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Sampling variance of species identification in fisheries-acoustic surveys based on automated procedures associating acoustic images and trawl hauls

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During the acoustic surveys of fish stocks, a small number of echo traces are identified to species by fishing. During data analysis, the process of echogram scrutiny leads to allocating echo-trace backscattered energies to species. While the precision of survey estimates is generally based on the spatial variation in the energy, no variance term accounts for species identification and energy allocation. In this paper, the sampling variance of species identification is developed and automated procedures are used allowing energy allocation to be carried out by a non-expert. The procedures are based on the fact that at the sampling stage trawl hauls are linked with particular acoustic images. The procedures have two steps: the classification step corresponds to species identification and the aggregation step to energy allocation. Classification is performed on the identified images and results in defining groups of images and estimating in each the sampling variability of the species identification. Aggregation is performed on non-identified images and results in post-stratifying the data. The estimation (map, abundance and variance per species) is then derived automatically and is conditioned by the post-stratification. Two approaches are followed, one based on the echo-trace characteristics making full use of the echogram (acoustic-image classification) and the other on the spatial continuity of the species composition between trawl hauls (trawl-haul classification). These methods are described and compared. The species-identification variance term is also compared to the spatial variance.

Keywords: abundance, acoustics, image classification, school echo traces, survey design, variance.

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Introduction

Acoustic-survey estimates of single fish stocks are based on the ability to allocate backscattered energy of echo traces to species (MacLennan and Simmonds, 1992; Diner and Marchand, 1995). Expert scrutiny of the echogram along with targeted midwater-trawl hauls are traditionally employed to link individual echo traces to species. Image-analysis procedures applied to digitally recorded echograms permit the automated analysis of echo-trace characteristics (Reid and Simmonds, 1993; Weill *et al.*, 1993; ICES, 2000) and have the potential to improve objectivity in the echogram-scrutiny process (Massé and Rouxel, 1991). Automated expert methods were developed to identify individual schools to species based on school characteristics. They amounted to training an algorithm on a set of identified, single-species schools. Then the algorithm was applied to non-identified schools (Rose and Leggett, 1988; Lu and Lee, 1995; Haralabous and Georgakarakos, 1996; Simmonds *et al.*, 1996). Success in this approach depended on target-strength differences between co-occurring species, the species-diagnostic power of school descriptors (Scalabrin *et al.*, 1996) and the use of ancillary variables together with school descriptors (Richards *et al.*, 1991; Lawson *et al.*, 2001).

In mixed-species ecosystems where school descriptors have little species-diagnostic power and where small schools are numerous, as in the Bay of Biscay, species identification depends heavily on identification via trawl hauls. Trawl catches do not allow for the identification of single schools but an ensemble of schools over several nautical miles, resulting in identifying groups of schools to species assemblages. The underlying hypothesis is that groups of echo traces show some consistency in space and time and are potentially diagnostic of species assemblages. The feasibility of the approach is justified by the existence of acoustic populations (Gerlotto, 1993), i.e. the concept that the acoustic characteristics of echo traces show a spatial pattern at a regional scale that is consistent over the years (Gerlotto, 1993, in Venezuela; Scalabrin and Massé, 1993; Massé, 1996, in Biscay; Petitgas and Lévénez, 1996, in Senegal). In linking this idea to that of a school cluster, a hotspot where schools aggregate with different characteristics in different zones, Hammond and Swartzman (2001) proposed a Bayesian framework to estimate the species proportions in hotspots based on previous knowledge of trawl catches at close geographical and seasonal locations with similar environmental features and echo traces. The present paper does not associate trawl hauls and school clusters in the same way. The approach in this case is based on the association at the sampling stage between a trawl haul and the acoustic image that triggered the decision to trawl. Estimates are made of the sampling variance of species identification for a given survey with no more information than that in the survey.

The fact that identification relies on trawl hauls implies consideration of survey design for the identification procedure and, in particular, where to locate the hauls (e.g. Massé and Retière, 1995). During the French acoustic surveys in Biscay, the trawl stations are conditioned on the positions of particular acoustic images that are considered to be representative of communities of echo traces during the survey. Two sets of acoustic images need to be distinguished: first, images associated with trawl hauls (i.e. identified images) and second, non-identified images. Different methods are available to associate trawl-haul catches with non-identified images. In this study, a method based on echo traces is applied and compared to more standard methods. The data used for this purpose came from the spring 2000 acoustic survey of IFREMER over the French shelf of Biscay, performed with the RV "Thalassa". Though the survey targeted anchovy and sardine, all the species found in the survey were considered because they were part of the process of species identification.

