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# Performance of multi-beam echo-sounder backscatter based classification for monitoring sediment distributions using multi-temporal large-scale ocean data sets

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## Abstract

Obtaining an overview of the spatial and temporal distribution of seabed sediments is of high interest for multiple research disciplines. Multi-beam echo-sounders allow for the mapping of seabed sediments with high area coverage. In this paper, the repeatability of acoustic classification derived from multi-beam echo-sounder backscatter is addressed. To this end, multi-beam echo-sounder backscatter data acquired on the Cleaver Bank (North Sea) during five different surveys is employed using two different classification methods, i.e., a method based on the principal component analyses and the Bayesian technique. Different vessels were used for the different surveys. The comparison of the classification results between the different surveys indicates good repeatability. This repeatability demonstrates the potential of using backscatter for long-term environmental monitoring. However, the use of different classification methods results in somewhat different classification maps. Monitoring, therefore, requires the consistent use of a single method. Furthermore, it is found that the statistical characteristics of backscatter is such that clustering algorithms are less suited to discern the number of sediment types present in the study area. The Bayesian technique accounting for backscatter statistics is therefore recommended. A strong positive correlation

27 between backscatter and median grain size for finer sediments ( $< 0.5$  mm) using a frequency  
28 of 300 kHz is observed within the study area, but an ambiguity is found for sediments with  
29 median grain sizes  $> 0.5$  mm. Consequently, for the situation considered a unique assignment  
30 of sediment type to acoustic class is not possible for these coarser sediments.

## 31 **1. Introduction**

32 Acoustic remote sensing with multi-beam echo-sounders (MBES) is extensively used for  
33 mapping the seafloor morphology because of the systems' capability to map large areas in  
34 relatively short time periods. However, capabilities of these acoustic underwater techniques  
35 extend beyond the determination of only the seafloor bathymetry. They also exhibit strong  
36 potential for classifying the seabed sediments by investigating the sediment backscatter  
37 strength that can be derived from the intensities of the received echo. The backscatter strength  
38 is physically attributed to seabed properties such as sediment bulk density, seafloor roughness,  
39 volume heterogeneity, discrete scatterers and sediment layering [1] [2] [3]. The contribution  
40 of each factor to the backscatter strength is dependent on the complexity of the seabed,  
41 acoustic frequency and angle of incidence [3]. Several regional studies have revealed a  
42 relationship of backscatter to sediment properties such as median grain size [4] [5], grain size  
43 distribution [6] [7] [8], or shell or gravel content [9] for a specific study area and frequency.  
44 However, other studies have shown that in diverse environments additional factors such as  
45 benthic fauna [10] [11], activity of benthic organisms [12], sediment compaction [13] or  
46 natural hydrocarbons [14] [15] may influence the backscatter strength of the seafloor as well.

47 In general, classification methods employing measured backscatter data can be divided into  
48 model-based and image-based methods [16]. Model-based methods are attributed to  
49 techniques that perform inversion based on physical backscatter models either to exploit the  
50 measured backscatter strength directly [17] or the angular backscatter response [18] to invert

51 for sediment properties (e.g. mean grain size, roughness spectrum, volume scattering  
52 coefficient). Image-based methods are based on statistical relationships and patterns within  
53 the backscatter data [19] [20]. Whereas model-based methods require accurate models for  
54 predicting the backscatter strength and well-calibrated systems for measuring backscatter  
55 strength [3] [21], image-based techniques are also applicable to relative backscatter values  
56 from poorly or uncalibrated systems.

57 Reference [22] gives a review of various strategies and methods employing acoustic remote  
58 sensing techniques including SBES, SSS and MBES to produce sediment or habitat maps.  
59 They present 147 studies utilizing acoustic survey techniques published during the last two  
60 decades. This is a good indicator for the intensive research already carried out and the still  
61 ongoing development in the scientific field of seafloor classification. Among others, they  
62 classify image-based methods in objective/subjective and supervised/unsupervised strategies.  
63 The classification methods applied in this study, i.e. the Principal Component Analysis (PCA)  
64 and Bayesian technique, can be referred to as image-based, objective and unsupervised  
65 strategies. The PCA and Bayesian techniques have been successfully applied to MBES  
66 backscatter in several studies [4], [20], [23], [24].

67 Using the full MBES acoustic data content gives the opportunity for the development of  
68 marine-landscape maps displaying topography and the seabed sediment spatial distribution  
69 simultaneously. Because of physical and biological, as well as anthropogenic processes, the  
70 seafloor is a time-varying environment. Monitoring this dynamic environment requires good  
71 repeatability of the methods for seabed sediment classification. That means the data gathering,  
72 processing, and interpretation must lead to equal results for different measurement campaigns  
73 if the environment does not change. However, regarding the use of MBES measurements for  
74 sediment classification, repeatability of the results is a topic of concern. Reference [21] points  
75 out the acoustic-instrument stability, settings, processing algorithms, range, environmental

76 conditions, and survey methods as critical factors influencing the classification results, and  
77 consequently, affect repeatability. Therefore, there is a strong demand from the MBES  
78 backscatter community for data quality control, standardised acquisition and processing steps  
79 as well as detailed documentation of the processing chain within MBES systems [25]. In the  
80 research field of seafloor classification with MBES the ultimate goal is to generate consistent  
81 and repeatable results within the same area under the same settings from backscatter data  
82 acquired by differing MBES systems or analysed by different processing procedures [26].

83 The goal of this paper is to apply two different classification methods to MBES backscatter  
84 data acquired on different vessels during different surveys carried out in various time periods  
85 and to investigate the repeatability and agreement of the resulting sediment maps. To  
86 accomplish this goal, the Bayesian approach and PCA in conjunction with k-means clustering  
87 approach are applied to backscatter data acquired on the Dutch vessels *Zirfaea* and *Arca* in the  
88 Cleaver Bank area in the time period from 2013 to 2015. This study site consists of a  
89 significant number of sediment types, and intersecting survey tracks within the source data of  
90 this study allow for the investigation of the repeatability of the results. The classification  
91 results are compared to ground truth data to investigate the relationship between acoustic  
92 classes and sediment properties. The spatial resolution capabilities of the classification  
93 methods are additionally addressed to illustrate the state of the art of methods for MBES  
94 seabed sediment classification.

95 This paper is organized as follows. In Section 2 the study area and the data are described.  
96 Section 3 gives an overview of the two classification methodologies that are applied. Then,  
97 Section 4 presents the results from applying the classification algorithms along with  
98 considerations such as the number of sediment classes that can be discerned. Section 5 is a  
99 discussion of the results, addressing the repeatability of the classification, the spatial

resolution, the issue of assigning sediment type to the acoustic classes, as well as a discussion on the ambiguity for large grain sizes. Finally, in Section 6 the conclusions are presented.

## 2. Study area and data

The Cleaver Bank area is located 160 km north-west from Den Helder in the Dutch North Sea (Fig. 1) and is part of the nature protection areas in the territory of the European Union. The area was formed as a terminal moraine of a glacier during the Weichselian Ice Age. The water depth mainly varies between 25 m and 50 m, but is divided from north-west to south-east by a 70 m deep channel called the Botney cut (Fig. 1). The Cleaver Bank extends over an area of about 900 km<sup>2</sup> and is the largest area within the Dutch North Sea with coarse sediments [27]. In comparison to the mostly sandy areas of the Dutch seafloor the Cleaver Bank consists of the entire grain size spectrum from mud to gravel with isolated boulders. The diverse geology of the Cleaver Bank seafloor is a result of the Weichselian Ice Age and is relatively well preserved due to the combination of the sufficiently large depth and the rocky bottom which reduces the erosive influence of waves [28].

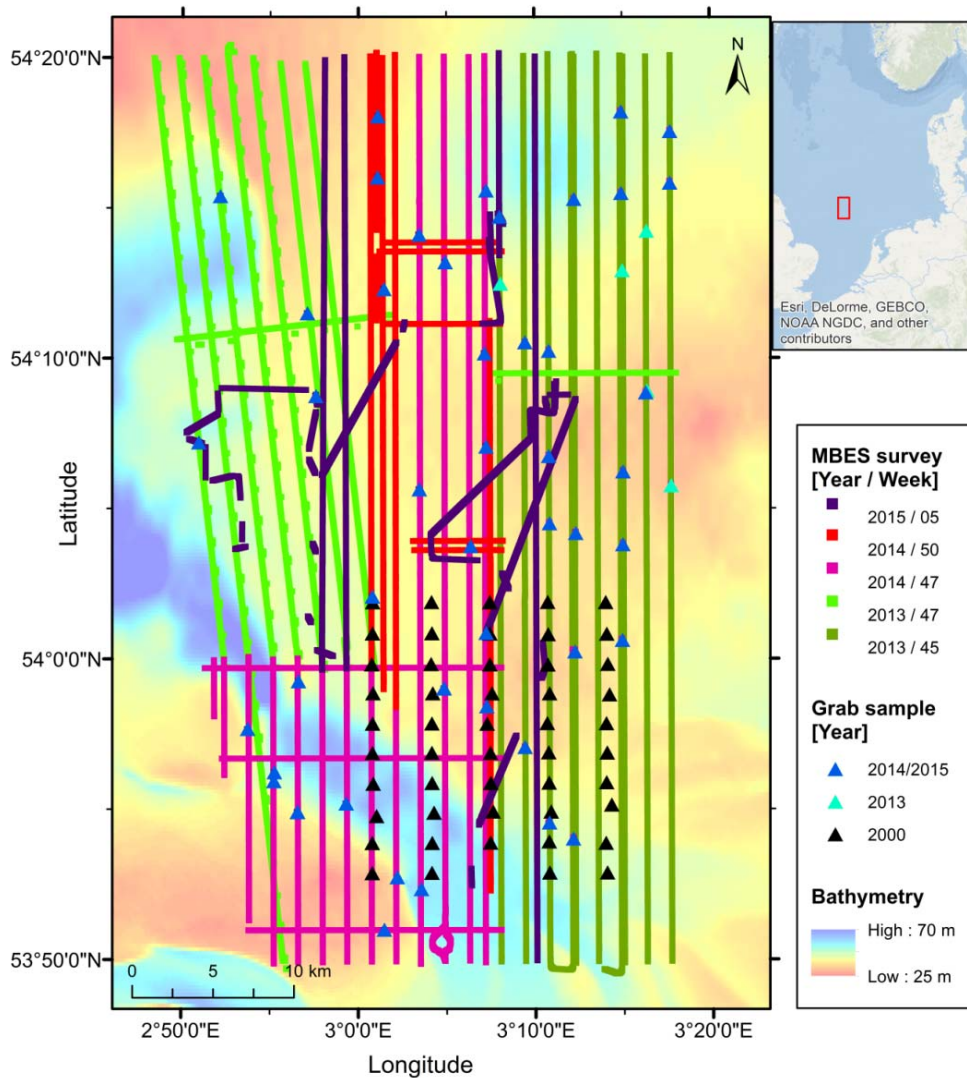
The MBES data considered in this work were acquired in the Cleaver Bank area during five surveys carried out within the period from November 2013 to February 2015. The entire survey area is 57 km in the north-south direction and 30 km in the west-east direction. In general, the survey lines are separated by approximately 1500 m except a few lines spaced closer together, overlapping lines, and several cross lines (Fig. 1). The swath width ranges from 90 m to 180 m depending on the water depth. Two different vessels, the *Zirfaea* and *Arca*, were both equipped with a Kongsberg EM3002 single head MBES sonar system using a central frequency of 300 kHz. The transmit and receive beam width are both 1.5° for nadir angles. The transmitted pulse length was set to 150 µs and the number of beams were 258 along the entire swath. These parameters were kept constant during each survey. Furthermore,

the same transmitted source level, receiver gain and time-varying gain were applied during the different surveys. The acquired MBES data were corrected for roll, pitch and heave. Depending on the different environmental conditions, the water absorption coefficient was calculated for each survey individually. The MBES data were also corrected for tidal effects.

