, QTC VIEW, or RoxAnn, are now used by researchers to extract habitat information from returning acoustic signals. However, recent advancements in airborne visual surveys can eliminate the limitations of traditional ship survey methods and have added advantages. Owing to high-speed data collection, the cost per kilometer from aircraft is 10% (or less) that of a ship survey [15]. In a single survey (< 8 h), aircraft can cover a study area that would require a week or more for a vessel. It is important to note that ground truthing could only be done by ship sampling but will still be under the time required. However, aircraft allow access to both water and terrestrial regions, and biological features are observed in situ without disturbance of the biotope.

The airborne laser (i.e., LiDAR) bathymetry is a technique for measuring the depths of very shallow and shallow coastal waters from the air using a scanning pulsed laser beam [16]–[19]. Indeed, it is a technique well suited to shore mapping because its laser system enables to provide an accurate Digital Depth Model (DDM) in a 1- to 50-m vertical range with 15-cm height accuracy. The depth detection essentially depends on water turbidity. Compared to passive remote-sensing systems, this active state-of-the-art technology can measure the depth at two to three times the Secchi depth and can measure depths as great as 60 m [20]. Moreover, topographic surveys above the water surface can simultaneously be conducted to draw seamless Digital Terrain Model, a key component of a better comprehension of the littoral structures and dynamics.

Despite the presence of noise (optical sensors) and the integration of several parameters acting within the water surface, water column, and bottom return, typical benthic waveform patterns are also evident, suggesting that the laser temporal signal may indeed comprise important, ad hoc, and added information related to the characterization of the shore habitat.
Fig. 1. Gray-scale rasterization of maximum elevation derived from SHOALS return over Paspébiac (20.77 km², 1-m resolution). The white polygon constitutes the analysis area. The terrestrial reflectance was specifically saturated to enhance this from the seabed.

Innovations in LiDAR technology have allowed researchers to demonstrate the potential for accurate sounding of seafloor at broad scales. Some of them have begun to use the intensity of the peak bottom to map the marine environment by draping intensity images over DDM or by combining intensity with passive image data using more sophisticated sensor or data fusion algorithms [20]–[24]. The full waveform remains notwithstanding not being entirely exploited. Assuming that benthic habitats, i.e., network of fauna and flora assemblages, could modify the seabed LiDAR backscatter, this paper aims at 1) developing a methodology to investigate the variability of the LiDAR backscatter to reveal relationships between this bottom return waveform and 2) related sediment and benthic community patterns over the site located near shore in Paspébiac, Gulf of St Lawrence, Canada (Fig. 1).

II. SHOALS SYSTEM

In hydrographic mode, the Scanning Hydrographic Operational Airborne LiDAR Survey (SHOALS) emits the 532- and 1064-nm wavelengths from a Neodymium-doped Yttrium Aluminium Garnet (Nd:YAG) laser with a beam divergence of 0.45 mrad. The first radiation (green) is typically used for seabed detection because of its high water penetration, whereas the second wavelength (near infrared) allows measuring the water surface because of its high water absorption. In addition, the transceiver records the laser energy return time series (waveforms) with four receivers. Therefore, one receiver records the infrared energy reflected from the water surface (surface return), and two receivers collect the green energy reflected from the sea bottom (Geiger Avalanche Photo Diode, shallow, 0.2–12 m, and, Photo Multiplier Tube, deep, ≥ 7 m). A fourth receiver records the Raman energy at 645 nm, which results from the excitation of water molecules at the sea surface by the green laser energy [20]. Hence, Raman also indicates the interface air/water. The infrared waveform is also used to distinguish dry land from water. For each channel, the received signal was converted into a voltage, which was itself transformed with a logarithmic amplifier and digitized at 1 GHz with 8 bits of resolution (256 levels). Assuming the celerity in physical elements, each bin, i.e., 1 ns, corresponds to a vertical resolution of 0.15 and 0.1125 m in air and water, respectively.

