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Investigating acoustic diversity of fish aggregations in coral reef ecosystems from multifrequency fishery sonar surveys

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ABSTRACT

Remote species classification using fisheries acoustic techniques in coral reef ecosystems remains one of the greatest hurdles in developing informative metrics and indicators required for ecosystem management. We reviewed long-term marine ecosystem acoustic surveys that have been carried out in the US Caribbean covering various coral reef habitat types and evaluated metrics that may be helpful in classifying multifrequency acoustic signatures of fish aggregations to taxonomic groups. We found that the energetic properties across frequencies, in particular the mean and the maximum volume backscattering coefficient, provided the majority of the discriminating power in separating schools and aggregations into distinct groups. To a lesser extent, school shape and geometry helped isolate a distinctive group of reef fishes based on shoaling behaviour. Schools and aggregations were clustered into five distinct groups. The use of underwater video surveys from a Remote Operating Vehicle (ROV) conducted in the proximity of the acoustic observations allowed us to associate the clusters with broad categories of species groups such as large predators, including fishery important species to small forage fishes. The remote classification methods described here are an important step toward improving marine ecosystem acoustics for the study and management of coral reef fish communities.

1. Introduction

Increased use of ecosystem approaches to support ocean planning and management of ecosystem resources requires rapid and synoptic collection and synthesis of geospatial data. Remote sensing approaches such as satellite, airborne or ship-based optical and acoustic sensors have proven useful in collecting high resolution seafloor imagery over very large spatial extents (Costa et al., 2009; Pittman and Brown, 2011). The power of these datasets is further improved when seafloor habitat types can be interpreted to geological form (e.g., rock, sediment) and biological cover (e.g., coral, vegetation). In coral reef ecosystems, distribution of reef fish has been closely associated with geomorphology, biological cover, and reef topographic complexity (Gratwicke and Speight, 2005; Komyakova et al., 2013; Kuffner et al., 2006; Luckhurst and Luckhurst, 1978; Roberts and Ormond, 1987; Walker et al., 2009). Because these complex habitats preclude the use of trawls and many other extractive fishing methods, the primary method to assess fish distributions in tropical reefs is through visual or optical surveys. However, limitations in coverage of these methods, especially in deeper waters, constrains our understanding of the distribution of fish over habitats across a range of spatial resolutions and extents. Further limitations in visual techniques arise when attempting to enumerate or characterize behaviours of large aggregations or schools of fish.

Fishery sonar surveys have been used for several decades as an assessment tool for temperate fish populations, but have not been used extensively in coral reef systems. The primary challenge in reef systems is the high diversity and the inability to identify species using sonar (echosounders) alone. A recent paper by Costa et al. (2014) found that maps of taxa-independent fish densities derived from fishery echosounder surveys conform to predictions based on seafloor habitat complexity (e.g., rugosity, depth, and slope; Pittman and Brown, 2011). Higher densities are found over seafloors of higher rugosity, slope and depth (where shallow depths are usually correlated with high-relief and high rugosity reefs).

To be the most useful to fisheries and ecosystem management goals, assessments of fish and other living marine resources in coral reefs would ideally provide density and biomass for each species over broad spatial extent and at fine spatial resolution. Currently,

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acoustic surveys of reef fishes have been able to separate fish densities according to broad size classes focusing on individual fish resolvable by the echosounder (Costa et al., 2014). This approach is not always applicable considering that many species aggregate into dense schools resulting in the overlapping of the individual fish echoes. For this reason, there is the need to improve the acoustic methodology and further develop approaches for data analysis. Multi-frequency fishery echosounders, as used in recent acoustic surveys for reef fishes, have shown some progress in recent years in discerning size and age classes, species or functional groups of mixed aggregations of fishes, and fish from marine invertebrates (Fablet et al., 2012; Fernandes, 2009; Horne 2000; Kloser et al., 2002; Korneliussen and Ona, 2003; Korneliussen et al., 2009). The approach relies on two acoustic properties of fishes and fish schools. First, fish species may have swim bladders (or not) with morphologies that differentially reflect sound across frequency bands. Second, species may form groups or schools that have unique shapes or internal densities that can be differentiated using acoustic backscatter.

For this paper, we evaluate existing metrics that describe the shape and acoustic backscatter (energetic) properties of Caribbean reef-fish aggregations and schools in order to investigate the fish acoustic diversity and identify meaningful patterns that could help to classify the acoustic signatures. We use an unsupervised statistical clustering approach and discuss the repeatability of the method for describing the acoustic variability in the coral reef areas. Finally, we use underwater video surveys of fish aggregations and schools from remotely operated vehicle (ROV) to guide our interpretation of the multi-frequency acoustic clustering approach.

2. Materials and methods

2.1. Study area

The research was conducted in the US Virgin Islands and Puerto Rico in spring 2011, 2013 and 2014. The surveys were part of a U.S. National Oceanic and Atmospheric Administration (NOAA) program to map the benthic habitats using multibeam echosounders and simultaneously map the distribution of fish using scientific splitbeam echosounders (Kracker et al., 2011). The fish acoustic surveys covered areas identified as "hotspots" for the presence of high abundance of commercially important species such as groupers and snappers (Fig. 1).

2.2. Splitbeam echosounder surveys

Acoustic sampling was conducted on board the NOAA Ship *Nancy Foster* during daytime (08:00–18:00) using a SIMRAD EK 60 splitbeam echosounder operating at 3 frequencies (38, 120, 200 kHz). Pulse length was set to 128 μs for the 120 kHz and 200 kHz and 256 μs on the 38 kHz. During some parts of the survey, a multibeam sonar (Reson 7125 operating at 400 kHz) was used to simultaneously map the seafloor. Pulse interval was defined automatically based on the range or depth and triggered by the pulse interval of the multibeam sonar. All the frequencies were calibrated following the standard sphere method using a tungsten carbide sphere (Foote et al., 1987). The survey design was generally based on parallel transects. The inter-transect distance, transect length and direction varied among sampling sites and were chosen according to the characteristics of the reef. The vessel speed was approximately 6.5 knots.

2.3. Data analysis

The acoustic data were processed using the software Echoview (ver. 6.0; Echoview Software Pty Ltd.). The data processing workflow consisted of three parts: first, data were corrected based on the transducer geometry and for vessel pitch and roll in order to get the correct beam directivity. In order to ensure a good degree of beam overlap across the frequencies, the data were compensated for the distance between the transducers along the longitudinal axes of the ship. In particular, the data were shifted by a number of pings that were equivalent to the distance between the transducers. Since the pulse length used at 38 kHz was different from the other two frequencies resulting in different vertical resolutions, the data at 120 and 200 kHz were integrated along the vertical axis to match the lower vertical resolution in the 38 kHz data (~4 cm). Noise from ship systems and unwanted backscatter from bubbles and other sources were removed from the data in order to get a "clean" echogram. In the second part, the data at each frequency were averaged generating a synthetic echogram and an image filtering procedure was used to stabilize the data following the method fully described in Korneliussen et al. (2009). Finally, automatic school detection was applied on the averaged and filtered data using the SHAPES algorithm in Echoview (Barange, 1994). The detection parameters used were: minimum total school length of 2 m, a minimum school height of 1 m, a minimum candidate length of 2 m, a minimum candidate height of 1m, a vertical linking distance of 1 m, a maximum horizontal gap distance of 5 m, and a minimum volume backscattering coefficient (Sv) of −60 dB. This set of parameters was selected based on the characteristics of the aggregations in the data in order to minimize the false detection of the schools. The schools were also visually scrutinized and edited when the algorithm failed to identify the correct structure of the aggregations. A series of metrics describing the characteristics of the schools were exported at each frequency using a Sv threshold of −60 dB. In particular, geometric, energetic and bathymetric parameters, which have been used previously for acoustic target classification (Haralabous and Georgakarakos, 1996; Korneliussen et al., 2009; Reid, 2000), were taken into account. These variables provide detailed information of the acoustic characteristics and behaviour of fish schools. The geometric features describe the morphology of the schools. The calculation of the geometric variables is based on image analysis techniques given that the echogram can be seen as a raster image where the pixels correspond to the data points. The geometric properties of each datapoint depend on frequency, pulse interval, pulse length and vessel speed (Reid, 2000). The energetic features provide information on both target characteristics (e.g., size, presence of swimbladder) and school behaviour (e.g., packing density, presence of patches inside the schools). The bathymetric variables give us an indication of habitat selection that can be species-specific. We included the majority of variables previously used in acoustic target classification so as not to omit any information that may be important for the classification, especially considering the high diversity of the system. The school descriptors with their relative meanings and references are listed in Table 1. The resulting schools library consisted of 2268 schools.

