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A conditional simulation of acoustic survey data: advantages and potential pitfalls

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Abstract

Standard geostatistical techniques provide effective methods for estimating the global abundance and precision of a variable of interest, for mapping its spatial distribution and for describing its spatial structure. In the case of acoustic survey data, however, obtaining a measure of precision of the global abundance estimate is confounded by the combination of variances from the interpolation of both the acoustic data and the concomitant fish length data. Even if the global estimation variance could be calculated, the distribution of the estimation error is not known and so confidence intervals cannot be determined. Furthermore, kriged distribution maps, in minimising the estimation variance, tend to smooth out local details of the attribute's spatial variation: small values can be overestimated and larger ones underestimated, such that the kriged map is smoother than reality. This can lead to serious shortcomings when trying to detect patterns of extreme attribute values, such as the high densities encountered in some fish schools. Stochastic geostatistical simulations, conditional on sampled locations, provide a solution to many of these problems. They can deliver a measure of uncertainty for local (density) estimates, a confidence interval estimation for the global mean density, and finally, reproduce global statistics, such as the sample histogram and variogram. In so doing, they also provide maps of the attribute, which are spatially realistic because the variogram is reproduced; these are generated as a number of equiprobable realisations. In the present paper, we apply these techniques to acoustic data from an acoustic survey of North Sea herring. Sequential gaussian simulations are used to generate realisations for fish length and values of the nautical area scattering coefficient. These are then combined to produce realisations of herring density. The combined set of multiple realisations is then used to provide confidence intervals for the global abundance estimate: 95% of the herring abundance estimates are between 5677 and 6271 millions of individuals. Although the method presented in this paper contributes to the assessment of total uncertainty for acoustic surveys, the approach may have suffered from bias due to the use of off-the-shelf data transformation algorithms on fisheries acoustic data, which are often very positively skewed. We discuss this limitation and propose corrections for future work.

Keywords: Geostatistics; Simulation; Fish density; Acoustic survey

1. Introduction

Fishery independent methods, such as research vessel surveys, are becoming increasingly important to determine the abundance and distribution of fish for effective stock assessment (NRC, 1998). Although these methods are not prone to the bias caused by illicit fishing activities that plague traditional fishery dependent methods, they are nonetheless subject to other uncertainties (such as sampling error). The widespread application of the precautionary approach (FAO, 1995) requires uncertainties relating to the size of stocks to be taken into account in its implementation. As a result, a variety of uncertainty estimates are now included in various assessment models (Patterson et al., 2001), but rarely are the variance estimates of the indices of abundance from research vessel surveys included.

There are various possible reasons for this omission. Overall, it is perhaps because uncertainty assessment is still a young science, and the techniques are yet to be established. There are very few examples where overall survey variability has been taken into account (Rose et al., 2000 give an example based on acoustic surveys). In most cases, measures of uncertainty have been based purely on sampling error, and even then, a wide variety of techniques have been proposed:

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Simmonds et al. (1992) have described a number for acoustic surveys; estimates of trawl survey variance have been calculated by Smith (1990), Pennington (1996), Stefansson (1996) and Smith (1997). Borchers et al. (1997) have described methods for egg surveys.

All survey data are similar in that they consist of estimates (samples) of a quantity (indicative of, or proportional to fish density) at a location (point). What usually differs is the placement of the sampling points in space (survey design) and this has implications for the analysis procedure. There are still disputes in fisheries science between advocates of systematic and random survey designs. In the presence of spatial gradients, it is widely acknowledged that a systematic design delivers a more precise estimate of (mean) abundance than a random design (Simmonds and Fryer, 1996). For this and other reasons, Hilborn and Walters (1992) have concluded that systematic grid sampling was better, despite their concession that the variance (precision) of the sample mean could not be assessed correctly using traditional formulas. This has long been the contention among advocates of random sampling design that has led various compromised schemes to be adopted to determine the variance (e.g. Jolly and Hampton, 1990). Geostatistics, however, has techniques that allow for the determination of sampling variance in a systematic design (Matheron, 1989).