Materials and methods

Acoustic sampling

Cross-shelf transect lines from coast (20-m depth) to shelf break (250-m depth) were sailed during daytime at 10 kn (Figure 1). Transects were parallel and regularly spaced with an inter-transect distance of 12 nautical miles (nmi). The acoustic equipment was a hull-mounted SIMRAD EK500 38 kHz echosounder with a nominal beam angle of 7.5°. The pulse duration was 1 ms and the ping repetition rate was 1 s^{-1}. The backscattered-acoustic signal was digitized providing acoustic samples of 10 cm in height and 5 m in length that formed the echogram. Acoustic samples with a volume backscatter higher than −70 dB were saved.

Midwater trawl hauls

The spacing of the trawl stations was decided by the positions of particular acoustic images (Figure 1). Schools were vertically organized in a layer in the altitude range of 0–40 m from the bottom. The school layer was identified using one trawl haul with a 25-m vertical opening positioned at the appropriate depth. The average trawl-haul duration was 45 min at 4 kn, representing a trawled distance of 3 nmi. The variogram of the number of schools per nmi (Figure 2) showed a small-range structure between 3 and 5 nmi compatible with that already seen on previous surveys (Petitgas, 2000). The trawl hauls were, therefore, seen as sampling clusters of schools that were vertically organized in a layer close to bottom.

Echo-trace descriptors

The survey was replayed for echo-integration by school using a sample threshold of −60 dB (Petitgas *et al.*, 1998). School objects were identified and extracted from the echogram using MOVIES software (Weill *et al.*, 1993). Thresholds were defined for minimum school object length (one ping: 5 m), height (two samples: 20 cm) and average density (−55 dB), which permitted their automated extraction. Extracted school objects with a length less than two pings at depth were rejected as being too small to be adequately characterized (Diner, 2001; ICES, 2000). The total-backscattered energy of the automatically extracted schools amounted to a value similar to that of the schools retained by the expert when scrutinizing the echogram. Finally, 26 571 schools were accepted as fish schools over a survey length of 1563 nmi containing 78 empty nautical miles.

Acoustic images and their characterization

The continuous recorded echogram was divided into 3 nmi bins, a spatial unit compatible with the average size of school clusters and the duration of trawl hauls. The binning resulted in 495 non-zero acoustic images. Each image was described by a line-data set of school parameters (the characterizing vector). Parameters belonged to four categories (ICES, 2000; Reid *et al.*, 2000): school position, school morphology, school density and the occupation of space by the schools. Each parameter was partitioned between three classes, delimited by the quantiles 0.33 and 0.66 (Table 1). For each image and parameter class, the schools were counted and expressed as a frequency relative to the number of schools in the image. The characterizing vector had 32 elements. The first 31 elements were the frequencies in the parameter classes. The last element was the number of schools in the image, accounting for the difference in school numbers between images.

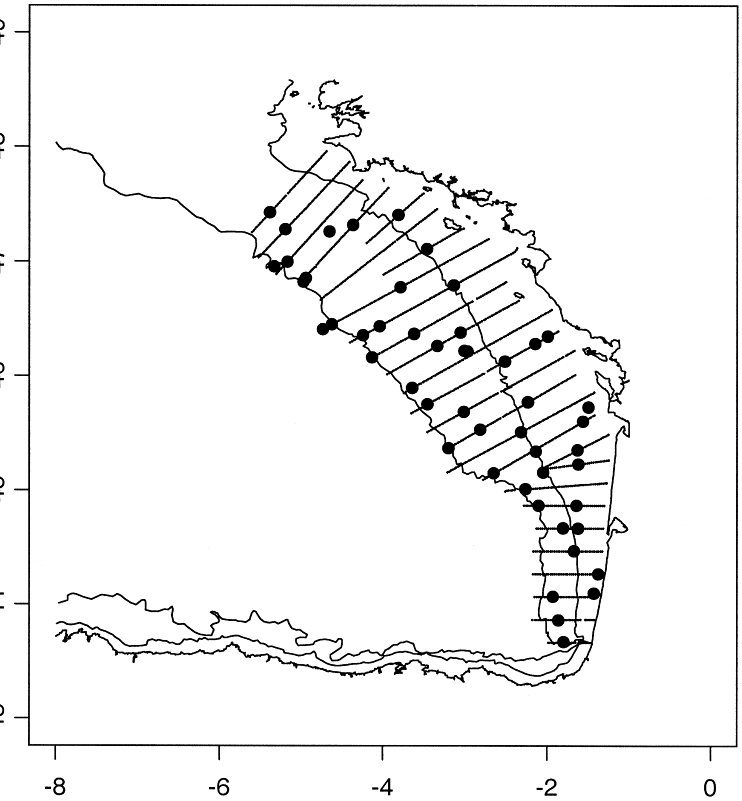

Figure 1. Survey design of the French fisheries-acoustic survey performed in Biscay in spring 2000 by IFREMER with RV "Thalassa" showing the acoustic transects, the location of the midwater identification trawl hauls and the 100 and 200 m isobaths. (The figures on the vertical axis denote the latitude in degrees North and those on the horizontal axis the longitude in degrees west.)

