ICES J. mar. Sci., 50: 369–381. 1993

Definition of the problem of estimating fish abundance over an area from acoustic line-transect measurements of density

K. G. Foote, and G. Stefánsson

Foote, K. G., and Stefánsson, G. Definition of the problem of estimating fish abundance over an area from acoustic line-transect measurements of density. – ICES J. mar. Sci., 50: 369–381.

The problem of acoustic abundance estimation is briefly reviewed. Under proper conditions, fish density can be measured with high precision along line transects. Observed variations in fish density consequently reflect biological variations, or inhomogeneity, in spatial distribution. The particular problem of estimating fish abundance over an area from line-transect measurements of fish density is defined. Related problems of estimating the variance of the abundance estimate and of mapping the spatial distribution are also defined. A partial list of candidate methods for solving the several problems is given. Among these, the so-called spatial statistical techniques appear to be most promising because of their exploitation of the observed spatial structure.

Le problème de l'estimation acoustique d'abondance est brièvement revu dans cette note. En présence de conditions correctes, la densité de poissons peut être mesurée avec une grande précision le long de coupes rectilignes. Les variations de densité observées sont le reflet de variations biologiques ou de non-homogénéité dans la répartition spatiale. Le problème particulier de l'estimation de l'abondance de poisson dans une zone à partir de mesures de densité sur des lignes est défini. Le problème du calcul de la variance de l'estimation d'abondance et de l'établissement des cartes de distribution est également présenté. Une liste partielle des méthodes possibles pour résoudre les divers problèmes est donnée. Parmi ces méthodes, celles appellées techniques de statistiques spatiales semblent être les plus prometteuses suite à la prise en compte de la structure spatiale des données.

Key words: fish abundance, line-transect estimates, spatial distributions, statistical techniques.

Received 24 January 1991; accepted 8 July 1993.

K. G. Foote: Institute of Marine Research, 5024 Bergen, Norway. G. Stefánsson: Marine Research Institute, Reykjavik, Iceland.

Introduction

Fish-stock estimation is a major occupation of large sectors of the ICES community. Acoustics is one of the basic tools used to quantify fish stocks. It is thus worthy of the closest examination, which is the *raison d'être* for the perennial meetings of the Working Group on Fisheries Acoustics Science and Technology, not to mention the impetus behind ICES sponsorship of several international symposia on fisheries acoustics over the past 20 years.

A particular outstanding problem in acoustic abundance estimation is the statistical combination of line-transect measurements of fish density to estimate abundance over the survey region. This has been recognized by ICES through a short series of two meetings: the Study Group Meeting on the Applicability of Spatial Statistical Techniques of Acoustic Survey Data, held at IFREMER in Brest, 4–6 April 1990 (Anon., 1990a), and the Workshop on the same subject, held at the Marine Research Institute, Reykjavik, 5–9 September 1991 (Anon., 1991a).

It is the present aim to contribute to the on-going discussion by defining the problem in terms intelligible to two separate groups: users of the acoustic method and statisticians. It is especially hoped that this second group will bring its insight and tools to bear on a problem of very practical importance.

In the course of presenting the statistical problem at a number of meetings in recent years, some of which were bald attempts to provoke ICES's interest, as at the 1989 Workshop on Spatial Statistical Techniques (Anon., 1989), doubts have been expressed about the acoustic method itself. Some have been well-founded, and these cannot be completely allayed here, but for the purpose of defining the statistical problem they are extraneous. Nonetheless, the ingredients of the acoustic method are

1054–3139/93/040369+13 $08.00/0

described and analyzed, if in summary fashion, as in earlier presentations (Foote, 1989, 1991a). The context for defining the statistical problem is thereby established. Various solution methods are categorized and briefly described. Several techniques which exploit observation of spatial structure are also identified as being particularly useful for global abundance estimation, variance estimation, and interpolation.

Method of acoustic abundance estimation

A certain minimum of equipment is necessary for performing an acoustic survey. This includes a transducer, which converts an electrical signal to mechanical vibrations and, vice versa; a platform to bear this over the survey region; some transmitting and receiving electronics to control pulsing of the transducer and reception of echoes, commonly called an echo sounder; and fish capture gear to identify the species and age or size distribution of observed fish. Additional electronic circuitry or other computing instrumentation is convenient for processing echo signals, while not being absolutely necessary.

Given a biologist's decision about the time and place to survey a particular fish stock or target species, the transducer is generally carried or towed across the identified region of fish occurrence. The ship's course or track line generally follows or forms a grid-like pattern. This is typically composed of parallel lines or zigzags. These usually aim to cover the total area as evenly as possible within the available time. Other strategies, especially adaptive schemes which place more samples in areas of high density, are also quite common.

While the vessel is sailing, its echo-sounding equipment is – or should be – in continuous operation. The transducer pulsing occurs at fixed, finite intervals, typically with a repetition rate of one per second. Given a vessel speed of 10 knots, or 5 m s^{-1}, nominal transducer beamwidth of 8 deg, and detection range of at least several hundred meters for individual target fish, the sampling is, to nearly all intents and purposes, essentially continuous.

Echoes are generally indicated by marks on a long strip of paper. If these are drawn across the paper in single lines corresponding to successive pings, in which depth is indicated by the distance from the side or other reference line, an echogram results. This is a visual image of what has been sensed by the acoustic pulse launched by the transducer, whether hull-mounted or towed.

Information is usually extracted from echoes by automatic processing. This was once done principally by analog circuitry; now it is done mainly by digital computer. Objects of the processing may be, for example, the number of individually resolved echoes over each designated sailing interval or a cumulative measure for the total number of scatterers, whether resolved or indistinguishably merged. The respective methods are those of echo counting and echo integration (Forbes and Nakken, 1972; MacLennan 1990), but others exist too.

By knowing the character of the target fish, thence species and size distribution, values of backscattering cross section, or target strength, and acoustic sampling volume may be assigned. These allow expression of the acoustic quantities in terms of the fish density; for example, number per unit volume or number per unit area along the survey track. If the equipment is calibrated and it performs stably, and if the various procedures described so far are successful, then the distribution of fish over the survey region is characterized by line-transect measurements of density.

These measurements must be interpolated, implicitly or explicitly, to describe the fish quantity over the entire survey region. In many surveys, especially those done on the large scale of marine stocks, the actual area of direct acoustic sampling is small or even miniscule compared to the whole area. In some special, but also important, situations, as in spawning concentrated over a small region, the relative degree of coverage may be quite high.

Following interpolation, the total abundance may be estimated by integrating the area density over the survey region. The result is generally expressed by a small set of numbers, indicating total number or mass of target species, distinguished by size or age group. This complements contour plots of the fish density derived in the interpolation process.

Analysis of the method

Many things must evidently happen at the same time in order for the acoustic abundance estimation method to be successful. One requirement is that the overall performance of transducer and echo-sounder system be stable. This is generally ensured by conducting calibration exercises at more or less regular intervals throughout the year, or at least once during each major survey. Accordingly, the stable, linear, and low-noise operation of the transmitting and receiving electronics in the echo sounder can be verified.

The time-varied gain function can also be verified in a calibration exercise, and deviations from the desired functional form determined for use in correcting estimates of the acoustic density distribution with depth. Measurement of the sum of source level and receiver voltage response and of the echo integrator scaling factor determines two quantities that are especially useful for long-term monitoring of system stability. The transducer beam pattern, thence equivalent beam angle, may also be measured. While errors may occur throughout the equipment, a calibration exercise is designed to catch these and facilitate their early correction. By means of a standard target, such as copper or tungsten carbide sphere (Foote and MacLennan, 1984), and the procedure recommended by ICES (Foote *et al.*, 1987), the system performance can be specified with an accuracy approaching ± 0.1 dB, or $\pm 2.3\%$.

