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Predicting spatial kelp abundance in shallow coastal waters using the acoustic ground discrimination system RoxAnn

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ABSTRACT

Kelp forests represent a major habitat type in coastal waters worldwide and their structure and distribution is predicted to change due to global warming. Despite their ecological and economical importance, there is still a lack of reliable spatial information on their abundance and distribution. In recent years, various hydroacoustic mapping techniques for sublittoral environments evolved. However, in turbid coastal waters, such as off the island of Helgoland (Germany, North Sea), the kelp vegetation is present in shallow water depths normally excluded from hydroacoustic surveys. In this study, single beam survey data consisting of the two seafloor parameters roughness and hardness were obtained with RoxAnn from water depth between 2 and 18 m. Our primary aim was to reliably detect the kelp forest habitat with different densities and distinguish it from other vegetated zones. Five habitat classes were identified using underwater-video and were applied for classification of acoustic signatures. Subsequently, spatial prediction maps were produced via two classification approaches: Linear discriminant analysis (LDA) and manual classification routine (MC). LDA was able to distinguish dense kelp forest from other habitats (i.e. mixed seaweed vegetation, sand, and barren bedrock), but no variances in kelp density. In contrast, MC also provided information on medium dense kelp distribution which is characterized by intermediate roughness and hardness values evoked by reduced kelp abundances. The prediction maps reach accordance levels of 62% (LDA) and 68% (MC). The presence of vegetation (kelp and mixed seaweed vegetation) was determined with higher prediction abilities of 75% (LDA) and 76% (MC). Since the different habitat classes reveal acoustic signatures that strongly overlap, the manual classification method was more appropriate for separating different kelp forest densities and low-lying vegetation. It became evident that the occurrence of kelp in this area is not simply linked to water depth. Moreover, this study shows that the two seafloor parameters collected with RoxAnn are suitable indicators for the discrimination of different densely vegetated seafloor habitats in shallow environments.

1. Introduction

Perennial brown macroalgae of the order *Laminariales* form unique three-dimensional habitats which provide food and shelter for many marine fishes, invertebrates, and other seaweed species and serve as natural coastal protection through their wave damping abilities (e.g. Schultze et al., 1990; Dubi and Tørum, 1994). Thus, changes in abundance and extent of these forests might have tremendous effects on coastal ecosystems, their production, functionality, and diversity. In recent years, it became evident that kelp forest ecosystems along the European coastlines and worldwide are still under pressure and negatively impacted by global warming (e.g. Wernberg et al., 2010; Díez et al., 2012; Voerman et al., 2013).

For a sustainable kelp-bed management it is important to develop reliable and sufficiently accurate and automated mapping routines for a spatial monitoring of these sublittoral habitats. Especially fast monitoring tools such as hydroacoustic devices capable to cover wide areas in a short time are promising. Classical monitoring methods of kelp beds are diving transects (e.g. Lüning, 1970; Pehlke and Bartsch, 2008) which are precise but highly time demanding and provide no spatial information. More recently,

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faster methods for seaweed mapping became established such as georeferenced underwater videos or airborne hyperspectral imaging techniques (e.g. Oppelt et al., 2012). Detection of submerged kelp forests with visual methods needs clear water conditions which are not always given in coastal turbid-water environments such as the southern North Sea (Gagnon et al., 2008).

In recent years, remote sensing of sublittoral benthic habitats using hydroacoustic devices became a fast evolving discipline (e.g. Hamilton et al., 1999; Cholwek et al., 2000; Kenny et al., 2003; Humborstad et al., 2004; Brown et al., 2005; Anderson et al., 2008; Freitas et al., 2011). Since the acoustic scattering process is a complex function of object size, shape, orientation, and material properties as well as acoustic frequency and wavelength (Stanton and Chu, 2000), transfer of approaches from one area or habitat to another is challenging. However, this method can strongly enhance monitoring speed and provides accurate spatial information about seafloor properties. Recently, many hydroacoustic studies applied and compared singlebeam echosounders (SBES), or multibeam echo sounders (MBES), and sidescan sonars in order to detect and classify seafloor vegetation in different regions of the world. Parnum et al., 2009; Rattray et al. (2009), Ierodiaconou et al. (2011), McGonigle et al. (2011), and van Rein et al. (2011), for example, used MBES and partially also sidescan sonar to identify benthic habitats and discriminate between different seaweed species in water depth of ~40 m. While it was simple to distinguish between physical habitats, discrimination between biological habitats was still afflicted with uncertainties (e.g. Méléder et al., 2010; Minami et al., 2010).

In shallow water, acoustic ground discrimination systems (AGDS) equipped with SBES can provide a high level of seabed discrimination (Brown et al., 2005) and when compared to MBES they are also affordable and easier to operate. However, they should be understood as complementary rather than competing devices (Foster-Smith et al., 2000). In this study, the employed AGDS (RoxAnn) delivers two parameters (roughness and hardness) describing the prevailing seafloor conditions. In combination, they can provide detailed information on seafloor characteristics (Hamilton et al., 1999; Mielck et al., in press).

Several studies focus on ground discrimination using SBES in order to classify seafloor vegetation down to 30 m (e.g. Kruss et al., 2006; Méléder et al., 2010; Minami et al., 2010). These investigations reveal that there are still problems in classifying gradual changes in seafloor environments which often occur in nature (Pinn and Robertson, 2003).

For this study, a hydroacoustic survey was conducted off the island of Helgoland (North Sea) in order to detect the distribution of different seaweed groups in shallow water depth between 2 and 18 m. The aims of the investigation were (1) to determine the acoustic signatures of the shallow sublittoral habitats using the two acoustic parameters provided by the seafloor-classification system RoxAnn and (2) to classify, map, and predict the spatial distribution and variable density of the dominant kelp habitat as well as other seafloor environments by means of two approaches: A linear discriminant analysis (LDA) and a manual classification (MC). Both combine hydroacoustic data sets with the results of a georeferenced video survey and evaluate the prediction abilities of the mapping approaches by comparison with additional echogram and dive prospection data.

2. Materials and methods

2.1. Study area

The seafloor of the SE North Sea is mainly characterized by Neogene, Pleistocene, and early Holocene unconsolidated sandy sediments (Zeiler et al., 2000), except for the surroundings of the island of Helgoland (Spaeth, 1990). Here, a Mesozoic platform was tectonically uplifted by a Permian salt diapir during the Tertiary (Spaeth, 1985). The seafloor is characterized by outcropping Mesozoic sediments such as red sandstone, shell-bearing limestone, and chalkstone that form a regular arrangement of ridges and channels. Within the euphotic zone these structures are mostly covered by diverse seaweed species (Bartsch and Kuhlenkamp, 2000). In deeper water the seafloor is generally barren (Lüning, 1990). The investigation area is located north of Helgoland (54.2°N, 7.8°E) and lies approximately 60 km off the German mainland (Fig. 1). It comprises 3.5 km^2 and is characterized by shallow waters between 2 and 18 m below sea chart datum.