To obtain a relatively good approximation of the backscatter strength from the received acoustic echo several steps are carried out within the Kongsberg MBES. The system corrects in real time for transmission loss (attenuation and geometrical spreading), insonified area as well as for transmission and reception beam pattern [29]. However, the real-time correction for the insonified area assumes a flat seafloor. Therefore, the backscatter data is corrected for the seafloor bathymetry slope in post processing to obtain the true insonified area [30]. However, some of the real-time correction performed by Kongsberg still includes simplification of the marine environment (e.g. constant absorption coefficient, flat seafloor assumption for reception process) which might affect the true backscatter strength [26]. In addition, a MBES calibration that would account for the alteration of sonar transducers' sensitivities or deviation of the system configuration from the manufacturer specification was not performed. Taking these factors into account, strictly speaking, the employed acoustic data represent a relative rather than absolute backscatter strength because the data might still not be entirely independent of the MBES configuration or environmental impacts. Therefore, we are using the term backscatter data or backscatter values in this paper instead of backscatter strength.

For validation and assignment of sediment type to acoustic class, 104 Hamon and Van Veen grab samples were taken during four different surveys in 2000, 2013, 2014 and 2015 (Fig. 1). The grab samples were sieved to separate the gravel and shell fragments from the sand and mud fraction. The latter part was analysed by laser-diffraction granulometry. The percentage of the different grains was used to classify the grab samples after the Folk scheme [30].

149 Almost no shell fragments or other biological particles were found to be present in the grab  
 150 samples. Because the seafloor dynamics of the Cleaver bank are low, the grab samples from  
 151 2000 are considered to be valid.



152  
 153 Fig. 1 . MBES tracks of five different surveys carried out from 2013 to 2015 are plotted over the bathymetry of the  
 154 Cleaver Bank. Bathymetry is received from EMODnet [31]. Grab samples taken in the years 2000 and 2013 to 2015  
 155 are denoted by triangles.

### 156 3. Classification methods

157 In this study two unsupervised sediment classification methods, the Bayesian technique and  
 158 PCA in conjunction with k-means clustering, are applied to the MBES data of the Cleaver



Bank. The Bayesian technique for seafloor classification was developed in [23] where also a detailed theory description is given. It has since been used in [4], [20], [24], and [32] among others. This section provides a brief overview of the basic concepts and the relevant processing steps to generate the sediment maps of the Cleaver Bank. The theory of PCA was first introduced by [33] [34]. Today many different variations of PCA exist which are adapted depending on the application purposes. A very detailed explanation of the application to MBES data is given by [20].

### 3.1 Bayesian technique

Assuming that a beam footprint contains a large number of scatter pixels, based on the central limit theorem, the backscatter strength per beam footprint can be assumed to be Gaussian distributed [23]. A scatter pixel here is the instantaneously insonified area of the sea floor within a beam footprint of the MBES. Given a constant frequency and angle of incidence, the backscatter strength is dependent on the seabed properties. It follows that if a survey area has a total of  $m$  different sediment types, with specific seabed properties, then the backscatter histogram from a selected oblique beam of the echo-sounder should be represented by a combination of  $m$  Gaussian distributions. Consequently, the model for the histogram of measured backscatter values per beam can be written as

$$f(y_j | \mathbf{x}) = \sum_{k=1}^m c_k \exp \left( -\frac{(y_j - \bar{y}_k)^2}{2\sigma_{y_k}^2} \right) \quad (1)$$

where  $f(y_j | \mathbf{x})$  is the value of the model at backscatter value  $y_j$ , and  $\mathbf{x}$  is the vector containing the unknown parameters,  $\mathbf{x} = (\bar{y}_1, \dots, \bar{y}_m, \sigma_{y_1}, \dots, \sigma_{y_m}, c_1, \dots, c_m)$ , i.e. the means  $\bar{y}_k$ , standard deviations  $\sigma_{y_k}$  and coefficients  $c_k$  of the Gaussian distributions that represent

179 each seafloor type. By fitting the above model to the measured histogram all unknowns are  
180 determined.

181 With a new data set, one may not know how many sediment types there are in the survey area.  
182 By conducting a  $\chi^2$  goodness of fit test, the optimal number of Gaussians  $m$  can be  
183 determined where  $\chi^2$  is defined as:

$$\chi^2 = \sum_{j=1}^M \frac{(n_j - f(y_j|\mathbf{x}))^2}{\sigma_j^2} \quad (2)$$

184

185 Here the  $n_j$  denote the number of measurements per bin (in our case the bin size is 0.5 dB ) of  
186 the previously mentioned histogram and  $M$  is the total number of bins in the histogram. For  
187 the  $n_j$  a Poisson-distribution is postulated<sup>1</sup>. The variances  $\sigma_j^2$  are thus equal to  $n_j$ . The  
188 goodness of fit statistic is  $\chi^2$  distributed with  $\nu = M - 3m$  degrees of freedom. The goodness-  
189 of-fit criterion is then further defined as the reduced- $\chi^2$  statistic ( $\chi_v^2 = \chi^2/\nu$ ) having a value  
190 close to one [35, pp. 68, 195 - 197]. The value of  $m$  for which a further increase of  $m$  does not  
191 generate a better fit of the model to the histogram, as quantified by the reduced- $\chi^2$  measure, is  
192 taken to be the number of seafloor types that can be discriminated in the survey area based on  
193 the backscatter data.

194 For the classification, the Bayes decision rule is applied, where there are  $m$  states or  
195 hypotheses. These hypotheses correspond to the  $m$  seafloor types present in the surveyed area.  
196 From Bayes and assuming all hypothesis to be equally likely, it is found that the intersections

---

<sup>1</sup> The requirements for an event being Poisson distributed are that (1.)  $E$  is the number of times the event in question occurs in an interval of time or space. (2.)  $E \in 0 \cup \mathbb{N}$  (3.) The events are independent. (4.) The probability of the event occurring does not vary with time. (5.) Two events cannot occur at the same time. (6.) The probability of an event in a small interval is proportional to the length of the interval.

197 of the  $m$  Gaussian PDFs provide the  $m$  non-overlapping backscatter acceptance regions,  
 198 corresponding to the  $m$  seafloor types.

### 199 3.2 Principal component analysis and k-means clustering

200 PCA is a statistical method to reduce the complexity of a dataset while preserving most of the  
 201 information content. This is achieved by transforming the original data set consisting of  $p$   
 202 (potentially) correlated variables to a new data set of  $\ell = 1, 2, \dots, p$  uncorrelated variables  $Y_\ell$ ,  
 203 the so-called principal components (PCs). Each PC can be seen to account for a part of the  
 204 variation in the feature values of the original data set. Therefore, the size of the original data  
 205 set can be reduced by considering only the PCs representing a significant portion of the data  
 206 variability.

207 The  $n$  measurements of the  $p$  variables, often called features, are summarized in an  $(n \times p)$   
 208 data matrix. To account for different magnitudes of the features, the data are standardized,  
 209 where for each feature the mean is determined and subtracted from the measurements of that  
 210 feature. In addition, the features are divided by their standard deviation. The matrix  $\mathbf{F}$  contains  
 211 these standardized measurements. The first step of PCA is the calculation of the covariance  
 212 matrix of  $\mathbf{F}$  as

$$\mathbf{R} = \frac{1}{n} \sum_{j=1}^n \mathbf{F}_j^T \mathbf{F}_j \quad (3)$$

213 with  $\mathbf{F}_j$  the  $j^{th}$  row of the matrix  $\mathbf{F}$ . Superscript  $T$  denotes the transpose. The second step is to  
 214 determine the eigenvectors and the corresponding eigenvalues of  $\mathbf{R}$  by solving

$$\mathbf{R}\mathbf{A} = \mathbf{A}\mathbf{\Lambda} \quad (4)$$

with  $\mathbf{A}$  the  $(p \times p)$  eigenvector matrix whose columns are the eigenvectors  $\mathbf{a}_\ell$  and  $\mathbf{\Lambda}$  the  $(p \times p)$  eigenvalue matrix where the diagonal elements are the corresponding eigenvalues  $\lambda_\ell$  of the covariance matrix  $\mathbf{R}$ .

The obtained eigenvector matrix  $\mathbf{A}$  is used to transform the original data set  $\mathbf{F}$  into the new data set consisting of the PCs. Thus, the original measurements  $\mathbf{F}_j$  can be written as a sum over the eigenvectors, i.e.,

$$\mathbf{F}_j = \mathbf{Y}_j \mathbf{A}^T \quad (5)$$

with the coefficients for the eigenvectors contained in the row vector  $\mathbf{Y}_j$  of matrix  $\mathbf{Y}$ . Thus, one finds

$$\mathbf{Y}_j = \mathbf{F}_j (\mathbf{A}^T)^{-1} \quad (6)$$

where the full matrix  $\mathbf{Y}$  is of size  $(n \times p)$ , as is the original matrix  $\mathbf{F}$ , and contains for the  $n$  measurements the  $p$  coefficients for the eigenvectors. In general, although different definitions exist, the  $\ell^{\text{th}}$  column  $\mathbf{Y}_\ell$  of  $\mathbf{Y}$  is considered as the  $\ell^{\text{th}}$  PC, given by

$$\mathbf{Y}_\ell = \mathbf{F} \mathbf{a}_\ell \quad (7)$$

The amount of variability in the original data set which is accounted for by the PC  $\mathbf{Y}_\ell$  is quantified by the eigenvalue  $\lambda_\ell$ . Based on these eigenvalues a subset of PCs can be selected that represent the majority of the variations in the measurements. For this work, the subset was selected such that 70% to 90 % of the data variability is accounted for. These PCs are then supplied to the k-means algorithm to group the PCs into different clusters [36].

231 The k-means clustering algorithm aims to assign the  $n$  data points for each of the PCs into  $k$   
 232 predefined clusters  $S_i$  ( $i = 1, \dots, k$ ). Thereby the sum of the squared Euclidean distance  
 233 between the data points and the average of all data points within the cluster, i.e., the so-called  
 234 cluster centroid, is minimised. The minimisation problem is thus

$$\min \sum_{i=1}^k \sum_{x_s \in S_i} |x_s - c_i|^2 \quad (8)$$

235 where  $x_s$  is a data point within the cluster  $i$  and  $c_i$  is the cluster centroid of the cluster  $i$ .

236 The application of the k-means algorithm to a dataset requires a predefined number of clusters  
 237  $k$ . However, the estimation of how many clusters to use is a well-known issue in unsupervised  
 238 classification methods [37] and is in general the most subjective part of a cluster analysis. In  
 239 this study three different statistical methods are applied to the MBES backscatter dataset to  
 240 determine the number of clusters.

241 The statistical methods are applied to the output of the clustering techniques using varying  
 242 numbers of clusters. The first method, the gap statistic, was proposed by [38]. This method  
 243 calculates the overall within-cluster variance of the dataset and compares this value to an  
 244 expected value calculated for an appropriate reference distribution. The estimated number of  
 245 clusters is defined where the logarithmic overall within-cluster variance value is minimized. A  
 246 detailed mathematical description is found in [38]. The second method, the Silhouette  
 247 statistic, is developed by [39]. The average distance of the observations within the clusters and  
 248 the average distance of the observations to the data points in the nearest clusters is calculated  
 249 for each number of clusters. The values are called the Silhouette coefficients. The optimal  
 250 number of clusters is selected where the Silhouette coefficient is maximized. Finally, the  
 251 David-Bouldin criterion is also used in this study [40]. This method examines the ratio of the

within-cluster distance and between-cluster distance. The optimal clustering solution is represented via the smallest David-Bouldin index. In [38], the performance of several cluster number estimation methods including the gap statistic and the Silhouette coefficient was investigated. That study demonstrated that the gap-statistic performs most efficiently.

