Discriminating between *Posidonia oceanica* meadows and sand substratum using multibeam sonar

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Material and methods

The study was carried out on the northwest coast of Sicily in the Bay of Mondello (Figure 1). The seabed there is characterized mainly by a sandy substratum colonized, from 2.5 to 38 m deep, by an extensive *P. oceanica* meadow (Calvo *et al.*, 1993). Before data collection, two areas at the same depth, mostly covered by sand and *P. oceanica* meadow, respectively, were selected using an existing map (Calvo *et al.*, 1993). Then, two plots per area,
representing training sets (plot A for \textit{P. oceanica}, \textit{A}' for sand) and test sets (plot B for \textit{P. oceanica}, \textit{B}' for sand), were chosen by scuba divers (Figure 2). Each plot, 10 × 10 m wide and at a depth of about 8 m, was delimited by reflecting targets to allow later identification via sonar. The depth, size, and position of plots were set so as to ensure their coverage by a single sonar swath and to avoid the possible noise of \textit{P. oceanica} canopy reflection induced by the beam’s slant angle at the outer sides of the swath. Weather conditions during the surveys were stable and characterized by high pressure and a calm sea.

Collection of sonar data
On 5 October 2007 and 17 January 2008, an MBS Reson SEABAT 8125 was used for data collection with the transducer hull-mounted on RV “Antonino Borzì” (www.unipa.it/cisac) and the array faces orientated vertically downwards. In that configuration, the receive array was mounted across-track, whereas the transmit array was mounted along-track and aft of the receive array. The Reson 8125 system works at 455 kHz, the coverage of a single beam is 0.5° × 1° with 240 beams within each swath, providing a sonar coverage of 120° across-track equivalent to 3.5 times the depth. The sonar system, interfaced with RESON PDS 2000 software package (Version 2.0; Reson, 2006) for positioning, data acquisition, and editing, was combined with motion- and gyrocompass-integrated sensors (TSS Mahrs) to compensate for boat movement. Differential GPS (OmniStar 3200L12) was also used for data positioning. The speed of sound in the water column was measured using a Reson SVP 15 probe, and the vessel speed during data collection was about 2 m s\(^{-1}\), with a sonar range of 15 m and a constant ping rate of 21.98 pps. Before the acoustic survey, the positioning system was calibrated for time (delay/latency) and the MBS system was calibrated for pitch, roll, and yaw/heading.

Field measurements and sample collection
Immediately after the acoustic surveys, measurement and sampling of the plots were carried out by scuba divers. The density was determined \textit{in situ} using a 40 × 40 cm quadrat with 10 replicates per plot. Ten shoots were collected in each plot for biometric measurements. Sampling of shoots was performed in both seasons, but meadow density was measured only in October because no significant variations were expected over four months (Hemminga and Duarte, 2000). The total length and width of each leaf, total leaf number, and sheath length, where present, were determined in the laboratory. These variables were used to calculate mean shoot surface, leaf-area index, and mean longest-leaf length.

In October in each of the sand plots, three replicate sediment samples were collected by scuba divers, using PoliVinilClorure pipes (10 cm long, 5 cm diameter). The sediment was treated with H\(_2\)O\(_2\) in 6% for 24 h (Carver, 1971) to remove organic matter by oxidation, then oven-dried (80°C for 12 h). The cores were then subsampled and analysed for grain-size distribution by dry-sieving for the principal coarser fractions (De Falco \textit{et al.}, 2000).
Data preprocessing and statistical analysis