2.2. Hydroacoustic data acquisition

This survey was conducted during times of high tide on 15th and 16th June 2011 – a time of the year when kelp bed development is generally most pronounced (Lüning, 1979). The AGDS RoxAnn (Model GD-X, Sonavision, Aberdeen, U.K.) was installed on the research vessel *Aade* (lengths: 9.2 m, draught: 1.5 m). The transducer was mounted on a long bracket at the ship's rail slightly below the water surface. Since the vessel has a low draught and the technical limit of RoxAnn is at 1.5 m water depth, it was possible to obtain hydroacoustic data in the shallow sublittoral.

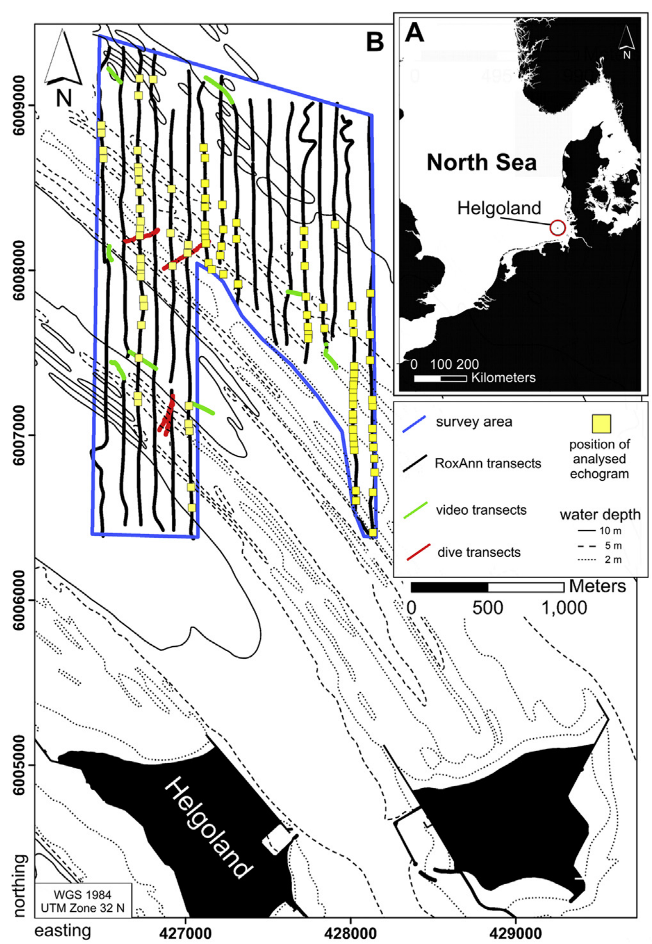

Fig. 1. Study area. (A) Location of the island of Helgoland in the German Bight (North Sea). (B) Survey area, RoxAnn transects, video and dive transects, and echo sounder ground-truth locations. Depth contours are indicated in meters below chart datum (according to sea chart 88, with allowance of the Federal Maritime and Hydrographic Agency, Germany).

A total of 16 transects with a track spacing of approximately 100 m and an overall length of about 35 km were surveyed, covering the study site in latitudinal direction (Fig. 1B). Vessel speed was kept at ~4 knots (~2 ms^{-1}). The SBES worked with a frequency of 200 kHz (output power: 200 W_{rms}, pulse-length 0.1 ms) and a beam width of 10°, providing a footprint with a diameter of approximately 17% of water depth on the seafloor. Approximately 20,000 echo envelopes were measured along the transect lines with a sampling frequency of 1 Hz. The values are given in direct-current voltages (V) from a minimum of 0.00 V to a maximum of 4.09 V (Cholwek et al., 2000). Additionally, the system delivers depth values. The associated backscatter parameters are calculated by the RoxAnn system from the last part of the first incoming echo ($E1$) and are an indicator of seafloor roughness. Smooth seafloor is indicated by a high initial peak and a short tail while lower initial peaks with long tails stand for rough seafloor conditions. The intensity of the second incoming echo ($E2$) is used as an indicator for seafloor hardness. Detailed descriptions of the calculated parameters can be found in e.g. Chivers et al. (1990) and Hamilton et al. (1999) and further interpretations are given in Chapter 4.

For additional ground truthing, seafloor characteristics were visually classified into four categories (dense kelp, medium dense kelp, mixed vegetation and barren seafloor) on the basis of echogram images provided by the shipboard echosounder Furuno FCV-612 working with a sound frequency of 50 kHz and a sampling rate of 1 Hz (Fig. 2.). The observations served as additional data to verify the prediction abilities of the habitat maps created from the RoxAnn data sets. The echograms were randomly recorded while sailing (see Fig. 1B) and later digitized and correlated with the GPS positions via the time stamp. For geographic positioning, a Leica 1200 differential GPS (Leica Geosystems, Munich, Germany) was used. The reference station was installed on the mainland on the top of a near-shore building.

2.3. Ground truthing

2.3.1. Video transects

In order to ground-truth the acoustic data, an underwater camera (Kongsberg oe14-106/107, Kongsberg Maritime AS, Kongsberg, Norway) was employed directly after the acoustic survey, especially in areas with ambiguous $E1/E2$ values to visually record the seafloor conditions. During the hydroacoustic survey 8 concurrent video transect were recorded. They had an overall length of ~1200 m with a total duration of 60 min. The videos were recorded at low vessel speed of approximately 0.5 knots (~0.25 ms^{-1}). For transect positions see Fig. 1B. The data were classified into four main categories and three subclasses based on the visually identified habitats. Simultaneously, RoxAnn measurements were acquired to assign the hydroacoustic properties of the different environments to the video recordings.

2.3.2. Diving transects

To verify the results of the hydroacoustic survey, additional ground truthing was achieved through four georeferenced diving transects accomplished between 28th June and 12th July 2011 with a total length of approximately 950 m. These transects were planned as part of another remote sensing campaign and thereby only cover part of the hydroacoustic survey and no shallow depths. During diving, every 6 m the percentage of kelp cover was estimated along a corridor of ±3–5 m (Pehlke and Bartsch, 2008). Georeferencing of the diving position was achieved by recording