The green laser produces about 7.5 mJ of light in a 6-ns pulse at a repetition rate of 3000 soundings per second. The beam is diverged using a lens in front of the laser. The divergence is chosen so that the irradiance at the sea surface satisfies Canada’s standard for exposure to laser light in the workplace [25]. This irradiance level is also safe for marine mammals [26]. The transmitted laser pulses are partially reflected from the water surface and from the sea bottom back to the airborne receiver. In effect, distances to the sea surface and bottom can be calculated by measuring the times of flight of the pulses to those locations and knowing the speed of light in air and water. The SHOALS is a monostatic system, i.e., the transmitter and receiver are collocated and share the same field of view (FOV) with a fixed nadir angle of 20°. In this paper, the medium sounding density was used, i.e., a shot every 4 m.

In addition, each SHOALS sounding receives its positioning from the Global Positioning System (GPS) in either differential GPS (DGPS) or kinematic GPS (KGPS) mode. With DGPS, the horizontal positioning of the aircraft is accurately known and directly translates to a known horizontal sounding/elevation position. Accurate vertical positioning for each measurement is then obtained by correlating the LiDAR surface return with independent water level measurements. In contrast, KGPS accurately provides both horizontal and vertical aircraft positioning; thus, the full 3-D positioning for each measurement is independent of supporting water level measurements. SHOALS depth measurements are accurate to the International Hydrographic Organization Order 1 standards, i.e., ±0.15 m in the vertical and ±1 or 3 m in the horizontal [27]–[29] with DGPS and KGPS, respectively. The roll, pitch, and yaw of the aircraft were also measured 200 times per second by an Inertial Measurement Unit to correct for changes in capture angle.
The maximum water depths detectable by SHOALS are limited by water clarity, or the amount of turbidity, in the water column. As the laser pulses travel through the water column, several processes occur that limit the amount of light to eventually reflect from the sea floor and return to the receivers in the aircraft. Light energy is lost during refraction and is scattered and absorbed by particles in the water and by water molecules themselves (Fig. 2) [27].

III. METHODOLOGY

LiDAR intensity is the ratio of received energy to transmitted energy. Its physical meaning is linked with parameter measurements integrated during the beam path. The bathymetric SHOALS return may be divided into three main parts: the water surface, the water column, and the benthic (bottom) return [20]. At the nadir angle, the altitude and all the loss parameters were correctly sustained during the survey. The signal equation is

\[ P_R = W P_T R \times e^{(-2KD)} \]  

where:
- \( P_R \) received power of the bathymetric LiDAR signal;
- \( W \) constant combining loss factors;
- \( P_T \) transmitted power;
- \( R \) benthic reflectance;
- \( K \) diffusive attenuation coefficient of water;
- \( D \) benthic depth.

Furthermore, transforming (1) with natural log, we can obtain an equation that is linear in depth, i.e.,

\[ \ln P_R = \ln(W P_T R) - 2KD \]  

The LiDAR intensity was recorded as a function of time. Only the PMT green deep receiver signal (out of the four channels) was analyzed in this paper. The signal is delimited by 250 A.U. (relative photon count) and 185 ns (Fig. 3).

A. Study Site

The survey covers 82 km² in 12 h and represents 80 million individual depth and elevation measurements. They were collected by SHOALS between July 1 and 3, 2006, over the Baie des Chaleurs, southern Gulf of St. Lawrence, Quebec, Canada. The maximum depth penetration reached was 16.7 m over sandy zones and 8 m over macroalgae.

The LiDAR data for this paper are focused on the subtidal nearshore of Paspébiac. This locality is hydrodynamically characterized by high energy [30]. Two sand pits, nourished by quaternary deposits and the east swell, join themselves to draw a typical triangle. Whereas rocky areas, i.e., boulder and cobble, are mainly populated by the macroalgae Laminaria sp. and the green urchin Strongylocentrotus droebachiensis, the sandy zones, i.e., from fine up to coarse sand, predominantly host the two spionidae Prionospio steenstrupi and Spiophanes bombyx, the “Sand Dollar” Echinarchnus parma, and, finally, the two bivalves Spisula sp. and Macoma balthica [31].