Errors may also enter the abundance estimation process in the course of signal processing. However, with increasing use of digital technology at steadily earlier points after reception, such errors should be entirely negligible. Naturally, a sufficient sampling rate and sufficient number of quantization levels are necessary, but granted these and the use of widely available processors on the personal computer or workstation level, signal quality remains essentially unimpaired by the sundry processing operations.

No matter how well the equipment performs, the survey can fail if the equipment is not used to best advantage. Both the survey technique and its time and place of application must be chosen with care. The degree of area coverage is also a crucial factor, but evaluation of its influence on the survey result is non-trivial, although persuasive results can be derived rather simply in some instances (Aglen, 1983a, 1989).

Bad conditions can also spoil a survey. Medium absorption and excess absorption due to the presence of extraneous scatterers, such as air bubbles and plankton, can also work against the success of a survey (Dalen and Løvik, 1981), although preliminary work has shown how the negative influence of absorption can be countered (Hall, 1989).

Extinction by dense or extended fish schools or layers may also bias measurements of fish density. Such effects are being studied (Olsen, 1986; Armstrong, F. *et al.*, 1989; MacLennan *et al.*, 1990; Foote *et al.*, 1992; Furusawa *et al.*, 1992), and a simple formula exists for correcting density estimates for extinction (Foote, 1990).

Identification of species and age or size composition of target fish is a process that is frequently fraught with uncertainty. Representativity in sampling by trawl, seine, gillnet, or longline, has been a *cause célèbre* among gear-and-behavior researchers for some years. As a consequence of a number of studies, for example those by Engås and Godø (1986, 1989a, b), Godø *et al.* (1990), Godø and Engås (1990), gear is being improved and attempts are being made to compensate for known selective avoidance effects when sufficient data exist for their quantification. For some commercially important fishes at certain times of the year, the occurrence is sufficiently pure so that little error is incurred due to the physical sampling process itself. Such situations of species purity are exploited whenever possible. Increased use of collateral data on fish occurrence, for example through monitoring of the hydrographic state or growth of plankton, may improve the identification process in the future.

As implied here, survey planning is also crucial to the success of the acoustic abundance estimation method. The biology of the target fish and possible other species in the same region must always be respected when planning a survey. Specific factors to be considered are the state of concentration or dispersion, the degree of mixing with other species, migration, and, in general, life history of target fish. Ease of registration of the fish, or even the possibility of this, is clearly of paramount importance. If the fish are not accessible to acoustics, as because of the bottom "dead zone" (Mitson, 1983) or near-surface or shallow-water occurrence, then the results must reflect this uncertainty. As with situations of species purity, situations of optimal availability are to be exploited.

Interpretation of the echo record is a quite subjective process. Through this, measures of fish density are allocated to species and age or size group on the basis of the appearance of the echogram, together with such supplementary information as catch data and the salinity–temperature–depth profile. Automatic classification may remove some of the subjectivity from the interpretation process, but this remains a task for the future.

Conversion of acoustic measures of fish density to biological measures, such as number density or biomass density, is also subject to error. In the particular case of the echo integration method, this depends on the aptness of chosen measures of mean fish backscattering cross section and effective equivalent beam angle. These are used, respectively, to determine the quantity of fish and to normalize this to the observation volume. Studies to define the backscattering cross section are extensive, as is evident from the bibliographies in Midttun (1984) and Foote (1991b), but continuing. Studies to specify the effective equivalent beam angle are fewer (Aglen, 1983b; Kalikhman and Tesler, 1983; Lassen, 1986; Ona and Hansen, 1986; Ona, 1987; Foote, 1991c), but this is beginning to attract the attention it deserves.

Through these various processes, fish density has been measured along the line transects of the survey grid. But how are these measurements to be interpolated between the transects, and what is the abundance of the fish stock over the survey region? What is often, but fortunately not always, done is to neglect the connectedness, or correlation, of both intra-track and inter-track measurements or estimates of fish density. Thus, a problem of unknown magnitude has been incurred in the abundance estimation process. This is the statistical problem defined in the next section.

The overall strength or robustness of the acoustic abundance estimation method can be likened to a chain, as in Figure 1. The message is that the whole is no stronger than the weakest link.

The statistical problem

It is assumed that the fish stock of interest is distributed over a bounded geographical region and that this can be surveyed acoustically in a time that is short compared to

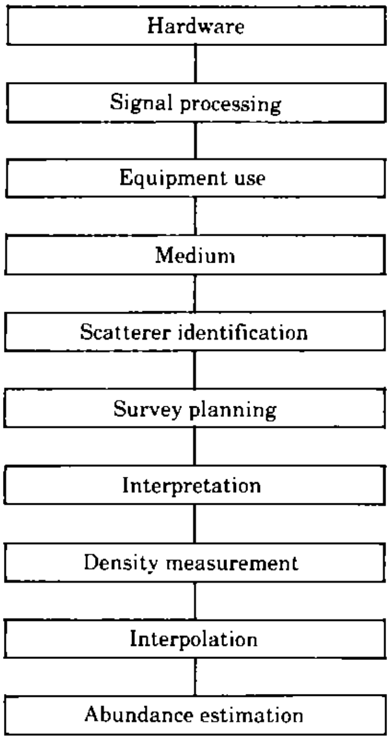

Figure 1. Chain analogy for the acoustic abundance estimation method.

characteristic times of large-scale movement of the fish. It is also assumed that the area fish density is measured, or sampled, without error along line transects that are not necessarily parallel or cover the area in uniform fashion. The problem is to estimate the total quantity of fish, or average density, over the survey region from these line-transect measurements. It is further desired to describe the variance of this estimate and to map the fish distribution over the region.

The acoustic method in this simplified form results in a set of values (x,y,z(x,y)), where (x,y) describes a transect and z(x,y) denotes the measured density at the point (x,y). The following sections will for the most part ignore the possibility of three-dimensional recording of density, measurements of depth of school, temperature, etc. In many cases, these factors can be included to reduce the variability in the estimated abundance. Further, the problem of aging of a given stock is ignored, as this introduces an entirely new dimension to the problem.

The quantity to be estimated is:

$$Q_V = \iint_V z(x,y)\,dx\,dy, \qquad (1)$$

where v is the region of interest and the "surface" z is only measured on the transects. The variance of the estimate, Q_V^*, of this quantity also needs to be evaluated. Notice that this variance may not have much relationship with the variation in the surface itself (as estimated, e.g. by an ordinary variance of the z-values), but should be a measure of how close one can expect Q_V^* to be to Q_V. A useful comparison is the estimation of the total amount in a heap of coal (Shepherd, 1986). An analysis, which considers the measurements along cross sections of the heap as being independent measurements, will inevitably obtain a high variance estimate. The reason is not inaccuracies in the measurements, but rather the structure of the coal heap. In fact, a method of analysis which initially maps the coal heap very accurately will also obtain a small error in the volume. This should be reflected in the variance estimate.

Most methods for the analysis of line-transect data are in some sense spatial by nature. Notable exceptions are methods which attempt to redefine the entire data collection and analysis so as to eliminate any spatial information. The following will be mostly restricted to methods which incorporate spatial information.

Candidate solution techniques

Classification of potential methods

It must be recognized that the following is by no means a complete enumeration of all possible computational analyses, but it is a fairly comprehensive list of methods that have been suggested for the analysis of line-transect data, incorporating in some way spatial information.