In the case of acoustic survey data, the variances obtained from geostatistics refer to the sampling error of the acoustic data alone. To convert this to fish density, it is necessary to know the size of the fish (MacLennan and Simmonds, 1992), and so samples of fish length are required: these have their own inherent variability. Although Rivoirard et al. (2000) have described an analysis, which takes into account both of these quantities to produce an estimate of abundance, they could not estimate the combined variance. They have suggested that a method based on simulations would be needed to take into account both the uncertainties of the acoustic density and the biological parameters (length).

Geostatistical simulation is an approach to modelling that attempts to reproduce the range of values (fish densities) present in the data, as well as the spatial variability described by the variograms (Chiles and Delfiner, 1999). Instead of producing a single, average case estimate, a geostatistical simulation produces several alternative and equiprobable joint realisations of the local values of a variable of interest (e.g. Goovaerts, 1997). This contrasts with the more common geostatistical estimation procedure, kriging, which does not reproduce local spatial detail (it is unrealistically smooth, despite honouring the sample values) and provides estimates whose variance is usually smaller than the sample variance. Furthermore, and more importantly, a simulation is able to produce many realisations, which form a statistical distribution of abundance estimates from which, for example, confidence intervals can be determined.

The objective of this paper is to produce a conditional simulation of herring density, based on data from an acoustic survey. By individually applying geostatistical simulation to the acoustic data and length data, a set of realisations of these data are obtained. These realisations are then combined to produce a set of herring density realisations, from which global estimates of abundance are derived with an associated statistical distribution, confidence intervals and realistic distribution maps. The method, as applied to these data delivers useable confidence intervals and, therefore, assesses much of the uncertainty in the fishery independent estimate of herring abundance. Despite the fact that the paper achieves the objective of producing confidence intervals, the results are likely to suffer from bias due to the use of off-the-shelf data transformation algorithms on fisheries acoustic data, which are often very positively skewed. We discuss this limitation and propose corrections for future work.

2. Materials and methods

Data were taken from the Orkney Shetland herring acoustic survey carried out in July 1999 by the fisheries research vessel *Scotia*. The survey is the major component of the ICES international North Sea herring acoustic survey and accounts for 80% of the adult abundance estimate (ICES, 2000). A 38 kHz Simrad EK500 scientific echosounder was used to gather acoustic data. Echo traces were verified by regular "ground-truth" trawling with a pelagic trawl, and then allocated to the appropriate fish species by visual scrutiny of the echogram. The scrutinised acoustic data, along with position, were output as values of the nautical area scattering coefficient (NASC, in $m^2\ nm^{-2}$) ascribed to herring, for an equivalent distance sample unit (EDSU) of 1 km. This resulted in 5308 acoustic data points (see Fig. 1 for the data histogram and a further statistical description). The length of herring was measured from samples of each trawl haul and summarised as the root mean square length (RMSL, in cm).

Conversion of the scrutinised acoustic data into estimates of fish numbers was carried out according to the procedures in ICES (2000) based on the principles laid out in Simmonds et al. (1992) using the Marine Laboratory echo Integrator survey Logging and Analysis Programme (MILAP). Further details of the methods employed and results obtained are available in the survey report (ICES, 2000).

A detailed illustration and discussion of the gaussian sequential approach to simulation used in this study is provided by Goovaerts (1997). The simulation procedure used, assumes that the data are multivariate gaussian. In the first instance, this requires the univariate (one-point) cumulative distribution function (CDF) to be normal. Both variables were, therefore, subject to a normal-score transformation, that entails setting up a correspondence table between equal p-quantiles of the gaussian CDF and the original distribution (see Goovaerts, 1997).