The spatial structure of the acoustic images

The spatial structure in the acoustic images was estimated by a multivariate function analogous to a variogram, called D^2 variogram. The variogram was defined (Matheron, 1971) as the spatial average of the squared differences between point values Z(x) and Z(x + h) separated by vector distance h: $\gamma(h) = 0.5E([Z(x) - Z(x+h)]^2)$. Here, instead of one value Z(x) at point x, we had a vector $[V_1(x), \ldots, V_{32}(x)]$ characterizing the acoustic image centred at x. The D^2 variogram was the spatial average of the multivariate Euclidean distance in parameter space, between pairs of acoustic images, as a function of the vector distance h in geographical space separating the images:

$$D^2_\gamma(h) = 0.5E\left(\sum_k [V_k(x) - V_k(x+h)]^2\right).$$

Species echo-integration factor X_{ei}

This was the factor multiplying the total-backscattered energy E_{tot} ($mV^2 m^2$) in the acoustic image to estimate the biomass B_e ($10^3 kg\,nmi^{-2}$) due to species e: $B_e = X_e E_{tot}$. The echo-integration factor for species e and trawl haul i, X_{ei}, was derived from a published target strength–length relationship (Diner and Marchand, 1995) and a length-to-weight relationship determined from the trawl catch. When the fish length histogram was multi-modal, echo-integration factors were first calculated for each length category, then summed to give one factor per species.

Methods for associating trawl hauls and acoustic images

The "Nearest Haul" method is the simplest one: any non-identified image was associated with the nearest trawl haul, irrespective of the echo traces. The "Expert" method (Massé, 1988) represented the current practice in analysing acoustic surveys in Biscay. Trawl hauls were grouped according to their species composition and geographical position, thus post-stratifying the surveyed area and using average biological parameters per species per strata. The definition of strata limits along transects and the identification of echo traces to species were made via expert scrutiny of the echogram. Neither of the methods provided a variance term for species identification. The derivation of such a term relied on the ability to post-stratify the data and estimate within-strata variability of each species echo-integration factor. Two post-stratification methods were

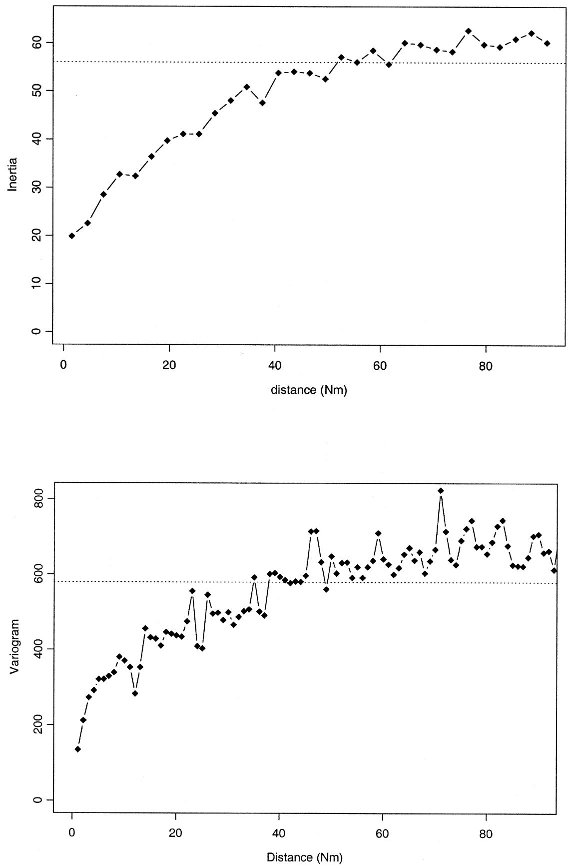

Figure 2. Experimental variograms. Top: D^2 variogram of acoustic images. Dashed line represents the total inertia (sum of all D^2 distances between images). Bottom: variogram of the school number per nmi. Dashed line represents variance of school number.

used, one based on echo-trace characteristics only and the other on species composition only.