The analysis area was covered by a series of two east–west overlapping flight lines at 270 ± 5 m altitude, enabling a swath width of 196 ± 3.6 m and a sample spacing of 4 m, i.e., 85,332 soundings covering 0.561 km² (Fig. 4).

B. Underwater Ground Truthing

For this experiment, four areas, A, B, C, and D (100 m × 10 m), were specified by the information derived from ground truth. Seafloor photographs were extracted with a digital high-resolution (five megapixels) camcorder fitted with a wide-angle lens and placed in a waterproof case. Two 250-W light sources allowed adjustment of the illumination according to the water turbidity and the position of the camcorder to the bottom. The system was mounted on a tetrapod frame that included a
reference ruler to evaluate the size of material of the seafloor. Throughout this study area, for each of these four stations surveyed, ten 0.16-m² images of the seafloor were collected when the camcorder reached the bottom.

C. Denoising and Nonlinear Regression

The integration of the environmental parameters acting underwater and the variability of the electronic instruments within the SHOALS backscatter imposed a denoising method. The fast Fourier transform algorithm decomposes the 1-D time series into its frequency components. By suppressing the high-frequency components, i.e., low-pass filtering, this method allowed to achieve a denoising effect.

The shape and power of the returned signal from the seafloor can significantly change with seafloor depth as a result of spreading losses and absorption, even if the seafloor habitat remains the same [13], [32]. Since SHOALS data were acquired at different depths, the alterations due to seafloor depth variation will affect the shape statistics being calculated by our classification algorithm, thus obscuring the changes due to variations in biosediment type. Note that since the laser beam is a cone (Fig. 2), the size of the sampled area, or footprint, is physically linked to the acquisition depth. To overcome this, the statistical variables, describing the bottom signal, were regressed on depth, and the residuals constituted the only variance analyzed. The regression was based on a nonlinear least-squares fit, that is to say, a linear combination of Gaussian and quadratic functions.

D. Data Analysis

Beforehand, data, contained, on the one hand, in .LAS files (i.e., geographical data), and on the other hand, in .INW files (i.e., waveforms), were gathered in accordance with the methodology of the “timestamp” bridge [45]. To determine the relevant utility of the underwater laser data to discern differences in benthic characteristics, deviations in the composition of habitats, visualized with ground truth, were emphasized. This was processed in two steps. First, to quantify the surface covered by the sediment and the epi-macro-benthos, a grid of 100 uniformly distributed points was superimposed on the photographs, and what was under each point was identified to give an estimate of the percentages of the surface covered by each component [33]. Second, the aerial percentages were submitted to multivariate statistical analyses to classify the stations by their similarity. The matrix of 40 stations by 17 variables, corresponding to the species- and sediment-type aerial percentages, was used to compute similarity matrices using the Bray–Curtis index [34]. The similarity matrices were then submitted to average linkage hierarchical clustering to classify the stations [35]. For each resulting classification, the mean relative aerial density and the percentage of contribution to within-group similarity were computed for the main components of the group [34].

The signal processing consists of extracting the portion of the waveform, which contains the relevant benthic information. The ad hoc portion is called “benthic signal” (Fig. 3). The signal curvature is studied by the first derivative. As a result, it becomes possible to retrieve the benthic signal. Then, two approaches were used to extract variables from backscatters. The first approach computed a series of descriptive statistical variables—namely, mean, variance, skewness, kurtosis, area under curve, length, absolute deviation, total, maximum, and minimum—derived from Raw signals (Rs), and the second treatment dealt with the same statistical variables but derived from quintic Gaussian (QG)-fitted curves. Both methods yield a data table of ten extracted variables (columns) and 85,332 backscatters (rows). Following an unsupervised classification, both data matrices were submitted to two types of multivariate statistical analysis. First, the correlation matrices of the ten variables, resulting from the benthic return description, were nonlinearly regressed on depth, and the residuals were reduced to three main dimensions (PC1, PC2, and PC3) using principal component analysis (PCA) [35] for sorting out the backscatters, which generally account for 90% or more of the total variance in a data set [14]. Then, the scores on the PCA components representing more than 2.5% (i.e., 1/40) of the total variance were submitted to a K-means cluster analysis based on a progressive-splitting process. At the end of the procedure, soundings with similar characters formed clusters that defined laser classes, which were mapped throughout the surveyed seabed.