The multigaussian assumption also requires the multivariate (two-point) CDF to be normal. To examine this two-point normality h-scatterplots for the two variables were inspected: these should appear elliptical with the long axis of the ellipse orientated along the one-to-one line (Tabachnick and Fidell,

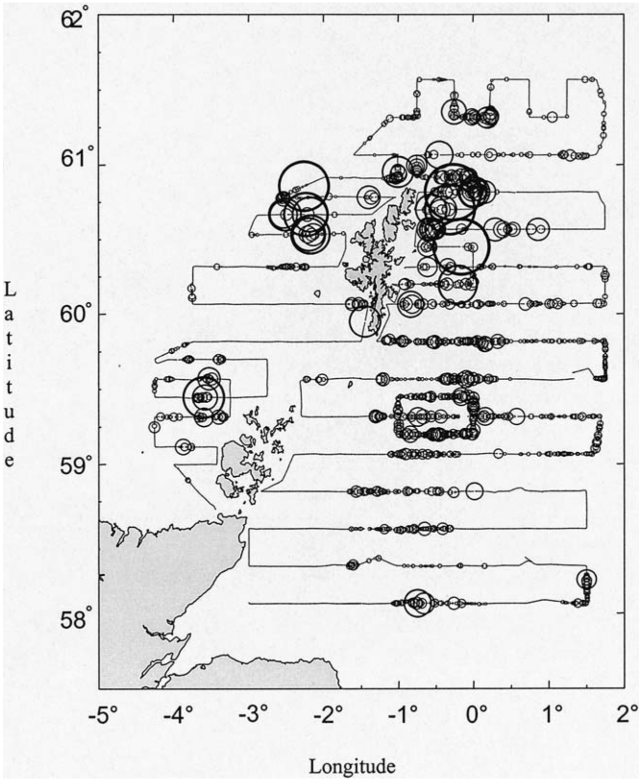

Fig. 1. Post plot with circle size proportional to NASC ($m^2\ nm^{-2}$) attributed to herring, from the Orkney Shetland herring acoustic survey in July 1999.

1989). In the case of the NASC, the *h*-scatterplots were elliptical and there was reasonable agreement with this assumption. In the case of the RMSL, there was an insufficient number of samples (31) to determine the shape of the *h*-scatterplots, and so it was not possible to ascertain whether these data conformed to the assumption. Nonetheless, as discussed below, simulations of RMSL reproduced satisfactory global statistics, such as the variogram, mean, coefficient of variation and quantiles.

Variography and simulation were then carried out in "gaussian space". Omnidirectional experimental variograms were calculated at a lag of 1 km for the NASC (Fig. 2a) and 30 km for the RMSL (Fig. 2b). In this case, no evidence of anisotropy was found from calculation of directional variograms (this might not be the case for other acoustic surveys). Gaussian, exponential, spherical and linear models were fitted according to a weighted least squares procedure (Fernandes and Rivoirard, 1999). This resulted in the adoption of a linear isotropic model for RMSL and an exponential isotropic model for NASC (Fig. 2). A domain encompassing the data was chosen and discretised at 1 km grid nodes (162 470 nodes).

The independence of NASC and RMSL was verified using scatterplots, which indicated that no dependence was apparent. The algorithms for the simulations were implemented in GSLIB Fortran routines (Deutsch and Journel, 1992). In the gaussian conditional simulation procedure, a random walk was performed on grid nodes superimposed on the study area. At each node, a gaussian conditional cumulative distribution function (CCDF) was built, with mean and variance obtained by simple kriging the data values and any existing simulated values. A simulated value was then drawn from this CCDF and, finally, the results were backtransformed in the original "data space".

Two sets of realisations were produced using simple kriging as the interpolation algorithm of the simulation: a set of 100 for RMSL and a set of 100 for NASC. Each realisation of one set was then combined with each realisation of the other set using Eq. (1), to create a total of 10 000 fish density realisations.