Acoustic image classification and species allocation

The method had three steps: the classification of identified images, the estimation of the average echo-integration factor per group per species and the aggregation of non-identified images to the defined groups. An identified image was defined as that closest to a given trawl haul. Identified images (i.e. a training set) were classified according to their characterizing vector, through principal component analysis (PCA) and hierarchical clustering in the principal component space using the Euclidean distance (Lebart *et al.*, 1995). In each group of images, there were several trawl hauls. The average species echo-integration factor for each group of images, $\overline{X}_{eg}$, its variance, $var(\overline{X}_{eg})$ and upper and lower 2.5% confidence limits were estimated by bootstrap re-sampling with the replacement of the trawl catches in each group (Manly, 1997). Non-identified images were then projected in the principal component space as passive individuals and aggregated to the groups of images in the training set. The aggregation method comprised attributing the image to the group, which had the closest centre. Non-identified images too far from any group centre were not attributed to any group; they were considered to be non-identifiable, though this situation did not occur in the survey considered here. The threshold distance retained for the aggregation was the maximum-observed distance between an identified image and its group centre. In the geographical space, the aggregation step resulted in mapping groups of images along the transects.

Table 1. School parameters in the acoustic image characterizing vector with their threshold limits defining classes (Lim.). Altitude is the distance between the bottom of the school and the seabed; bottom depth is that below the school, latitude is that of the school centre (mid-geographical point of school echo trace); length is the maximum horizontal distance between start and end of the school; height is the maximum vertical distance between start and end of the school; fractal dimension is the log of the circularity coefficient ($100 \log (P^2/4\pi A)$ with P the school perimeter (m) and A the school area (m^2)); energy is the integrated-backscattered energy of the school; Rv (index of volume reverberation) is the average for school pixels of the volume-backscattered energy expressed in dB ($10 \log (E_{pixel}/V_{pixel})$ with E the pixel-backscattered energy and V the pixel cross-section); CV of Rv is the coefficient of variation of the pixel Rv values inside the school.

	Minimum	Lim. 1	Lim. 2	Maximum
Altitude (m)	0	2	40	500
Bottom depth (m)	10	60	120	250
Latitude (degrees)	43	45	47	49
Length (m)	0	8	16	110
Height (m)	0	1	2	70
Fract. dim	100	150	171	2400
Energy ($mV^2 m^2$)	0	44	134	700 000
Average Rv ($dB\, m^{-3}$)	−60	−53	−48	−19
CV Rv (%)	0	26	41	300

Trawl-haul classification and species allocation

The methodology was similar to that of acoustic image classification and species allocation (AICASA). First, the trawl hauls were classified on their species composition using the same combination of PCA and clustering as in AICASA. The PCA was applied on the correlation matrix of the species-weight proportions in the catches. Second, the average echo-integration factor per species and its variance were estimated for each group of hauls with the bootstrap procedure as described above. Finally, the non-identified acoustic images were associated with the hauls using the criteria of closest, geographical distance as in the "Nearest Haul" method.

Maps, abundance estimate and variance terms

Mapping was done by combining the geographic distributions of species echo-integration factors from the aggregation step with those of the backscattered energy. The mean abundance estimate was:

$$\overline{B}_e = \sum_g w_g \overline{X}_{eg} \overline{E}_g \tag{1}$$

where, for group g, $\overline{E}_g$ was the average-backscattered energy; $\overline{X}_{eg}$ the average species echo-integration factor and w_g the geographical weight. The design being regular, w_g was estimated by the number of images in group g divided by the total number of images from the survey.

The variance of the mean abundance was estimated as the sum of two independent terms, coming from the variabilities of the backscattered energy and the species echo-integration factor, respectively:

$$\mathrm{var}(\overline{B}_e) = \sum_g w_g^2 \overline{X}_{eg}^2 \mathrm{var}(\overline{E}_g) + \sum_g w_g^2 \overline{E}_g^2 \mathrm{var}(\overline{X}_{eg}) \tag{2}$$

$\mathrm{var}(\overline{E}_g)$ was estimated assuming the backscattered energies were spatially non-correlated within each group. Thus $\mathrm{var}(\overline{E}_g) = \sigma^2(E_g)/n_g$, providing a conservative estimate of variance. Non-correlation between X_e and E was tested visually on scatter plots, and $\mathrm{var}(\overline{X}_{eg})$ was obtained from the bootstrap estimate in each group. Equations (1) and (2) applied to any post-stratification of the data.

Results

Spatial structure of the acoustic images

Variograms were computed for different lag distances and averaged in the various directions. The variogram of school number per nmi displayed two nested structures, the short-range approximating 3 nmi and the long-range, 50 nmi. The D^2 variogram of acoustic images (3 nmi in length) displayed one long-range structure also around 50 nmi (Figure 2). The long-range structure envisaged the concept of an acoustic population, i.e. image groups, while the short-range structure corresponded to that of a school cluster.

Classification of acoustic images identified by trawling

Fifty trawl hauls were made, allowing for the identification of 50 images out of 495. PCA was performed on the correlation matrix of the 50 characterizing vectors. Hierarchical clustering was performed in the principal component space of the first eight axes that explained 85% of total variance. Four groups were retained which displayed a spatial pattern in agreement with the D^2 variogram range: groups 1 and 2 were mainly coastal, south and north of 46°30′N, respectively; group 3 was mainly on the mid-shelf south of 46°30′N and group 4 was mainly at the shelf break both in north and south as well as on the mid-shelf north of 46°30′N.