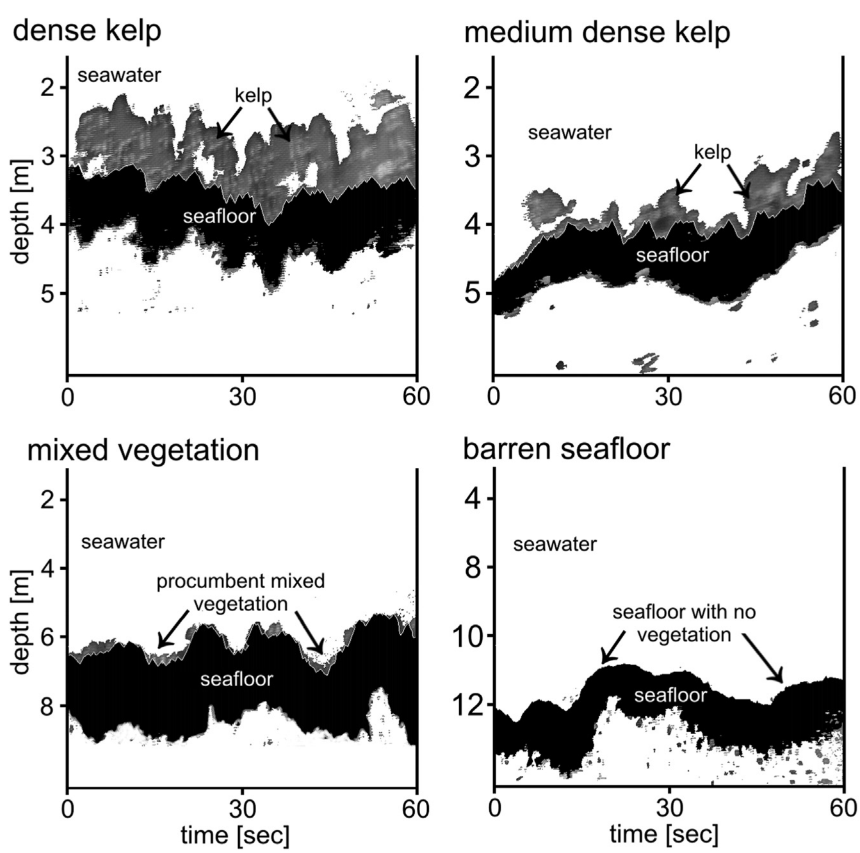

Fig. 2. Detection and classification of different vegetation densities by means of echo- reflection images provided by the shipboard echo sounder (Furuno FCV-612).

the position of a surface buoy (GPS: iBlue 747A+EU, TranSystem Inc., Taiwan) straightly connected by a line with the diver and by aligning position and diving time. The information of the diving prospection was classified and visualized in ArcGIS 9.3 (ESRI, Redlands, California).

2.4. Data post-processing

Bad and implausible RoxAnn data were filtered by means of self-programmed filter algorithms using MATLAB R2009b (The Mathworks™) which are able to detect measure anomalies. Bad data were generally produced by bubbles within the water column as well as by pitching and rolling of the ship which led to wrong depth values. Another reason might be steep seafloor slopes. After filtering, ~17.500 data strings remained in the dataset. Since RoxAnn only delivers along-track point data, the raster interpolation technique *ordinate kriging* (covariant transformation, spherical model type) using ArcGIS 9.3 was applied to produce two 2D and two 3D raster maps of the roughness ($E1$) and the hardness ($E2$) properties of the seafloor. All raster data sets were interpolated with a grid size of 10 m. To calculate the underwater terrain model, the depth values of the RoxAnn measurements were used. Tidal correction of the bathymetric data was carried out using gauge data from 'Helgoland Inner Harbour' (Water and Shipping Authority Tönning, Germany).

2.5. Validation

The video records allowed a visual differentiation between various types of vegetation and sediments. To create a habitat map of the whole survey area, it was necessary to determine the typical acoustic properties ($E1$ and $E2$ values) of the prevailing habitats. Therefore, the underwater videos were subdivided into 10-second sequences. The respective seafloor features which became visible in each of these segments were classified into one of the four habitat classes described in Section 2.2. Since habitats were very patchy, only distinctly classifiable video sequences were used. The corresponding RoxAnn values that were measured simultaneously during the video survey were averaged over 10 s as recommended by Brown et al. (2005) resulting in one $E1/E2$ value pair for each 10-second sequence. Cross-reference of video data with the acoustic data was achieved via the positioning signal and the time stamp. Subsequently, an assignment of $E1$ and $E2$ values to each habitat was possible, resulting in a validated RoxAnn data set which was used as training data for the two classification approaches.

2.6. Habitat classification approaches

2.6.1. Linear discriminant analysis (LDA)

The aim of the LDA was to distinguish predefined groups on the basis of linear discriminant functions. The functions maximize the variation of data between the groups and minimize the variation within the groups (Hair et al., 1995). In this study, a LDA was applied to predict the habitat-class membership of the measured RoxAnn variables $E1$ and $E2$. The linear model was built on (1) the non-validated $E1$ and $E2$ raster maps that were created from all RoxAnn parameters using interpolation procedures and (2) the RoxAnn data set validated via video recording. Subsequently, it was used to predict the distribution of habitat classes resulting in a seafloor habitat map (grid size 10 m) showing four classes (i.e. dense kelp vegetation, mixed seaweed vegetation, barren sand, and bedrock). Statistical analyses and illustrations were performed using the software R (version 2.15.1, package MASS, Venables and Ripley (2002)) and ArcGIS 9.3.

2.6.2. Manual classification (MC)

An additional manual classification method was applied as we also wanted to discriminate dense and medium dense kelp fields that became apparent in the underwater videos and are also known from the area (Pehlke and Bartsch, 2008). For this approach, both validated and non-validated hydroacoustic data sets (obtained along the RoxAnn transects and the video transects) were plotted on a Cartesian XY chart, while the ground-truthed $E1$ and $E2$ values of the video transects were marked in different colors. According to their group membership, they form colored agglomerations in the XY plot that represent the acoustic properties of each habitat class. Subsequently, all non-validated RoxAnn data were assigned to one of these classes, while the borders were manually aligned along the agglomerations. The linear arrangements of the vegetation classes within the plot along the y-axis allowed an interpolation procedure (*ordinate kriging*) regarding the density gradient of the vegetation. A habitat map (grid size of 10 m) that additionally includes the medium dense kelp forests was created, while the borders between the differently densely vegetated habitats are depending on the validated RoxAnn values. The barren bedrock habitats were treated separately. Their presence was determined by locating the corresponding acoustic signatures (high hardness) in the survey area, where they form spatially restricted zones. Their extent was determined manually.

2.7. Evaluation of the two approaches

To evaluate the prediction ability of the two classification approaches and their ensuing habitat maps, the results of the echogram classification were compared with the corresponding grids of the habitat maps using a distance tolerance of $\leq$25 m. The ratio between the prediction grids that matched with class membership of echograms and the grids that were not coinciding were given in percentage and quantify the level of accordance. The ground truth data obtained during the diving prospection were visually compared with the created habitat maps.

3. Results

3.1. RoxAnn raw data

In order to analyze and evaluate the RoxAnn observations, the data were plotted in a number of XY charts: Fig. 3A shows the filtered 17,500 $E1 - E2$-value pairs in a scatter plot. With increasing $E2$ values, $E1$ values only slightly increase, while high E1 values rather correspond with low $E2$ values and vice versa. Data points that simultaneously show high roughness and high hardness values do not occur. Fig. 3B and C illustrate the absolute frequency distribution of the observed parameters. The $E1$ and $E2$ values show a bimodal distribution and unimodal distribution, respectively. $E1$ and $E2$ values as a function of water depth are presented in Fig. 3D and E. It becomes apparent that in shallow waters (<5 m) the $E1$ values are highly diverse. Below 5 m water depth, $E1$ parameters considerably decrease, while below 15 m a slight increase is observable. The $E2$ values reveal increasing hardness with increasing water depths with highest $E2$ values present in depth $\geq$17 m.