The NASC values were extrapolated to a max of 40 000 rather than being cut off at observed maximum (35 000). This was a plausible value for the study area and reflected the possibility that the real maximum was not recorded. It should be stressed, however, that, because a hyperbolic model was

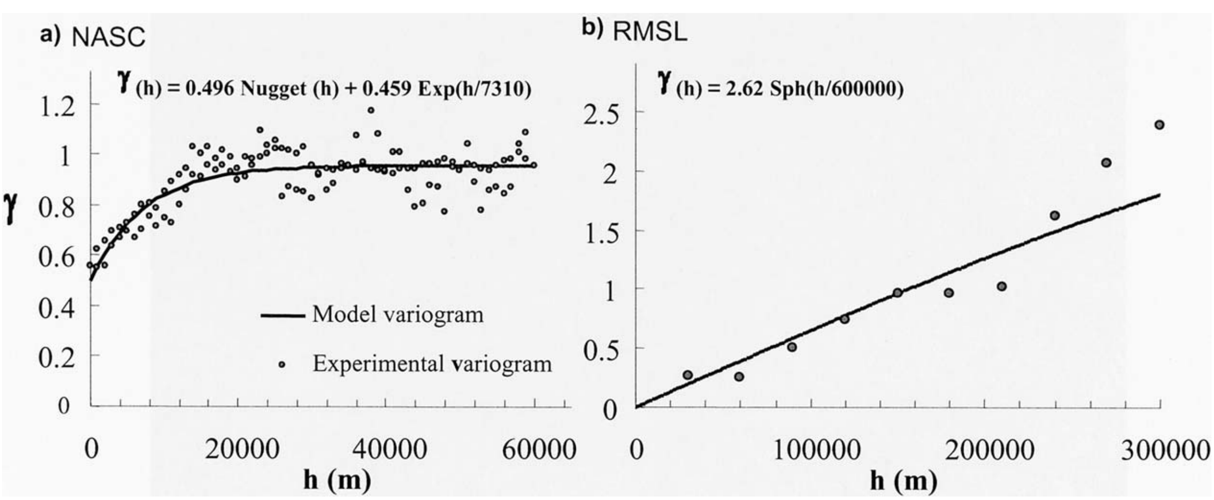

Fig. 2. Experimental variograms and fitted models for: (a) the NASC derived from the echosounder and attributed to herring; and (b) the RMSL of herring taken from pelagic trawls. Note, that the form of the variogram model in the case of RMSL (b) is linear, although the actual model fitted was a long range spherical model. This was a software requirement: the two models are equivalent inside the search radius used.