Species echo-integration factors per group of acoustic images

For each group and each species, the average echo-integration factor $\overline{X}_{eg}$, its variance $\mathrm{var}(\overline{X}_{eg})$ and its lower and upper 2.5% confidence limits were obtained from 400 bootstrap estimates of the trawl catches in each group (Figure 3). Distribution of the estimates was not symmetrical. The species belonged to different image groups and, therefore, formed different school types depending on their location and composition. There was some correspondence between acoustic image groups and species assemblages: group 1 (coastal south) was dominated by anchovy, sprat, mackerel and chub-mackerel, with mackerel showing considerable variability; group 2 (coastal north) by sardine and horse mackerel; group 3 (mid-shelf south) by sardine with all species showing low variability and group 4 (shelf break and mid-shelf north) by sardine, mackerel and horse mackerel with mackerel showing considerable variability. High proportions of a particular non-target species in a few trawl hauls (e.g. mackerel in groups 1 and 4) increased the variance of the estimate for the target species of anchovy and sardine.

Maps, abundance estimates and variances for target species

For anchovy and sardine, maps produced by the different methods showed good general agreement with some local differences (Figures 4 and 5). There were differences in areas with few trawl hauls and where post-stratification differed between methods. All methods produced similar abundance estimates (Table 2). The target strength of anchovy and sardine being approximately $-30\,\mathrm{dB\,kg^{-1}}$, small differences between methods in the partition of energy between species resulted in similar differences in abundance. AICASA and trawl-haul classification (THC) gave similar estimation CVs for sardine but THC gave a lower CV for anchovy. This was because, in the THC method, strata where anchovy was present were homogeneous in species composition. Although CVs for anchovy and sardine were generally in the acceptable range of 10–20%, the species-identification term represented 60–80% of total variance, indicating that this source of error was critical.

Maps, abundance estimates and variances for non-target species

For mackerel, methods "Nearest Haul" and "Expert" were similar, as were methods AICASA and THC. The former pair gave lower estimates of abundance (Table 2). For horse mackerel, the "Nearest Haul" method was in closer agreement with AICASA and THC. Differences between methods depended on energy allocation, trawl performance, target strength and schooling. In allocating backscattered energy to species, the "Nearest Haul" approach restricted the area of influence of the trawl stations, and the "Expert" method probably did so as well. Mackerel had a target

