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Identification of geographic origin of Norwegian spring-spawning herring (*Clupea harengus* L.) based on measurements of scale annuli

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The Norwegian spring-spawning herring stock is characterised by a highly variable recruitment. The juveniles are found from the fjords of west Norway to the north-eastern Barents Sea, in a nursery area covering both temperate and boreal waters. High recruitment to the spawning stock is associated with year-classes that are mostly distributed in the Barents Sea as juveniles. The growth, maturation, and recruitment patterns of the fish spending their first years of life in the Barents Sea are distinct from those of the herring further south along the Norwegian west coast.

For the management of this stock, it is important to identify the fish from the different nursery areas as they recruit to the fishery and the spawning stock. A method to discriminate the fish from the Barents Sea and the Norwegian west coast nursery areas is based on the width of the scale annuli. The success rate of the derived classification rule is estimated to be about 90%. The proportion of fish from each area in a sample can be estimated with a precision of ±4%.

Key words: Norwegian spring-spawning herring, geographic origin, nursery area, classification, discrimination, scale measurements.

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Introduction

The analysis of growth patterns or shapes of scales is a common method for separating fish stocks and has been applied to fish species such as bass, herring, walleye, and salmon (e.g., Riley and Carline, 1982; Reddin, 1986; Messieh *et al.*, 1989; Margraf and Riley, 1993). The identification of subpopulations or components within fish stocks has been less frequently reported, although Lea (1929) addressed this question in herring. In this study we describe a procedure to discriminate between individuals of Norwegian spring-spawning herring originating from two distinct nursery areas.

Norwegian spring-spawning herring spawn in January–March along the west coast of Norway from approximately 58°N to 69°N, and the larvae drift north-eastward into the fjords and the Barents Sea (Dragesund *et al.*, 1980; Hamre, 1989). The nursery area extends from about 60°N to 80°N and includes areas of both temperate and arctic water masses (Fig. 1). The large differences in environmental regimes within the nursery area are reflected in the conditions for growth of the juvenile herring. The herring spending their juvenile period in the areas off Finnmark and in the Barents Sea have a markedly slower growth than those found in the fjords along the Norwegian west coast (Dragesund *et al.*, 1980). While the slower-growing Barents Sea juveniles spend 3–5 years in the nursery area, the fish from the Norwegian west coast leave the nursery areas at an age of 1–2 years.

The Norwegian spring-spawning herring stock is characterised by large fluctuations in abundance and recruitment (Hjort, 1914; Garrod, 1982) that are often accompanied by pronounced changes in the growth and maturation patterns (Runnstrømm, 1936; Seliverstova, 1990; Toresen, 1990). This variability amplifies the difficulties associated with the assessment of this highly migratory stock, and an increased understanding of the factors associated with the variability is therefore crucial for improving the assessment procedures.