The methods can be initially classified into three groups:

1. Methods based on stratification. These methods use averages within squares or regions and perform integration by adding these averages, weighted by the areas. A "contour map" in this instance usually consists of shading the regions.
2. Generalized linear models, which are extensions of linear regression techniques for fitting a model ("response surface") to the observed densities. Integration and contouring are then based on the fitted surface.
3. Smoothing and interpolation techniques which use some form of averaging to interpolate to points outside the transects, typically onto a grid, to be used for numerical integration and contouring.

The methods within a group can further be classified according to whether and how data are transformed prior to processing and/or according to distributional assumptions (e.g. assuming a Gaussian distribution, log-transforming, or taking a non-parametric approach).

In what follows, logarithms will always be natural logarithms, denoted ln.

Most methods in the three classes can give not only an estimate of abundance but also a variance estimate. The latter is essential for an evaluation of the quality of the abundance estimate. Unfortunately, a number of methods of analysis in use do not yield a variance estimate. Further, some methods discard entirely the spatial information and regard the survey as a result of some sort of random sampling scheme. Such a method may well lead to a variance estimate which is much higher than is realistic, when the nature of the patches is considered (cf. the coal example above). It may also lead, in certain other situations, to a variance which is unrealistically low.

Methods based on stratification

Stratified analysis is based on splitting the survey area into strata, each of which is effectively assumed to be homogenous with respect to fish density. The total volume is then estimated by adding strata averages, weighted by area. Possibly some transformations are performed on the raw data.

A proper choice of strata can considerably reduce the variance from that obtained without any stratification.

For later reference, it is useful to note that this estimation procedure can be thought of as first fitting a step function with constant value in each stratum, and then integrating to compute the volume.

Methods which start out from stratified sampling (Cochran, 1977) estimate a single mean within each stratum. This is equivalent to assuming homogeneity and independence within each stratum, i.e. all the density measurements are assumed to be statistically independent and are measurements of the same overall mean. Both of these statements are likely to be false, and certainly so when acoustic measurements are made. If a transect cuts across a school of fish, then values near the middle may tend to be higher than those near the edges, and this phenomenon violates such implicit assumptions behind the classical analysis associated with stratified sampling. The failure of these assumptions casts severe doubt on the usual variance estimates.

One version of the variance estimate is computed as if the measurements along a transect were all measuring a single mean. If a school density is, for example, quadratic along the transect, then clearly a variance estimate of the density along the transect, which utilizes individual measurements but ignores structure, will be an overestimate, as compared to a variance estimate based on knowledge of the structure.

An alternative for parallel transects is to lump values along each transect into a single measurement and to reduce the estimation to one dimension (Hampton *et al.*, 1990; Jolly and Hampton, 1990a, b). Again, if a school structure is clear in that direction (e.g. quadratic), then a method which treats all transect averages as measurements of a single mean will tend to overestimate the error in the integral.

Even ignoring homogeneity and independence, the variances are only useful if the built-in distributional assumptions are (approximately) correct. The highly-skewed distributions typically seen in fisheries tend to need special treatment. Extreme data values thus tend to occur and in some cases the overall average is severely affected by a single value. Simplified analyses of such data sets may well indicate the presence of outliers.

Unfortunately, these "outliers" are usually very important data values, since they tend to indicate where most of the fish are concentrated! This implies that the outliers found in acoustic data cannot be simply thrown away, but great care must be taken in order that their weight is not spread incorrectly over a large area.

Finally, it should be mentioned that data transformations can cause severe problems when integrating the fitted surface. This applies to all methods which use data transformations and will be treated further below.

Some specific data transformations in the context of stratified analysis include the log-transform (or $\ln(z+c)$) and the Box–Cox family of power transforms. The latter family has been described by MacLennan and MacKenzie (1988), and lognormal-based estimators for trawl survey data are described, for example in Pennington (1983), where the common problem of a high frequency of zero values is also accounted for.

Generalized linear models

Generalized linear models (GLMs) have been used extensively for modeling trawl survey data, and have been suggested for the analysis of acoustic data (see, for example, Myers and Pepin, 1986; Shepherd, 1986; Anon., 1990a, b).

A generalized linear model is specified by describing: (1) the connection between a linear predictor and the expected value of a response; and (2) the distribution of the response around that mean. A very useful introduction is given in Aitkin *et al.* (1989), but other relevant references include Nelder and Wedderburn (1972), McCullagh (1983), and McCullagh and Nelder (1989).

For acoustic (or trawl survey) data, these models can range from a very simple quadratic response:

$$E[\ln(Z(x,y)+1)] = \alpha + \beta x + \delta y + \zeta x^2 + \xi y^2 + \eta xy,$$

where E is used to denote the expected value, to the much more complex responses, even modeling zero and non-zero values separately. Within this framework it is in fact easy to model fixed-station trawl surveys by analyzing first the probability of a non-zero catch tow, p (using $\hat{p}=0$ if zero tow, $\hat{p}=1$ if positive), and then the actual number caught, z, in non-zero catch tows. For example, one can take logit(p), which is defined by $\text{logit}(p)=\ln(p/1-p)$, as one linear function of measured parameters and ln(z) as another linear function. In this set-up one might assume a Bernoulli distribution of the 0/1 values and a gamma distribution for the fish counts in non-zero tows, as in

Stefánsson (1991). Such models can easily be fit within the GLIM (generalized linear interactive modeling) statistical package, cf. Baker and Nelder (1978) or Splus (Becker *et al.*, 1988; Anon., 1991b).

This class of models has received endorsement for catch-per-unit-effort (cpue) data from the ICES Working Group on Methods of Fish Stock Assessment (Anon., 1990b). The models can be thought of as fitting a surface to the measurements, using the well-known techniques of (generalized linear) regression. The term response surface is normally used in this context. The fitted surface can be integrated using any numerical integration technique to obtain the volume, which is the required stock abundance estimate.

The primary potential of GLMs (as opposed to simple averages or regressions) lies in the possibility of explicitly specifying the distribution of the response (Z) around its mean, along with a link function relating the expected value to the linear predictor. Thus, quite badly behaved distributions can be accommodated. As an example, it is possible to specify a model which includes a log-quadratic functional dependence on location and depth and a gamma density at each point:

$Z(x,y)$ are independently gamma-distributed with mean μ and variance σ^2.

$$\ln\mu = \alpha + \beta x + \delta y + \zeta x^2 + \xi y^2 + \eta xy + \theta d + \psi d^2$$
$$\sigma^2 = k\mu^2,$$

where d is the depth at location (x,y).

It must be noted that no explicit log-transform is performed. Further, since maximum likelihood is used for estimating the parameters, the estimates satisfy a large number of criteria for optimality. Unfortunately, it is often quite hard to specify the appropriate density. In the case of the gamma distribution, the constant k cannot be easily estimated and the gamma density cannot accommodate zero values.

Further, in linear models (as in most classical statistics), any autocorrelations among the residuals of the fitted model are usually regarded as nuisance parameters.

Acoustic measurements are usually collected on a fairly fine scale along the transects, and large biological variation is often detected. This means that the response surface may have large flat sections and occasional, very high, thin peaks. In principle, it is quite feasible to use a polynomial model as indicated above, using an arbitrarily high-degree polynomial in x and y, to model acoustic measurements. Tests using these methods for acoustic data seem to indicate that (at least for some data sets) very high-degree polynomials need to be used since several peaks may be quite well defined due to the large number of measurements (Anon., 1990a, 1991a). Numerical problems abound, however, when high-degree polynomials are used. Even if orthogonal polynomials are used to eliminate the numerical problems, the surfaces will tend to wander in strange directions at region boundaries or between transects when the degree of the polynomial is high.