The direct quantitative comparison of classification algorithm performances is based on the confusion matrix (CM), whose information will, in the following, be often summarized by the overall accuracy A, defined as the ratio of the number of validation pixels that are correctly classified to the total number of validation pixels irrespective of the class [36]. A further important CM statistics used here is the Kappa coefficient κ, which describes the proportion of correctly classified validation sites after random agreements are removed [37].

To produce a raster image of the bathymetry, the bin difference between the surface and bottom peaks multiplied by 0.1125 m was binned into 0.1-m raster pixels. The pixel coordinates correspond to those of each sounding point. The outcome of this procedure is to generate a highly accurate seabed raster image from the SHOALS data. To further study the potential use of this active image, a shaded relief image of the DDM, i.e., a 3-D rendering of grid of squares, was produced.

IV. RESULTS

A. Ground-Truth Sampling

From the analysis of the photographs (Fig. 5), the seafloor sediments on the studied subset of Paspébiac are either coarse with a dominance of boulders or fine sand. Large boulders (> 40 cm) were common (up to 64%) in the middle east of the area. Fine sand coverage, located on the closer part of the beach, reached almost 99%. Several benthic communities were identified from the analysis of the photographs, and they tended to be distributed over distinct areas. The most common taxa were Laminaria sp., Echinoidea, and Asteroidea. The algal species were very abundant, particularly on boulders and commonly in large cobbles, rarely overturned, on which Laminaria sp. holdfast settle down. In contrast, Echinoidea frequently cover cobbles without Laminaria sp. They seem to prefer light and
are (a) boulder with Asteroidea, (b) fine sand with dejecta of polychaetes, to the four main habitat types surveyed with SHOALS. The selected habitats can be related to composition, overlapping the four ground-truth sites: group 1 actually mainly sorted by both their sediment and biological epi-macrobenthos aerial percentages identified four groups trix computed from the combination of sediments and algae were abundant. The application of the implemented algorithm classifier on the statistical parameters derived from Raw signal data showed a good performance of accuracy as the assessment clues emphasized it. The Laminaria sp. on boulder (G1) and the fine sand (G2) habitats were correctly identified \((A = 88.5\%, K = 0.81, A = 85.9\%, K = 0.88)\). The two other habitats (G3 and G4) were consistently characterized by poorer performances both statistically \((A = 76.2\%, K = 0.75, A = 77.9\%, K = 0.73)\) and visually.

Running the same classifier over statistical parameters extracted from the QG-fitted signal gave a slightly worse classification. The two validation sites (G1 and G2) were relatively well classified \((A = 84.3\%, K = 0.80, A = 79.1\%, K = 0.74)\), whereas the accuracy statistics of both last ones
Fig. 6. Rainbow raster image of the DDM applied to the study area (0.561 km², 0.1-m resolution). The color ramp ranges from 2.18 to 12.87 m.

Fig. 7. Projection of the SHOALS benthic returns on the three first principal component axes (79.14% of the initial variance). Those points were characterized by the Raw signal (Rs) submitted to a K-means approach [gray □: Laminaria sp. on boulder (G1); gray X: fine sand (G2); black +: Echinoidea on cobbles (G3); black o: boulder with Asteroidea (G4)].

(G3 and G4) displayed the least robust identification ($A = 69.3\%, K = 0.66$, and $A = 70.7\%, K = 0.64$).