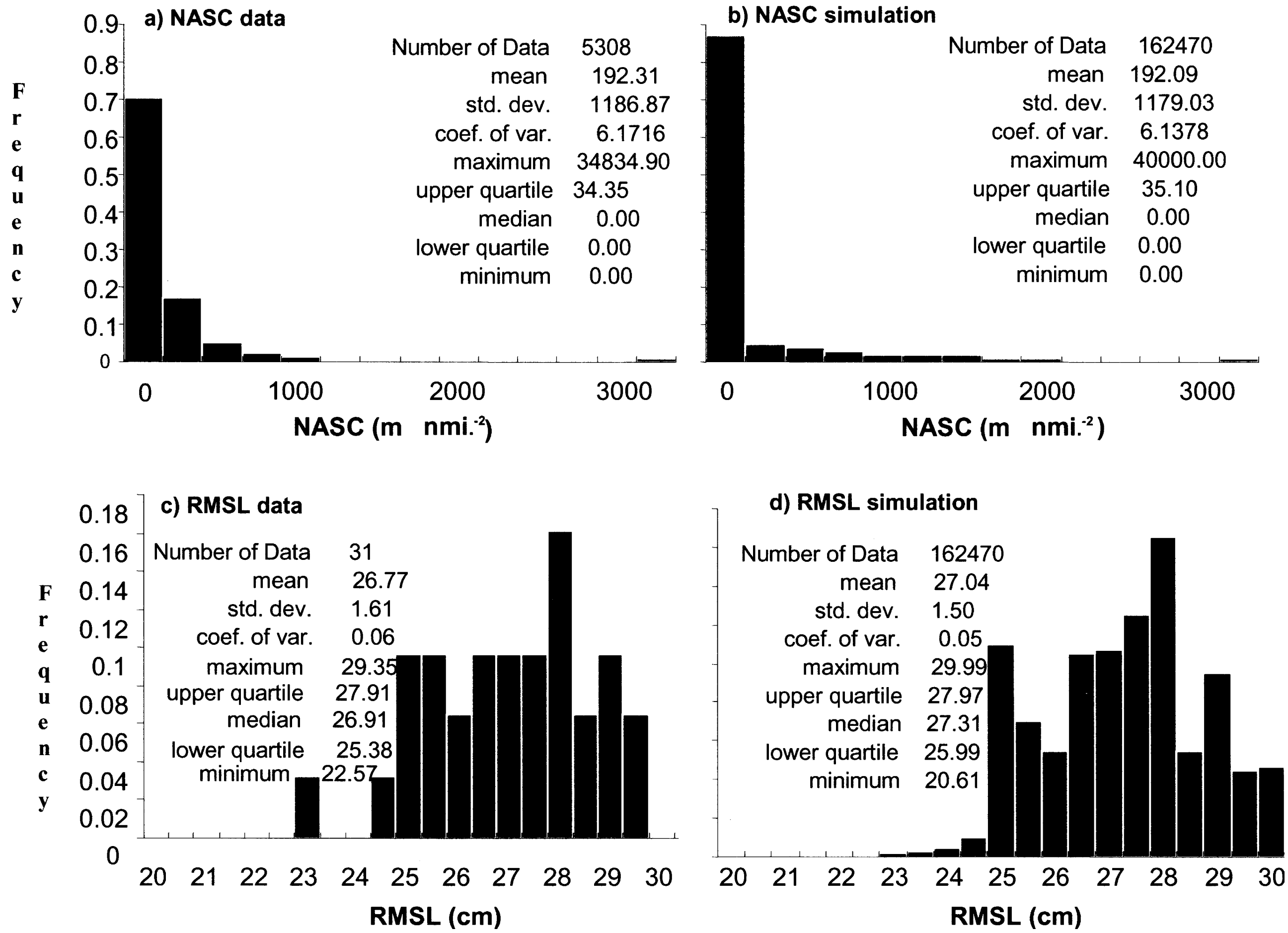

Fig. 3. Frequency distributions and summary statistics of: (a) the raw NASC data; (b) one realisation of the simulation of NASC; (c) the raw RMSL data; and (d) one realisation of the simulation of RMSL.

used for extrapolation with an *omega* parameter = 1.5, there were relatively few simulated values close to 40 000.

Eq. (1) used a target strength to length relationship for herring approved by ICES (2000). The calculation of fish density was performed at each grid node. Realisations of global abundance were then calculated by summing the individual grid nodes values for each abundance realisation.

$$\rho_a = \frac{S_A}{4\pi\ \mathrm{RMSL}^2 \times 10^{-7.12}\ 1.852} \qquad (1)$$

To compare the estimates of the present study with those obtained by (ICES, 2000) for the same area and period, we applied a similar mask to the estimated values (see Fig. 5). The mask excluded pixels, where depth was greater than 200 m, as well as areas of land and areas not covered by the survey to which the simulation extrapolates, as it assumes a rectangular and continuous grid when performing the random walk. This stage might have introduced some bias in the reproduction of the statistics, and a more sound procedure would have been to avoid simulating the nodes to be masked out.