## 4. Results

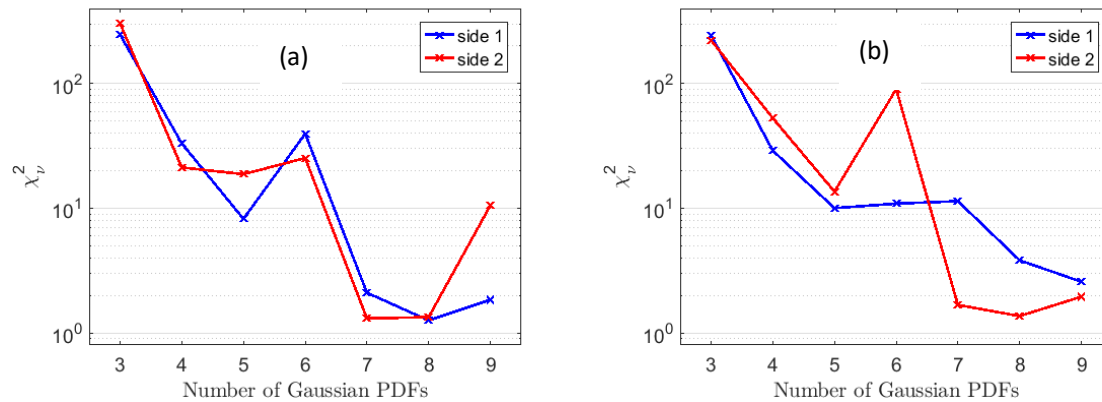
In this section, the results of the two classification methods are presented. Both methods employ the MBES backscatter data for the classification of the seafloor.

### 4.1 Bayesian method

For the application of the Bayesian method we use receiving beams between 20° and 60°. The beams between nadir and 20° are not used because firstly, there are too few scatter pixels to meet the central limit theorem requirement and secondly, these beams are less sensitive to sediment properties (e.g. roughness) variation than the outer beams [41]. Often receive beams beyond 60° can also be used for classification but for the data considered here, those beams tended to be too noisy to yield reasonable results.

The estimation of the optimal number of classes is a well-known issue in unsupervised classification methods [37]. For the Bayes method, however, a statistically sound approach is available. Here, the curve fitting procedure as described in Section 3.1 is executed for increasing numbers of sediment types  $m$ . The number of sediment types present in the area is taken as that value of  $m$  for which a further increase in  $m$  does not result in a further improvement of the fit. The goodness of fit is quantified through the reduced  $\chi^2_v$  statistic. For the Cleaver Bank data, it is found that a maximum of seven sediment types can be discriminated based on the available backscatter data. Fig. 2 shows an example of the  $\chi^2_v$  statistic for an increasing number of Gaussians and for the 48° beam from nadir, for both the

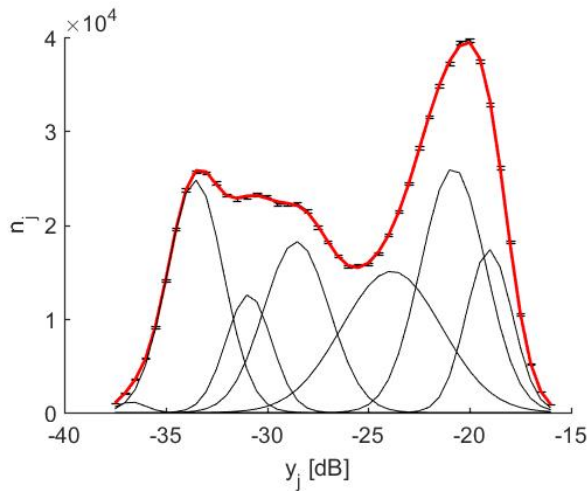
2013 and 2014/2015 data, as well as the two sides (starboard and port). It is seen that for the 2013 data as well as for side 2 of the 2014 and 2015 data the use of 7 Gaussians provides a very good fit between modelled and measured histogram, with the  $\chi^2_v$  statistic being close to 1. An example, indicating that sometimes the  $\chi^2_v$  statistic is inconclusive about the number of Gaussians, is shown for side 1 in Fig. 2b. In general, such behaviour is found for a limited number of cases and, therefore, these results are discarded when determining the number of sediment types. These analyses have been carried out for beam angles between  $46^\circ$  and  $60^\circ$  and for all surveys, not all of which are plotted here. In general, a single outer beam is used to determine the number of Gaussians, but given that our data is noisy, we choose to investigate a number of beams. The use of 7 Gaussians is found to reproduce the measurements best.



**Fig. 2. The reduced  $\chi^2_v$  statistic for the  $48^\circ$  beam angle. The two curves are for the two sides of the echo-sounder respectively. a) 2013 data and b) 2014 and 2015 data.**

As an example, Fig. 3 presents the result of the fitting procedure for seven Gaussians. Here the histogram of the measured backscatter data  $n_j$  (black line with error bars) per 0.5 dB bin is almost hidden by the modelled backscatter in red. The variance of the measured data is indicated by the error bars. Also seen are the 7 Gaussians used for the curve fitting in black. After a good fit is found per beam angle and per experiment, the intersections of the unscaled Gaussians are used to derive the ranges of backscatter, corresponding to the different acoustic classes, from which the acoustic class map is derived as explained in [23]. Acoustic classes 1-

295 7 correspond to the Gaussians from left to right, and from lowest to highest backscatter  
 296 values.



297  
 298 Fig. 3. Shown here is the histogram of the measured backscatter data  $n_j$  per 0.5 dB bin  $y_j$  from the data collected in  
 299 2014 and 2015 (black line with error bars) which is almost hidden by the modelled  $f(y_j|x)$  in red. Also displayed are  
 300 the 7 Gaussians in black.

301

302 The resulting classification map is shown in Fig. 4 where each acoustic class is presented with  
 303 a separate colour. Colours have been selected such that from green to purple the backscatter  
 304 value increases.

## 305 4.2 PCA and k-means clustering

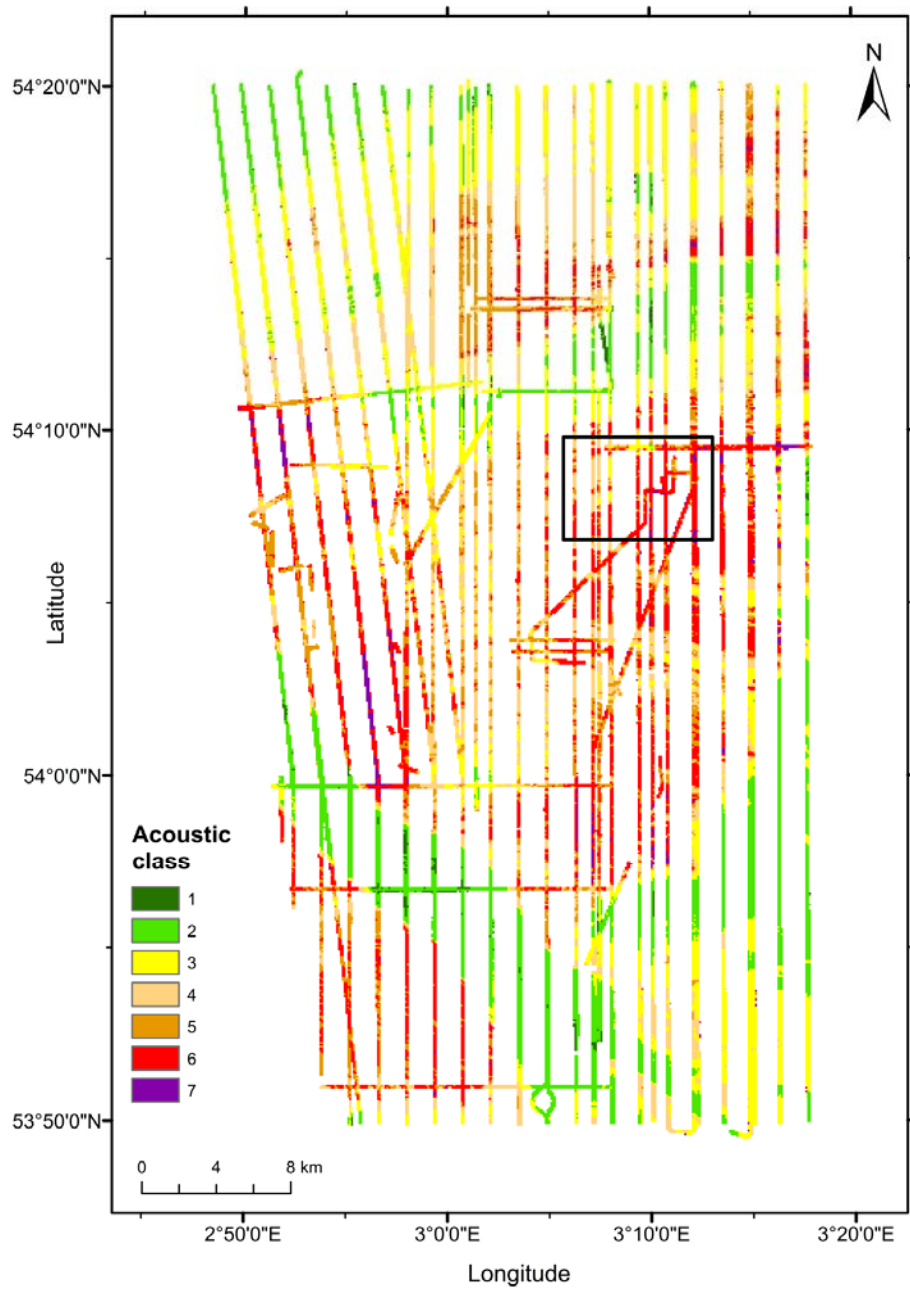
306 PCA in conjunction with a clustering algorithm is a common unsupervised classification  
 307 technique for seafloor classification based on backscatter [24], [19]. This technique is  
 308 applicable to relative backscatter values and, therefore, does not necessarily require calibrated  
 309 MBES. In recent studies, this method was also applied to backscatter and bathymetry  
 310 simultaneously [20], [4]. However, in this study PCA and k-means clustering are only applied  
 311 to backscatter so that a direct comparison with the classification from the Bayes method can  
 312 be made.



As with the Bayesian technique, for PCA and k-means clustering, beam angles from  $20^\circ$  to  $60^\circ$  are considered. The backscatter data are averaged over seven pings in the along-track direction and over an angle range of  $2^\circ$  to  $4^\circ$  in across-track direction. To eliminate the angular dependency of backscatter the global Z-score approach is applied, which is the subtraction of the mean value from the backscatter value, and then divided by the standard deviation at each angle [20] [42] (henceforth simply referred to as backscatter). To obtain the same resolution among the entire survey area, surface patches of 10 m x 10 m are constructed similar to [32].

For each surface patch eight statistical features of the backscatter distribution are calculated (Table 1). The arithmetic mean gives the averaged backscatter value within the patch. If the distribution is not symmetric, the median value differs from the mean and provides the middle of the distribution. Therefore, the median can be considered as an additional valuable feature. The mode represents the value with the highest occurrence within a patch and defines the main tendency of the feature [20]. The standard deviation shows the variability of the backscatter and might be valuable to characterise the heterogeneity of the sediment. Due to the fact that outliers are removed during processing, the minimum and maximum value can be used to define data extremes and might also indicate specific characteristics of the seabed. The higher statistical moments, skewness and kurtosis, are measures of the shape of a probability distribution. In previous studies it was shown that the K-distribution can be used to describe the skewed distribution of backscatter data for all sediment types and the shape parameter of the K-distribution can be used as tool for seafloor classification [43] [44] [32] [45]. Therefore, the skewness and kurtosis might provide valuable information about the sediment distribution.