Although the CM statistics indicated a marginally better performance of the algorithm on Rs than QGs, both classifications were in satisfactory agreement and captured well the general known benthic structures, which were mostly homogeneous. Indeed, G1 and G2 were constituted by substrata distinctly characterized by a low spectral variability, i.e., bedrock and sand, whereas G3 and G4 could be confused with each other but above all with both previous groups due to the heterogeneity of the cobble and boulder size.

The color mapping was chosen to render the visual inspection as an apparent correlation between the brightness and texture of the classification image and bottom type. Precisely, the fine sand (G2) and urchins on cobble (G3) were bright and smooth, whereas the macroalgae on boulder (G1) and the seastars on cobble (G4) were dark and rough. As a result, the unsupervised classification delimited four classes, as initialized, which significantly tended to draw relevant overlapping with the four habitats described; thus, classes 1, 2, 3, and 4 are related to G1, G2, G3, and G4, respectively. Due to the overlapping flights of the survey, mild linear artifacts appeared within the Class #2.

V. DISCUSSION

First, the ground-truth analysis of photographs showed that the intrasite and intersite variabilities of the sediment and benthic community types were, respectively, sufficiently low and high to be statistically discriminated. Second, bathymetric LiDAR backscatters can significantly differentiate between the four characterized habitats, whether the signal is “Raw” or fitted with a “QG” curve.

The resulting classifications based on those previous methods brought out that fitting a QG curve onto the signal did not differentiate itself from this raw signal but tended to slightly misclassify. The fitting curve reduced the variability of the intensity, which consequently gathered some soundings, distinguished by the other extraction method.

As the species encountered in this paper live in preferred sediment types, we assumed that the sediment distribution was implicitly involved in the SHOALS discrimination of the benthic communities. Afterward, as the sediment intersite variability was rather high, consequently, the sediment pattern itself would have been hypothetically sufficiently variable to compare with a laser classification. Nevertheless, some ancillary factors are also used to characterize a habitat such as water depth, seafloor geomorphology, habitat complexity, current speed, food supply, temperature range, predation pressure, and disturbance by fishing activities [8]. These environmental factors certainly influence the pattern of benthic community distribution and should be taken into account in the interpretation of SHOALS classifications.
Fig. 8. Resulting images of the classifier algorithm of the benthic SHOALS return based on the statistical parameters derived from (a) the raw signal and (b) the QG-fitted signal. The images are composed of the four cluster classes and the null class.

Table II

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<tr>
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<th>A (C)</th>
<th>G2 (B)</th>
<th>G3 (D)</th>
<th>G4 (A)</th>
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<tr>
<td>Rs</td>
<td>88.5</td>
<td>0.81</td>
<td>85.9</td>
<td>0.88</td>
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<tr>
<td>QGs</td>
<td>84.3</td>
<td>0.80</td>
<td>79.1</td>
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At Paspébiac, large boulders were found on areas with strong currents and gravel substratum, two factors that are essential for larval dispersion and larval settlement [38]. This hydrodynamic regime coupled with heterogeneous topography is a keystone to aggregate and retain large abundances of epibenthic species [39]. The ground-truth photographs revealed abundant seastars, sea urchins, and burrows of marine polychaetes; those constitute the main diet of *Homarus americanus*. Hence, the region is well known as a productive lobster region. Indeed, rocky areas covered by tall algae where young lobsters can hide in the crevices from predators and prolific food set up an *ad hoc* habitat favoring the retention of this lobster population in this specific area. Focusing on these suitable patches, namely, *Laminaria* sp. on boulders (G1 and Class #1), it became possible, under apposite ecological and biological assumptions, e.g., daily locomotor behavior of *H. americanus*, its scale-dependent perception, to predict a map of lobster habitat suitability. A program was implemented to create a buffer-zone image from a classification image. Each pixel in the output image was the nearest distance, in pixels, from any Class #1 pixel (Fig. 9). A stepwise fringe of interest has, therefore, been constituted, ranging from 0 pixel (in purple) to approximately 30 pixels (yellow) distant from any assumed lobster habitat, pixel scaled. At this spatial local scale, this map could have things in common with a map of the probability of occurrence of suitable lobster habitat, in which the habitat probability would be inversely related to the distance.