2.4. Clustering

An unsupervised clustering approach was used for the classification of aggregations. This approach does not require "a priori" information about the school category and the species class label will be inferred on the basis of the school descriptors considered. The basic assumption using this method is that the detected classes of aggregations correspond to biologically meaningful structures that can be related, for instance, to morphological similarity between species, similar aggregation behaviour etc. In particular the Robust Sparse K-Means (RSKM) was applied (Kondo et al., 2012). This method is the combination of the trimmed k-means (Gordaliza, 1991a,b) and the sparse k-means (Witten and

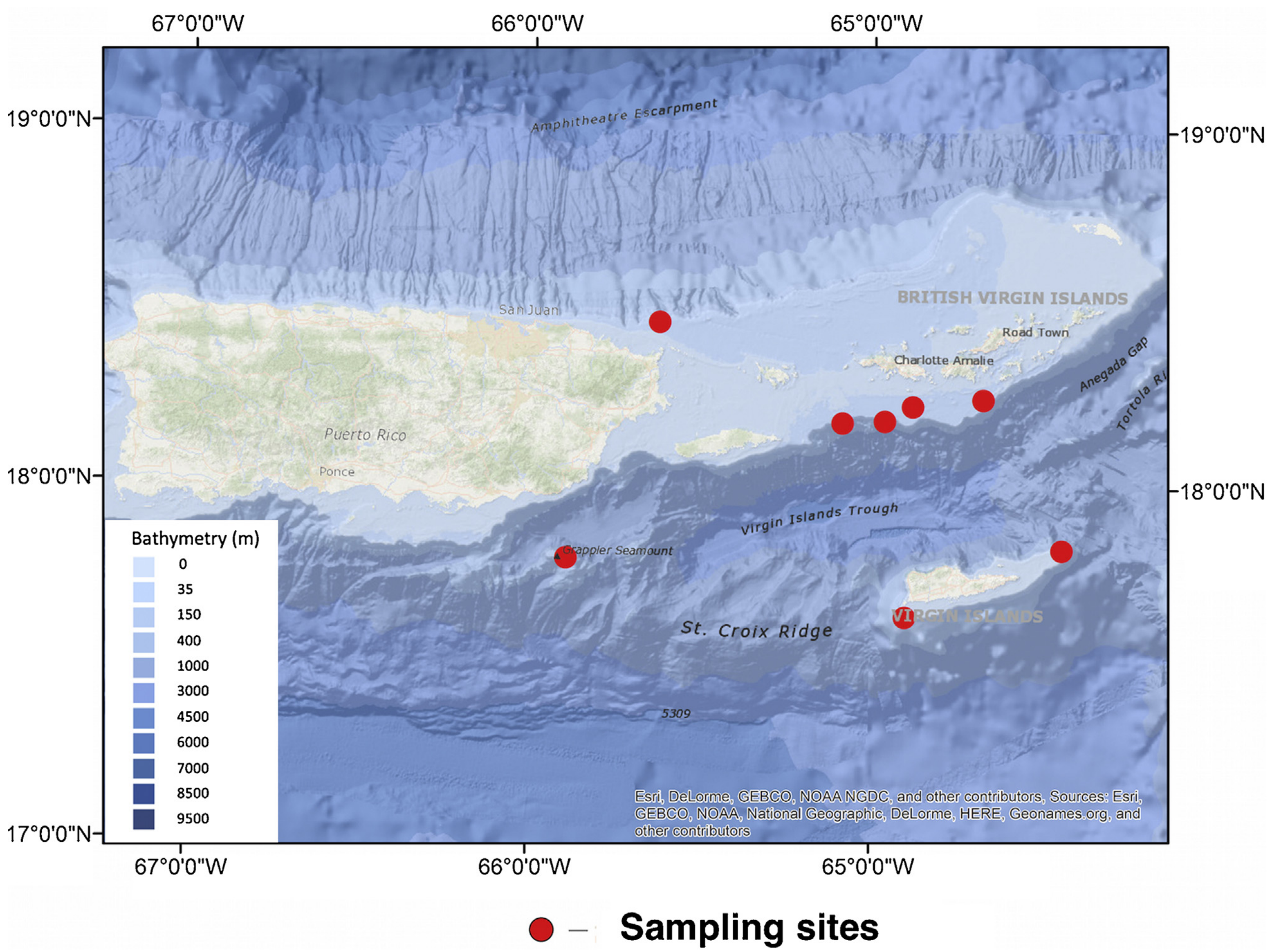

Fig. 1. Map of the study area. The circles correspond to the different acoustic sampling sites.

Tibshirani, 2010) which are both derived forms of k-means. The use of RSKM overcomes a weakness of standard k-means when datasets contain noisy features and are affected by the presence of outliers. Thus the k-means approach seeks to maximize the dissimilarity between clusters based on the squared Euclidean distance which is the square of the standard Euclidean distance and give progressively more weight to the points that are farther apart. The method can be divided into two parts. The first part the algorithm assumes that the dissimilarity between clusters is additive and depends on the contribution of each individual feature. In order to optimize the maximization function and identify the features that contribute to the separation of clusters, a weight **w** is associated with each feature. This allowed us to reduce the potential negative effect on clustering results when using a high number of variables. The **w** is calculated according to the Lasso method (Tibshirani, 1994) which constrains the weight to a tuning parameter $\mathbf{l}_1$. Specifically, the norm of the weight vector has to be less than the $\mathbf{l}_1$ parameter. The tuning parameter can have values between 1 and sqrt(number of features). Small values of the tuning parameter will increase the degree of sparsity of the feature weight vector resulting in an increase of the number of features that receive a zero weight. In this work the $\mathbf{l}_1$ was set to 5 obtaining non-zero weights for all the features.

The second part of the method is aimed at reducing the effect of the outliers on the clustering results. For each iteration, 10% of the data points furthest from the cluster centres are trimmed in the subsequent calculation of new cluster centres. A crucial step in k-means is the selection of the number of clusters that have to be chosen “a priori”. This was done by means of the “Clest” algorithm (Dudoit and Fridlyand, 2002; Kondo et al., 2012). The algorithm selects the optimal number of clusters based on the evaluation of the predictive power of the classification using a set of validation datasets generated randomly partitioning the original dataset (in this work, random and validation datasets were generated 15 times). The index used to estimate the agreement between training and validation datasets was the Classification Error Rate (CER) (Chipman and Tibshirani, 2006). The CERs obtained considering different number of clusters ($obsCER_k$) were compared to the expected CER values ($expCER_1$) under a null hypothesis (number of clusters = 1). The expected CER was calculated using 5 different datasets generated by Monte Carlo resampling. Finally Clest chooses the optimal number of clusters minimizing the following function:

$$n.of\ clusters = minimum\{d_k = median(obsCER_k) - median(expCER_1)\},$$

if the percentage of the expCERs greater than the obsCER is less than 5%. The comparison of the obsCER with the expCER takes into account a potential absence of structure in the dataset. The revised silhouette plot was estimated to assess how well each data point was clustered. (Kondo et al., 2012; Rouesseeuw, 1987). The

Table 1
List of school descriptors used for clustering.