Data transformations, or alternate distributions, may alleviate the fitting problem somewhat, but even a ln(z) or ln(z+1) transform, or specifying a gamma density, is often not sufficient (Anon., 1991a).

With the primary interest being the volume under "the surface", it would seem highly desirable to take into account clusters of points which all lie above the surface, by stating that: (1) there is spatial autocorrelation present; and (2) since the points in a region are above the surface, the volume should be increased somewhat (potentially reducing the variance of the volume estimate). This philosophy is in direct contrast with the classical approach which tries to eliminate or forget the spatial autocorrelation. On the other hand, this approach is at the heart of methods which treat the surface as a realization of a random process.

Smoothing and interpolation techniques

A huge body of literature exists on different techniques for smoothing and interpolation. The techniques which have received most attention for estimating and mapping fish-stock abundance have their origin in geostatistics, and kriging is already quite widely used.

Other methods have received attention in different fields. Some robust and non-parametric methods have been proposed for handling ill-behaved data, but care must be taken in using them, since such methods may well reduce the effect of extreme values so much as to effectively throw away most of the stock in some circumstances.

Ad hoc methods abound, and Brown and Shepherd (1978) and Shepherd (1989) give a general smoothing technique, which seems to behave quite reasonably for trawl survey data (cf. Anon., 1990b, where the method was tested). The method is well suited for contouring and integrating, but no variance of the total biomass estimate is automatically produced. Another method, which has been implemented in package form, is given in Akima (1978). Different, also promising, approaches to smoothing are considered by Breiman and Friedman (1985) and by Cleveland and Devlin (1988).

Splines are usually not suitable for use with data as variable (noisy) as those observed when stock abundance is measured. However, Stolyarenko (1988) gives a spline approximating method for estimating the surface. This method has been tested somewhat for acoustic data, but is not in general use.

Since kriging and related methods are widely used and seem acceptable for many purposes, emphasis will be placed on these techniques. Appropriate references include Matheron (1963, 1967, 1971), Conan (1985), Conan *et al.* (1988a), and Guillard *et al.* (1990) for an application to acoustic data. Books on the topic of kriging, among other things, include David (1977), Journel and Huijbreghts (1978), and Cressie (1991). For a more complete exposition of general smoothing techniques, the reader is referred to Ripley (1981) and to Cleveland (1979) for presentation of a more robust smoothing method. Objective analysis is an approach used in meteorology (the primary reference is Gandin, 1965, but see also Eddy, 1967, and Bleck, 1975) and oceanography (see, for example, Bretherton *et al.*, 1976), which is related to kriging. This method would therefore seem to be a potential competitor to kriging, although apparently untested within the field of mapping and estimating stock abundance. It should be noted that Creutin and Obled (1982) have shown that objective analysis is superior to kriging. However, Hardy (1984) shows that objective analysis (optimal interpolation) is equivalent to universal kriging (defined below), at least in essence, although implementational differences exist.

The basis for kriging is a spatial model of the entire observed surface, z(x,y). The principal aim of point kriging is to predict points on this surface by use of linear combinations of the data values. The quality criterion used is the expected squared difference between the predictor and the observed. In order to make statements concerning the quality of the estimated surface, some probabilistic model is required.

The observed surface is interpreted probabilistically as a realization of a random process, Z(x,y), possessing certain spatial characteristics. These are generally classified by the degree of stationarity. The most common, strong assumption is that of second-order stationarity. According to this, the mean of the process is constant:

$$E[Z(x,y)] = \mu, \tag{2}$$

and the covariance of Z at two points, (x,y) and (x′,y′), depends only on the vector distance h between the points, i.e.:

$$E[(Z(x,y)-\mu)(Z(x',y')-\mu)] = C(h). \tag{3}$$

Another common but weaker assumption is embodied in the intrinsic hypothesis. According to this, the expectation of the difference in Z at two points vanishes, and the expectation of the squared difference depends only on the vector difference h in position, namely:

$$E[\{(Z(x,y)-Z(x',y')\}^2] = 2\gamma(h), \tag{4}$$

where $\gamma(h)$ defines the variogram. Thus, a random function which obeys second-order stationarity also fulfills the intrinsic hypothesis, but the converse is not necessarily true.

The first step in applying kriging is to obtain a measure of the correlation or covariance between the measurements. This may be done through the covariance matrix, if the covariance exists, or more generally through the variogram $\gamma(h)$. Values of this may be estimated by grouping the z-values according to distances between pairs of measurement locations and computing the variance, or average of $(z_i - z_j)^2/2$, within each group. It is usual practice to plot these values and to fit a parametric model of the function $\gamma(h)$ to the data. Several methods exist to fit the variogram, but visual inspection of the values is essential, since the plot can indicate deviations from the model. Robust estimation of the variogram has been considered, e.g. by Cressie and Hawkins (1980) and Cressie (1985), and robust kriging is considered by Hawkins and Cressie (1984).

Anisotropies can be addressed by allowing the variogram to depend on direction in addition to distance. In practice, different variograms are computed, each as a function of distance in a specific direction, with some tolerance. Kriging can thus exploit anisotropic structure (Journel and Huijbregts, 1978; Cressie, 1991).

Having obtained the variogram, point kriging is based on solving the appropriate equations to give the best point estimates in terms of minimum variance. These equations are based on the variogram and their solution gives the coefficients for a linear combination of the data values to be used for predicting the points.

It is seen that the basic kriging model and GLMs are two extreme models of the same phenomenon. If we write $z = \mu + \varepsilon$, with $E[z] = \mu$, then GLMs typically assume that all of the structural information is in the mean function μ, and that ε is simply random error (independent deviations). The basic kriging model, on the other hand, treats μ as a constant and assumes that all of the structural information is in the correlation structure of ε. Most likely, the best model is between the two extremes, with a mean function, some autocorrelated deviations ("process error"), and uncorrelated errors as well ("observation error").

The two approaches may be extended. For example, GLMs can be fitted with autocorrelated errors, and in fact, maximum-likelihood estimation for fitting the response surface under the kriging assumptions has been used by Polacheck and Vølstad (1993). Further, kriging can be applied after a trend or drift, expressed through the function $\mu(x,y)$, has been removed.

Clearly, trend removal or filtering is necessary in the analysis of some acoustic survey data. There are a variety of techniques for doing this. Several are briefly described here.

Regression approach

This presumes the availability of additional, non-acoustic data, which are correlated with the acoustic data. By regressing the acoustic variable of interest, z(x,y), on the other variable or variables, the mean function $\mu(x,y)$ can be determined, hence removed from z(x,y). This is illustrated by the depth effect, which can be quite pronounced for some fish species. In this case $\mu(x,y)$ depends on at least depth and can be modeled as such. For a quadratic dependence of $\mu(x,y)$ on depth d, for example:

$$\mu(x,y) = \alpha + \beta d + \delta d^2.$$

If the measurements were independent (and Gaussian), then α, β, and γ should be estimated from:

$$\min_{\alpha,\beta,\delta} \Sigma\, [z(x,y) - \mu(x,y)]^2.$$

Of course, the estimates are not independent, but this is one way to start the process. The next step is to compute:

$$W(x,y) = z(x,y) - \hat{\mu}(x,y),$$

and perform kriging on these new W-values. This yields a variogram and smoothed W-values for any desired new location. A predicted point on the observed surface is now given by:

$$\hat{z}(x,y) = \hat{\mu}(x,y) + \hat{W}(x,y).$$

The second part of the procedure yields estimates of the covariances which were ignored in the first part; therefore it is possible to iterate, using these covariances in the regression part. This approach is described by Ripley (1981) and Hardy (1984), where it is called universal kriging, which is in contrast with the usual definition given below.