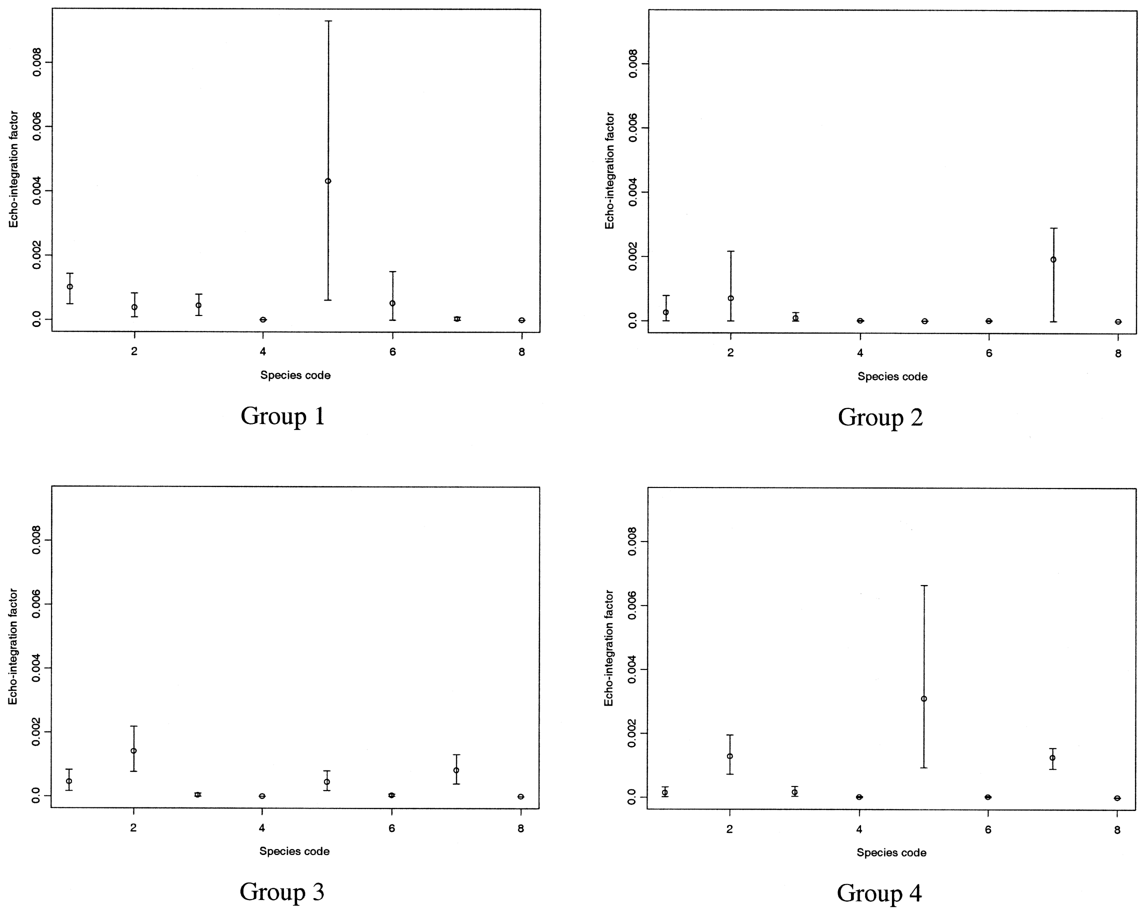

Figure 3. Mean species echo-integration factor X_e ($10^3\,kg\,nmi^{-2}\,mV^{-2}\,m^{-2}$) in each group of identified acoustic images with their upper and lower 2.5% confidence limits (bootstrap step of the AICASA method). Species codes are: (1) anchovy (*Engraulis encrasicolus*); (2) sardine (*Sardina pilchardus*); (3) sprat (*Sprattus sprattus*); (4) blue whiting (*Micromesistius poutassou*); (5) mackerel (*Scomber scombrus*); (6) chub-mackerel (*Scomber japonicus*); (7) horse mackerel (*Trachurus trachurus*); (8) Mediterranean horse mackerel (*Trachurus mediterraneus*).

strength about 15 dB kg^{-1} lower than that of anchovy or sardine; thus 30% difference in the abundance estimate was equivalent to 10% difference in energy allocation. In Biscay, mackerel was not easily identified from echogram scrutiny and its fishing was unsatisfactory, resulting in considerable variability in the trawl catches. For horse mackerel, the situation was different: the "Expert" method suggested that schooling behaviour had changed over 3 years, resulting in possible under-allocation of energy to this species compared with the automatic procedures.

Discussion and conclusions

Factors affecting variability in the estimates

The results of the automated procedures depended on the number and locations of the trawl hauls, the number and variance of the post-strata, trawl catchability and the presence of non-target species. Dependence on the trawl location is expected to be stronger for "Nearest Haul" and THC methods in contrast to AICASA, because the former are based on defining an area of influence around the trawl stations. The definition of post-strata was based on the data structure and, in particular, on the coherence in the spatial pattern. Variability in the trawl performance and the manner of image identification were not separable from the true variability in species composition. Since the true species composition remained unknown, the computed variance reflected sampling variability but not the accuracy of the estimate. The non-target mackerel was unreliably identified by trawling, which increased species-identification variance for the targets, anchovy and sardine, but had less effect on their abundance estimates because anchovy and sardine have a strong target strength.