Sonar data were processed using the Reson PDS 2000 software package to remove manually acquisition errors and to correct tidal variations. A grid with a pixel size of 1 m$^2$ was then constructed. The standard deviation and depth range of the original beams falling within each pixel were calculated and used as proxy of substrata spatial complexity and height, respectively. As each plot was 10 x 10 m, a total of 400 pixels was generated. Within the training set (plots A and A’), potentially different features of pixels occupied by P. oceanica and the sandy substratum were explored. Differences in the mean standard deviation and the mean depth range for the two bottom typologies were assessed by an independent $t$-test. The homogeneity of variances was tested by Levene’s test and, when necessary, data were log- or arcsin-transformed. After transformation, if homoscedasticity was still rejected, the Welch–Satterthwaite $t$-test was applied to assess the mean differences (Sawilowsky, 2002). In addition, histograms were generated to provide a screening of the shape and dispersion of both variables. The observations were then classified into two groups using a classification tree (Breiman et al., 1984), a non-parametric procedure of binary partitioning that can detect the optimal cut-off between two groups.

Cross-validation was performed to evaluate the classification accuracy. In particular, the class boundaries obtained from the training set were used to classify the test set. Multiple measures of classification accuracy, subdivided into overall, user’s, and producer’s accuracies, were calculated (Congalton, 1991). The overall accuracy is the ratio between the sum of the pixels in the diagonal of the error matrix and the total number of pixels in the matrix. The producer’s accuracy is the probability of an actual pixel being correctly detected, and the user’s accuracy is the probability that a pixel classified on the map represents the actual category.

Results

The meadow features exhibited substantial similarities between P. oceanica plots (Table 1) and are representative of dense seagrass canopies. Shoot density of the meadow averaged 411.9 ± 56.9 shoots m$^2$. The shoot surface ranged from 150.1 ± 38.0 cm$^2$ in winter to 190.2 ± 65.5 cm$^2$ in autumn. Mean longest-leaf length was 43.6 ± 9.0 cm in winter and 82.3 ± 15.7 cm in autumn. In the sandy substratum, sediment granulometry, following the Shepard classification, was 99.98 and 99.96% sand, respectively, in plots A and B’.

The bottom topographic profile recorded in both seasons in training sets (plots A and A’) highlighted very different spatial patterns between the swaths on P. oceanica and sand (Figure 3). The main difference between the two bottom categories was the variability of the beam bathymetric position. The number of beams per pixel in the DTM (digital terrain model) averaged 113. Both variables in the P. oceanica bed were significantly higher than on the sandy substratum in both seasons (Welch–Satterthwaite $t$-test, $p < 0.01$; Figure 4).

Histograms revealed clear differences in frequency distribution, and there were only small overlapping zones between the two bottom typologies (Figure 5). For the standard deviation, the cut-off points between the two groups estimated by classification tree in October and January were 0.034 and 0.031 m, respectively, whereas for the depth range, the cut-off points were 0.20 and 0.17 m, respectively (Figure 6). Combining the histogram analysis with the cut-off estimates, class boundaries per bottom type were defined (Table 2).

Classification of the entire swath coverage revealed similar spatial patterns between the seasons, with both classes clearly separated in the middle of the map. Very few pixels (maximum 1.4%) with values outside class boundaries (labelled unknown) were detected (Figure 7). The classification accuracy using standard deviation performed on the test set in both seasons showed an overall accuracy ranging from 98 to 99% (Table 3). Overall, 98 and 97% of the pixels actually occupied by P. oceanica (producer’s accuracy) were detected in October and January, respectively, and 100% of the pixels classified as P. oceanica were correct on the map (user’s accuracy). Producer’s accuracy of sandy substratum was always 100%, whereas user’s accuracy ranged from 97.1 to 98%, with a maximum of three pixels misclassified as P. oceanica. A similar pattern of multiple accuracies was estimated for the depth-range classification. The user’s accuracy of P. oceanica was always 100%, and producer’s accuracy ranged from 96 to 97%. The latter for “sandy” was always 100%, and the user’s accuracy ranged from 96.2 to 97.1%, with a maximum of four pixels misclassified as P. oceanica.