To identify the most valuable of these features, PCA is applied. PCA analysis indicates that the first 3 PCs contain most of the data variability of around 85%. Fig. 5 displays the ratio of the sum of the correlation between the first three PCs and the eight backscatter features to the



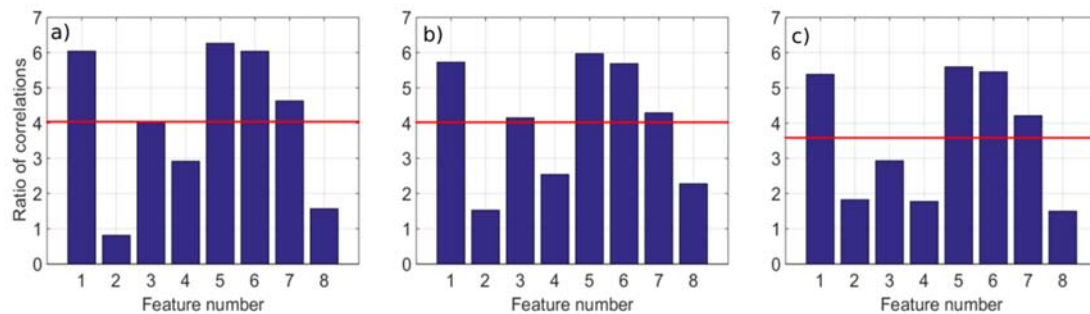
**Fig. 4. Acoustic classification result of the Bayesian technique. The grid is resampled to a size of 100 m by 100 m using the mode value of the finer grid. The black square indicates the extent of the area zoomed in Fig. 10.**

sum of correlation between the remaining PCs and the eight backscatter features. In reference [20], the threshold value has been chosen considering three conditions: (1) it is similar to the mean value (red line), (2) it includes an adequate number of features for PCA and (3) it

generates consistent results for each survey. Considering these three conditions the mean, median, mode and the minimum of the backscatter data are revealed as the most informative features. PCA analysis indicates that the first 3 PCs contain most of the data variability of around 85%. Fig. 5 displays the ratio of the sum of the correlation between the first three PCs and the eight backscatter features to the sum of correlation between the remaining PCs and the eight backscatter features. In [20], the threshold value has been chosen considering three conditions: (1) it is similar to the mean value (red line), (2) it includes an adequate number of features for PCA and (3) it generates consistent results for each survey. Considering these three conditions the mean, median, mode and the minimum of the backscatter data are revealed as the most informative features.

**Table 1. Backscatter features considered in the first application of PCA.**

Number	1	2	3	4	5	6	7	8
BS feature	Mean	Std. deviation	Skewness	Kurtosis	Median	Mode	Min.	Max.



**Fig. 5. Ratio of the sum of the correlation between the first 3 PCs and backscatter features to the sum of the correlation between the remaining PCs and backscatter features. The different surveys are considered separately: a) 2013, b) 2014 and c) 2015. The red line indicates the mean value of the ratio of correlation.**

These features were used as an input for a second application of PCA to further reduce the complexity of the dataset and simplify the application of the k-means clustering. The analysis shows that the first PC accounts for 98% of the data variability which indicates high correlation between the selected four backscatter features. Therefore, only this component is used in the k-means clustering.

To estimate the optimal number of acoustic classes that can be distinguished within the data, the gap statistic, silhouette coefficient and Davies-Bouldin method are applied. The methods use the output of the k-means algorithm which is applied to varying numbers of clusters in the range from 2 to 10. The results of each method are plotted in Fig. 6. Each method has different magnitudes of criterion values and therefore the values are normalised. The optimal number of classes estimated and suggested by each method is two, which is indicated by the red dots. This can be understood from Fig. 3, showing a histogram of the backscatter data. Clearly two main peaks are present. These two main peaks are estimated as individual clusters by the statistical methods. However, this is in disagreement with both the ground truth data which reveals eight sediment types, and the Bayesian technique which estimates seven clusters, similar to the ground truth data.

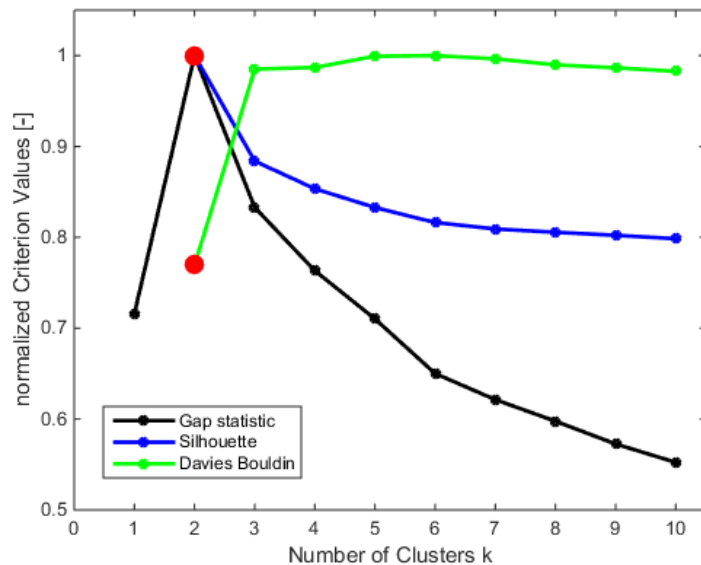


Fig. 6. Estimating the number of clusters via Gap statistics, Silhouette coefficient and Davies-Bouldin method. Red circle indicates optimal number of clusters estimated by each method.

To further investigate why the statistical methods only identify two clusters within the backscatter data the Gap statistics, Silhouette coefficient and Davies-Bouldin methods are applied to synthetic backscatter histograms. Four different synthetic backscatter histograms with varying degree of overlap and number of main peaks are shown in Fig. 7. Fig. 7c

represents a similar backscatter histogram as the measured histogram (Fig. 3). Again, the methods only identify the two main peaks as individual clusters. Modelling backscatter histograms with four and seven main peaks, respectively (Fig. 7b and Fig. 7d) and applying the statistical methods show that even when the individual peaks are clearly visible, the overlap hampers the clustering methods' ability to identify the peaks as individual clusters. Only the synthetic backscatter histogram in Fig. 7a having peaks with very distinct separations were correctly found to have four clusters by the three methods. This demonstrates that the statistical methods trying to estimate the number of clusters require a clear segmentation of the individual clusters which is not always the case for backscatter data. Seafloor backscattering is a random process having statistical fluctuation leading to a natural overlap of the backscatter data [1]. In addition, the mostly heterogeneous seabed does not show clear boundaries between sediment types, increasing the overlap within the measured backscatter data. In this study, the backscatter features are highly correlated. It is hypothesized that for situations where this correlation is less, or when additional information such as those derived from bathymetry are added, the overlap in clusters diminishes and separation between clusters would be higher. The Bayesian technique accounts for the statistical fluctuation of the backscatter data [23] and, therefore, is able to distinguish between individual overlapping clusters in this study as well. This method estimates seven clusters to be present in the data set. Based on the result of the Bayesian technique and taking into account the fact that the ground truth data reveals eight sediment types (defined by the Folk scheme) (Section 4.3) as well as to have consistency between the Bayes and PCA/k-means methods, k-means clustering is applied with a choice of seven clusters.

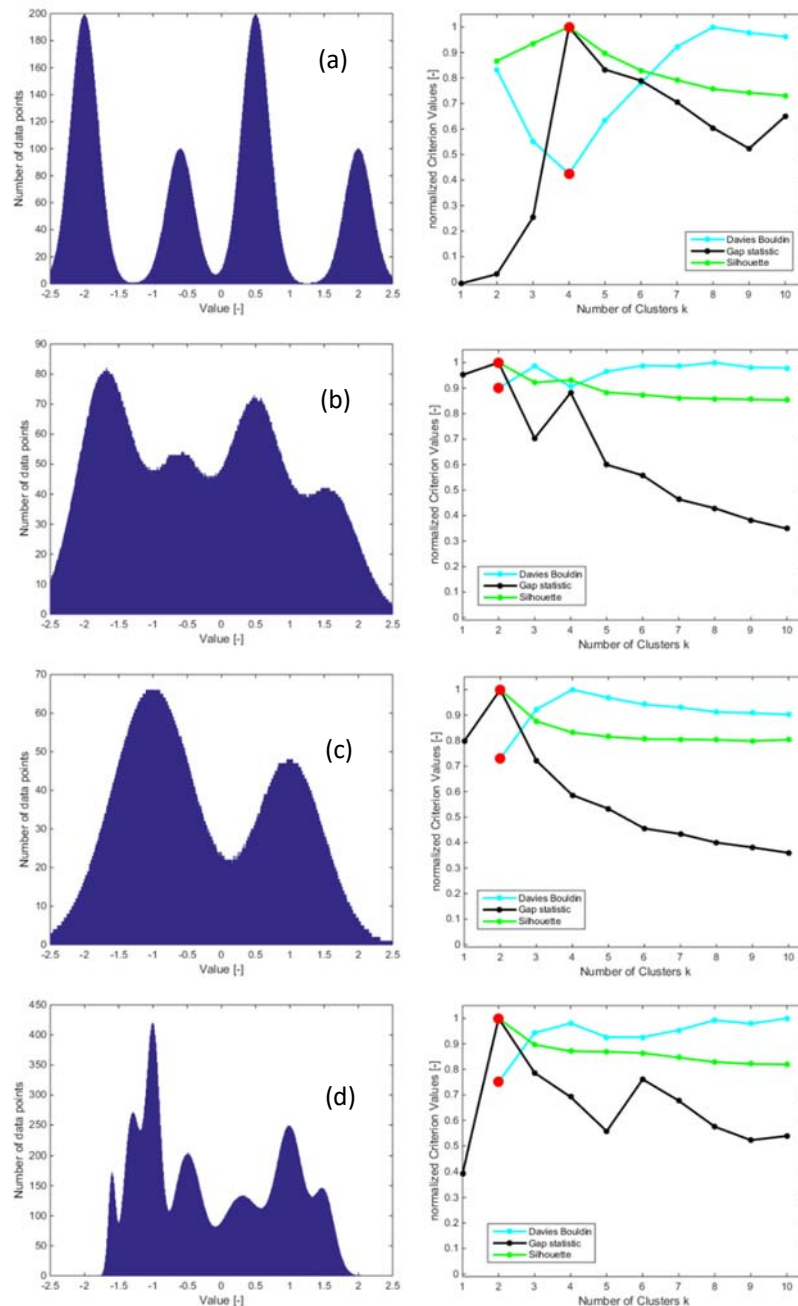


Fig. 7 Synthetic histograms generated by modelling a different number of Gaussians (left). Application of Davies Bouldin, Gap statistic and Silhouette coefficient to synthetic data (right). (a) 4 clearly segmented Gaussians. Each statistical method gives 4 clusters as a result. (b) 4 Gaussians with overlapping segmentation. Statistical methods are not able to identify 4 individual clusters. (c) 2 Gaussians representing a hypothetical histogram of backscatter data of the Cleaver Bank. Statistical methods identify 2 clusters. (d) 7 Gaussians that approximately reproduce the histogram of the backscatter data of the Cleaver Bank but with added separation. Even in this modelled and simplified case, statistical methods suggest 2 clusters as the optimal number.