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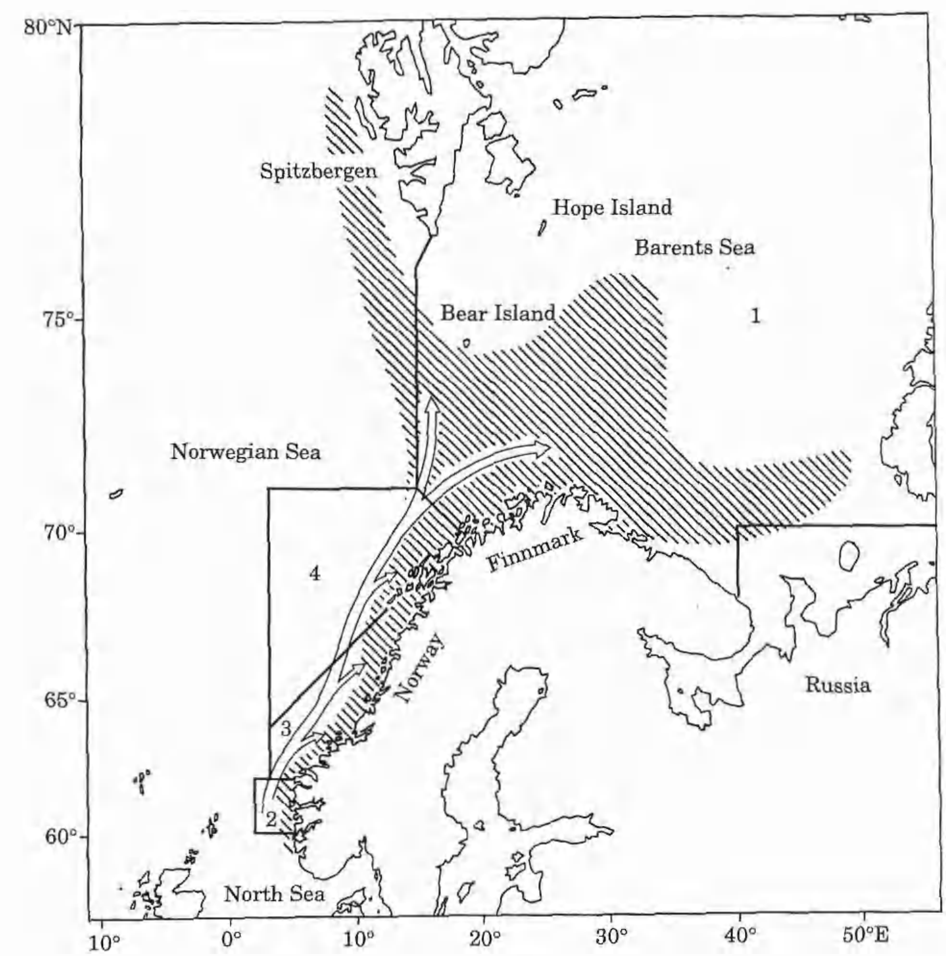

Figure 1. Areas defined for selection of samples. Drift of larvae/0-group (arrow) and nurseries (hatched) of N spring-spawning herring indicated (modified from Dragesund *et al.*, 1980 with kind permission from the authors).

Several authors (e.g. Ottestad, 1934; Runnstrømm, 1936; Østvedt, 1958; Seliverstova, 1968, 1990; Dragesund, 1970) have shown that the growth, maturation, and year-class strength of the different herring cohorts are all strongly influenced by the geographical distribution of the early life stages, and especially by how large a proportion of the year-class is present in the Barents Sea. In particular, high recruitment to the spawning stock and the fishery seems to occur only when a large proportion of the juveniles is present in the Barents Sea (Dragesund, 1970; Seliverstova, 1970, 1990).

The ability to determine the nursery area of origin of individual fish, and particularly the proportion of fish from the Barents Sea nursery area, in the population is therefore important in improving the assessment of the stock and understanding the factors underlying its dynamics.

Until the collapse of the stock in the late 1960s, the herring sampled by the Institute of Marine Research in Bergen, Norway were routinely classified as "N or "Southern" type, using Lea's (1929) meth on a subtle evaluation of the scale structu classification, however, was discontinued in 1 replaced by the measurement of the radii of annuli.

The Barents Sea component, which disappe lowing the late 1960s stock collapse, reappear spawning stock with the recruitment of the 19 class in 1987 (Røttingen, 1989; Seliverstova, 1 substantial recruitment is expected from this the near future (Anon., 1994). A technique fore needed for separating the individuals f Norwegian west coast and Barents Sea nurseries the expertise involved in applying Lea's method been lost.