Class	School Descriptor	Unit	Description	Reference
Energetic	MVBS 38, 120, 200 kHz **(MVBS38, MVBS120, MVBS200)**	db re 1 m^{-1}	Mean volume backscattering coefficient	Simmonds and Maclennan (2005)
	Sv max 38, 120, 200 kHz **(sv_max38, sv_max120, sv_max200)**	db re 1 m^{-1}	Max volume backscattering coefficient	Simmonds and Maclennan (2005)
	Horizontal roughness 38 kHz **(hor_rough)**	db re 1 m^{-1}	Measure of the dispersion of acoustic energy in the horizontal direction	Nero and Magnuson (1989)
	Vertical roughness 38 kHz **(ver_rough)**	db re 1 m^{-1}	Measure of the dispersion of acoustic energy in the vertical direction	Nero and Magnuson (1989)
	Skewness 38 kHz **(skew)**	–	Skewness of the sample values in a school	Lawson et al., 2001
	Standard Deviation (**SD**)	–	Standard deviation of the Sv values in the school	
	Coefficient of Variation (**CV**)	–	Coefficient of variation of the Sv values in the school	
	r(f) 200/38 **(freq_resp200)**	db re 1 m^{-1}	Relative frequency response: volume-backscattering coefficient at 200 kHz relative to 38 kHz considered as reference frequency	Korneliussen and Ona (2003)
	r(f) 120/38 **(freq_resp120)**	db re 1 m^{-1}	Relative frequency response: volume-backscattering coefficient at 120 kHz relative to 38 kHz considered as reference frequency	Korneliussen and Ona (2003)
Geometric	Corrected length **(length)**	m	Horizontal dimension in the plane of the echogram corrected for known beam geometry	Reid, 2000
	Corrected thickness **(thick)**	m	Vertical dimension in the plane of the echogram corrected for known beam geometry	Reid, 2000
	Corrected perimeter **(perim)**	m	Length of the perimeter (in the plane of the echogram) corrected for known beam geometry	Reid, 2000
	Corrected area **(area)**	m^2	Cross sectional area (in the plane of the echogram) of a school represented by a region on an echogram corrected for known beam geometry	Reid, 2000
	Image compactness **(compact)**	–	Measure of the shape of a school calculated as the ratio between the perimeter and the area	Reid, 2000
	3D school volume **(vol_3d)**	m^3	Estimated volume of a school assuming it is cylindrical	
	Rectangularity **(rectangul)**	–	(Length × Thickness)/Area	Scalabrin and Massé, 1993; Haralabous and Georgakarakos, 1996
	Circularity (**circul**)	–	$(4\pi \times \text{Area})/\text{Perimeter}^2$	Korneliussen et al., 2009
	Uneveness **(unev)**	–	Relation between the school perimeter and the rectangle perimeter computed from the school height and length	Weill et al., 1993
	Fractal dimension **(fractal)**	–	Index of shape complexity (Ln (Perimeter/4) × 2)/Ln(number of samples)	Nero and Magnuson, 1989; Barange, 1994
	Elongation **(elong)**	–	Length/Thickness	Coetzee, 2000
Bathymetric	Depth mean **(school depth)**	m	The distance from the sea surface to the geometric center of the fish school	
	Mean dist bottom **(dist)**	m	The distance from the bottom to the geometric center of the fish school	
	Depth **(depth)**	m		

revised silhouette takes values between 0 and 1. A value equal to 1 indicates that the data point is perfectly clustered and it coincides with the cluster centre. In order to assess the stability of the method, the clustering results were evaluated using a validation procedure based on bootstrapping. The original dataset was resampled 100 times and the clustering algorithm was applied to each resampled dataset. The similarity between the clusters obtained from the resample datasets and those from the original datasets was calculated using the Jaccard index. The average value of the similarity index for each cluster was used as an index of stability of the clusters (Hennig, 2007). A valid stable cluster should have a mean Jaccard similarity value of 0.75 or more. Values over 0.85 indicate highly stable clusters. Values between 0.6 and 0.75 indicate the presence of certain patterns in the data but the cluster assignment is not precise. Values below 0.6 indicate unreliable results.

Principal components analysis (PCA; Zuur et al., 2007) was used to show the clusters obtained and the influence of the features on the results. The characteristics of the clusters were explored using the parallel coordinate plot. In addition, to evaluate the dispersion of the most important parameters associated with the clusters, the Inter Quartile Range (IQR) was also calculated. Data analysis was conducted in R using the RSKC package and the fpc package (Hennig, 2015; Kondo et al., 2012; Kondo, 2014).

2.5. ROV sampling and visual validation

High resolution underwater videos and images were taken by a remote operated vehicle (ROV, model: Super Phantom S2 or Sub-Atlantic Mohawk18) with standard definition or high definition video cameras (for Mohawk ROV: Insite Pacific Mini Zeus II HD video camera, Kongsberg Maritime OE14-408 digital still camera; for Phantom S2 ROV: Sony color CCD video camera with 460+ lines of resolution) in order to detect species composition and schooling behaviour of the fish communities in the area. The ROV transects varied in length and the sites for deployment were chosen based on location of schools detected by the splitbeam echosounder. The ROV dives were carried out within approximately two hours of the acoustic transects. ROV tracking was provided by the ship's GPS with offset provided by an ultra-short baseline tracking system (USBL system: ORE trackpoint II, ORE transponder, KVH compass, Northstar 951x DGPS).

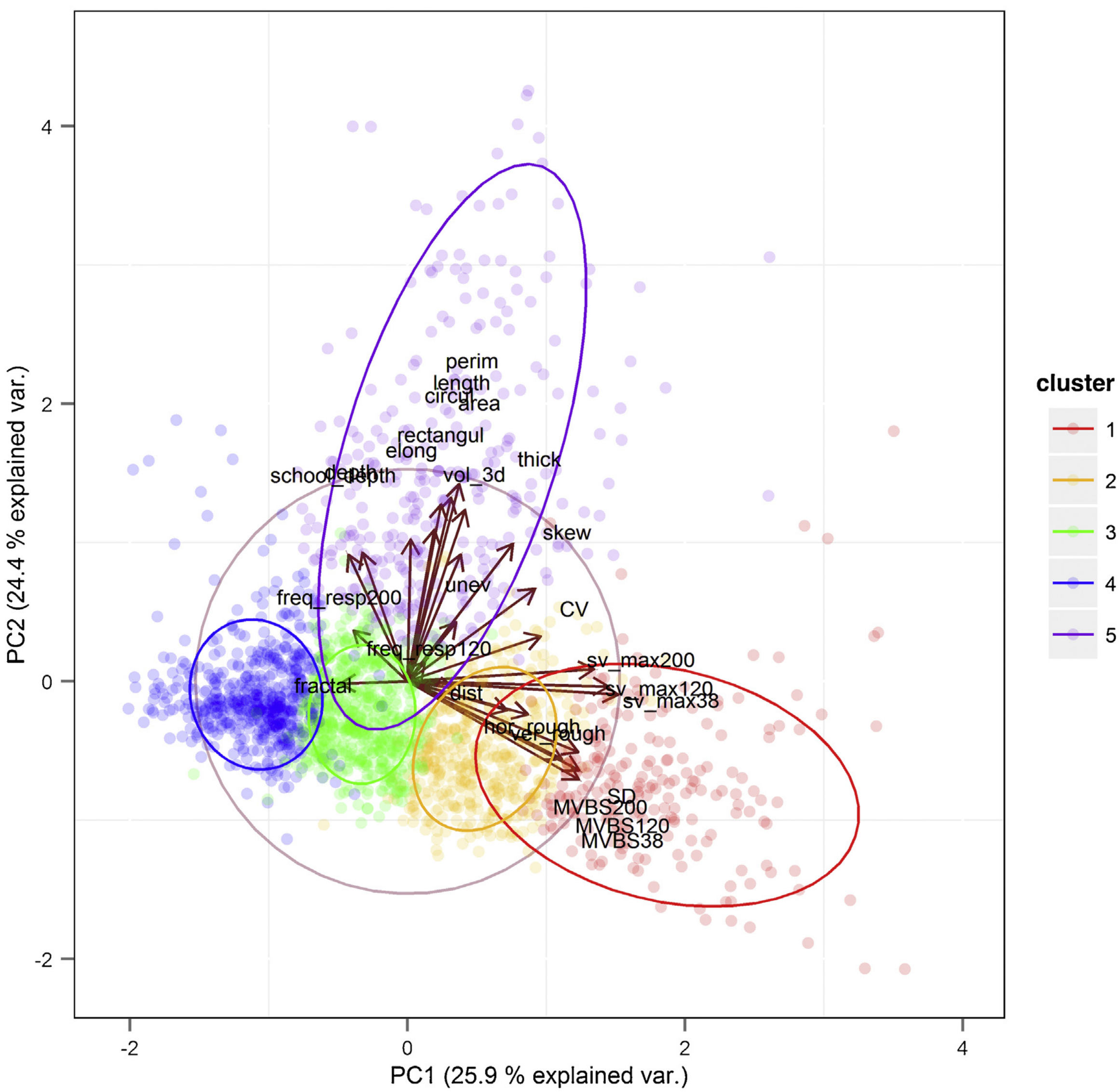

Fig. 2. Clusters obtained from the RSKM plotted on a PCA biplot. The ellipses surrounded the clusters show the 68 percent confidence intervals.