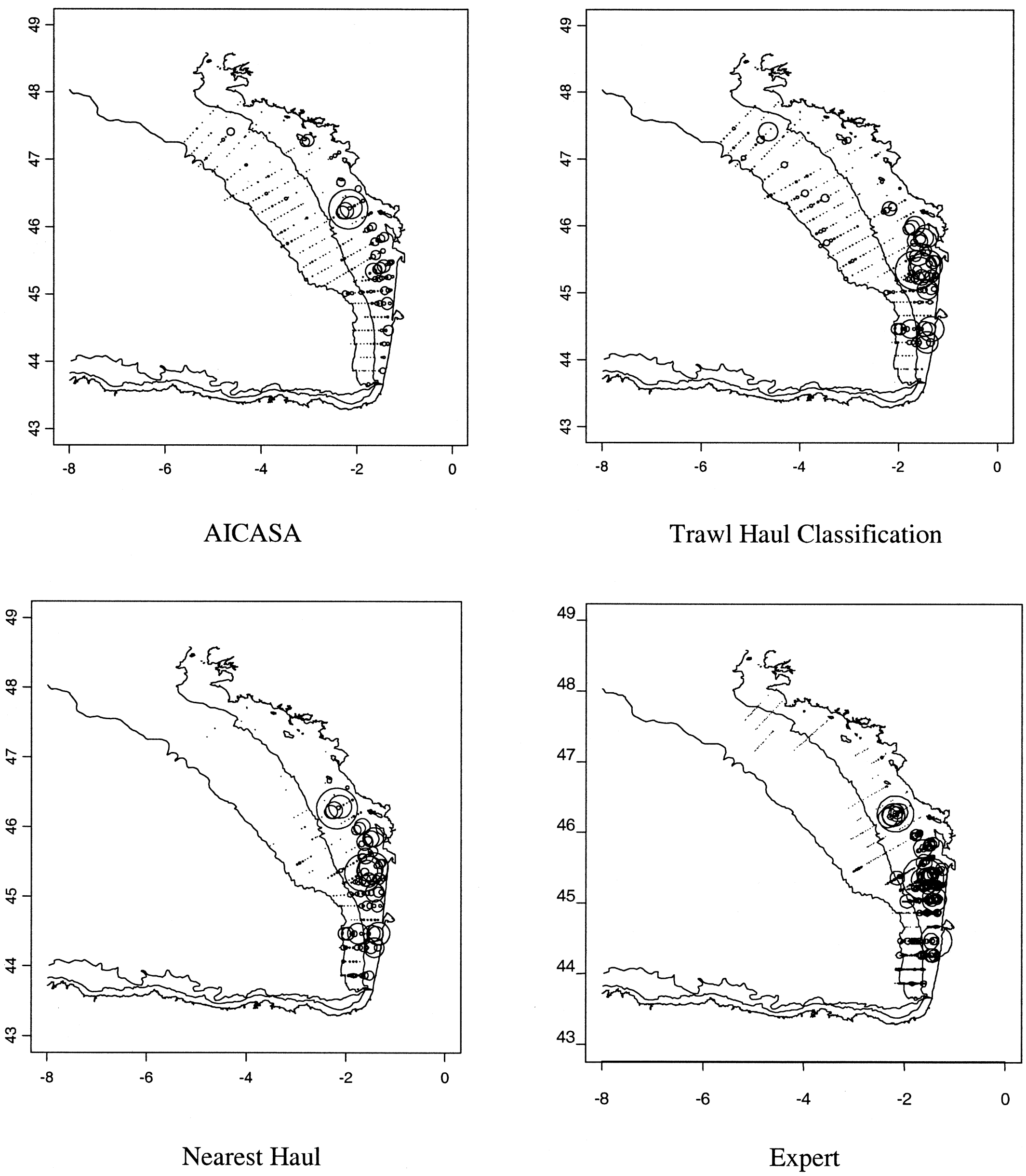

Figure 4. Maps of anchovy (*Engraulis encrasicolus*) abundance obtained by various methods. In each map, circle radius is proportional to the abundance scaled by the maximum for that map.

Comparison of results

All methods agreed for the target species anchovy and sardine in the estimates of abundance and variance, and in the general pattern of the mapped distributions. Differences between AICASA and THC methods were explained by the fact that AICASA-generated post-strata built to be homogeneous in terms of echo traces but not in terms of species composition, while THC-generated post-strata built to be homogeneous in terms of species composition but not in terms of echo traces. General agreement in the results between methods was explained by these species having strong target strength, making the estimation only a little sensitive to differences in energy allocation. Also, the acoustic images displayed a long-range spatial structure, driving both methods similarly in space and with the acoustic populations being in good agreement with species assemblages. The diagnostic power of individual schools for species identification was poor as the same species were present in different groups of images, a result already found in Biscay (Scalabrin and Massé, 1993; Massé, 1996). Because of the good coherence between the acoustic