Universal kriging
Notwithstanding its name, the realm of application of universal kriging is quite proscribed, as it addresses the problem of estimation for the additive model where the surface z(x,y) is the sum of a drift and an independent residual. The drift is modeled as a linear combination of basis functions in the geometric coordinates, with unknown coefficients. The structure of the residuals must, however, be known. Sometimes this is the case from *a priori* information or can be determined because of special circumstances, for example, absence of a trend in a particular direction. In the general case, however, the structure of the residual can only be determined after the unknown drift is removed. The risk of biasing is high. A basic reference is Matheron (1971).

A concept which is related to universal kriging is known under the name BLUP (best linear unbiased prediction) in classical statistics; see e.g. Henderson (1975) and Corsten (1989).

Intrinsic random function of order k, IRF(k)
The use of IRF(k) allows filtering of polynomial functions of the geometric coordinates. In contrast to the regression approach, the coefficients of the determined polynomial filter do not have to be determined. Rather, the trend is directly removed in application of the kriging weights, which are determined together with a filtering condition. The basic reference is Matheron (1973), but additional useful references are Delfiner (1979), Matheron and Delfiner (1980), Ripley (1981), David *et al.* (1986), Carr and Roberts (1989) and Anon. (1990a, 1991a).

Kriging with external drift
The method of external drift resembles that of IRF(k), but with this difference: the filtering is performed with respect to other variables than the geometric coordinates (Galli and Meunier, 1987).

Block kriging and spatial domains for kriging
Several ways to perform these kriging techniques are mentioned. Block kriging is used to estimate averages within blocks. Unique-neighborhood kriging makes use of all data for single-point or single-block estimation. Moving-neighborhood kriging makes use of only the data within a window or limited region centered on the point or block to be estimated. This last technique alleviates somewhat the problem of too many observations, as well as relaxing problems with trend, cf. Journel and Rossi (1989).

Bayesian kriging
This may remedy the problem of too few or scanty observations when there is prior knowledge about the spatial phenomenon under estimation. In particular, kriging techniques can be adapted to incorporate prior guesses, to which uncertainties can be assigned. Two useful references are Omre (1987) and Omre and Halvorsen (1989).

Non-linear estimation
The kriging techniques described so far belong to the class of linear estimators. Two non-linear estimator techniques are disjunctive kriging, or cokriging indicators, and conditional expectation (Rivoirard, 1990). They are frequently applied to non-linear problems; for instance, determining whether an unknown local concentration exceeds a threshold.

Crucial elements in the use of kriging
These are the following: (1) determination of spatial structure, e.g. degree of polynomial drift, and model for variogram, or covariance; and (2) choice of the neighborhood for evaluating weights in the kriging procedure. A potential numerical problem involves the size of the covariance or variogram matrix, which must be inverted.

Variance estimation

Given that acoustic measurements of fish density along line transects do reveal structure in the occurrence or distribution of fish, it is reasonable to exploit knowledge of this in the variance estimate. This is done through the quantity $\mathrm{Var}[Q_V - Q_V^*]$, where Q_V^* is the estimate of Q_V, defined in Equation (1). Note that if $E[Q_V^*] = E[Q_V]$, then this is equal to $E[(Q_V - Q_V^*)^2]$.

It is observed in particular that Q_V^* estimates the realized fish distribution. The corresponding variance estimate is to be contrasted with that associated with the expected value I of the process, where:

$$I = E[Q_V] = E[\iint Z(x,y)dxdy]. \tag{5}$$

The variance associated with the estimate I^*, $Var[I - I^*]$, is fundamentally different from that of $Var[Q_V - Q_V^*]$. Even when I^* and Q_V^* are identical, the two variance estimates may be quite different. It is argued here, as in Anon. (1991a), that it is the quantity $Var[Q_V - Q_V^*]$ that is most realistic for characterizing abundance estimates of fish derived from acoustic data.

Estimation of variance in a global sense has been addressed by Petitgas (1990, 1991) and Petitgas and Rivoirard (1991). Particularly noteworthy, apropos of the stratification method used by Jolly and Hampton (1990a, b), referred to above, is Petitgas's original treatments of surveys consisting of parallel, regularly-spaced transects by a one-dimensional geostatistical analysis based on the total, or cumulated, measure of fish quantity along each transect.

For completeness, it is noted that the more common quantity for manipulation in global estimations is the average, $Z_V = Q_V/V$. This is widely used in the geostatistical literature, as in the cited works by Petitgas and Rivoirard, among others.

A note on data transformations

The data values observed in acoustic surveys (or trawl surveys) tend to be heavily skewed. This is sometimes dealt with by initially transforming the data (using power or log transforms). Thus, the datum $z(x,y)$ is first transformed into e.g. $w(x,y) = \ln(z(x,y))$, and then smoothing or surface-fitting is performed to obtain a full surface $w^*(x^*,y^*)$ at coordinates (x^*,y^*), where the integration is to be performed.

In a stratified analysis the smoothing step is to compute the strata averages, $w^*(x^*,y^*)$, at strata centers, (x^*,y^*). The next step is to transform back with the inverse function, e.g.:

$$z^*(x^*,y^*) = \exp\{w^*(x^*,y^*)\}.$$

In this way, one obtains smoothed z-values on the original scale for each stratum. These smoothed z-data are then used for integration.

Thus, for the stratified analysis, the approach is essentially to transform the data, fit a surface, transform back, and finally integrate. This is fairly simple, since the function to be integrated is a step function.

It must be kept in mind that bias may be introduced during the transform/backtransform process. This is well known with the log-transform, as is the method to correct for it (see, for example, Pennington, 1983). Unfortunately, the correction factor involves the estimate s^2 of variance, and this is a quantity which can be highly variable. Thus, the bias correction in the backtransform gives back variability. Laurec and Perodou (1987) indicate that the bias correction may not be worthwhile due to this added variability. Further, Myers and Pepin (1987) have found that use of the log transform can be quite ineffective and sometimes severely biased when the true underlying density is different from lognormal. The log-transform may therefore cause biases, even with the application of a bias correction team, if the true density is, for example, a gamma, in which case the regular sample mean is expected to perform better.

If the raw data are transformed, then the fitted values must be transformed back to the original scale before integration (A. Laurec, pers. comm.). This is obvious when written down mathematically. The quantity of interest is:

$$Q_V = \iint z(x,y)dxdy.$$

If smoothing and/or interpolation is based on $w(x,y) = \ln(z(x,y))$, for example, with derived smoothed surface $w^*(x^*,y^*)$, then:

$$Q' = \exp[\iint w^*(x,y)dxdy] = \exp[\iint \ln[z(x,y)]^* dxdy]$$

bears no obvious relationship at all to Q_V. Note that the first expression is simply an integral to find the volume, Q_V, and is not an expected value. Hence the concept of "bias-correction" is not of relevance when comparing Q_V and Q'. However, it is quite feasible to transform back each point with $z = \exp(w)$ and compute:

$$Q_V^* = \iint z^*(x,y)dxdy = \iint e^{w^*}(x,y)dxdy.$$

The optimality fallacy

Many of the methods mentioned above satisfy some optimality criterion. When normality is assumed, GLMs and kriging are both "optimal" in the sense of unbiasedness and minimum variability. However, the precise definition of these terms and underlying assumptions show that the conditions under which each is the optimal method to use are entirely different.