Fish schools and aggregations observed by the ROV were assigned geographic coordinates along the transect and paired with the closest aggregations and clusters from the analysis of the echosounder surveys. Fish behaviour (e.g., packing density, number of fish in the schools, school shape, distance from the bottom) was also evaluated comparing apparent patterns in clusters with species observed.

3. Results

3.1. Clustering

The outcomes of the RSKM were plotted on the first two principal components of the PCA which explained the 50.3% of the total variation (Fig. 2). Principal Component 1 (PC1) summarized the variation of the main energetic parameters while Principal Component 2 (PC2) was more related to the morphometric variability of the schools and the bathymetric characteristics (Table 2). The optimal number of clusters estimated by the Clest algorithm was 5 (Table 3). The use of Clest algorithm allowed us to test the stability of the clustering results. The median value of the observed Classification Error Rate (CER) was 0.0463 indicating a very high agreement between the training and the validation datasets. The validation performed using the bootstrapping-based method highlighted the high stability of the clustering results. In particular, the average Jaccard similarity coefficient was greater than 0.9 for all the clusters.

The weights associated with each variable assigned by the RSKM algorithm are shown in Fig. 3 and Table 2. The variables that were most influential in the clustering were the energetic parameters (maximum Sv and MVBS) followed by several geometric parameters (rectangularity, length, elongation, perimeter and thickness). Bathymetric variables and frequency response were relatively unimportant. The first component, driven by the energetic variables (PC1), separated 4 groups of schools corresponding to: cluster 1, clusters 2 and 3, cluster 4, cluster 5. The second component, driven by the geometric parameters (PC2), separated two groups of schools corresponding to: cluster 3 and clusters 1, 2, 4 and 5. The revised silhouette plot (Fig. 4) indicated a moderate level of separation between the clusters with

Table 2
Weights values of the school descriptors estimated by the RSKM and contribution of the variables to the first two components of the PCA.

Variables	RSKM weights	PCA1[a]	PCA2[a]
Energetic			
sv_max38	0.38	**13.39**	0.06
MVBS120	0.35	**8.91**	2.70
sv_max120	0.35	**12.20**	0.01
MVBS38	0.34	**8.87**	3.30
sv_max200	0.31	**10.48**	0.05
MVBS200	0.25	**7.18**	2.05
SD	0.17	**8.82**	1.71
skew	0.16	**4.90**	2.93
CV	0.11	**5.35**	0.69
freq_resp200	0.06	0.89	0.89
ver_rough	0.02	**4.37**	0.37
freq_resp120	0.01	0.09	0.13
hor_rough	0.01	3.00	0.28
Geometric			
rectangul	0.28	0.21	**7.87**
length	0.23	0.57	**11.57**
elong	0.21	0.00	**6.90**
perim	0.18	0.80	**13.32**
thick	0.17	3.36	**6.49**
circul	0.13	0.34	**10.73**
area	0.10	1.00	**10.06**
fractal	0.04	1.38	0.00
unev	0.03	0.70	1.20
vol_3d	0.02	0.86	**5.52**
Bathymetric			
school_depth	0.08	1.05	**5.48**
depth	0.05	0.61	**5.65**
dist	0.04	0.67	0.02

[a] The variables with a contribution value >3.8 (the value if the contributions of all the variables were uniform) were considered important in the interpretation of the components (in bold).

Table 3
Results of the Clest algorithm for the selection of the optimal number of clusters. The bold line indicates the best result. (d_k = test statistics, obsCER − refCER; obsCER = CERs (Classification Error Rates) estimated on the observed value, refCER = expected CER value under the null hypothesis that all the cases are from the same cluster; p-value = probability of observing CER more extreme than the CER under the null hypothesis).

k	d_k	*obsCER*	*refCER*	*P-value*
2	0.0363	0.1036	0.0673	1.00
3	0.1647	0.2981	0.1334	1.00
4	−0.0730	0.0613	0.1344	0.00
5	**−0.1206**	**0.0463**	**0.1669**	**0.00**
6	0.0177	0.1266	0.1089	0.60
7	−0.0438	0.0953	0.1391	0.00
8	−0.0102	0.1163	0.1265	0.40
9	0.0001	0.1165	0.1164	0.40

an average silhouette value of 0.54. The stability of the results highlighted by the Clest results, indicated that the variables considered in the clustering were able to identify patterns that may be related to the biological characteristics of the species that are manifested by a combination of energetic and geometric characteristics.

3.2. Clusters characteristics

Parallel coordinate plot and summary statistics of the main variables used for the classification were used to describe the characteristics of the clusters (Fig. 5, Table 4). Names were associated to the clusters based on the characteristics observed. The clusters were called: "high energy" (cluster 1), "moderate energy" (cluster 2), "low energy" (cluster 3), "very low energy" (cluster 4) and "serpentine" (cluster 5). The first 4 clusters were well separated in terms of energetic parameters. This is clearly shown in the parallel coordinate plot where the profiles corresponding to the energetic parameters (left side of the plot) are far apart and not overlapped. The profile corresponding to the "serpentine" cluster showed a stronger separation from the others in terms of geometric parameters (right side of the plot in Fig. 5).

The "high energy" cluster was characterized by relatively large schools (average area: 53 m^2) with the highest level of backscattering strength at all frequencies (Table 4). The morphometric variables did not show strong patterns except for the thickness that presented values higher than the overall average across all clusters. The aggregations in "high energy" were mainly distributed in the water column with an average distance from the sea floor of 3.66 m. The "weak energy" cluster was constituted by small schools with low-moderate backscattering strength and low values of thickness (Fig. 6, Table 4). Moreover, the high values of fractal dimension detected in this cluster indicated a high complexity in the school shape (Table 4). The "moderate energy" and the "low energy" clusters had intermediate characteristics between the "high energy" and "very low energy" clusters considering all energetic variables and some specific geometric variables (area, thickness and fractal dimension). The "serpentine" cluster was separated from the others mainly based on the geometric variables. The schools presented a characteristic ribbon-elongated shape, at times extending over long distances (length range: 50.3–1417 m) with a moderate level of acoustic energy (Fig. 6). Moreover, these schools occupied the deepest regions of the study areas (average depth: 49.4 m; Table 4).

The IQR values reported in Table 4showed that variables presented a high level of variability among the clusters, in particular the "high energy" and the "serpentine" clusters (Fig. 5). This large variability is also seen in the PCA biplot where the cluster data points were more scattered and the ellipses surrounding them were extended along axes.

3.3. ROV visual observation

A total of 7 ROV dives were used for visually interpreting the species that form schools, aggregations or loose groups that may comprise the clusters we analysed acoustically (suppl. materials). The deployment of the ROV occurred within approximately two hours from the acoustic surveys except for dive 7 where the dive started 3.5 h after the acoustic survey. The species detected in each ROV video and a qualitative description of their behavioural patterns are listed in Table 5. A total number of 9 species belonging to 7 different families were identified. Two schools were classified to family-level. The most common species recorded by the ROV was black durgon (*Melichtys niger*) followed by creole wrasse (*Clepticus parrae*). Carangidae was the only family with at least one species recorded in each dive.

Carangids, dog snapper (*Lutjanus jocu*) and bermuda chub (*Kyphosus sectatrix*) were the species with the highest visible packing density (qualitatively determined). Carangids were observed mostly in the water column separated from the seafloor. Balistidae–black durgon (*Melichtys niger*) and ocean trigger (*Canthidermis sufflamen*)–aggregated into small shoals with low-moderate density with black durgon presenting a less coordinated swimming behaviour than the ocean trigger. Creole wrasse (*Clepticus parrae*) showed a specific behaviour pattern with schools mostly distributed in the water column forming big swarms that extended for long distances. A similar behaviour was also observed in damselfish. The aggregation behaviour of the fish species observed in the ROV videos recorded during this project is consistent with the behaviour observed in other ROV obser-

Table 4
Mean, minimum and maximum values of the main clustering features separated by cluster (units of measure: sv_max 38, MVBS38, MVBS120, MVBS200, freq_resp120, freq_resp_200 = db re 1 m^{-1}; length, thick, dist, school_depth = m; area = m^2; rectangul, elong, fractal, skew = unitless). For the name of the variables refer to Table 1.