3. Results

One of the principal benefits of a conditional simulation is that each realisation broadly reproduces the statistics of the original data. This was shown here: the frequency distributions, means, minima, maxima and percentiles in the simulated realisations were close to the statistics of the sample data (e.g. Fig. 3). The reproduction of statistics in the NASC realisations (Fig. 3a) was better than those of RMSL (Fig. 3b): this is undoubtedly due to the former's much larger sample size and, therefore, the larger amount of conditioning data. The variograms were also reproduced. The realisations of RMSL reflect the high continuity expressed by the linear variogram. Each realisation (a single example is given in Fig. 4) represents an equiprobable distribution of RMSL, which is a more realistic distribution than a kriged map. The realisations of NASC were very similar in appearance to those of herring density (Fig. 5), as these are just conversions based on Eq. (1). The density realisation is difficult to visualise, because of the very high resolution coupled with the extremely skewed nature of the data (Fig. 3b). It should be borne in mind that the statistics of each realisation fluctuate

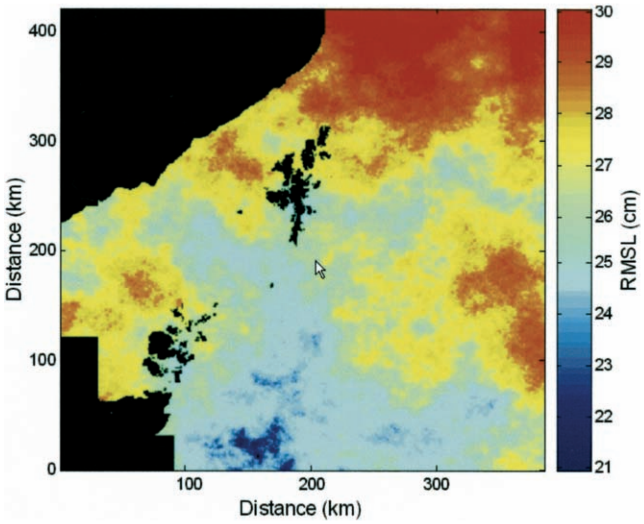

Fig. 4. A realisation of RMSL based on trawl data taken during the Orkney Shetland herring acoustic survey in July 1999. Blacked out regions indicate areas masked out due to land (Orkney Shetland Islands, Scottish mainland), sampled areas, and depths beyond the continental shelf (>200 m, top left).

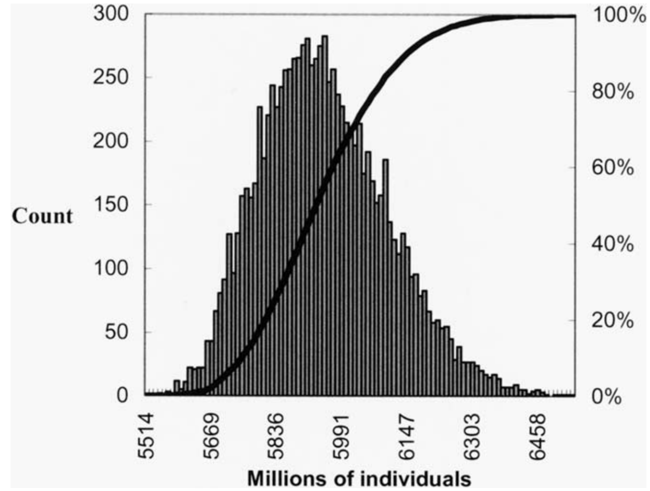

Fig. 6. Frequency distribution of 10 000 abundance estimates based on 100 × 100 realisations of NASC and RMSL combined according to Eq. (1).

around the real ones, as perfect reproduction with this approach could only be guaranteed on an infinite grid.

The frequency distribution of the 10 000 realisations of global fish abundance is presented in Fig. 6, and the summary statistics are given in Table 1. The mean abundance was 5942 million fish; 95% of the estimates were between 5677 and 6271 millions. This median-centred 95% probability interval was based on the whole set of 10 000 realisations.