Acoustic classes are obtained from the output of the k-mean clustering by sorting the seven clusters according to the averaged backscatter value of each cluster. Fig. 8 displays the

resulting acoustic classification map. Compared to the acoustic map of the Bayesian approach (Fig. 4) acoustic class 1 and 7 have a very large contribution to the entire map. The resulting map can be divided in seven distinct areas based on the criterion of high and low acoustic classes as well as homogeneity and heterogeneity. The most of obvious areas are 1) the heterogeneous centrum consisting of mainly acoustic classes with higher backscatter values; 2) and 3) the homogenous north-western and south-eastern parts with lower backscatter values; 4) the very homogeneous Botney cut characterised by only acoustic class number 1 in the south of the central part; 5) the south-western area which is characterised by homogeneously distributed sediments with high backscatter values; and 6) just north of the centre a stripe of low backscatter, homogeneously distributed sediment is located; 7) further north in the north-eastern part of the map a very small stripe of heterogeneous, high acoustic classes, sediment is present. These distinct areas are also visible in the acoustic map of the Bayesian technique (Fig. 4). The main differences to consider belong to a shift between the acoustic classes, in particular at the low and high classes. A more detailed view and discussion of these maps follows in sections 5.1 and 5.3.

### 4.3 Ground truth

The analyses of the grab samples indicate the presence of eight different sediment Folk classes, ranging from sandy mud to sandy gravel in the Cleaver Bank. The grab samples containing gravel are located in the northern and middle part of the survey area as well as in the south of the Botney cut (see Fig. 13). Sandy mud grab samples are only available within in the Botney cut and muddy sand occurs mainly around the Botney cut. The grab samples from 2013 to 2015 are located directly on the MBES track whereas some grab samples taken in 2000 are located about 500 m away from a MBES survey line (Fig. 1).

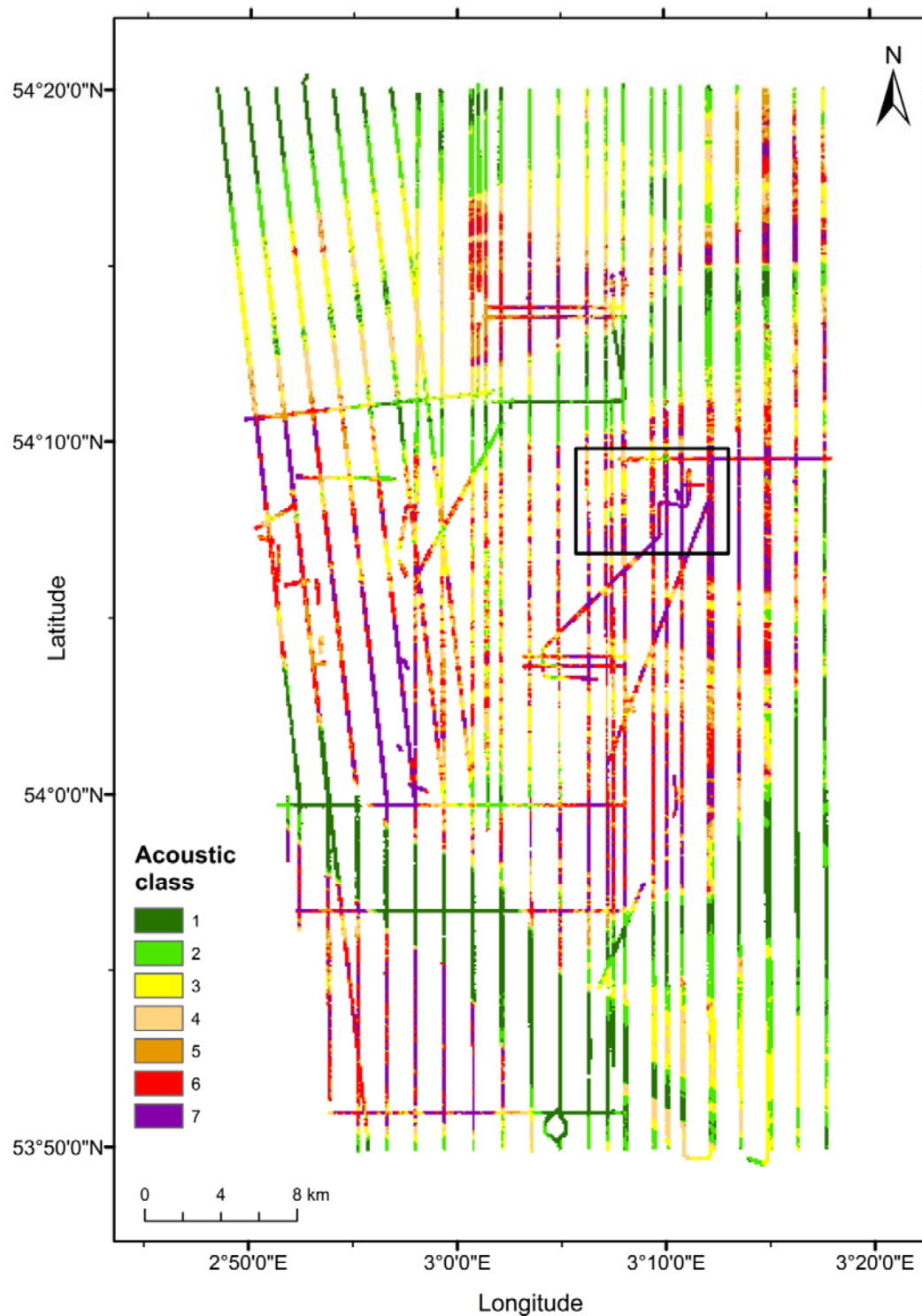


Fig. 8. Acoustic classification result of PCA in conjunction with k-mean clustering using 7 acoustic classes. The grid is resampled to a size of 100 m by 100 m. The black square indicates the extent of the area zoomed in Fig. 9 and Fig. 10.



## 5. Discussion

In this section the repeatability of the classification results is discussed by comparing the different surveys. The assignment of acoustic classes to sediment classes based on the correlation of ground truth data with acoustic classes is also examined. Furthermore, the spatial resolution and the reliability of the classification results is analysed. Finally, the relationship between median grain size and backscatter values is investigated.

### 5.1 Repeatability and consistency of classification results

In order to examine the repeatability of the classification results over the different surveys, a small area of the Cleaver Bank is shown in Fig. 9 and Fig. 10 with a total of ten intersections of survey lines. All five surveys are represented in this small area of the map. Clearly there is a high agreement in the classification results obtained from the data from different surveys. Examples are the intersection of the easternmost 2013 week 45 vertical line that intersects with the 2015 diagonal line (indicated by area D in the plot). In this intersection features as narrow as eight meters are clearly visible and are in very good agreement for the two surveys. At the intersection of the most western 2013 week 45 line and the 2013 week 47 line (area A) both surveys show an area of acoustic class 3, surrounded by class 6. Area B indicates for both surveys the presence of acoustic classes 2 to 6 in good agreement. The high repeatability is also apparent in Fig. 11. Here the Bayes acoustic classes determined for the intersecting areas of the 2013 and 2014/2015 surveys are presented in a scatter plot. It is shown that for the majority of the cases the results are in good agreement. However, discrepancies also occur, for example at the intersection of the 2015 survey and the 2013 week 47 survey in area C of Fig. 9 and 10 the 2013 data shows acoustic class 2 whereas the 2015 data shows acoustic class 1 for PCA. The Bayesian results in this intersection show class 3 for the 2013 data and class 2 for the 2015 data. This is the most apparent disagreement seen on this part of the map,

and there are a few plausible explanations for this and other disagreements. Firstly, even though it would not be expected, it is possible that there was a sediment change from 2013 to 2015, that would explain why the discrepancy is present for both classification methods in area C. To prove a sediment change at any point a grab sample from both periods at the location would be required but this is not available. According to Fig. 11 there are discrepancies between the 2013 and the 2014/2015 data but they are not greater than 1 acoustic class except for 1 instance. It is possible that the backscatter from locations with different classifications are close to a class boundary and happen to fall within the 1 class discrepancy range. A further reason for a mismatch could be a directional small-scale morphological influence because of different sailing directions [46]. Given that this is data from five different surveys carried out over the time period from 2013 to 2015 and that the data were acquired by different vessels, crews, MBES systems and environmental conditions,

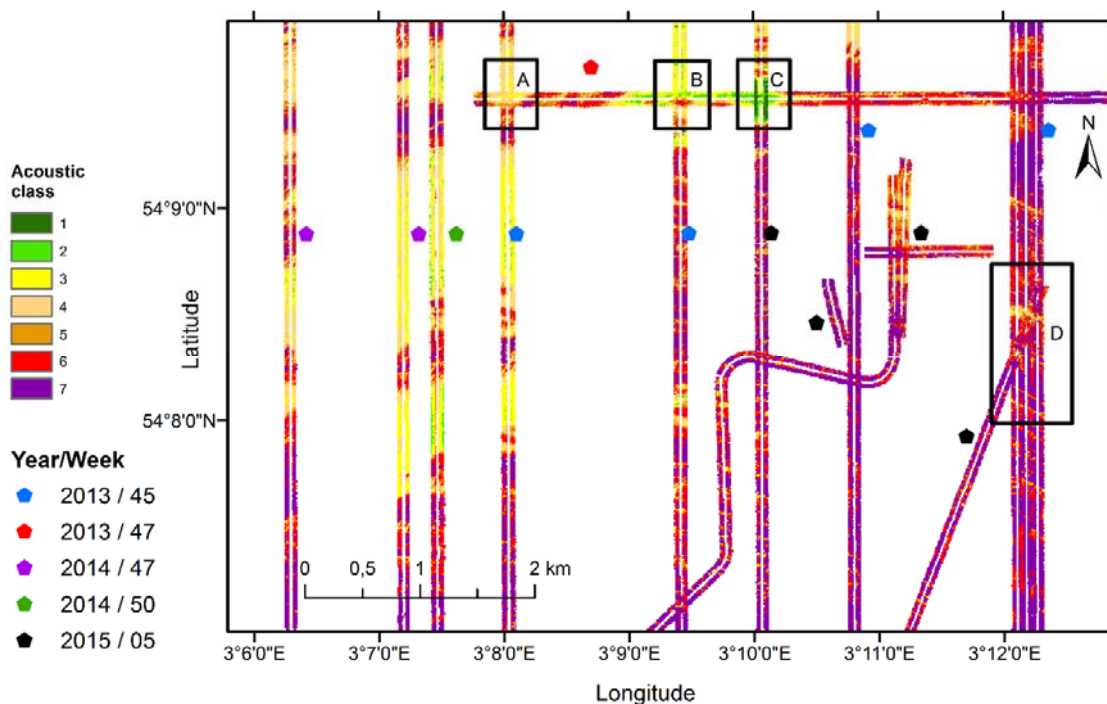


Fig. 9. Zoomed in area of acoustic class map generated by PCA. Different survey lines denoted by the coloured pentagons are visible. The grid size is 10 by 10 m and represents the size of the surface patches.