		Energetic							*Geometric*						*Bathymetric*	
Cluster		**sv_max 38**	**MVBS 38**	**MVBS 120**	**MVBS 200**	**skew**	**freq_resp 120**	**freq_resp 200**	**rectangul**	**length**	**elong**	**area**	**thick**	**fractal**	**school depth**	**dist**
"high energy"	mean	−32.79	−43.13	−45.10	−45.42	3.52	0.97	0.95	2.39	26.03	6.56	53.60	4.63	1.68	34.96	3.66
	min	−38.32	−50.76	−49.95	−54.20	1.30	0.81	0.65	1.23	0.74	0.24	1.76	0.84	0.28	16.56	0.30
	max	−23.96	−28.73	−37.75	−36.39	14.48	1.21	1.28	17.61	264.98	66.91	700.69	26.16	3.18	82.13	16.88
	IQR	3.07	2.74	2.88	2.93	1.75	0.05	0.06	1.06	22.25	4.96	58.77	3.80	0.35	9.51	3.69
"moderate energy"	mean	−38.08	−47.78	−48.52	−49.23	2.95	0.97	0.96	2.43	25.11	9.34	32.75	3.21	1.86	37.10	2.48
	min	−44.79	−54.13	−55.83	−57.05	0.97	0.76	0.60	1.21	0.91	0.65	0.42	0.84	0.21	8.76	0.05
	max	−33.67	−38.76	−36.81	−43.64	7.77	1.30	1.13	6.69	192.14	69.96	238.58	12.84	11.29	100.32	26.28
	IQR	2.68	2.14	2.27	2.17	1.50	0.05	0.07	1.16	25.47	8.56	33.41	2.48	0.34	7.97	2.87
"low energy"	mean	−42.28	−51.18	−51.94	−51.33	2.38	0.97	0.99	2.53	32.00	14.66	29.85	2.38	1.97	40.66	1.58
	min	−47.26	−55.19	−55.58	−57.64	0.67	0.83	0.69	1.27	1.25	0.62	1.17	0.84	1.15	8.33	0.11
	max	−37.52	−42.86	−47.20	−44.62	7.09	1.32	1.47	6.80	148.70	88.35	265.74	9.68	12.27	72.73	28.46
	IQR	2.26	1.90	1.95	1.83	1.06	0.05	0.07	1.25	33.91	14.30	28.88	1.67	0.29	5.39	1.20
"very low energy"	mean	−45.97	−53.82	−54.58	−53.63	1.77	0.96	1.00	2.50	27.51	15.73	20.35	1.72	2.16	43.03	1.87
	min	−54.52	−60.94	−60.44	−60.98	−0.02	0.68	0.59	1.29	1.70	0.77	1.13	0.84	1.36	8.02	0.12
	max	−40.84	−46.49	−46.66	−49.08	6.66	1.37	1.48	8.63	217.90	76.72	187.87	8.40	7.13	97.42	38.84
	IQR	2.54	1.63	1.85	2.11	0.88	0.07	0.10	0.96	24.30	11.61	16.27	0.94	0.38	5.24	0.85
"serpentine"	mean	−39.31	−52.07	−52.93	−51.97	4.12	0.96	1.01	6.60	324.35	55.01	363.98	6.61	1.90	47.59	1.88
	min	−46.29	−60.70	−59.77	−59.62	1.67	0.78	0.83	2.29	50.31	3.24	20.08	1.29	1.38	27.33	0.32
	max	−30.81	−47.42	−47.51	−48.34	16.58	1.17	1.17	24.64	1417.15	237.02	3915.75	29.68	2.57	97.18	9.43
	IQR	4.98	2.66	2.58	2.15	1.75	0.03	0.04	3.26	221.39	41.15	292.20	3.85	0.15	6.93	1.10

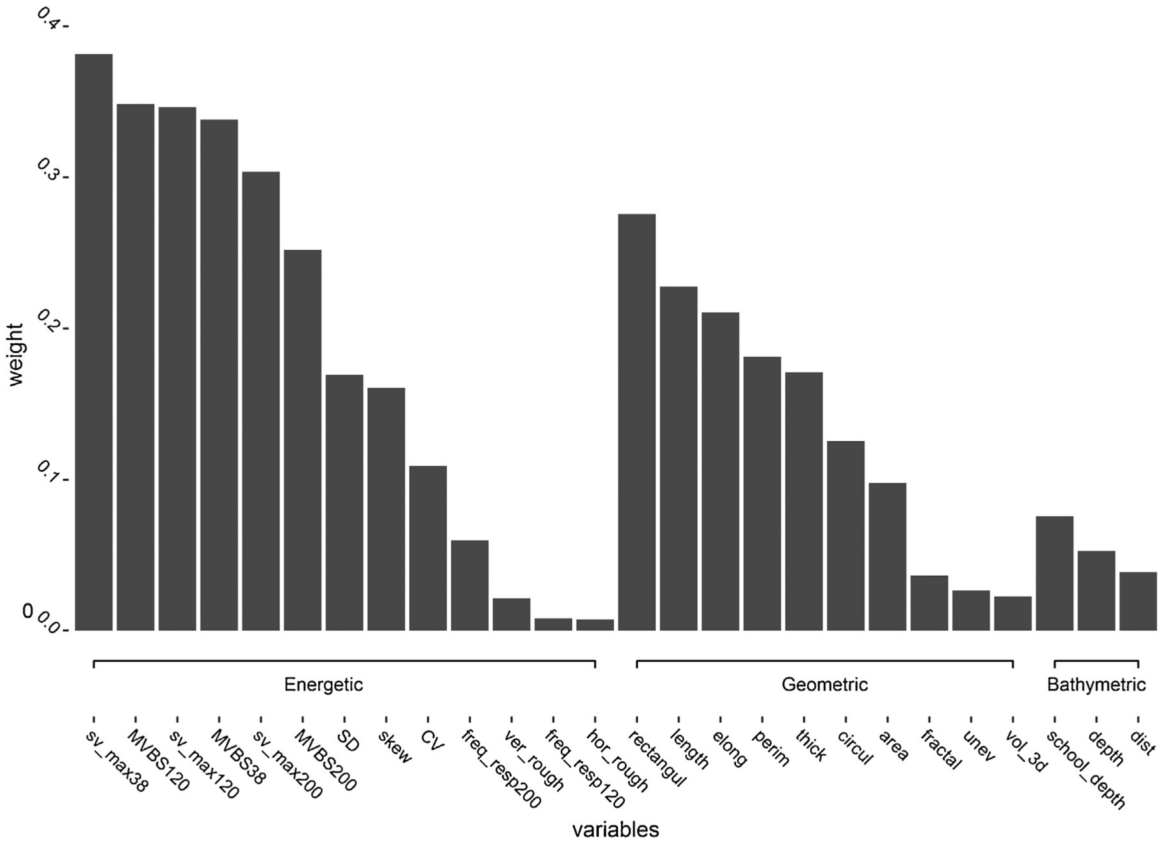

Fig. 3. Weights of the clustering features estimated by the RSKM algorithm.