One point which must be made is that GLMs are only optimal if not only all the distributional assumptions are met, but the model is also known (i.e. all the terms are known). When terms are missing, the definition of optimality in GLMs is somewhat vague. Similarly, the kriging approach tacitly assumes that the variogram is an appropriate summary of the spatial correlations. If this assumption is incorrect, then the optimality statements are likely to be false. Finally, GLMs attempt to estimate the mean function, but the kriging approach is based on estimating the realization of the random process.

In like manner, textbook statements concerning the optimality of classical stratified sampling schemes are also likely to be fallacious, due to the spatial structure involved when fish species are being considered.

Discussion

Three classes of methods have been proposed to evaluate the different techniques for analysis of line-transect data: simulation, repeated surveys, and backwards comparison with virtual population analysis (VPA). All three have good and bad points.

The simulation approach has the virtue that the correct result is known. The disadvantage, however, is that simulated data may not reflect accurately the real world.

Using repeated surveys over a single aggregation of fish has the advantage that repeated estimates, Q_V^*, of the stock biomass and/or index, Q_V, become possible Foote (1993). This enables the computation of a variance of Q_V^*, which can be compared to the estimated variances given by the procedure itself. The drawbacks of this approach are: (1) the true size of the aggregation is unknown (so that only the variance can be checked, not the mean); and (2) the number of available repetitions is usually small, which will result in an unreliable variance estimate based on the (few) different Q_V^*-values. Potentially, this results in just an indication of how well a method estimates variability.

Finally, when a series of annual surveys of a stock is available, it is possible to compare the acoustic estimates with backcalculations based on VPA (cf. Jakobsson, 1983). This has been used as an aid in tuning VPA (Halldorsson *et al.*, 1986) and gives an estimate of the variance in the acoustic estimates. This approach is probably the ideal one, when the data are available. However, it requires: (1) a minimum of measurement error and discards in the catch-at-age data (for the VPA to perform reliably); and (2) the raw data from the full series of acoustic surveys.

It is expected that each of the mentioned techniques has a particular domain of applicability, which depends on the characteristics of the fish distribution. These may have to be learned or determined on a case-by-case basis. Nonetheless, the advantages of such tedious work are clear: guidelines can be established for the analysis of line-transect measurements of density. Ultimately, improvements in survey design may result from reliable estimation of abundance and its variance, and mapping of the resource. These might, for instance, relate the degree of coverage or sampling to the precision of the result, or, given use of prior information about the fish distribution, allow specification of a different, perhaps irregular, survey grid to increase precision for the same expenditure of effort.

The problems that are being discussed here with respect to acoustic surveying of fish also apply to trawl surveys, both of fish (Petitgas and Poulard, 1989), shellfish (Buestel *et al.*, 1985; Stolyarenko *et al.*, 1988; Armstrong, M. *et al.*, 1989), and crustaceans (Conan *et al.*, 1988b; Ivanov *et al.*, 1988; Simard *et al.*, 1992). The estimation of biomass, in general, whether marine (Gohin, 1985) or other, is likely to be enhanced by the use of spatial statistical techniques, at least in those cases where sufficient allowance can be made for the peculiarities of the particular subject organism.

The described techniques, and associated problems, thus also apply to krill in the Southern Ocean (Everson, 1977). The usefulness of spatial statistics in the acoustic abundance estimation of krill is currently being considered within the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) (Anon., 1990c). By extension, the same spatial statistical techniques may also be applied to the acoustic abundance estimation of other zooplankton species.

Conclusions

The acoustic abundance estimation method may be assumed in many important instances to yield measures of fish density along line transects over the survey region. Statistical combination of these constitutes a well-formulated problem with the following aims:

1. estimation of the total quantity of fish, or average density, over the survey region;
2. specification of the variance of this estimate; and
3. mapping the fish distribution over the region.

Candidate spatial statistical methods for solving the problem make explicit use of the observed spatial structure. The technique and likely degree of success to be achieved for the arbitrary fish stock will undoubtedly depend on both biological factors and the conditions of registration. Notwithstanding lack of a universal solution, valuable information may be derived by use of the best technique for each individual target stock and survey situation. It may be hoped that a future study will identify particular statistical techniques or analysis methods for application to specific types of fish distribution.

Acknowledgments

Drs O. R. Godø and E. Murphy are thanked for their respective reviews of the acoustics and statistics parts of the manuscript. Dr J. Rivoirard's criticism of the description of geostatistical techniques is valued. N. Diner is thanked for rendering the abstract.

References

Aglen, A. 1983a. Random errors of acoustic fish abundance estimates in relation to the survey grid density applied. FAO Fisheries Report, 300: 293–298.

Aglen, A. 1983b. Echo integrator threshold and fish density distribution. FAO Fisheries Report, 300: 35–44.

Aglen, A. 1989. Empirical results on precision–effort relationships during acoustic surveys. Chapter 3 in Dr Scient. thesis. Department of Fisheries Biology, University of Bergen, Norway. 106 pp.

Aitkin, M., Anderson, D., Francis, B., and Hinde, J. 1989. Statistical modelling in GLIM. Clarendon Press, Oxford. 375 pp.

Akima, H. 1978. A method of bivariate interpolation and smooth surface fitting for irregularly distributed data points. ACM Transactions on Mathematical Software, 4: 148–159.

Anon. 1989. Report of the Workshop on Spatial Statistical Techniques. ICES CM 1989/K:38, 42 pp.

Anon. 1990a. Report of the Study Group on the Applicability of Spatial Statistical Techniques to Acoustic Survey Data, Brest, 4–6 April, 1990. ICES CM 1990/D:34, 103 pp.

Anon. 1990b. Report on the Working Group on Methods of Fish Stock Assessments. ICES CM 1990/Assess:15, 95 pp.

Anon. 1990c. Report of the second meeting of the Working Group on Krill. SC-CAMLR-IX/4. 52 pp.

Anon. 1991a. Report of the Workshop on the Applicability of Spatial Statistical Techniques to Acoustic Survey Data. ICES CM 1991/D:40, 71 pp.

Anon. 1991b. Splus user's manual. Statistical Sciences, Inc., Seattle, Washington, USA.

Armstrong, F., Simmonds, E. J., and MacLennan, D. N. 1989. Sound losses through aggregations of fish. Proceedings of the IOA, 11(3): 35–43.

Armstrong, M., Renard, D., and Berthou, P. 1989. Applying geostatistics to the estimation of a population of bivalves. ICES CM 1989/K:37, 23 pp.

Baker, R. J., and Nelder, J. A. 1978. The GLIM system, release 3. Numerical Algorithms Group, Oxford.

Becker, R. A., Chambers, J. M., and Wilks, A. R. 1988. The New S language. A programming environment for data analysis and graphics. Wadsworth & Brooks/Cole Advanced Books & Software, Pacific Grove, California.

Bleck, R. 1975. An economical approach to the use of wind data in the optimum interpolation of geo- and Montgomery potential fields. Monthly Weather Review, 103: 807–816.

Breiman, L., and Friedman, J. H. 1985. Estimating optimal transformations for correlation and regression. Journal of the American Statistical Association, 80: 580–598.

Bretherton, F. P., Davis, R. E., and Fandry, C. B. 1976. A technique for objective analysis and design of oceanographic experiments applied to MODE-73. Deep-Sea Research, 23: 559–582.

Brown, J., and Shepherd, J. G. 1978. A novel method for interpolating irregularly spaced data onto a regular rectangular grid. Unpublished manuscript.