Discussion

The reflectivity of P. oceanica leaves to the high-frequency acoustic signal of the Reson SEABAT 8125, combined with the large number of beams, permits the detection of the intricate, three-dimensional seagrass-canopy architecture (Hemminga and Duarte, 2000) with respect to the substantial bi-dimensionality of the sandy substratum. Our results suggest that the depth range obtained by MBS can be considered a proxy of longest-leaf length, although it has been demonstrated that season does affect the accuracy of the estimations. The depth ranges recorded in winter were consistent with longest-leaf length measured in the laboratory (38 vs. 43 cm), but in October, the depth range was on average ~30% lower than the bio-metric measures. In that period, the leaf length was considerably different from the canopy height because it bends and aligns in a more or less horizontal position, depending on water movement, giving the appearance of an enclosed umbrella-like canopy (Smith and Walker, 2002; Gonzalez-Correa et al., 2007). Moreover, leaf biometry combined with shoot density provides a leaf-area index.

### Table 1. Average values of features of P. oceanica shoots sampled inside plot A (training set) and plot B (test set), with standard deviation in parentheses, assuming a constant meadow density during the two sampling seasons (see text).

<table>
<thead>
<tr>
<th>Month</th>
<th>Plot</th>
<th>Shoot density (shoots m$^{-2}$)</th>
<th>Shoot surface (cm$^2$)</th>
<th>Leaf-area index (m$^2$ m$^{-2}$)</th>
<th>Longest leaves per shoot (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>October</td>
<td>A</td>
<td>412.5 (39.5)</td>
<td>197.3 (74.1)</td>
<td>8.1</td>
<td>82.6 (17.3)</td>
</tr>
<tr>
<td>B</td>
<td>411.2 (75.6)</td>
<td>183.7 (61.0)</td>
<td>7.6</td>
<td>82.0 (14.8)</td>
<td></td>
</tr>
<tr>
<td>Total mean</td>
<td>4113.9 (56.9)</td>
<td>190.2 (66.5)</td>
<td>7.9</td>
<td>82.3 (15.7)</td>
<td></td>
</tr>
<tr>
<td>January</td>
<td>A</td>
<td>–</td>
<td>164.3 (27.7)</td>
<td>6.8</td>
<td>47.4 (8.4)</td>
</tr>
<tr>
<td>B</td>
<td>–</td>
<td>135.8 (42.8)</td>
<td>5.6</td>
<td>39.9 (8.3)</td>
<td></td>
</tr>
<tr>
<td>Total mean</td>
<td>–</td>
<td>150.1 (38.0)</td>
<td>6.2</td>
<td>43.6 (9.0)</td>
<td></td>
</tr>
</tbody>
</table>

...
of about 8 m$^2$ m$^{-2}$. Under those circumstances, within a pixel of 1 m$^2$, there is very little space available through which the beams of light (about 13 cm$^2$ wide) can penetrate to the seabed, so most beams are probably reflected by the topmost canopy layers. In contrast, the leaves are less responsive to water movement in winter because of their small size; hence, they are more vertically oriented. In that case, the topmost canopy layer corresponds to the longest-leaf length and the acoustic beams have a much greater chance of reaching the seabed. The reflectivity of these layers to MBS signals has already been exploited to estimate the vertical distribution and volume of seagrass canopy (Komatsu et al., 2003; Parnum et al., 2004). Our results suggest that MBS allows the acquisition of remote information not only at the canopy level, but also at the shoot level, because its size can be determined precisely in winter. Recent studies of multivariate analysis performed on several $P.$ oceanica descriptors show that shoot surface is one of the best candidates to assess meadow vitality (Moreno et al., 2001; Romero et al., 2007; Fernández-Torquemada et al., 2008). Moreover, given the high correlation between shoot surface and longest-leaf per shoot, shoot surface can be replaced in analyses by longest-leaf per shoot, because this variable can be measured directly in the field in a non-destructive way (Lopez y Royo et al., 2010). Therefore, monitoring the longest-leaf per shoot with MBS could be considered an efficient method because the meadow status can be determined precisely, with a very high density of measurements over a wide area.