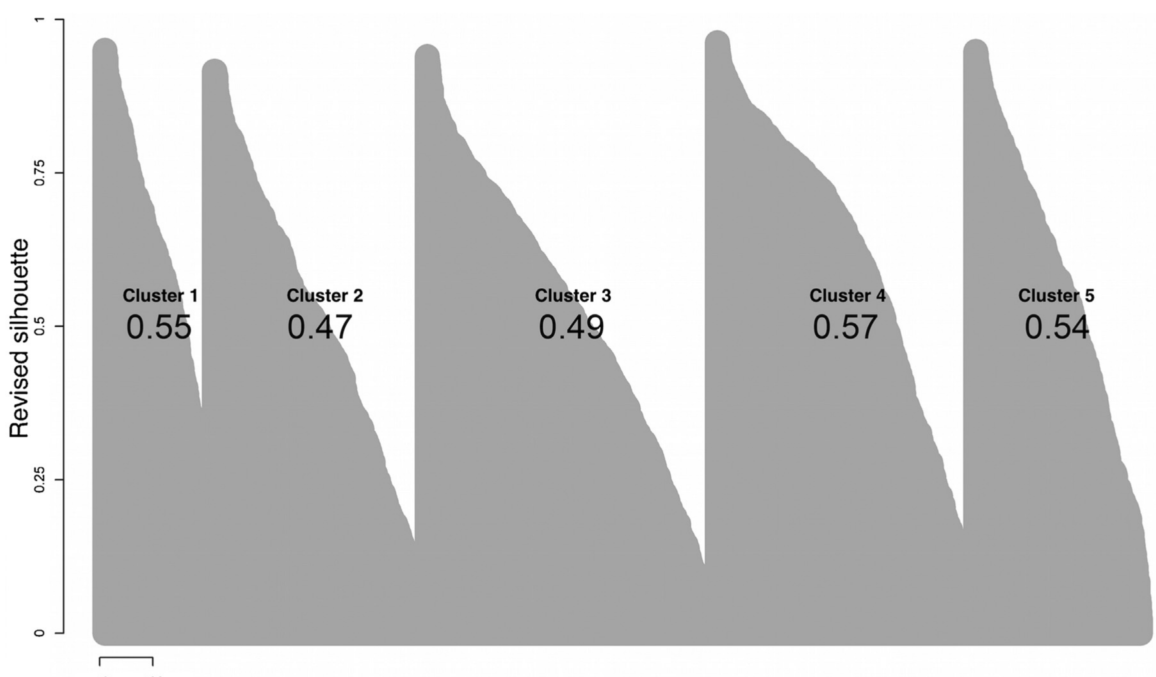

Fig. 4. Revised silhouette plot. Each histogram (silhouette) represents a cluster (composed of a horizontal line representing each observation), and their width represents the strength of each observation's membership in a cluster. The values on each silhouette indicate the average revised silhouette value for each cluster.

vations, not directly paired with the acoustics surveys presented here, but those that have been carried out in the same study area.

The number of schools detected in the echograms in the vicinity of the ROV dives separated by clusters are reported in Table 6. The average silhouette values were used as an index of dissimilarity of the school from the cluster centre. The most abundant

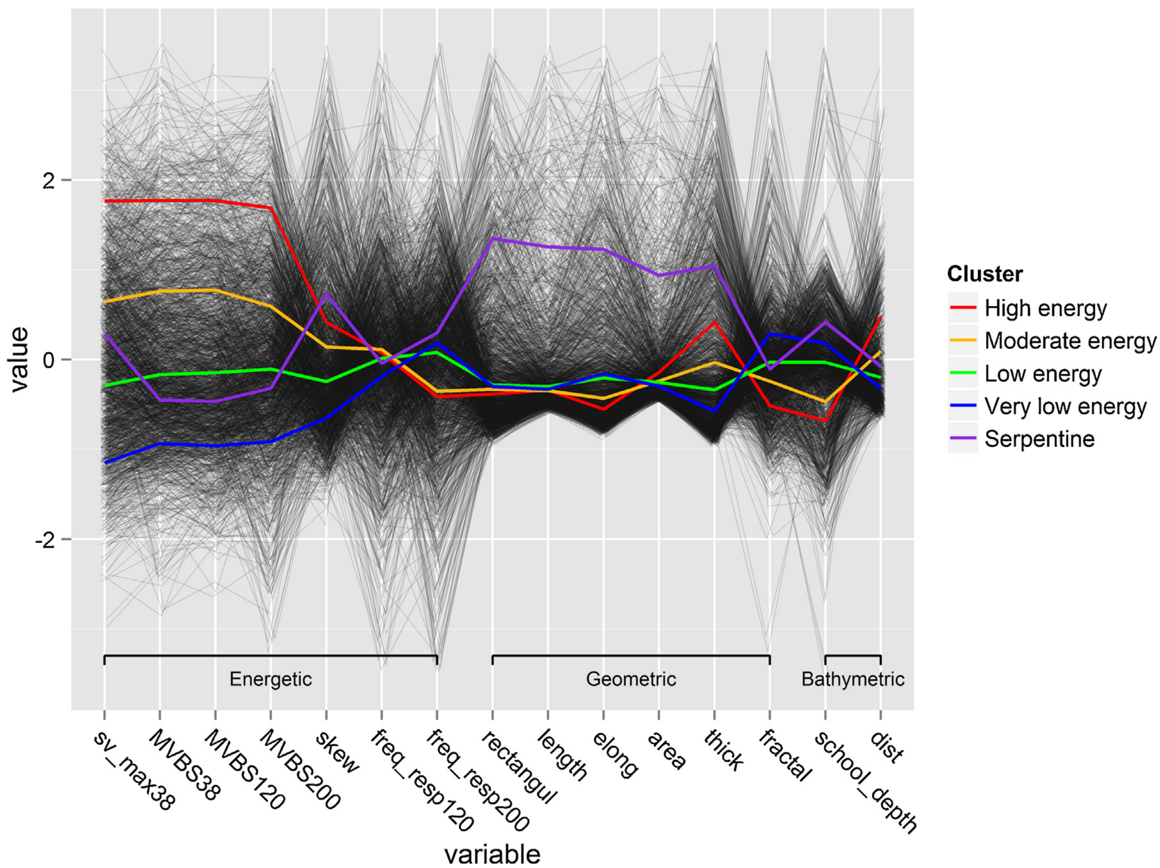

Fig. 5. Parallel coordinate plot of the main variables describing the characteristics of the clusters. The variables are on the x axis and the scaled values of the variables are on the y axis. The black lines represent the features vector of each fish school and the colored lines are the average feature vector for each cluster.

cluster identified was the "moderate energy" followed by the "high energy", "low energy", very low energy" and "serpentine". ROV stations 1, 2 and 6 were dominated by "high energy" and "moderate energy" clusters with an overall good value of silhouette. Dive 7 was characterized by the presence of all clusters but with a prevalence of "low energy" and "very low energy". Schools belonging to clusters with intermediate characteristics were detected in dive 5. The ribbon-shaped schools ("serpentine") were prevalent in dive 4. The possible association between clusters, species and school behaviour is summarized in Table 7.

4. Discussion

This study is the first work that describes the acoustic patterns and diversity of fish aggregations in a coral reef system, building the basis for a more extensive use of acoustic techniques in diverse and complex ecosystem. The approach used was able to identify consistent patterns in the acoustic backscatter and shape of schools ascribable to the different morphologies of individuals and behaviours of groups and schools of coral reef fishes. The stability of the clustering results, highlighted by the outcome of the Clest algorithm and the bootstrapping-based validation indicates that the parameters used were informative and the automatic feature selection performed by the Robuste Sparse K-Means (RSKM) improved the overall results of the clustering. This also allowed for an objective and repeatable approach with a relatively low level decision-making by the operator.

Most of the prior research conducted on target classification are based on supervised approach and rely on training datasets derived by ground truthing (Horne, 2000). Many of these efforts have been done in high latitude areas where the fish communities studied are comprised of relatively small number of pelagic species allowing the collection of effective groundtruth data (Cabreira et al., 2009; Fernandes, 2009; Korneliussen et al., 2009).

The same approach cannot be followed in coral reef ecosystems where the high fish species diversity and habitat complexity limit non-selective methods to validate the acoustic data. For this reason, instead of attempting to classify the fish encountered to species or similar taxonomic level, we used an unsupervised approach, letting the data explain whether the acoustic diversity could be used as an indicator of the fish community assemblage in the area. The semi-automated approach allows for rapid analysis of fishery acoustic survey data that could guide visual surveys to groundtruth and validate species composition.