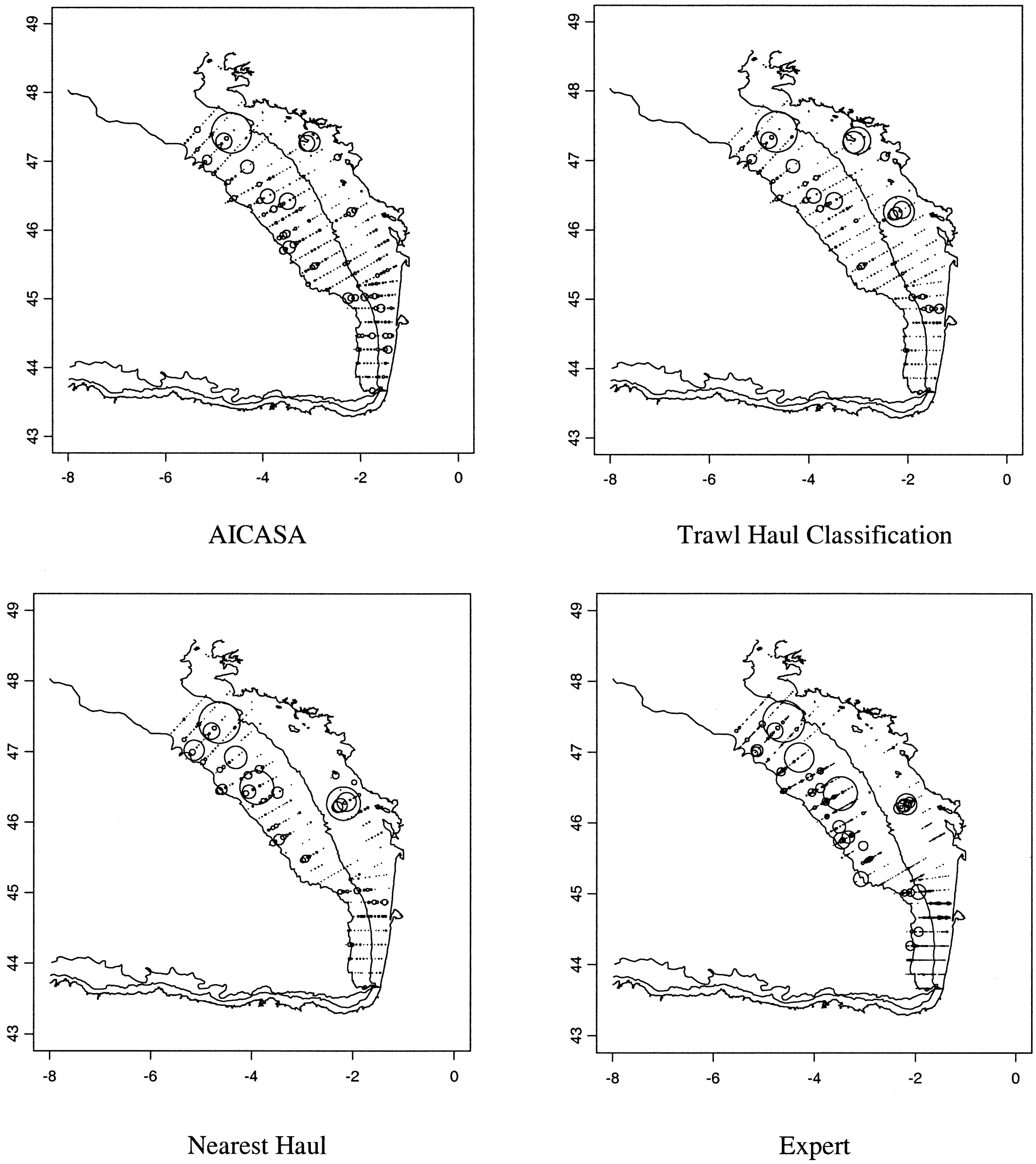

Figure 5. Maps of sardine (*Sardina pilchardus*) obtained by various methods. In each map, circle radius is proportional to the abundance scaled by the maximum for that map.

populations and the species assemblages, the AICASA method using the fine-scale echogram details did not perform better than the simpler THC method.

Variation in schooling behaviour

In Biscay, school type could be more dependent on the habitat than on species or species composition or changes in acoustic populations over the years. Consistency or variation in the school characteristics for a particular species over the years could be studied by analysing the dataset pairs (identified acoustic image, associated trawl-haul catch) for a series of surveys. This could serve to control the reliability of the "Expert" method of echogram scrutiny as well as demonstrating the importance of multi-year information for analysing the current year's survey.

Acknowledgements

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Table 2. Abundance estimates for the different species and methods considered. Species codes are: (1) anchovy (*Engraulis encrasicolus*); (2) sardine (*Sardina pilchardus*); (3) sprat (*Sprattus sprattus*); (4) blue whiting (*Micromesistius poutassou*); (5) mackerel (*Scomber scombrus*); (6) chub-mackerel (*Scomber japonicus*); (7) horse mackerel (*Trachurus trachurus*); (8) Mediterranean horse mackerel (*Trachurus mediterraneus*). m is the mean density (10^3 kg nmi^{-2}); cv is the coefficient of variance (square root of total variance divided by m); id (%) is the species-identification variance divided by the total variance (see Equation (2)).

	1	2	3	4	5	6	7	8
AICASA								
m	16.36	34.97	7.67	0.30	94.04	5.98	33.80	0.06
cv	0.21	0.20	0.30	0.50	0.36	0.84	0.19	0.60
id	0.78	0.81	0.89	0.95	0.93	0.98	0.57	0.95
Trawl-haul classification								
m	18.26	40.89	6.66	0.31	80.46	2.34	29.99	0.06
cv	0.12	0.19	0.29	0.49	0.33	0.28	0.17	0.59
id	0.62	0.60	0.94	0.97	0.92	0.12	0.59	0.90
Nearest haul								
m	18.41	43.87	3.66	0.25	63.94	2.25	31.28	0.05
Expert								
m	17.46	43.31	3.92	1.15	35.48	2.77	11.66	0.02

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