Afterward, the scattering patterns of the return signals projected onto the three first PCs (Fig. 7) could reveal the biophysical aspects of the habitat sounded. Indeed, in computing the variability of the distance point centroid within Fig. 7, *Laminaria* sp. on boulders (G1) displayed a greater variability than the three other habitats (Table III). Thus, the greater heterogeneity bound to algae on the bedrock site could highlight the growth of entropy, whereas the other habitats, characterized by denser point clouds, showed biosediment sites spectrally more homogeneous in this paper. Within this outlook, it will be relevant to find out specific sets of extracted variables that could be used to correctly and significantly identify the nature of the...
habitat surveyed and the influence of species aerial percentages on SHOALS signatures.

Depth variation has been shown in the literature to affect our capacity to detect and differentiate remote-sensed signatures [9], [10], [13]. The depth regression that considers the variance due to other parameters than depth obviously generated some interesting classifications. In this respect, the relation between the depth and the first PC was plotted, and the linear Pearson correlation coefficient was computed. Assuming that the three first PC axes, reaching 79.14% of the total initial variance, were a consistent indicator, the multiple correlation coefficient of depth on these three synthetic variables (0.03) did not show a depth dependence of the synthetic variable.

Even with the depth regression and the consequent low correlation between the synthetic variable and depth, the physical meanings of the variation of the benthic signal with depth need to be explored. A lack of a normalization procedure could be problematic, particularly because it is recognized that benthic assemblages are distributed in patchiness on scales ranging from centimeters, meters, and kilometers in the deep sea [40] or the intertidal zone [41], [42]. Hence, the effects of uncorrected depth fluctuations are likely to overshadow the variation inherent in the nature and the slope of the seabed, and fatally link the laser signatures to depth-related variables. To properly normalize the signal with depth, the returned signal inherent to a seafloor depth ($d$) could be normalized to a reference seafloor depth ($d_0$) and the statistics calculated at the reference seafloor depth, with no regression any more (Fig. 10). Then, power adjustment would remove the effect of spherical spreading, and temporal spreading would correct. Indeed, the SHOALS waveform is expressed as amplitude as a function of time, and the bottom return is therefore stretched when the relative slope increases [13], [24]. To perform accurate depth normalization, corrective measures of the attenuation coefficient of water should be precisely measured regarding the rate at which the light is absorbed as it travels through water, i.e., slope of the water column in Fig. 3. Further laboratory experiments will investigate this effect on the bottom return signal, and their results will draw some numerical fundamentals for modeling the underwater pathway of a laser beam.

Moreover, the depth-regressed algorithm used in this paper works well unless: 1) fog produces a near-surface return that is stronger than the surface return; 2) fish near the surface produce a stronger return; or 3) a shallow bottom produces a stronger return [42]. As a result, little artifacts due to the overlapping flight were specifically revealed at the depth of 3 m. Now according to researchers, there is more scatter than other depths [24]. This is probably due to the double focusing effect on the LiDAR pulse by the water surface, an effect that is characteristic of a monostatic LiDAR configuration such as SHOALS. Double focusing by a wavy surface results in an increase in both the amplitude and the variance of the SHOALS bottom return at shallow depths [24].

An evaluation of polarization diversity LiDAR can monitor some kind of water column and bottom microphysical information currently measured only through in situ sampling methods. In particular, LiDAR polarization measurements are indicated to be sensitive to the morphological composition of the underwater reflectors [44]. The cross-polarized component of the reflected light, i.e., the component for which the linear polarization is orthogonal to the polarization of the laser beam, could be used because it produces the best contrast between large and smaller reflectors in the water and over the seabed.

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