The acoustic metrics considered in this work have been extensively used in remote species identification studies in other marine and freshwater ecosystems. Morphometric features derived from image analysis techniques and single frequency energetic metrics (Cabreira et al., 2009; Haralabous and Georgakarakos, 1996; Lawson et al., 2001; Massé et al., 1996; Weill et al., 1993) have been used combined with different statistical approaches (e.g. discriminant function analysis, principal component analysis, artificial neural network) to classify acoustic targets at different taxonomic levels. The recent advances of multifrequency technology and the development of sophisticated software for the analysis of these data allowed for increased discriminatory power of this approach including a larger number of metrics related to the acoustic "signature" of the targets and the use of semi-automated post processing

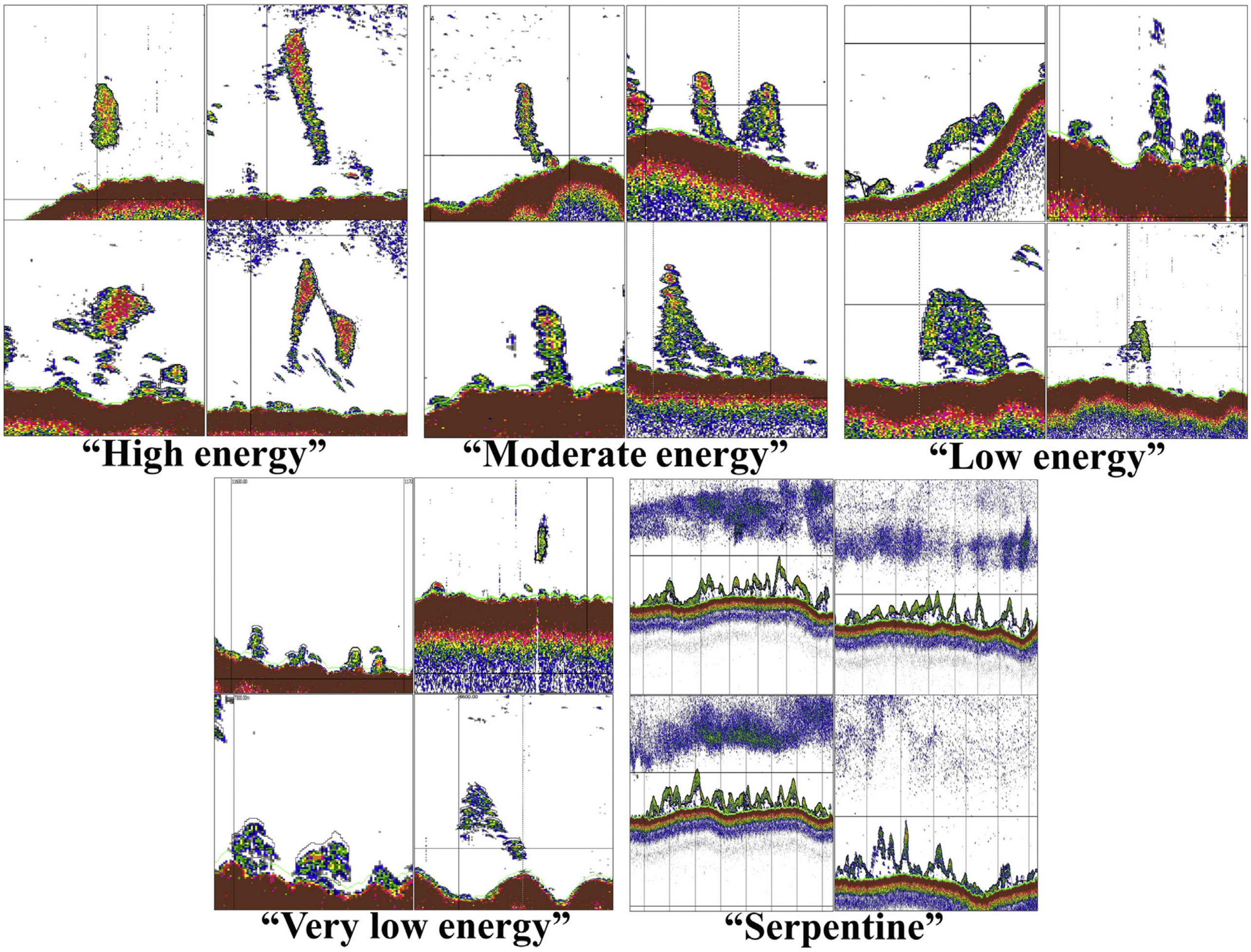

Fig. 6. Examples of echograms of the schools separated into clusters. Refer to text for description of each cluster.

techniques (Fernandes, 2009; Kloser et al., 2002; Korneliussen and Ona, 2003).

The energetic features were identified as the most important variables for clustering indicating that fish size and/or packing density of the schools were the main drivers of the classification. The geometric features were less important probably because the school shape can vary largely between and within species in response to internal and external stimuli such as ontogeny, feeding and predation (Fréon et al., 1992). Furthermore, our surveys using splitbeam echosounders with relatively narrow beam apertures sample a narrow slice within the school and may not always describe the "average" shape when sampled near the edge of the school. However, the geometric features, in particular the rectangularity, were able to effectively identify a particular cluster ("serpentine") that was composed of schools with peculiar shape characteristics. Rectangularity has also been used in other target classification studies and was the most successful feature for discriminating anchovy, sardine and horse mackerel aggregations in the Mediterranean Sea (Haralabous and Georgakarakos, 1996). Frequency response did not have much influence on the classification. This is a reasonable result considering that all the species sampled have a gas-filled swimmbladder and they should have a similar acoustic response. Moreover possible frequency response patterns could have been masked due to the high species diversity in the area.

The structure of an aggregation can be described based on its shape and internal density. These two factors can be related to the intrinsic characteristics of the species but also can vary in response to a large number of external stimuli (Fréon et al., 1992). Fish species in coral reef ecosystems can exhibit broad behavioural patterns that include periodic formation of aggregations, shoals and schools for the purpose of migration, spawning, feeding and avoiding predators. Feeding is one of the main drivers affecting schooling behaviour. Planktivorous species can form large and loose aggregations while they are feeding and aggregate into denser schools in response to predators attacks (Pitcher, 1986). Large piscivorous fish can have an individual swimming behaviour or can form small groups for foraging. A large number of piscivorous species can also aggregate during the spawning season forming large fish spawning aggregations (FSAs). Serranidae and Lutjanidae (groupers and snappers) are families with a large number of species that exhibit this specific behaviour (Claydon, 2004). The majorities of these species are large-sized and have a high commercial value. The aggregations can be very dense and are usually distributed in the pelagic environment. FSAs can also be predicted in time and space as these species select habitat with particular physical and environmental features (Sadovy de Mitcheson and Colin, 2012). Other predator species such as Carangids exhibit a schooling behaviour for most of their life cycle. They are usually very mobile species and can swim fast covering long distances across the reef looking for preys. Invertebrate feeders such as snappers and grunts

Table 5
Species observed in the ROV dives and their schooling characteristics. Number of schools, packing density and schools size are summarized in each cell. Number of schools: *single* (1 school), *few* (2–5 schools), *several* (>5 schools); packing density: *loose* (fish loosely aggregated), *moderate* (moderately packed schools), *tight* (high density schools); school size: *small* (1–25 individuals), *medium* (25–250 individuals), *large* (>500 individuals).

		ROV dives						
Scientific name	Common name	*1*	*2*	*3*	*4*	*5*	*6*	*7*
Carangidae								
Caranx ruber	Bar jack	Several moderate–tight, small-medium-large	X	Few, tight, small-medium	X	X	Few, moderate small	X
Caranx latus	Horse eye jack	Few, moderate-tight, large	X	X	X	X	Several, tight, small	Few, moderate, small
Selar crumenophtalmus	Bigeye scad			X	Single, tight, medium	X	X	X
Unidentified carangid	–		Single, tight, medium	X	X	Single, tight, large	X	X
Labridae								
Clepticus parrae	Creole wrasse	Single, loose, small	Several, moderate, small-medium-large	X	X	Single, loose, medium–large	X	Few, moderate, medium–large
Balistidae								
Canthidermis sufflamen	Ocean triggerfish	X	X	X	X	X	Several, loose-moderate, small–medium	Single, moderate, small
Melichtys niger	Black durgon	X	Few, loose, small	Several, loose, small	X	Several, loose, small	Few, loose, small	Few, loose, small
Lutjanidae								
Lutjanus jocu	Dog snapper	X	X	X	X	X	Single, tight, small	X
Ephippidae								
Chaetodipterus faber	Spadefish	Single, moderate, small	X	X	X	X	X	X
Kyphosidae								
Kyphosus sectatrix	Bermuda chub	X	X	X	X	X	Few, tight, medium	Single, moderate, small
Pomacentridae								
Unidentified damselfish	–	X	X	X	Single, loose, medium	X	X	X

Table 6
Number of schools acoustically detected in the proximity of the ROV dives and associated to their corresponding cluster. The numbers in brackets are the average silhouette values of the schools.