4. Discussion

A number of attempts have been made to estimate the sampling error of a survey using a variety of techniques (Simmonds et al., 1992), including geostatistics (Petitgas, 1993; Porteiro et al., 1995; Williamson and Traynor, 1996; Rivoirard et al., 2000). However, in no case have the three factors of length variability, acoustic data variability, and the spatial autocorrelation (of each) been taken into account so far. The conditional simulation presented provides an example on how to both incorporate all of these factors and deliver a full statistical distribution of possible abundance estimates. The simulation provides an estimate of uncertainty

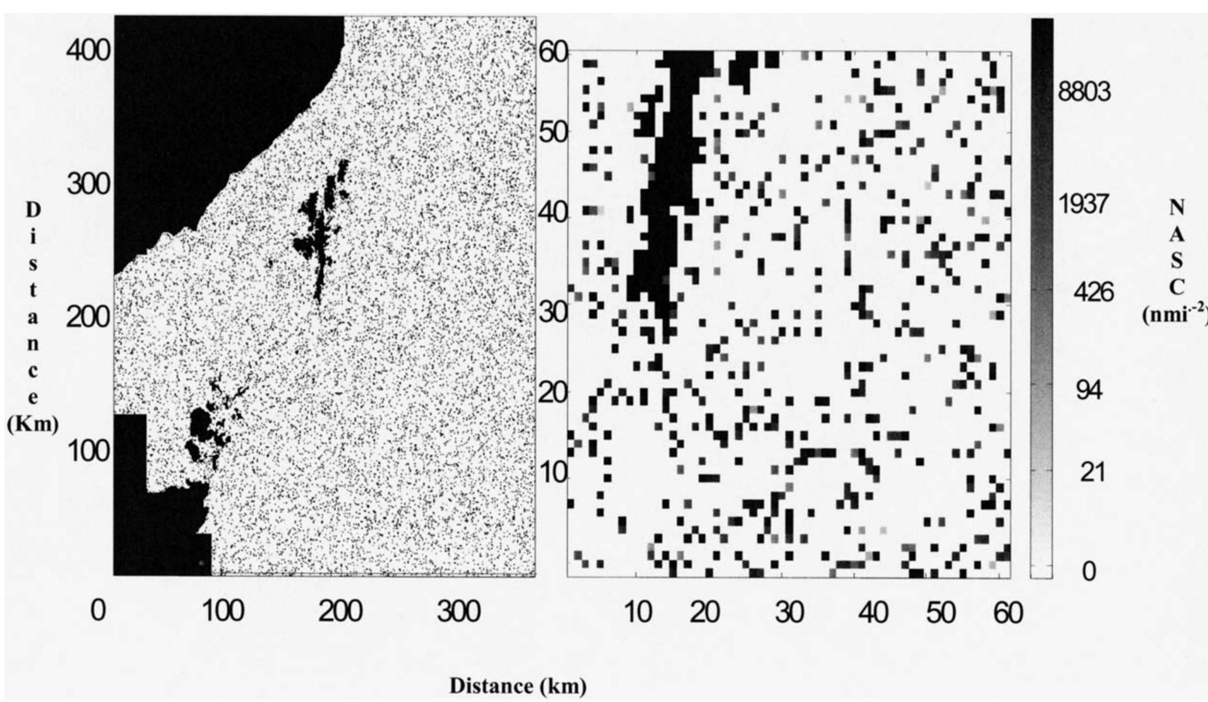

Fig. 5. A realisation of the NASC based on acoustic data taken during the Orkney Shetland herring acoustic survey in July 1999. The right panel is an expanded (zoomed) section of the left panel as illustrated. Blacked out regions indicate areas masked as per Fig. 3.

Table 1
Summary statistics of the 10 000 abundance estimates of herring based on 100 × 100 realisations of the NASC and the RMSL combined according to Eq. (1)

Mean	5 942
Median	5 930
Mode	5 961
Standard deviation	154
Sample variance	23 677
Kurtosis	–0.004
Skewness	0.398
Range	1 038
Minimum	5 514
Maximum	6 552
Count	10 000
2.5 percentile	5 677
97.5 percentile	6 271

that is easy to interpret—i.e. a 95% median based probability interval. This statistic may be used in current assessment models as a measure of uncertainty in the acoustic abundance index. An elaboration would be required to break the estimate down on the basis of fish ages, but this could be achieved by simulating proportions at age as an additional set of realisations (Rivoirard et al., 2000).