Buestel, D., Dao, J. C., and Gohin, F. 1985. Estimation d'un stock naturel du coquilles Saint Jaques par une methode combinant les dragages et la plongee. Traitement des resultats par une methode geostatistique. ICES CM 1985/K:18, 19 pp.

Carr, J. R., and Roberts, K. P. 1989. Application of universal kriging for estimation of earthquake ground motion: Statistical significance of results. Journal of the International Association of Mathematical Geology, 21: 255–265.

Cleveland, W. S. 1979. Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association, 74: 829–836.

Cleveland, W. S., and Devlin, S. J. 1988. Locally weighted regression: an approach to regression analysis by local fitting. Journal of the American Statistical Association, 83: 596–610.

Cochran, W. G. 1977. Sampling techniques. 3rd edn. J. Wiley & Sons, New York. 428 pp.

Conan, G. Y. 1985. Assessment of shellfish stocks by geostatistical techniques. ICES CM 1985/K:30, 24 pp.

Conan, G. Y., Buerkle, U., Wade, E., Chadwick, M., and Cumeau, M. 1988a. Geostatistical analyses of spatial distribution in a school of herring. ICES CM 1988/D:21, 8 pp.

Conan, G. Y., Moriyasu, M., Wade, E., and Cumeau, M. 1988b. Assessment and spatial distribution surveys of snow crab stocks by geostatistics. ICES CM 1988/K:10, 12 pp.

Corsten, L. C. A. 1989. Interpolation and optimal linear prediction. Statistica Neerlandica, 43: 69–84.

Cressie, N. 1985. Fitting variogram models by weighted least squares. Journal of the International Association of Mathematical Geology, 17: 563–586.

Cressie, N. 1991. Statistics for spatial data. J. Wiley & Sons, New York. 900 pp.

Cressie, N., and Hawkins, D. M. 1980. Robust estimation of the variogram: I. Journal of the International Association of Mathematical Geology, 12: 115–125.

Creutin, J. D., and Obled, C. 1982. Objective analyses and mapping techniques for rainfall fields: an objective comparison. Water Resources Research, 18 April 1982.

Dalen, J., and Løvik, A. 1981. The influence of wind-induced bubbles in the ocean on echo integration surveys. Journal of the Acoustical Society of America, 69: 1653–1659.

David, M. 1977. Geostatistical ore reserve estimation. Elsevier, New York. 364 pp.

David, M., Crozel, D., and Robb, J. M. 1986. Automated mapping of the ocean floor using the theory of intrinsic random functions of order K. Marine Geophysics Research, 8: 49–74.

Delfiner, P. 1979. The intrinsic model of order k. Ecole Nationale Supérieure des Mines de Paris, Centre de Géostatistique, Cours C-77. Fontainebleau, France. 49 pp.

Eddy, A. 1967. The statistical analysis of scalar data fields. Journal of Applied Meteorology, 6: 597–609.

Engås, A., and Godø, O. R. 1986. Influence of trawl geometry and vertical distribution of fish on sampling with bottom trawl. Journal of Northwest Atlantic Fisheries Science, 7: 35–42.

Engås, A., and Godø, O. R. 1989a. The effect of different sweep lengths on the length composition of bottom-sampling trawl catches. Journal du Conseil International pour l'Exploration de la Mer, 45: 263–268.

Engås, A., and Godø, O. R. 1989b. Escape of fish under the fishing line of a Norwegian sampling trawl and its influence on survey results. Journal du Conseil International pour l'Exploration de la Mer, 45: 269–276.

Everson, I. 1977. The living resources of the Southern Ocean. FAO GLO/SO/77/1. 155 pp.

Foote, K. G. 1989. Fisheries acoustics: diagnosis and prognosis. Proceedings of the IOA, 11(3): 1–10.

Foote, K. G. 1990. Correcting acoustic measurement of scatterer density for extinction. Journal of the Acoustical Society of America, 88: 1543–1546.

Foote, K. G. 1991a. Abundance estimation of pelagic fish stocks by acoustic surveying. ICES CM 1991/B:33, 8 pp.

Foote, K. G. 1991b. Summary of methods for determining fish target strength at ultrasonic frequencies. ICES Journal of Marine Science, 48: 211–217.

Foote, K. G. 1991c. Acoustic sampling volume. Journal of the Acoustical Society of America, 90: 959–964.

Foote, K. G. 1993. Abundance estimation of herring hibernating in a fjord. ICES CM 1993/D:45, 12 pp.

Foote, K. G., and MacLennan, D. N. 1984. Comparison of copper and tungsten carbide calibration spheres. Journal of the Acoustical Society of America, 75: 612–616.

Foote, K. G., Knudsen, H. P., Vestnes, G., MacLennan, D. N., and Simmonds, E. J. 1987. Calibration of acoustic instruments for fish density estimation: a practical guide. ICES Cooperative Research Report, 144. 69 pp.

Foote, K. G., Ona, E., and Toresen, R. 1992. Determining the extinction cross section of aggregating fish. Journal of the Acoustical Society of America, 91: 1983–1989.

Forbes, S. T., and Nakken, O. (eds) 1972. Manual of methods for fisheries resource survey and appraisal. Part 2. The use of acoustic instruments for fish detection and abundance estimation. FAO Manual of Fisheries Science, 5: 1–138.

Furusawa, M., Ishii, K., and Miyanohana, Y. 1992. Attenuation of sound by schooling fish. Journal of the Acoustical Society of America, 92: 987–994.

Galli, A., and Meunier, G. 1987. Study of a gas reservoir using the external drift method. *In* Geostatistical case studies, pp. 105–119. Ed. by G. Matheron, and, M. Armstrong. D. Reidel, Dordrecht.

Gandin, L. S. 1965. Objective analysis of meteorological fields. Israel Program for Scientific Translations, Jerusalem. 242 pp.

Godø, O. R., and Engås, A. 1990. Swept area variation with depth and its influence on abundance indices of groundfish from trawl surveys. Journal of Northwest Atlantic Fisheries Science, 9: 133–139.

Godø, O. R., Pennington, M., and Vølstad, J. H. 1990. Effect of tow duration on length composition of trawl catches. Fisheries Research, 9: 165–179.

Gohin, F. 1985. Planification des expériences et interprétation par la théorie des variables régionalisées: application à l'estimation de la biomasse d'une plage. ICES CM 1985/D:3, 11 pp.

Guillard, J., Gerdeaux, D., and Chautru, J.-M. 1990. The use of geostatistics for abundance estimation by echo integration in lakes: the example of Lake Annecy. Rapports et Procès-Verbaux des Réunions du Conseil International pour l'Exploration de la Mer, 189: 410–414.

Hall, M. V. 1989. A comprehensive model of wind generated bubbles in the ocean and predictions of the effects on sound propagation at frequencies up to 40 kHz. Journal of the Acoustical Society of America, 86: 1103–1117.

Halldórsson, Ó., Reynisson, P., and Stefánsson, G. 1986. A method for estimating terminal F's from a series of acoustic surveys – comparison of VPA and acoustic estimates of the Icelandic herring. ICES CM 1986/H:62, 13 pp.

Hampton, I., Armstrong, M. J., Jolly, G. M., and Shelton, P. A. 1990. Assessment of anchovy spawner biomass off South Africa through combined acoustic and egg-production surveys. Rapports et Procès-Verbaux des Réunions du Conseil International pour l'Exploration de la Mer, 189: 18–32.