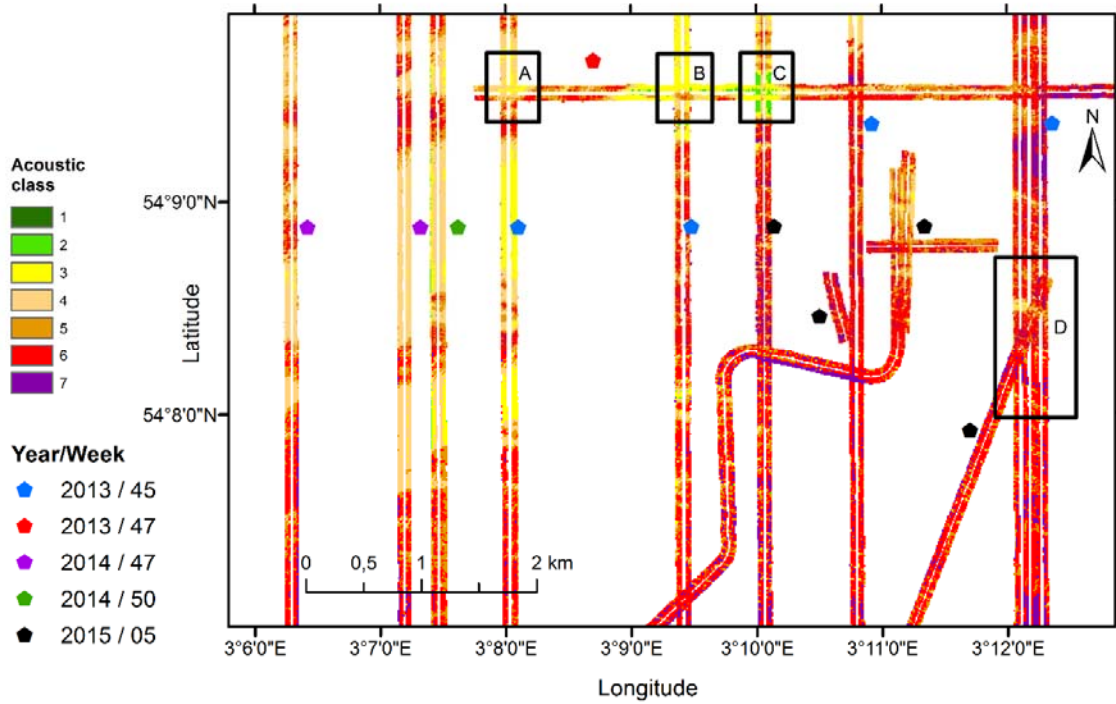


Fig. 10. Zoomed in area of acoustic class map generated by Bayesian technique. Different survey lines denoted by the coloured pentagons are visible. The grid is resampled to a size of 10 m by 10 m using the mode value of the finer grid.

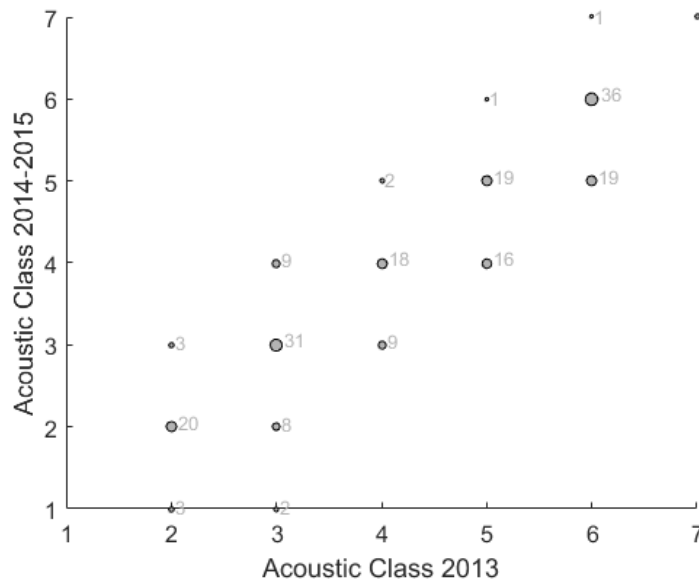


Fig. 11. Correlation plot of the acoustic classes determined with the Bayesian method. The size of the dots and the number indicate the number of matches for the acoustic classes determined for the intersecting areas using the backscatter data from the different surveys in 2013, 2014, 2015.

the results still demonstrate the high degree of repeatability and consistency of the acoustic classifications for both methods. Although the classification results are in good agreement

when comparing the classification from different surveys for one method, the comparison between classification results from applying different methods reveals differences. Whereas the Bayes classification indicates the presence of mainly five types of sediments, since acoustic classes 1 and 7 are hardly present, the PCA classification shows all sediment types to be almost equally present. The deviations from PCA and Bayesian within the low and high acoustic class ranges are related to the different mathematical approaches of the methods. Considering Fig. 3, it is seen that the PDFs of acoustic class 1 and 7 have only a very small contribution to the histogram of backscatter measurements. For k-means clustering 7 sediment types are assumed. K-means clustering defines the clusters on a simple similarity measurement of the first PC and assigns these clusters based on an increasing backscatter value. This leads to a more balanced number of data points within the individual clusters, i.e., acoustic classes. Therefore, the PCA results show, in contrast to Bayes, a significant presence of acoustic class 1 and 7. Still, the maps obtained with the two different methods indicate a similar spatial distribution of the different sediment types over the area.

## **5.2 Mapping Folk class by combining acoustic classes with ground truth data**

Often, for mapping the spatial distribution of sediments, use is made of maps presenting the Folk class. Here it is investigated to what extent these types of maps can be derived from the acoustic classification results by assigning sediment types to the acoustic classes. For this, we use the grab samples that are located at a distance less than 25 m from a survey track, i.e. slightly more than the 20 m recommended in [46], and that are in areas with little spatial variation in sediment type. As such, the initial 104 grab samples (Fig. 1) are reduced to 77 grab samples.

As a first step, it is assumed that the lowest acoustic class represents finer sediments whereas the highest acoustic class represents coarser sediments. Here the order of Folk classes is

selected such that it is assumed to represent increasing median grain size. The resulting number of matches between acoustic class number and sediment type at the grab sample location are plotted in Fig. 12 for the Bayes and PCA results, respectively. In general, indeed increasing acoustic class is seen to correspond to an increasing median grain size, as represented by the sediment type.

The PCA results show a good match of acoustic class 1 with the sediment type sandy mud. For example, this indicates that the Botney cut is covered by sandy mud. However, the assignment of the sand sediment types from muddy sand to sandy gravel are less clear. For instance, the sediment type sand shows a uniform distribution from acoustic class 1 to 5. This indicates additional factors influencing the backscatter data and causes difficulties in the assignment of sediment type sand to a distinct acoustic class. For the Bayes results (Fig. 12a) it is found that acoustic class 1 does not correlate to any grab sample. For all other acoustic classes there is some ambiguity in the relation between sediment type and acoustic class.

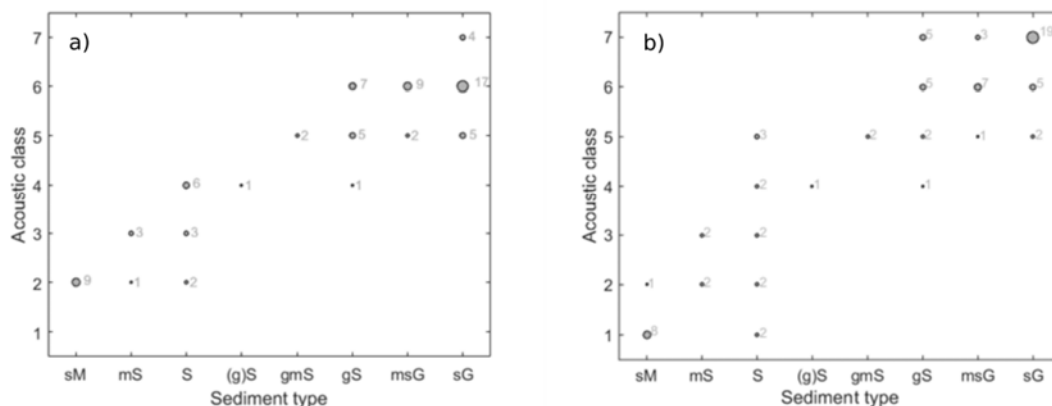


Fig. 12. Correlation between acoustic class and sediment type at grab sample locations. a) Bayesian method, b) PCA. Dots indicate the number of matches between acoustic class and sediment type. The sediment type is determined after Folk [22].

Fig. 13 shows the Folk class map based on the Bayes classification accounting for the mentioned non-uniqueness. The proposed assignment of Folk class to sediment type used is presented in table 2. It should be noted, however, that especially for acoustic class 5 a unique relation with Folk class is not found and for Fig. 13 it is taken to correspond mainly to

gravelly sand and muddy sandy gravel. A similar map can be made for the results of PCA, but here only the Bayes results in Fig. 13 are presented.

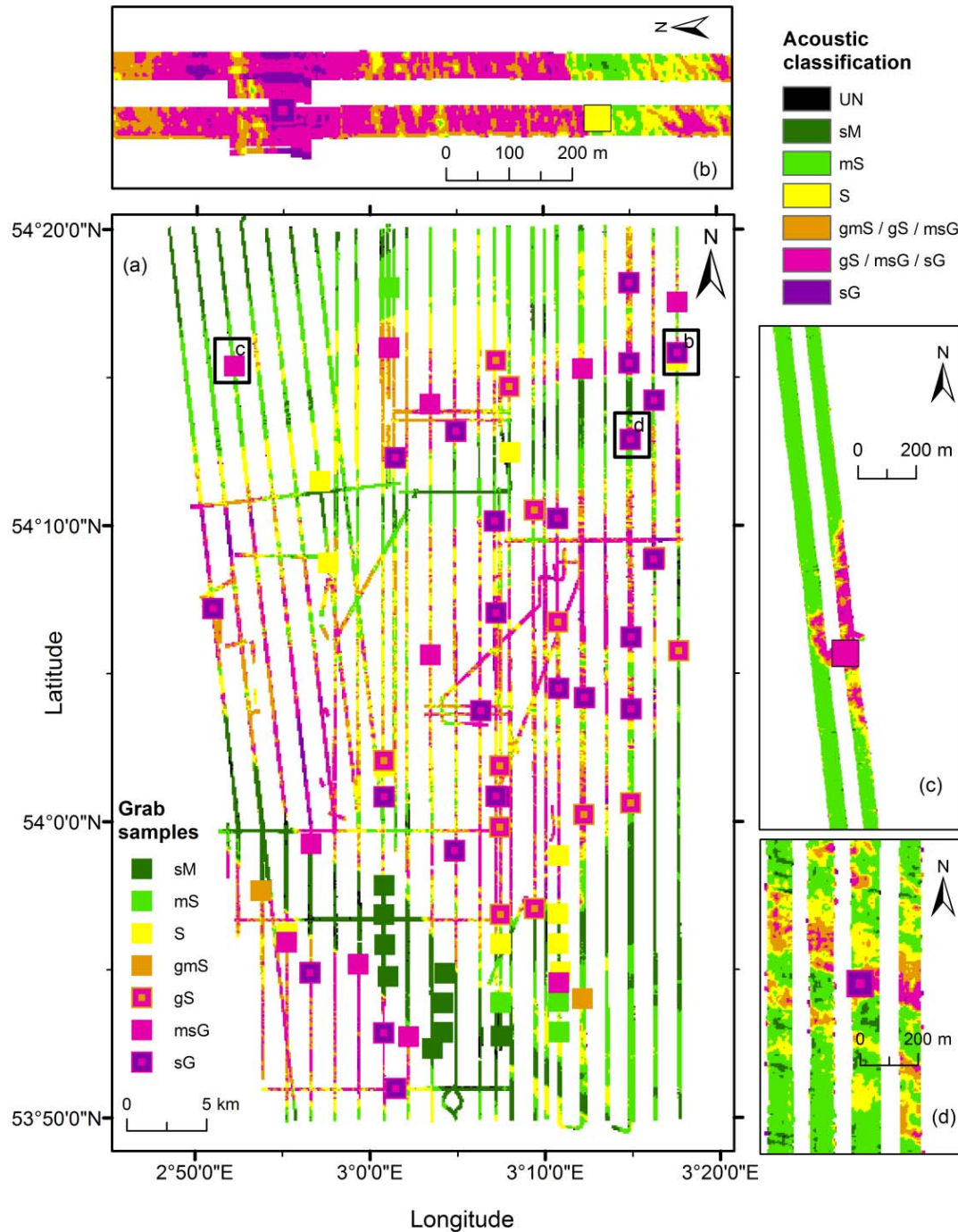
**Table 2 Assignment of sediment type (Folk scheme) to acoustic class. Acoustic classes are obtained from applying the Bayes classification method.**