3.2. Hardness and roughness prediction maps

The prevailing bathymetry and the interpolated roughness and hardness conditions of the seafloor derived from the RoxAnn measurements are shown in Fig. 4.

The morphology reveals a ridge of ~600 m length in the west which stretches from northwest to southeast and extends between

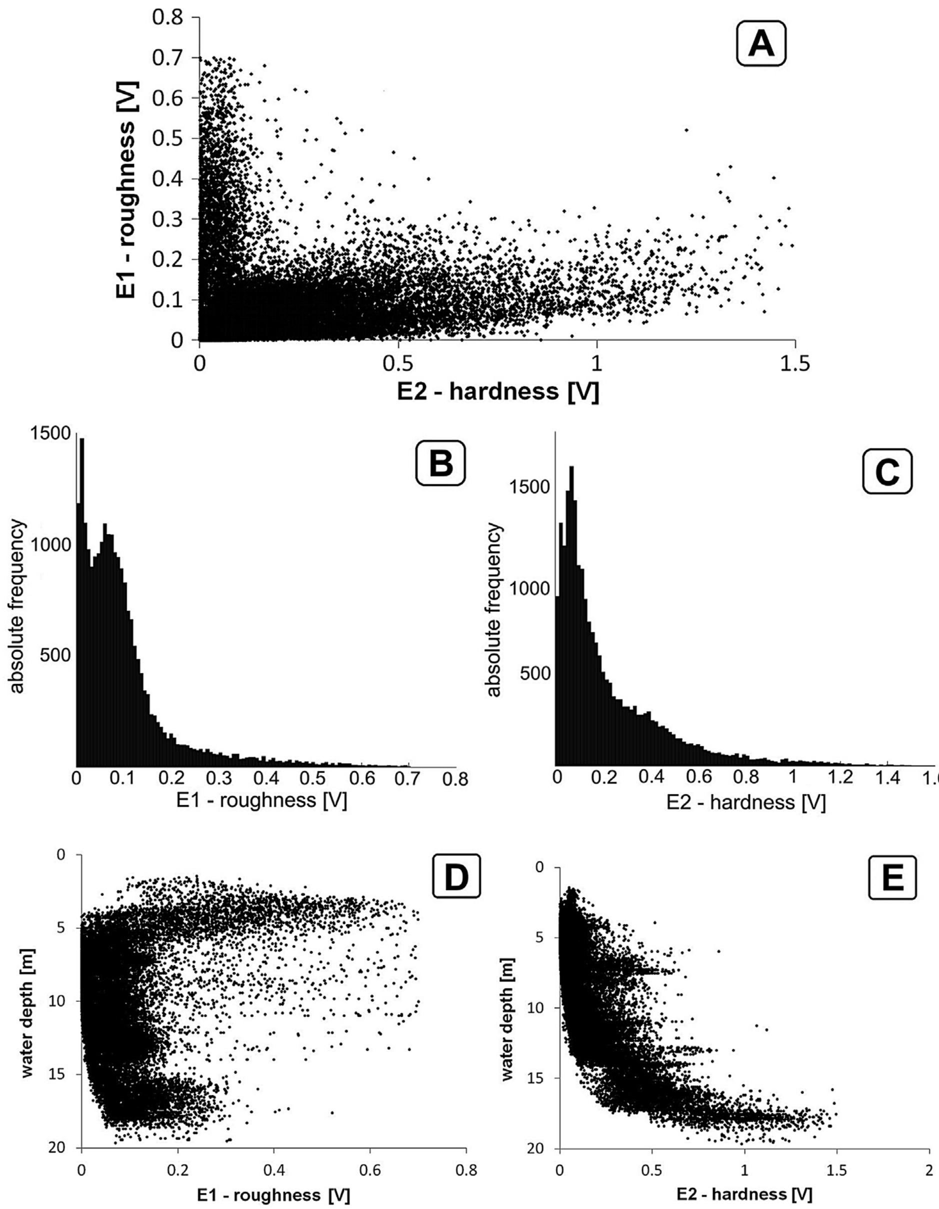

Fig. 3. Distribution of roughness (*E*1) and hardness (*E*2) values measured with RoxAnn: (A) Correlation of roughness with hardness, (B and C) absolute frequency of roughness and hardness values, (D and E) roughness and hardness values as a function of water depth below sea chart datum.

~4 and ~15 m water depth. The ridge shows particularly high roughness and low hardness values at its crest. An additional ridge appears further south. However, its crest is about 2.5 m lower while the surface is slightly smoother and harder. Between the ridges, the seafloor is deep (18 m) and essentially rough and hard. Shallow areas are present in a broad zone in the east. Here, a long ridge slowly deepens from 8 to 15 m and is characterized by low roughness and moderate to high hardness values.

3.3. Video ground truthing and seafloor validation

The videos show that rocks and coarse-grained sediments dominate the investigation area. They are frequently covered with seaweeds of various densities. On the basis of these recordings, biological and sedimentary features were distinguished, resulting in four major seafloor classes and three subclasses (Fig. 5): **(1) dense kelp vegetation** (dense stocks of *Laminaria hyperborea* with a canopy cover of ≥100% of the seafloor), **(2) barren sand/gravel fields, (3) cobbles/hard rock** with a certain proportion of sand, and **(4) mixed vegetation zones** which were further divided into three sub-types: **(4a) medium dense kelp** beds, where *L. hyperborea* is still dominant but present in variable densities with <100% cover, **(4b) mixed brown algae** of variable density mainly composed of small *Laminaria* ssp., bushy *Desmarestia aculeata* and/or low lying *Saccharina latissima*, and **(4c) bushy procumbent red algae** with variable density. In the mixed vegetation zone, the algal density is generally reduced so that the seafloor (red sandstone, shell or lime bedrock or bedrock covered with cobbles and/or loose sandy sediments) becomes partially visible.