The results presented here show that the intrinsic heterogeneity of $P.$ oceanica canopy architecture and the relatively simple morphology of sandy substrata can easily be contrasted using simple statistical indices such as the standard deviation or range of beam depth. These indices exhibit a high power of discrimination,
with a fivefold magnitude of difference between the two bottom categories. In an earlier study, bathymetric standard deviation was calculated in cell sizes ranging from 225 to 416,025 m², to quantify the topographic complexity of an area of seabed (Pittman et al., 2007). However, at those levels of spatial resolution, no threshold values were detected to separate seagrass areas from sandy regions, so both typologies were grouped in the “soft-bottom” category. Our study has clearly demonstrated that the greater density of bathymetric measurements possible via MBS (127 m² on average) provides standard deviations of depth within cells only 1 m² in size. Based on these findings and for the first time, seagrass and sand have been discriminated by automated classification of MBS bathymetric data, and the accuracy levels have been estimated by cross-validation. The probability of *P. oceanica* being omitted on the map using standard deviation or depth range as predictors is ≏3%, whereas the probability that an area classified as *P. oceanica* on the map does not actually correspond to the seagrass *in situ* is consistently negligible.

The accuracy pattern of the sandy substratum is practically opposite to that of the seagrass, because only these two categories were explored. In other words, there is residual confusion that leads to a slight overestimate of sand coverage and a slight underestimate of *P. oceanica* which is consistent over the two seasons under review.

Although the class boundaries have been estimated at a spatial scale of hundreds of square metres, it is likely that the class limits could be representative of the two bottom typologies at a larger spatial scale (thousands of square metres) at the same depth, because few unclassified pixels were discovered on the whole swath. The depth range of unclassified pixels within *P. oceanica* averaged 0.98 m, suggesting that some of those pixels were

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**Table 2. Class boundaries of bottom typology for depth standard deviation and depth range in the two seasons analysed.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Month</th>
<th>Class boundaries (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth standard deviation</td>
<td></td>
<td>October: 0.01 &lt; sand &lt; 0.03 &lt; <em>P. oceanica</em> &lt; 0.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td>January: 0.01 &lt; sand &lt; 0.03 &lt; <em>P. oceanica</em> &lt; 0.16</td>
</tr>
<tr>
<td>Depth range</td>
<td></td>
<td>October: 0.07 &lt; sand &lt; 0.20 &lt; <em>P. oceanica</em> &lt; 0.75</td>
</tr>
<tr>
<td></td>
<td></td>
<td>January: 0.07 &lt; sand &lt; 0.17 &lt; <em>P. oceanica</em> &lt; 0.66</td>
</tr>
</tbody>
</table>

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**Figure 5.** Histograms of the standard deviation and the depth range in the two categories. The ovals indicate overlapping zones between the two histogram types.

**Figure 6.** Classification-tree model of two substrata, showing the splitting variables with their cut-off values. The number of observations is shown in parenthesis.
falling on the boundaries of bathymetric holes in the meadow. These erosive structures are fairly frequent within the *P. oceanica* meadow and become more evident in MBS analysis in October (Figure 7), when they are delimited by a higher leaf canopy. Several studies focused on seabed mapping by acoustic methods suggest the sidescan-sonar system as the most used and appropriate technology for *P. oceanica* detection (Meinesz *et al.*, 1981; Pasqualini *et al.*, 1998; Piazz *et al.*, 2000). Like the MBS,

Figure 7. Classification by standard deviation of depth and depth range (both in metres) of *P. oceanica* (dark grey) and sand (light grey) detected along the MBS swath. The unknown (black) squares represent pixel values outside the class limits.

Table 3. Error matrix resulting from bottom classification using standard deviation and depth range as predictors.