Sediment type	<b>sM</b> sandy mud	<b>mS</b> muddy sand	<b>S</b> sand	<b>gmS</b> gravelly muddy sand	<b>gS</b> gravelly sand	<b>msG</b> muddy sandy gravel	<b>sG</b> sandy gravel
Acoustic class	2	3	4	5	5-6	5-6	6-7

### 5.3 Spatial resolution of classification results

To investigate the scale of information obtained from the acoustic classification, Fig. 13 shows more detailed pictures of selected areas in the Cleaver Bank. These areas are selected because grab samples are available and abrupt changes in the acoustic class occur within a mainly homogeneous area. Whereas, on the main sediment map the high resolution and the agreement between grabs sample and classification result are not obvious, the zoomed in plots do demonstrate these items. Each picture depicts strong changes in sediment classes over tens of meters resolved by the acoustic classification method. The sediment type of the grab samples denoted by the coloured squares matches well with the classification result. In particular, Fig. 13b shows an abrupt change in the sediment map which matches perfectly with the ground truth given sandy gravel and sand as a sediment type. It is notable that the sand grab sample is only approximately 10 m away from the estimated sand to gravel boundary but is perfectly resolved on the sediment map. Fig. 13c displays an area which seems to be a homogeneous sandy mud to muddy sand region on the main map but the detailed view reveals a gravelly sediment patch within this area. This patch matches very well with the grab sample of muddy sandy gravel. The detailed pictures display only a few examples of the match between classification result and grab sample. The main map of the Cleaver Bank, in general, also shows good agreement between classification results and

556 ground truth. For instance, the Botney cut is classified with sandy mud which fits to each grab  
557 sample taken in that area.



558

559 Fig. 13. Sediment map of the Cleaver Bank obtained from the Bayesian method and ground truth data. Sediment  
560 classes range from sandy mud (sM) to sandy gravel (sG). a) Sediment map of the entire survey area of the Cleaver  
561 Bank with a resolution of 100 m by 100 m. b), c) and d) represent small areas of the sediment map with a resolution of  
562 3 m by 3 m. The grab samples can be seen in the main map as a colour coded squares.

#### 5.4 Relation of acoustic classes with sediment median grain size

In Section 5.2 the relation between acoustic class and Folk class is investigated. It is found that no unique relation holds for the frequency and sediments considered in this study. Therefore, in this section it is investigated whether a more unique relationship between acoustic class and median grain size exists. To this end, the median grain sizes (D50 value) of the grab samples are now considered as in [47]. Except for class 7, the median values increase with class number as seen in Fig. 14 which presents the median of the D50 values as a function of acoustic class. This reflects an increasing backscatter value with increasing class number. Class 7 does not have a mean or median value higher than that of class 6. This indicates a situation where the highest backscatter values (class 7) apparently correspond to median grain sizes that are not necessarily higher than those belonging to class 6. Based on this result it can be concluded that, especially for the higher acoustic classes, as for the Folk class also no unique relationship between acoustic class and median grain size exists in the data.

To further investigate this we consider standardized backscatter values instead of acoustic class. In Fig. 15 the backscatter values (averaged over measurements within 25 m around a grab sample location) are shown as a function of D50 values. The backscatter values are additionally normalized by dividing each backscatter value by the maximum backscatter value thus yielding values strictly between -1 and 1. Fig. 15 shows a significant positive correlation between backscatter and median grain size for the fine fraction ( $< 1\phi$  (0.5 mm)). From the data, however, it is found that the magnitude of increase in backscatter with increasing median grain size is less significant between  $1$  and  $-1\phi$  (0.5 mm - 2 mm), followed by a plateau and a decrease for even coarser sediments. This indicates an ambiguity for the relationship between backscatter values and median grain size exists and hinders the discrimination of sediment types with median grain sizes larger than  $1\phi$  (0.5 mm) using acoustic classification methods



based only on backscatter data. This is in agreement with the findings of section 5.2. and indicates that there is no one-to-one relationship between median grain size and backscatter for the entire grain size spectrum. Such a positive correlation between backscatter and median grain size followed by a negative correlation was also observed in [4]. They referred to this change in relationship as a transition point. The transition point in the study of [4] occurred at  $-3.5 \phi$  (11 mm) using a frequency of 300 kHz. We estimate the transition point at approximately  $-2 \phi$  (4 mm). The transition point in [4] and the transition point in this study both occur roughly around the acoustic wavelength (5 mm) of the MBES.

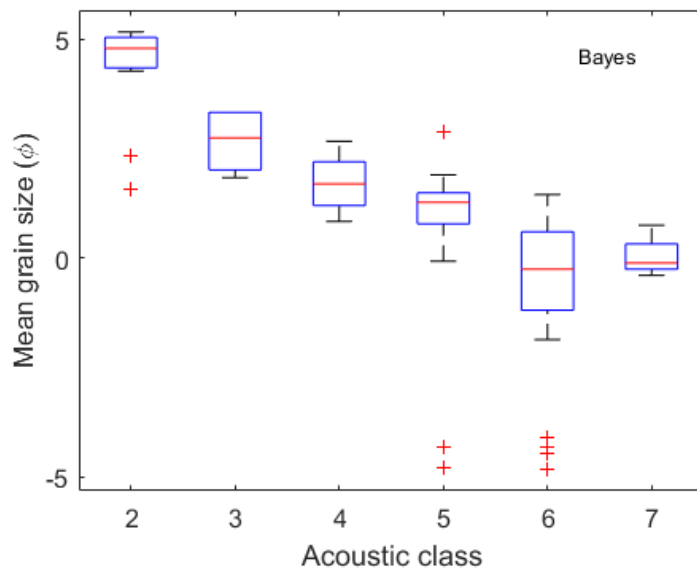


Fig. 14. Box plots of sediment samples that fall within the same acoustic class. The bottom and top of the blue rectangle represent the 25<sup>th</sup> and 75<sup>th</sup> percentiles, respectively, whereas the red line indicates the median value. The whiskers extend to the minimum and maximum value of the D50 values that are not considered outliers (i.e. they are no more than  $\pm 2.7\sigma$  apart). Outliers are marked with red crosses. The results for PCA, not plotted, are very similar.

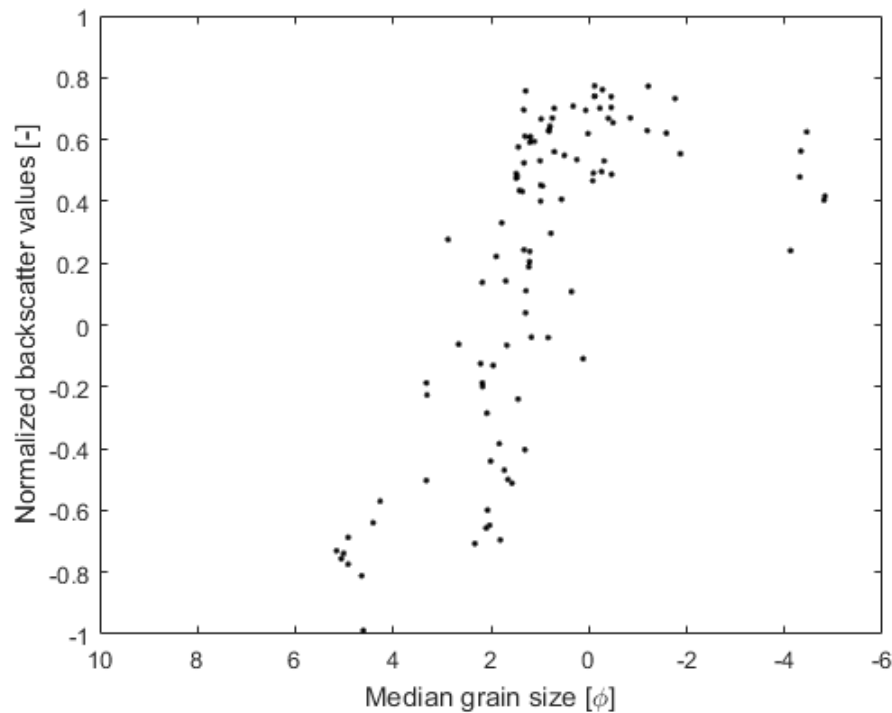


Fig. 15. Backscatter values as a function of the median grain size (D50) of grab samples. Dots indicate the averaged and standardized backscatter values within a maximum radius of 25 m around the grab sample.

## 6. Summary and conclusions

In this study two different acoustic classification methods, namely the Bayesian method and the PCA in conjunction with k-means clustering, were applied to MBES backscatter data from the Cleaver Bank in the Dutch North Sea. For both methods, the classification is based on changes in backscatter values for different sediment types. The data were acquired on two different Dutch vessels during five different surveys carried out in various time periods from 2013 to 2015.

The resulting maps show a high consistency between the classification results obtained from the different surveys and using a single classification method, despite the use of different vessels and varying time periods. Some discrepancies are observed (a difference of 1 acoustic

class); to gain a better understanding of these would require repeated surveys following the same survey patterns and supported by repeated grab samples for each of those surveys. Despite the discrepancies, this study demonstrates the potential of using backscatter data for achieving repeatable seabed sediment classification results even if the backscatter data is acquired during different time periods and from MBES systems which are mounted on different ships and thus subjected to different calibrations, survey settings, and ship crews. It can be concluded that the current state of MBES sediment classification techniques is such that it can be applied for marine sediment monitoring purposes where the aim is to identify changes in the sediment over time.

However, the current study clearly shows that monitoring requires the use of a single classification technique. Although, the same large-scale features are resolved, the two different techniques result in different maps. For the two techniques considered and using backscatter data only, the difference fully stems from the different approaches used for assigning backscatter measurements to a certain acoustic class. The Bayesian technique accounts for the statistical characteristics of the backscatter by assuming Gaussian distributed backscatter values. Whereas PCA in conjunction with the k-means algorithm uses a cluster technique to classify a dataset with respect to similarities of predefined properties and, thereby, neglects the natural fluctuation of backscatter which can superimpose the backscatter variation due to different seabed properties. The latter was found to underestimate the number of sediment types within the study area. Still, if additional information, such as bathymetry derived features, is considered the PCA method becomes an essential tool due to the ability of selecting the most valuable features [4], [20].

Finally, it was investigated to what extent Folk classes and median grain sizes can be assigned to acoustic classes. In general, this step is hindered by the fact that sediment bulk density, seafloor roughness, volume heterogeneity, discrete scatterers and sediment layering all

contribute to backscatter strength depending on the seabed complexity, acoustic frequency and incident angle [1], [2], [3]. For the Cleaver Bank area and the multi-beam (300 kHz) considered here, no unique relation between Folk class and acoustic class could be established. To still be able to map Folk class, a conversion scheme accounting for this non-uniqueness was introduced where a range of Folk classes is assigned to a single acoustic class. With regards to the relationship between median grain size and backscatter (acoustic class), a strong positive correlation for the fine fraction ( $< 0.5$  mm) followed by a decrease in positive correlation and a change into negative correlation for coarser sediments ( $> 4$  mm) are observed. This constitutes an ambiguity in the relationship between backscatter and median grain size. Therefore, care must be taken when assigning sediment properties or types (e.g. median grain size or Folk class) to an acoustic class based on MBES backscatter.