The occurrence of one habitat class is often interrupted by small-scale patches of other classes. In total, 295 video sequences were assigned to one of the six habitat classes (35: dense kelp, 54: medium dense kelp, 41: brown algae, 80: red algae, 56: sand/gravel, 29: cobbles/hardrock). Since all video sequences are equipped with

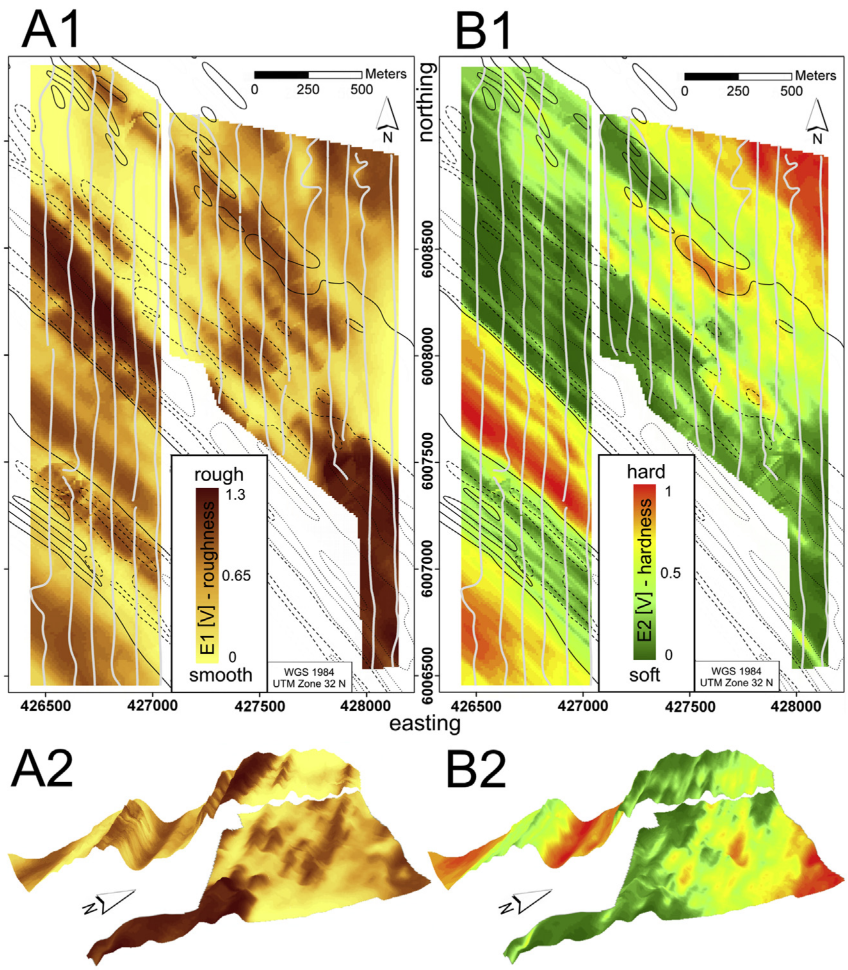

Fig. 4. Interpolated 2D-maps (1) and 3D-bathymetric maps (2) showing the distribution of roughness (A) and hardness (B) values. Bathymetric data were taken from RoxAnn depth measurements. White lines indicate RoxAnn survey tracks. Grid size: 10 m. Vertical exaggeration: 35. For explanation of depth contour lines see Fig. 1.

an $E1$ and an $E2$ value, they were used to calibrate the RoxAnn XY space. The respective value pairs corresponding to the different habitat classes are plotted in Fig. 6A.

The signature of the dense kelp vegetation (brown dots) is considerable rough and soft (generally: $E1 > 0.2$ V, $E2 < 0.2$ V), and there is no correlation between $E1$ and $E2$ values. Hence, this class is mostly characterized by its high roughness and low hardness values. The mixed vegetation zone, including the subclasses medium dense kelp (orange dots), mixed brown algae (pink), and bushy red algae (violet), is more widespread within the scatter plot.

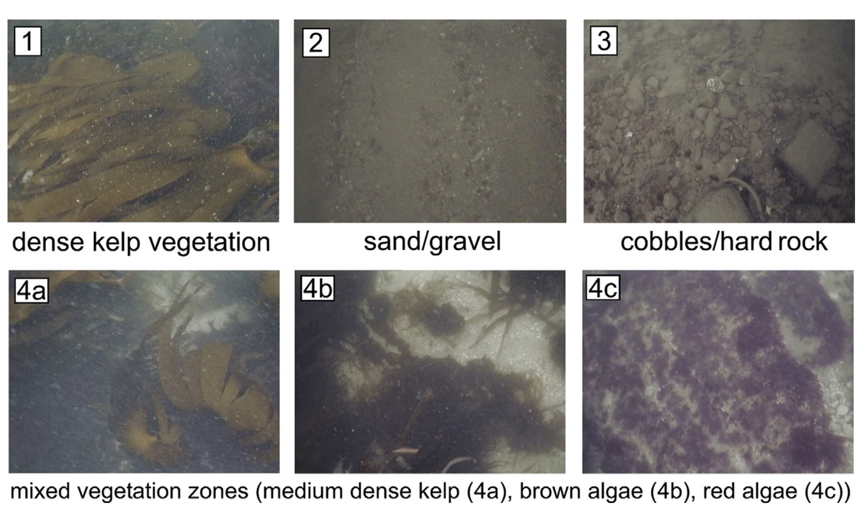

Fig. 5. Visual examples of four major seafloor classes and three sub-classes as suggested by underwater video interpretations.

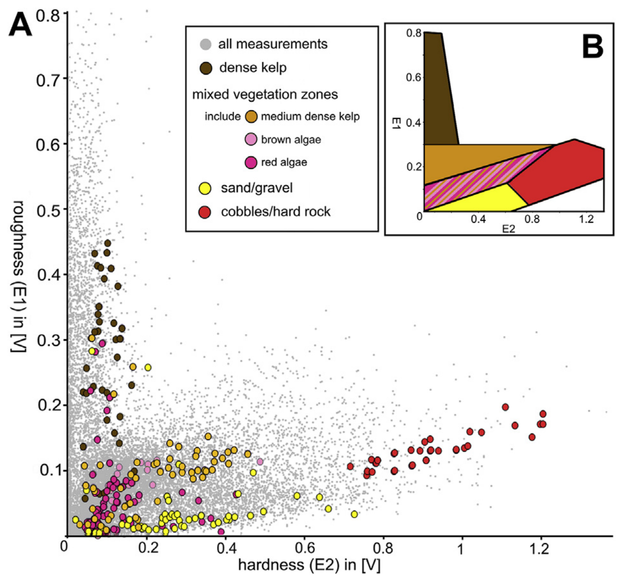

Fig. 6. Scatter plot of RoxAnn hardness and roughness values (gray). The color-coded points show RoxAnn values measured during the video survey assigned to one of the six defined habitat classes (A). Class demarcations used for the MC including 'medium dense kelp' (B). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

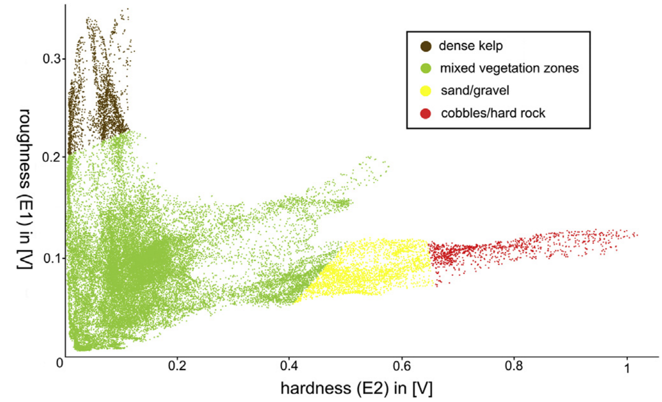

Fig. 7. Scatter plot of hardness and roughness values showing the four major habitat classes separated by LDA.