<table>
<thead>
<tr>
<th></th>
<th>Classified</th>
<th>Actual</th>
<th>Omission error (%)</th>
<th>User accuracy (%)</th>
<th>Month</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sand</td>
<td><em>P. oceanica</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>By depth standard deviation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sand (n)</td>
<td>100</td>
<td>2</td>
<td>2.0 (3.0)</td>
<td>98.0 (2.7)</td>
<td>October</td>
</tr>
<tr>
<td><em>P. oceanica</em> (n)</td>
<td>0</td>
<td>98</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Omission error (%)</td>
<td>0</td>
<td>2 (1.9)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Producer accuracy (%)</td>
<td>100</td>
<td>98 (2.7)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>99.0 (0.44)</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Sand (n)</td>
<td>100</td>
<td>3</td>
<td>2.9 (2.8)</td>
<td>97.1 (2.0)</td>
<td>January</td>
</tr>
<tr>
<td><em>P. oceanica</em> (n)</td>
<td>0</td>
<td>97</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Omission error (%)</td>
<td>0</td>
<td>3 (2.8)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Producer accuracy (%)</td>
<td>100</td>
<td>97 (3.0)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>98.5 (1.5)</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>By depth range</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sand (n)</td>
<td>100</td>
<td>4</td>
<td>3.8 (3.7)</td>
<td>96.2 (3.7)</td>
<td>October</td>
</tr>
<tr>
<td><em>P. oceanica</em> (n)</td>
<td>0</td>
<td>96</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Omission error (%)</td>
<td>0</td>
<td>4 (3.0)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Producer accuracy (%)</td>
<td>100</td>
<td>96 (2.8)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>98.0 (2.0)</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Sand (n)</td>
<td>100</td>
<td>3</td>
<td>2.9 (2.8)</td>
<td>97.1 (2.0)</td>
<td>January</td>
</tr>
<tr>
<td><em>P. oceanica</em> (n)</td>
<td>0</td>
<td>97</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Omission error (%)</td>
<td>0</td>
<td>3 (2.8)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Producer accuracy (%)</td>
<td>100</td>
<td>97 (3.0)</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>98.5 (1.5)</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
</tbody>
</table>

The accuracy for each bottom category is reported with the confidence intervals at 95% in parenthesis. For 100 and 0%, no confidence interval was estimated because the variance is 0.
sidescan-sonar images can be organized using remote-sensing classification (see, for instance, Pasqualini et al., 2000), and specific software has been developed for automatic classification. However, the classification in this case was performed without appropriate class-accuracy estimation, so this approach is not directly comparable with other automated classification procedures.

The classification adopted here is based purely on statistical criteria, which is crucial for achieving more objective and comparable classification systems (Anderson et al., 2008). A comparison between the accuracies estimated here and those available for other remote-sensing classification involving statistical procedures reveals that MBS can be considered to be an accurate tool for mapping _P. oceanica_ and sand substrata (Table 4). In particular, the accuracies are generally similar to SPOT and IKONOS image classifications. Although satellite remote sensing is widely used for large-scale mapping, it becomes ineffective with water turbidity classifications. Although satellite remote sensing is widely used for large-scale mapping, it becomes ineffective with water turbidity classifications.

Table 4. Comparison of the reported accuracies between MBS and other optically based automated remote-sensing classifications via images acquired from IKONOS and SPOT 5 satellites. For the present study the highest values of accuracy are listed.

<table>
<thead>
<tr>
<th><em>P. oceanica</em></th>
<th>Sand</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>User accuracy (%)</strong></td>
<td><strong>Producer accuracy (%)</strong></td>
</tr>
<tr>
<td>-----------------</td>
<td>-----------------</td>
</tr>
<tr>
<td>100</td>
<td>98 ± 2.7</td>
</tr>
<tr>
<td>91</td>
<td>93</td>
</tr>
<tr>
<td>91</td>
<td>93</td>
</tr>
<tr>
<td>91</td>
<td>93</td>
</tr>
</tbody>
</table>

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References


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