The success and wide adoption of geostatistics in fisheries science has, to date, also been compromised by the highly skewed nature of the density distributions, which renders poor structure when using the classical variogram estimator and low confidence in subsequent modelling (Murray, 1996; Maravelias et al., 1996). As structure is often evident in the log domain (Porteiro et al., 1995), a solution to this problem based on a log backtransformed variogram has been proposed (Guiblin et al., 1995). In the present paper, we used a normal score-transformation to estimate the variogram, because this is required by our simulation procedure. This proved to be less noisy (Fig. 2) than the log transform. The effective range of the modelled variogram (21 km) is in agreement with previous estimates of the autocorrelation range of this fish stock (Rivoirard et al., 2000).

Despite the success of this study in pooling length and acoustic data, to provide valid confidence intervals for the estimate of total abundance of fish, a potentially serious problem must be highlighted. The normal-score transformation and backtransformation procedure used (required by gaussian conditional simulations) is likely to have introduced some bias. Prior to transformation, the data must be ranked, and, because the transformation is monotonic, when data of the same value are encountered, ties are broken randomly in the GSLIB implementation. Given that there are many zeroes in our data sets, this is likely to have biased the nugget effect upwards, ultimately leading to a biased estimation of the data values. This is likely to contribute to explain the discrepancy between our results and those in ICES (2000). Therefore, our results caution against the use of “off-the-shelf” solutions for data sets with a high number of zeros. A possible alternative would be the implementation of a modified backtransformation, as described in Saito and Goovaerts (2000).

Providing a correction for backtransformation bias can be implemented, the method has distinct advantages in the estimation of local uncertainty when compared to the more popular kriging method. Kriging is locally optimal in the sense that the local error variance is minimised at each grid node. However, kriging does not reproduce local spatial detail (it is unrealistically smooth). Although it can honour the data, the degree of smoothing depends on their spatial configuration, increasing with distance from the data. This smoothing effect often results in a failure to reproduce the data variogram. Unlike kriging, in a simulation, the modelled values depend on the joint estimates of the variable of interest in the kriging neighbourhood. Uncertainty of local values also depends on data rather than just on their spatial configuration, as in the case of the kriging variance.

The maps produced by simulation are single realisations, which are a much better reflection of reality than smooth kriged maps. However, in the case of herring density, they are difficult to visualise (Fig. 5a,b), because the fish are distributed patchily and the patches are of high density and occur quite rarely in space. Nonetheless, this represents reality, in that most of the area does not actually contain herring. Expansion of scale improves the visual effect (Fig. 5b). The mean abundance obtained (5942 million fish) is somewhat lower than that reported (7635 million fish) using the same data in ICES (2000). The latter approach used the rectangular grid method of interpolation (MacLennan and Simmonds, 1992). The different methods should not in theory provide vastly different estimates of mean abundance, as the data were on a regular grid. One reason for the difference is likely to be due to a combination of factors: differences in the extent of the masks used in the two analyses, the masking procedure followed in this paper, and the bias introduced by the gaussian transformation. A further improvement in the estimates would be achieved by having additional length samples, although Rivoirard et al. (2000) suggest that the variability of density is mainly driven by the acoustic data. Further improvement of the length data could be obtained by considering the entire length distribution rather than using the summary RMSL value. As discussed above, the incorporation of age would also be very useful, particularly for this herring stock, because an index of abundance at age is used for stock assessment of North Sea herring (ICES, 2001).

This analysis provides steps towards an estimate of uncertainty specific to the sampling of length and acoustic data. Problems were encountered with some bias, due to the use of off-the-shelf transformation techniques, but solutions to these may be available as discussed above. Further uncertainties associated with the individual acoustic measurements could be incorporated by, for example, providing estimates of uncertainty associated with the coefficients of Eq. (1) and in the measurement of NASC and RMSL. The method could then approach a determination of total uncertainty, which would be invaluable to the rational management of fisheries resources.

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