It is characterized by rather low roughness values (generally <0.125 V) and low to intermediate hardness values ranging between 0.05 and ~0.5 V. In contrast to the vegetated habitats, the barren seafloor which is dominated by sand/gravel (yellow dots) and cobbles/hard rock (red dots) show clear non-overlapping *E*1 and *E*2 characteristics with specific acoustic backscatter pattern that are generally characterized by low roughness and high hardness values. With increasing grain sizes also roughness and hardness signatures increase.

3.4. Classification approaches

3.4.1. Linear discriminant analysis (LDA)

In order to transfer the four major seafloor classes defined by the video analysis into a spatial scale, a linear discriminant analysis was applied on the basis of the validated RoxAnn data set. The resulting linear discriminant model predicts the associated habitat class for the *E*1 and *E*2 raster data sets illustrated in Fig. 4, and hence for the interpolated parts of the working area. Fig. 7 shows the predicted raster classification in an XY scatter plot. The three subclasses of the mixed vegetation class could not be discriminated by the model.

Subsequently, this information was used to create a seafloor map showing the spatial distribution of acoustically classifiable seafloor habitats based on the linear discriminant model (Fig. 8A): According to this classification, nearly 10% of the seafloor in the investigation area is characterized by more or less barren sandy sediments and gravel (Table 1), particularly in water depth >10 m. Only ~3% are covered by cobbles and solid bedrock without any vegetation. That zone exclusively occurs in depths >15 m. The dense kelp vegetation class covers ~8% and is generally situated in shallow waters between 2 and 5 m. The mixed vegetation zone dominates the investigation area with ~84% and mainly occurs between 5 and 15 m water depth.

3.4.2. Manual classification (MC)

Since the LDA was not able to discriminate between the subclasses of the mixed vegetation zones, an additional manual classification was performed. It is based on the fact that roughness values significantly increase with increasing vegetation densities which can be observed in the validated scatter plot (Fig. 6A): All detected vegetation classes are distributed along the *y*-axis, while yielding relatively low hardness values. Since the agglomerations of the mixed vegetation zone have an overlap with the dense kelp agglomeration, it is concluded that there is a vegetation cover gradient ranging from dense to medium dense kelp vegetation to procumbent mixed vegetation. To reflect this situation, data points that show roughness values between 0.125 V and 0.3 V were treated as medium dense kelp (as shown in Fig. 6B). This manual classification was applied according to the distribution of the validated medium dense kelp data points in the scatter plot which overlap with the mixed vegetation and dense kelp forest domain.

To generate a more detailed picture of the vegetation zones, an additional 2D raster map was created illustrating the distribution of roughness similar to Fig. 4A. However in this map all value pairs showing hardness values higher than 0.5 V were excluded in order to remove the non-vegetated habitats. This classification approach created the new class medium dense kelp which is located 'between' the dense kelp and the mixed vegetation zone. In a second step the non-vegetated habitats were added. The resulting map is shown in Fig. 8B. Similarly as in the LDA, approximately 76% of the investigation area is covered by algal vegetation. However, the area of the dense kelp class distinctly increased from 6% in the LDA map to 13% in the MC map (especially obvious on the western ridge), while the mixed vegetation zones decreased to 72%. This zone became subdivided into medium dense kelp (34%) and other procumbent mixed vegetation consisting of red and brown algae (38%, see Table 1).

The cobbles/hard rock class without any vegetation is easy to locate in the scatter diagram (Fig. 6A), since it yields high hardness values (>0.7 V). The size of this area (~3%) is similar compared to that of the LDA. The extent of the barren sand/gravel class which is characterized by lower hardness values than bedrock (approximately >0.4 V and <0.7 V), increase compared to the LDA and represents 15% of the area in the MC. Some parts of the mixed vegetation zones shown in the LDA map, especially in the east, are assigned to the sand/gravel class in the MC map. Within the deeper areas in the west and in the southwest the extent of the sandy area decreased in the MC map compared to the LDA map.

3.5. Additional data for accordance assessments

During the four georeferenced diving prospections, the percentage cover of seaweeds was estimated at 143 stations. The