In conclusion, although limitations exist, current seafloor classification capabilities are such that they are a valuable asset in long-term monitoring efforts of the marine environment.

## **7. Acknowledgements**

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661 **Bibliography**  
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- [1] D. R. Jackson and M. D. Richardson, *High-Frequency Seafloor Acoustics*, New York: Springer Science, 2007.
- [2] A. N. Ivakin, "Scattering from discrete inclusions in marine sediments," in *Proc. Seventh European Conference on Underwater Acoustics. Delft University of Technology*, Delft, The Netherlands, 2004.
- [3] K. L. Williams, D. R. Jackson, D. Tang, K. B. Briggs and E. I. Thorsos, "Acoustic backscattering from a sand and a sand/mud environment: Experiments and data/model comparison," *IEEE Journal of Oceanic engineering*, vol. 34, no. 4, pp. 388-398, 2009.
- [4] D. Eleftherakis, M. Snellen, A. Amiri-Simkoei and D. G. Simons, "Observations regarding coarse sediment classification based on multi-beam echo-sounder's backscatter strength and depth residuals in Dutch rivers," *J. Acoustic. Soc. Am.*, vol. 135, no. 6, pp. 3305-3315, 2014.
- [5] J. S. Collier and C. J. Brown, "Correlation of sidescan backscatter with grain size distribution of surficial seabed sediments," *Marine Geology*, vol. 214, no. 4, pp. 431-449, 2005.
- [6] G. De Falco, R. Tonielli, G. Di Martino, S. Innangi, S. Simeone and I. M. Parnum, "Relationships between multibeam backscatter, sediment grain size and *Posidonia oceanica* seagrass distribution," *Continental Shelf Research*, vol. 30, pp. 1941-1950, 2010.
- [7] J. A. Goff, H. C. Olson and C. S. Duncan, "Correlation of side scan backscatter intensity with grain size distribution of shelf sediments," *Geo-marine Letters*, vol. 20, pp. 43-49, 2000.
- [8] T. Medialdea, I. Somoza, R. F. M. Leon, G. Ercilla, A. Maestro, D. Casas, E. Llave, F. J. F.-P. M. C. Hernandez-Molina and B. Alonso, "Multibeam backscatter as a tool for sea-floor characterization and identification of oil spills in the Galicia Bank," *Marine Geology*, vol. 249, pp. 93-107, 2008.
- [9] D. G. Simons, M. Snellen and M. Ainslie, "A multivariate correlation analysis of high-frequency bottom backscattering strength measurements with geotechnical parameters," *IEEE J. Ocean. Eng.*, vol. 32, pp. 640-650, 2007.
- [10] B. D. Edwards, P. Dartnell and H. Chezar, "Characterizing benthic substrates of Santa Monica Bay with seafloor photography and multibeam sonar imagery," *Marine Environmental Research*, vol. 56, no. 1-2, pp. 47-66, 2003.
- [11] V. E. Kostylev, R. C. Courtney, G. Robert and B. J. Todd, "Stock evaluation of giant scallop (*Placopecton magellanicus*) using high-resolution acoustics for seabed mapping," *Fisheries Research*, vol. 60, no. 2-3, pp. 479-492, 2003.
- [12] J. C. Borgeld, J. E. Hughes Clark, J. A. Goff, L. A. Mayer and J. A. Curtis, "Acoustic backscatter of the 1995 flood deposit on the Eel shelf," *Marine Geology*, vol. 154, pp. 197-210, 1999.

- [13] F. O. Nitsche, R. Bell, S. M. Carbotte, W. B. F. Ryan and R. Flood, "Process-related classification of acoustic data from the Hudson River Estuary," *Marine Geology*, vol. 209, pp. 131-145, 2004.
- [14] L. Fonseca, L. Mayer, D. Orange and N. Driscoll, "The high-frequency backscattering angular response of gassy sediments: model/data comparison from Eel River Margin, California," *The Journal of the Acoustical Society of America*, vol. 111, no. 6, pp. 2621-2631, 2002.
- [15] K. Siemes, M. Snellen, A. R. Amiri-Simkooei, D. G. Simons and J.-P. Hermand, "Predicting Spatial Variability of Sediment Properties From Hydrographic Data for Geoacoustic Inversion," *IEEE Journal of Oceanic Engineering*, vol. 35, no. 4, pp. 766-778, 2010.
- [16] C. McGonigle and J. Collier, "Interlinking backscatter, grain size and benthic community structure," *Estuar. Coast. Shelf Sci.*, vol. 147, pp. 123-136, 2014.
- [17] D. D. Sternlicht and C. P. de Moustier, "Remote sensing of sediment characteristics by optimized echo-envelope matching," *The Journal of the Acoustical Society of America*, vol. 114, no. 5, pp. 2727-2743, 2003.
- [18] L. Fonseca, C. Brown, B. Calder, L. Mayer and Y. Rzhannov, "Angular range analysis of acoustic themes from Stanton banks Ireland: a link between visual interpretation and multibeam echosounder angular signatures," *Applied Acoustic*, vol. 70, pp. 1298-1304, 2009.
- [19] C. J. Brown, B. J. Todd, V. E. Kostylev and R. A. Pickrill, "Image-based classification of multibeam sonar backscatter data for objective surficial sediment mapping of Georges Bank, Canada," *Continental Shelf Research*, vol. 31, pp. 110-119, 2010.
- [20] D. Eleftherakis, A. Amiri-Simkooei, M. Snellen and D. G. Simons, "Improving riverbed sediment classification using backscatter and depth residual features of multi-beam echo-sounder systems," *J. Acoust. Soc.*, vol. 131, no. 5, pp. 3710-3725, 2012.
- [21] J. Anderson, D. van Holliday, R. Kloser, D. Reid and Y. Simard, "Acoustic seabed classification: current practice and future directions," *ICES Journal of Marine Science*, vol. 65, pp. 1004-1011, 2008.
- [22] C. J. Brown, S. J. Smith, P. Lawton and J. T. Anderson, "Benthic habitat mapping: A review of progress towards improved understanding of the spatial ecology of the seafloor using acoustic techniques," *Estuarine, Coastal and Shelf Science*, vol. 92, pp. 502-520, 2011.
- [23] D. G. Simons and M. Snellen, "A Bayesian approach to seafloor classification using multi-beam echo-sounder backscatter data," *Applied Acoustics*, vol. 70, pp. 1258-1268, 2009.
- [24] E. Alevizos, M. Snellen, D. G. Simons, K. Siemes and J. Greinert, "Acoustic discrimination of relatively homogeneous fine sediments using Bayesian classification on MBES data," *Marine Geology*, vol. 370, pp. 31-42, 2015.
- [25] E. Heffron, M. Doucet, C. Brown, G. Lamarche and R. Cooper, "Multibeam Backscatter Workshop - State of the Technology, Tools & Techniques: Overview," GeoHab Annual Conference,

Fiorentino, A., Rome, Italy, 2013.

- [26] X. Lurton, G. Lamarche, C. Brown, V. Lucieer, G. Rice, A. Schimel and T. Weber, "Backscatter measurements by seafloor-mapping sonars. Guidelines and Recommendations," 2015.
- [27] H. J. Lindeboom, R. Witbaard, O. G. Bos and E. Meesters, "Gebiedsbescherming Noordzee. Habitattypen, instandhoudingsdoelen en beheersmaatregelen," *Wettelijke Onderzoekstaken Natuur & Milieu*, vol. 114, 2008.
- [28] N. Schrieken, A. Gittenberger, J. W. P. Coolen and W. Lengkeek, "Marine fauna of hard substrata of the Cleaver Bank and Dogger Bank," *Nederlandse Faunistische Mededelingen*, vol. 41, pp. 69-78, 2013.
- [29] E. Hammerstedt, "EM technical note: backscattering and seabed image reflectivity 1-5," 2000.
- [30] R. L. Folk, "The distinction between grain size and mineral composition in sedimentary-rock nomenclature," *J Geol*, vol. 62, no. 4, pp. 344-359, 1954.
- [31] EMODnet, "<http://www.emodnet-hydrography.eu/>," European Marine Observation and Data Network, 2016. [Online]. [Accessed 5 August 2016].
- [32] A. R. Amiri-Simkooei, M. Snellen and D. G. Simons, "Riverbed sediment classification using multi-beam echo-sounder backscatter data," *J. Acoust.*, vol. 126, pp. 1724-1738, 2009.
- [33] K. Pearson, "On lines and planes of closet fit to systems of points in space," *Philos. Mag.*, vol. 2, no. 6, pp. 559-572, 1901.
- [34] H. Hotelling, "Analysis of a complex of statistical variables into principal components," *J. Educ. Psychol.*, vol. 24, no. 7, pp. 498-520, 1933.
- [35] P. R. Bevington and D. K. Robinson, *Data Reduction and Error Analysis for the Physical Sciences* 3rd edition, New York: McGraw-Hill, 2003.
- [36] Siswadi, A. Muslim and T. Bakhtiar, "Variable selection using principal component and procrustes analyses and ITS application in educational data," *Journal of Asian Scientific Research*, vol. 2, no. 12, pp. 856-865, 2012.
- [37] M. J. Canty, *Image Analysis, Classification and Change Detection in Remote Sensing with Algorithms for ENVI/IDL*, Boca Raton: CRC Press, Taylor & Francis Group, 2007.
- [38] R. Tibshirani, G. Walther and T. Hastie, "Estimating the number of clusters in a data set via the gap statistic," *J. R. Statist. Soc. B*, vol. 63, pp. 411-423, 2001.
- [39] L. Kaufman and P. Rousseeuw, *Findings Groups in Data: an Introduction to Cluster Analysis*, New York: Wiley, 1990.

- [40] D. Davies and D. Bouldin, "A cluster separation measure," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vols. PAMI-1, no. 2, pp. 224-227, 1979.
- [41] X. Lurton, *An Introduction to Underwater Acoustics*, Heidelberg: Springer-Verlag, 2010.
- [42] J. M. Preston, A. C. Christney, S. F. Bloomer and I. L. Beaudet, "Seabed Classification of Multibeam Sonar Images," in *MTS/IEEE Oceans 2001 Conference*, Honolulu, HI, 2001.
- [43] A. N. Gavrilov and I. M. Parum, "Fluctuations of Seafloor Backscatter Data From Multibeam Sonar systems," *IEEE Journal of Oceanic Engineering*, vol. 35, no. 2, pp. 209-219, 2010.
- [44] E. Jakeman and P. N. Pusey, "Significance of K distributions in scattering elements," *Physical Review Letters*, vol. 40, no. 9, pp. 546-550, 1978.
- [45] L. Hellequin, J. M. Boucher and X. Lurton, "Processing of high-frequency multibeam echo sounder data for seafloor characterization," *IEEE Journal of Oceanic Engineering*, vol. 28, no. 1, pp. 78-89, 2003.
- [46] T. F. Sutherland, J. Galloway, R. Loschiavo, C. D. Levings and R. Hare, "Calibration techniques and sampling resolution requirements for groundtruthing multi-beam acoustic backscatter (EM3000) and QTC VIEW classification technology," *Estuarine Coastal and Shelf Science*, vol. 75, pp. 447-458, 2007.
- [47] E. Alevizos, T. Schoenning, K. Koeser, M. Snellen and J. Greinert, "Quantifying the fine-scale distribution of Mn-nodules: insights from AUV multi-beam and imagery data fusion," *Currently in press*, 2017.

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