ROV	Clusters				
	High energy	*Moderate energy*	*Low energy*	*Very low energy*	*Serpentine*
1	6 (0.49)	9 (0.54)	1 (0.54)	–	–
2	3 (0.41)	5 (0.58)	4 (0.57)	–	1 (0.86)
3	4 (0.56)	4 (0.16)	1 (0.08)	–	–
4	–	1 (0.18)	–	–	2 (0.29)
5	–	3(0.46)	2 (0.4)	1 (0.16)	–
6	5 (0.45)	1 (0.03)	–	–	–
7	2 (0.2)	2 (0.46)	4 (0.67)	6 (0.53)	1 (0.20)

can stay around the reef during the day individually or in small groups and aggregate during the night to perform feeding migrations toward more suitable areas (Deloach, 1999; McGinley, 2014; Sale, 1991).

Basic knowledge of the behaviour of fish assemblages in Caribbean coral reefs and the outcomes of the few ROV dives helped to identify the possible association of the species and the clusters obtained by the RSKM (Table 7). Based on this information, Carangids could belong to the "high energy" and the "moderate energy" clusters. Jacks (Carangids) are widely distributed in tropical reefs including the US Caribbean. They are medium to large size predators with strong aggregation behaviour and can form large schools with high packing density. Several Carangid species (bar jacks, horse eye jacks and bigeye scad) were observed in the ROV videos showing characteristics (e.g. tight schools and pelagic distribution) that conform to the visible patterns associated with the "high energy" and the "moderate energy" clusters. Moreover, there was a good spatial correspondence between the schools detected in the acoustic transects and the respective ROV dives. In particular, these species were always observed in the ROV videos when the "high energy" and the "moderate energy" cluster were detected in the echograms. Other species that were observed in the ROV videos that have characteristics ascribable to these two clusters are triggerfish (*Canthidermis sufflamis*), spadefish (*Chaetodipterus faber)* and Bermuda chub (*Kiphosus sectatrix*).

The patterns identified in the schools grouped in the "serpentine" cluster suggest a possible association with small sized planktivorous fish including creole wrasse (*Clepticus parrae*), damselfish (*Stegastes* spp.) or chromis (*Chromis* spp.). These species have a diurnal feeding behaviour and aggregate into large "swarms" in the water column as a defensive strategy to minimize predation (Sale, 1991). Such behaviour was also observed in several ROV videos over the course of these surveys. Moreover, the "serpentine" cluster was always detected in the same vicinity when the planktivorous species were observed in the ROV videos. The "low energy" cluster presented similar energetic characteristics compared to the "serpentine" cluster and considering that the planktivorous species can also form smaller aggregations it

Table 7
Association of the acoustic clusters with the reef fish species and behavior observed in the ROV videos.

Cluster	Acoustic features	Species	Behavior
High energy	- high backscattering - high thickness - large size schools	Large carangids: *Caranx ruber, Caranx latus* Spadefish: *Chaetodipterus faber*	Moderate to highly packed schools Organized and coordinated schools
Moderate energy	- high/moderate backscattering - moderate size schools	Small size carangids:*Selar crumenophtalmus* Dog and gray snapper: *Lutjianus jocu, L. griseus* Bermuda chub: *Kyphosus sectatrix* Triggerfish: *Canthidermis sufflamis*	Moderate to highly packed schools with smaller body size Organized and coordinated schools
Low energy	- moderate/low backscattering - moderate size schools	Black durgon *Melichtys niger* Creole wrasse: *Clepticus parrae* Damselfish:	Moderate/low packing density Shoaling behavior
Very low energy	- low backscattering - small schools	Small mixed species	Low packing density Shoaling behavior
Serpentine	- moderate/low backscattering - highly elongated - large size schools	Creole wrasse*: Clepticus parrae* Damselfish Small planktivorous	Large and elongated schools Organized and coordinated movements

is reasonable to associate them with the "low energy" cluster as well where they might form smaller groups. The "very low energy" cluster could finally be linked with a mix of small to medium sized species that loosely aggregate in small schools. Based on the species-clusters association described before, we can say that the "high energy" and the "moderate energy" may include mainly large bodied predator species and includes species with commercial importance. In contrast, the remaining clusters may include small-bodied species that are not typically harvested commercially but still have important ecological roles in the system.

An important step of our approach was the selection "a priori" of the number of clusters. The use of a prediction-based resampling method such as the Clest algorithm allowed us to select the most reproducible and stable results which are the requirements to build a stable classifier in order to classify new datasets. Moreover, the high stability of the results was confirmed by the outcome of the bootstrapping-validation.

The results obtained in this work showed a certain level of variability in terms of variance within clusters. This unexplained variability could be linked to the high diversity of the species associated with each cluster in terms of taxonomy, morphology and behaviour. Future studies should address this aspect, taking into account other factors that could affect species variability.

One of the aspects that was not considered in this work is species associations with habitat type. Many coral reef species are known to be largely related to the characteristics of the seafloor (Pittman and Brown, 2011). Several studies that use habitat type metrics to predict the distribution of coral reef fish have been conducted recently confirming the high importance of the habitat complexity derived from seafloor topography (Costa et al., 2014; Pittman and Brown, 2011). The integration of habitat-related metrics may also increase the ability to separate species detected during acoustic surveys.

The reliability of the association of the species with the clusters was limited by the low separation between the clusters shown by the silhouette index. This could be related to the intrinsic nature of the data we wanted to classify which is comprised of a potentially large number of species. Because of this fact, it is unlikely to obtain well separated clusters using acoustic school descriptors. Since the RSKM is a hard clustering method we could not obtain a probability of assignment associated to each cluster to evaluate the level of overlapping between the clusters. However, the use of the silhouette index can be a good measure of clustering uncertainty by being able to identify the schools that may be outliers in the clusters.

This method could be potentially used for the study and the monitoring of FSAs. Spawning aggregations have been extensively studied in several coral reef areas (Sadovy de Mitcheson and Colin, 2012) and an attempt to use acoustic methods to detect FSAs was made by Taylor et al. (2006). While we did not observe large groups of snapper or grouper during our ROV surveys, we would predict that our classes "high energy" and "moderate energy" would have similar features to species that form FSAs. First, the large size of the schools and the strong acoustic response observed in these clusters could be an indication of species that aggregate with high packing density. Large size species can also generate strong backscatter. Other information, such as habitat characteristics and location could give more strength to this statement.

A primary advantage of fishery acoustic surveys of marine ecosystems is the ability to rapidly survey large areas at fine spatial and temporal resolution (Trenkel et al., 2011). Until this study, it was only possible to characterize distributions of reef fish from acoustic surveys by broad size classes or taxa-independent metrics like density or biomass (Costa et al., 2014). The ability to discriminate large-bodied predators and other aggregations and schools of reef species is an important step forward in improving our interpretation of maps of reef-fish densities and biomass surveyed using fishery acoustics. In the context of ecosystem management, new maps can now be generated that show distribution and biomass of types or classes of reef-fish schools, including separating schools into those likely made up of large bodied predators possibly including commercially important species. These new maps can be used to guide focused visual surveys and inform marine ecosystem management and ocean planning objectives by identifying hotspots of fish schools and aggregations, now with additional metrics describing their shapes and characteristics in greater detail. The use of acoustic methods in these areas also would allow the estimation of acoustic-based ecosystem indicators potentially providing useful information for an ecosystem-based management of fisheries. Trenkel et al. (2011) have recently pointed out the great potential that acoustics have in providing such information. Specifically, the classes can be considered as surrogates for species or trophic levels giving a good indication of diversity and the possible interactions between species in the study area. Moreover, the ability to discriminate commercially important species from non-commercial species can help to evaluate the effects of fishing activities in the area considering that the proportion of these two components could change as a result of different level of exploitation (Rochet and Trenkel, 2003).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2016.03.027.

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