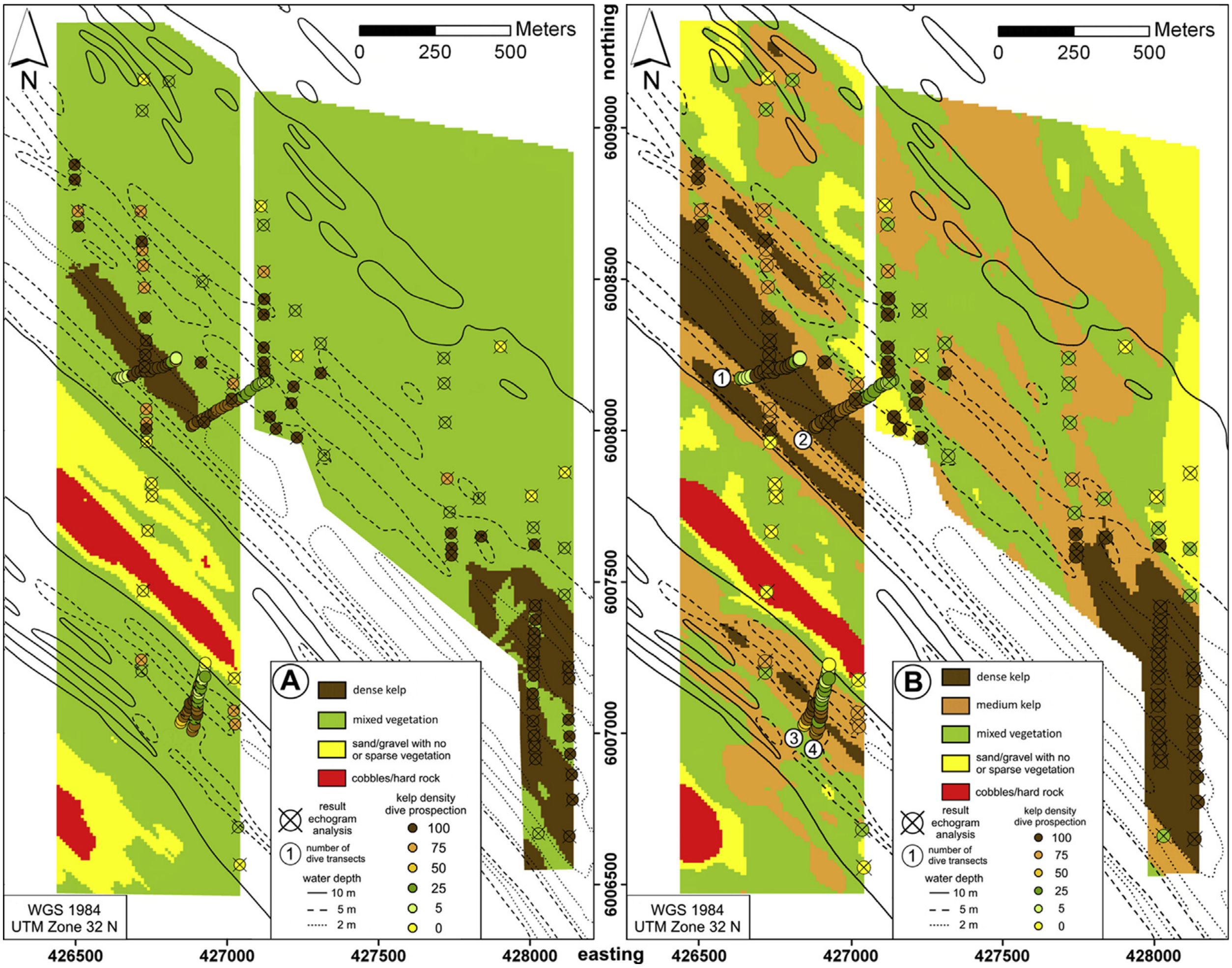

Fig. 8. Comparison between the predicted habitat maps created with two approaches: (A) Habitat distribution determined by LDA. (B) Habitat distribution generated with MC (illustrated in Fig. 5B) and by a linear interpolation of the roughness values (excluding high hardness values). Grid size 10 m.

results are summarized in Fig. 8. Moreover, the figure shows the positions of the 94 echograms recorded with the Furuno system which were used to validate the RoxAnn classification (see Fig. 2). Unfortunately, it was not possible to distinguish between hardrock and sand. These results enable an independent qualitative accordance assessment on both classification approaches (LDA and MC).

4. Discussion

This study demonstrates that the AGDS system RoxAnn can be used to determine the occurrence of vegetation realistically as well as sediment distribution in shallow turbid coastal environments between 2 and 18 m. The two models (LDA and MC) were used to predict the occurrences by combining hydroacoustic data with georeferenced video recordings within a GIS framework. In order to validate and evaluate the two classification approaches, ground-truth information collected by diving prospection and independent echo-sounder data derived from the Furuno System were examined. This study links different mapping approaches which act on different scales such as optical remote sensing in intertidal areas (Hennig et al., 2007; Oppelt et al., 2012) and MBES techniques in deeper waters (Komatsu et al., 2003; Rattray et al., 2009; Ierodiaconou et al., 2011; McGonigle et al., 2011; ; van Rein et al., 2011).

Table 1
Comparison between the results of LDA and MC. Size of the habitats and their relative frequency of occurrence.

Habitat	LDA – habitat sizes	MC – habitat sizes
Dense kelp	222,400 m^2 (~6%)	445,700 m^2 (~13%)
Medium dense kelp	–	1,169,700 m^2 (~34%)
Mixed vegetation	2,899,100 m^2 (~84%)	1,332,800 m^2 (~38%)
Sand	243,700 m^2 (~7%)	401,400 m^2 (~15%)
Cobbles/hard rock	102,700 m^2 (~3%)	118,600 m^2 (~3%)
Algal vegetation	3,121,500 m^2 (~90%)	~2,948,200 m^2 (~85%)
No/sparse vegetation	346,400 m^2 (~10%)	~520,000 m^2 (~15%)

4.1. Accordance to diving prospection

A visual comparison between the results of the diving prospection and the prediction maps shows adequate accordance of ground-truth data and interpolated data: The occurrence of the wide dense kelp forest in the northwest was verified (dive profiles 1 and 2). While the prediction abilities of the MC approach seems to be sufficient, the LDA method does not display the whole extent of the kelp forest. Dive transects 3 and 4 reveal that the smaller dense kelp patches and the transition to medium dense kelp and mixed vegetation further to the south only show moderate accordance with the prediction maps. Especially the LDA did not predict any dense kelp in this area, while the MC yields medium dense kelp in zones where rather procumbent vegetation was detected by divers. These inaccuracies might be due to imprecise position data which are inherent in the diving prospection with offsets up to 30 m between the real position and the GPS measurement. The extent of the dense kelp areas located along the arcuate submarine cliff (see Fig. 1) as well as the smaller kelp accumulation in the southwestern part of the investigation area seem to be underestimated in the LDA map, as it shows less accordance to the results of the diving prospection in contrast to the MC map.

4.2. Accordance to echogram analysis

The results of the echogram classification were compared with the corresponding prediction grids of the two mapping approaches regarding their class membership. For this evaluation a tolerance width of ≤25 m was used. The accordance is given in Table 2.

The overall degree of predictability reaches 62% for the LDA and 68% for the MC. According to this validation, the MC approach is quite reliable in predicting vegetated environments with an accordance greater than 76%. The MC was more reliable in predicting dense kelp forests achieving an accordance rate of 69% compared to 49% for the LDA. Unfortunately, the LDA was not able to differentiate medium dense kelp from mixed vegetation. This is a result of partially overlapping $E1$ and $E2$ characteristics of both classes resulting in a single huge class of mixed vegetation. Thus, this class is still included in the mixed vegetation zone with the result that the classification approach can reach an accordance ratio of 100% for these vast zones.

The overlapping effect is most likely due to uncertainties regarding an obvious classification during visual analysis of the video records. Further uncertainties due to overlapping or gradually changing seabed features might partially explain the diffuse distribution of the classes within the RoxAnn space. This is a known problem and was already described by e.g. Chivers et al. (1990), Collins and Voulgaris (1993), Hamilton et al. (1999), and Brown et al. (2005).

Table 2
Accordance comparing the habitat maps with the four classes of the visual echosounder analysis. Distance tolerance ≤25 m.

Habitat	Ground truth count	Water depth	Count	LDA	MC
Dense kelp	49	2–5 m	38	49%	69%
		5–10 m	11		
		10–15 m	0		
		15–17 m	0		
		>17 m	0		
Medium dense kelp	13	2–5 m	4	–	92%
		5–10 m	9		
		10–15 m	0		
		15–17 m	0		
		>17 m	0		
Mixed vegetation	19	2–5 m	2	100%	68%
		5–10 m	17		
		10–15 m	0		
		15–17 m	0		
		>17 m	0		
Algal vegetation (mean of three groups)	81	2–5 m	44	75%	76%
		5–10 m	37		
		10–15 m	0		
		15–17 m	0		
		>17 m	0		
No vegetation	13	2–5 m	0	38%	38%
		5–10 m	6		
		10–15 m	6		
		15–17 m	1		
		>17 m	0		
Overall accordance (mean of four groups)	94	2–5 m	44	62%	68%
		5–10 m	43		
		10–15 m	6		
		15–17 m	1		
		>17 m	0		