Hardy, R. L. 1984. Universal kriging, least squares collocation and optimum interpolation (what's the difference). MS, 16th European meeting of statisticians (EMS). University of Marburg, Germany, 3–7 September 1984.

Hawkins, D. M., and Cressie, N. 1984. Robust kriging – a proposal. Journal of the International Association of Mathematical Geology, 16: 3–18.

Henderson, C. R. 1975. Best linear unbiased estimation and prediction under a selection model. Biometrics, 31: 423–447.

Ivanov, B. G., Stolyarenko, D. A., and Berenboim, B. I. 1988. The stock assessment of the deep water shrimp (Pandalus borealis) off Spitsbergen and Bear Island with a usage of the spline survey designer software. ICES CM 1988/K:13, 19 pp.

Jakobsson, J. 1983. Echo surveying of the Icelandic summer spawning herring 1973–1982. FAO Fisheries Report, 300: 240–248.

Jolly, G. M., and Hampton, I. 1990a. A stratified random transect design for acoustic surveys of fish stocks. Canadian Journal of Fisheries and Aquatic Science, 47: 1282–1291.

Jolly, G. M., and Hampton, I. 1990b. Some problems in the statistical design and analysis of acoustic surveys to assess fish biomass. Rapports et Procès-Verbaux des Réunions du Conseil International pour l'Exploration de la Mer, 189: 415–420.

Journel, A. G., and Huijbregts, Ch. J. 1978. Mining geostatistics. Academic Press, London. 600 pp.

Journel, A. G., and Rossi, M. E. 1989. When do we need a trend model in kriging. Journal of the International Association of Mathematical Geology, 21: 715–739.

Kalikhman, I. L., and Tesler, W. D. 1983. The effective parameters of the real acoustic beam. FAO Fisheries Report, 300: 9–17.

Lassen, H. 1986. Signal threshold in echointegration. ICES CM 1986/B:35, 10 pp.

Laurec, A., and Perodou, J. B. 1987. Considérations statistiques et informatiques sur l'analyse des puissances de pêche et des abondances apparentes. ICES CM 1987/D:9, 27 pp.

MacLennan, D. N. 1990. Acoustical measurement of fish abundance. Journal of the Acoustical Society of America, 87: 1–15.

MacLennan, D. N., and MacKenzie, I. G. 1988. Precision of acoustic fish stock estimates. Canadian Journal of Fisheries and Aquatic Sciences, 45: 605–616.

MacLennan, D. N., Armstrong, F., and Simmonds, E. J. 1990. Further observations on the attenuation of sound by aggregations of fish. Proceedings of the IOA, 12(1): 99–106.

Matheron, G. 1963. Principles of geostatistics. Economic Geology, 58: 1246–1266.

Matheron, G. 1967. Kriging, or polynomial interpolation procedures. Canadian Mining and Metallurgical Bulletin, 60: 1041–1045.

Matheron, G. 1971. The theory of regionalized variables and its applications. Ecole Nationale Supérieure des Mines de Paris, Fontainebleau, France. 211 pp.

Matheron, G. 1973. The intrinsic random functions and their applications. Advanced Applied Probability, 5: 439–468.

Matheron, G., and Delfiner, P. 1980. Les fonctions aléatoires intrinèques d'ordre k. Ecole Nationale Supérieure des Mines de Paris, Centre de Géostatistique, Cours C-84. Fontainebleau, France. 36 pp.

McCullagh, P. 1983. Quasi-likelihood functions. Annals of Statistics, 11: 59–67.

McCullagh, P., and Nelder, J. A. 1989. Generalized linear models, 2nd edn. Chapman and Hall, London. 511 pp.

Midttun, L. 1984. Fish and other organisms as acoustic targets. Rapports et Procès-Verbaux des Réunions du Conseil International pour l'Exploration de la Mer, 184: 25–33.

Mitson, R. B. 1983. Acoustic detection and estimation of fish near the sea-bed and surface. FAO Fisheries Report, 300: 27–34.

Myers, R. A., and Pepin, P. 1986. The estimation of population size from research surveys using regression models. ICES CM 1986/D:9, 21 pp.

Myers, R. A., and Pepin, P. 1987. The robustness of lognormal based estimators of abundance. ICES CM 1987/D:2.

Nelder, J. A., and Wedderburn, R. W. M. 1972. Generalized linear models. Journal of the Royal Statistical Society, A, 135: 370–384.

Olsen, K. 1986. Sound attenuation within schools of herring. ICES CM 1986/B:44, 15 pp.

Omre, H. 1987. Bayesian kriging – merging observations and qualified guesses in kriging. Mathematical Geology, 19: 25–39.

Omre, H., and Halvorsen, K. B. 1989. The Bayesian bridge between simple and universal kriging. Mathematical Geology, 21: 767–786.

Ona, E. 1987. The equivalent beam angle and its effective value when applying an integrator threshold. ICES CM 1987/B:35, 13 pp.

Ona, E., and Hansen, K. 1986. *In situ* target strength observations on haddock. ICES CM 1986/B:39, 14 pp.

Pennington, M. 1983. Efficient estimators of abundance, for fish and plankton surveys. Biometrics, 39: 281–286.

Petitgas, P. 1990. A geostatistical variance of the total abundance estimate for a regular sampling grid. ICES CM 1990/D:12, 21 pp.

Petitgas, P. 1991. Contributions géostatistiques a la biologie des pêches maritimes. Dr thesis. Ecole Nationale Supérieure des Mines de Paris, Fontainebleau. 157 pp.

Petitgas, P., and Poulard, J. C. 1989. Applying stationary geostatistics to fisheries: a study on hake in the Bay of Biscay. ICES CM 1989/G:62, 21 pp.

Petitgas, P., and Rivoirard, J. 1991. Global estimation: σ^2/n and the geostatistical estimation variance. Working paper, Workshop on the Applicability of Spatial Statistical Methods to Acoustic Survey Data, Reykjavik, 5–9 September 1991. 20 pp.

Polacheck, T., and Vølstad, J. H. 1993. Analysis of spatial variability of Georges Bank haddock (*Melanogrammus aeglefinus*) from trawl survey data using a linear regression model with spatial interaction. ICES Journal of Marine Science, 50: 1–8.

Ripley, B. D. 1981. Spatial statistics. J. Wiley & Sons, New York. 252 pp.

Rivoirard, J. 1990. Introduction to disjunctive kriging and nonlinear geostatistics. Ecole Nationale Supérieure des Mines de Paris, Centre de Géostatistique, Cours C-143. Fontainebleau, France. 89 pp.

Shepherd, J. G. 1986. Proc Verbaux de la Reunion (p. 147), CIEM, 1986.

Shepherd, J. G. 1989. Indices of abundance derived from numerical integration over smoothed grid-point representations of survey data. MS presented at the 1989 meeting of the Working Group on Methods of Fish Stock Assessments.

Simard, Y., Legendre, P., Lavoie, C., and Marcotte, D. 1992. Mapping, estimating biomass, and optimizing sampling programs for spatially autocorrelated data: case study of the northern shrimp (*Pandalus borealis*). Canadian Journal of Fisheries and Aquatic Sciences, 49: 32–45.

Stefánsson, G. 1991. Analysis of groundfish survey data: Combining the GLM and delta approaches. ICES CM 1991/D:9.

Stolyarenko, D. A. 1988. Local integral measurements: An advanced spline approximation method for trawl, echo sounding and television surveys. ICES CM 1988/D:1.

Stolyarenko, D. A., Ivanov, B. G., and Berenboim, B. I. 1988. The survey of Icelandic scallop off Bear Island: a use of new methods. ICES CM 1988/K:15. 7 pp.