Dense kelp forests have a leaf area index (LAI) of >1 covering the ground substrate with several blade layers (Pehlke and Bartsch, 2008). Since the macroalgae can only thrive on hard substratum (Lüning, 1990; Bartsch and Kuhlenkamp, 2000), it can further be expected that there are cobbles and rocks wherever macroalgae occur. The reduced blade area over ground in the kelp park (LAI < 1) induces a gradual decrease of roughness and increase of hardness values in these domains as the acoustic signal not only hits the rough and soft blades but also the hard and rugged bedrock substrate. Hence, the combination of intermediate roughness and hardness values are a suitable indicator for the occurrence of medium dense kelp vegetation. Additionally, kelp forest densities decrease with increasing water depth due to reduced light availability (Lüning, 1970; Pehlke and Bartsch, 2008) which is a complementary indicator for kelp distribution in this area (Fig. 3A). In shallow water (<5 m), the roughness values are widespread resulting in a bimodal distribution and indicating a great variety of seafloor features (Fig. 3B), however, including dense kelp forest vegetation. Highest kelp biomass and plant density off Helgoland is between 2 and 5 m water depths (Pehlke and Bartsch, 2008). Below 5 m water depth, where the density of kelp decreases, also the roughness values decrease significantly (Fig. 3D). In order to differentiate between kelp forest densities, the additional subclass medium dense kelp was created in the MC approach and reaches an accordance of 92% in the prediction map. Possible misclassification within the kelp forest might be induced by diverse movements of the lamina (due to changing currents) that may influence the scattering process.

Areas which were classified as barren seafloor yield relatively low accordance ratios in both approaches (38% for LDA and for MC). The heterogeneity of the seafloor might be the reason for the low accordance between the echogram classification and the prediction maps regarding this sand-dominated region. Smaller patches of vegetation could immensely affect the hydroacoustic properties but single plants and small vegetation patches usually are not clearly recognizable in the echograms and thus may cause misclassification. Since the hardrock/cobbles class was not ascertainable in the echograms as well, no conclusions regarding the prediction ability for this habitat can be drawn. The differences between the two mapping approaches are primarily caused by the demarcations between the habitat classes in the $E1/E2$-space. The LDA was an attempt to automate the classification. However, the supervised MC delivers more resolution with respect to habitat distribution and reveals higher accordance levels.

Similar accordance levels were achieved in other studies using RoxAnn: Pinn and Robertson (2003) reported an accuracy level higher than 80% for their seabed classification. Serpetti et al. (2011) revealed prediction abilities of 83% in discrimination of sediment types and Mielck et al. (in press) achieved prediction abilities between 69% and 90% in a case study in sandy environments. The predictive abilities of the classifiers used by Rattray et al. (2009) and Ierodiaconou et al. (2011) reached 87% and 80%, respectively, using multibeam echo sounders. These authors were even able to discriminate between zones of mixed brown algae and mixed red algae on the shallow south Australian continental shelf in water depth >7 m. This was impossible in our study. It seems that the habitats north of Helgoland are too patchy and heterogeneous for a clear-cut classification. The problem might be solved by applying along track distances smaller than 100 m in future surveys. In similar studies (e.g. Freitas et al., 2008; Serpetti et al., 2011) even larger transect distances were successfully applied with good results. It can thus be concluded that track spacing has to be adjusted to habitat conditions. For areas with small-scale habitat structures, it is advantageous to reduce track spacing to ≤50 m in order to improve the resolution.

4.3. Kelp occurrence and water depth

At first glance, both classifications show that vegetated habitats are rather restricted to shallow water, while barren seafloor generally appears in deeper areas. The dense kelp beds are mostly situated in depths between 2 and 5 m. At the edges of the dense kelp beds in water depth >5 m, medium-dense kelp beds and mixed vegetation occur which is in accordance with the current knowledge of kelp bed structures off Helgoland (Lüning, 1970; Pehlke and Bartsch, 2008). These zones are mainly situated between 5 m and 15 m depths. Below 15 m water depth vegetated zones are rare. Similar results were obtained by van Rein et al. (2011) in Church Bay, Irish Sea. They detected strong backscatter intensities in shallow water, where kelp density was high. With increasing water depth, kelp density and thus backscatter intensity decreased.

Besides the three algae-dominated areas, two non-vegetated sediment classes were detected. It became evident that sand-covered bedrock areas mainly occur in water depths of 10–17 m. Below 17 m, exclusively bedrock with or without cobbles are present. At this water depth, the hardness values significantly increase, indicating barren bedrocks (Fig. 3e). According to Serpetti et al. (2011), a loose packed sandy seafloor reveals rather soft and smooth signatures. Hence, the higher the amount of sand within these areas, the lower the hardness values. However, the distribution of barren seafloor and vegetation is not simply controlled by water depth. This study reveals that barren seafloor is also present in the euphotic zone in water depth up to 5 m (see Table 3). Hence, the distribution of differently dense algae vegetation is obviously not only a function of water depth but most probably also of geomorphological characteristics present in the area. Generally, seaweed vegetation depends on stable hardrock substrates and there are only few species which are able to grow on mobile cobbles or on sand covered bedrock (Lüning, 1990).

This highlights the need for the development and application of reliable spatial monitoring tools as the absence and presence of kelp cannot simply be judged from a correlation of their depth distribution with sublittoral terrain models.

The methods presented in this study will help to complement other long-term programs to monitor kelp abundances, and thereby may help to decipher the proposed impact of environmental change in the years to come (e.g. Müller et al., 2009). However, several authors reported considerable variabilities regarding the RoxAnn parameters during different sea conditions and when using various research vessels or vessel speeds (Hamilton et al., 1999; Wilding et al., 2003). This must be considered and compensated during repetitive monitoring measurements. At our survey, the vessel type did not change and the measurements were done at constant sea conditions. Hence, influences regarding these effects can be foreclosed. However, to achieve higher accuracy levels it is recommended to apply a different validation approach with more ground truth videos separated into training and validation points for the calculation of kappa values. This is a standard procedure in optical airborne remote sensing (Foody, 2002) and could be transferred to acoustic methods as well.

Table 3
Habitat occurrence in MC prediction map vs. water depth below chart datum.

Water depth	Relative frequency of occurring habitat class				
	Dense kelp	Medium dense kelp	Mixed vegetation	Sand/gravel	Cobbles/hard rock
2–5 m	61%	32%	6%	0%	0%
5–10 m	2%	38%	48%	12%	0%
10–15 m	0%	34%	48%	16%	2%
15–17 m	0%	0%	36%	25%	39%
>17 m	0%	0%	0%	0%	100%

5. Conclusion

Hydroacoustic gear were used to map an area covering 3.5 km^2 within an acquisition time of ~12 h. A linear discriminant analysis (LDA) and a manual classification (MC) routine were applied to produce maps of the spatial distribution of kelp and other seafloor habitats with an overall accordance level between 62% and 68% related to an image-based echogram classification. Both approaches were able to distinguish between different types of barren seafloor and vegetated habitats. In contrast to the LDA, the MC allowed to additionally determine kelp forests of different densities. Furthermore, MC was more appropriate to discriminated between different seaweed types that generally use to overlap each other. For future surveys it should be considered to measure small well-analyzed and ground-truthed calibration areas with and without vegetation to improve the classification concept. The study presented here, will be complementing the long-term kelp-monitoring activities in the submarine nature reserve around Helgoland to assess the response of this unique habitat to environmental change.

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