In this paper we describe a classification p that is based only on the measurements of sca routinely taken for the assessment of the age c tion of the Norwegian spring-spawning herring

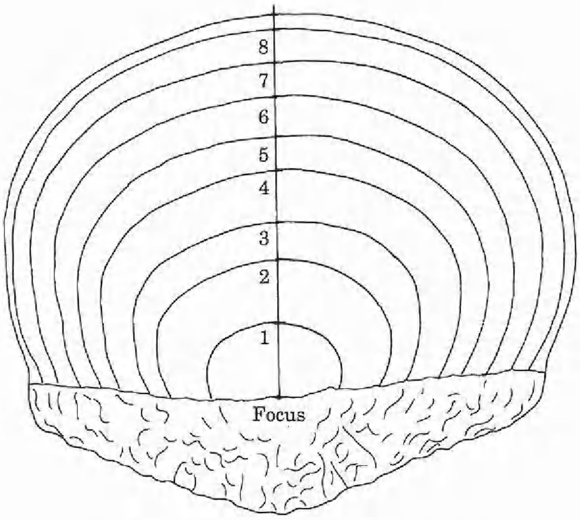

Figure 2. Schematic drawing of a herring scale from an 8-year-old individual caught in summer. Line used for measuring growth increments with age of corresponding annuli indicated.

Materials and methods

The Institute of Marine Research, Bergen, Norway (IMR) has collected individual biological measurements on herring of the Norwegian spring-spawning herring stock (Atlanto-Scandian herring group) since the end of the last century. In this study, we used samples dating from 1937 to 1994. They were collected from drift-net, beach-seine, purse-seine, and trawl catches, taken both by commercial and scientific vessels. In general, the samples consisted of 100 fish, although a number of early samples included 200 individuals. Each fish was weighed, the total length measured and standard parameters such as sex, maturation stage, and relative fatness taken. When available, up to four scales were collected from the area just behind the operculum, along the mid body line. The scales were mounted on glass plates and the yearly rings were identified and the age determined using a stereomicroscope fitted with an ocular micrometer. The total radius of the scale and the radius of each annulus up to the 6th or 9th were measured along a line running from the focus of the scale to the edge of the scale or the inner point of the corresponding winter ring, respectively (Fig. 2).

Definition of the nursery areas

Although juvenile herring are distributed continuously along most of the Norwegian west coast and into the Barents Sea, for classification purposes it is necessary to divide this continuum into separate nursery areas. Since the position of many of the earlier herring samples is given only in terms of the statistical areas used by IMR for the reporting of catch statistics, these statistical areas were used to define the nursery areas.

Although several authors (e.g. Seliverstova, 1990) distinguished between fish from the open areas of the Barents Sea from those spending the first months of life in the fjords of the Finnmark coast, Dragesund (1970) showed that these two groups of fish mix in the open sea as early as after their first winter. It is therefore not possible to separate them after the 0-group stage, and for the purposes of this work they were considered as a single group. We therefore define the Barents Sea component of the juvenile Norwegian spring-spawning herring as all those fish spending the first years of life north of 70°N (Fig. 1), while all fish growing up south of this line are included in the Norwegian west coast component.

Selection of the observations

To estimate and test the classification rule, it is necessary to use fish of known geographic origin. The majority of the herring growing up in the Barents Sea start migrating into the Norwegian Sea in the spring of the year that they reach 3 years of age, but some may stay in the area for up to 6–7 years (Dragesund *et al.*, 1980). Immigration of juveniles or adult herring northwards into the Barents Sea has not been observed, and is assumed to be negligible. Accordingly, all fish sampled inside the Barents Sea (area 1, Fig. 1) were assumed to have grown up in this area, irrespective of the age at which they were sampled. For selecting the fish from the Norwegian west coast component, however, it is necessary to achieve a compromise between minimising the risk of mixing fish from the different nurseries and securing enough information on the individual growth history of the fish. Given that fish from the Barents Sea are not expected to be found on the west coast area before they reached 3 years of age, it was decided to use only fish aged 3 years. It is still necessary to take into consideration that in some years an important part of the Barents Sea component may migrate into the Norwegian west coast area as early as May (Røttingen, 1989). Accordingly, the Norwegian west coast area was subdivided in three sub-areas (Fig. 1), and the following criteria were used to assign fish to the Norwegian west coast component; 3-year old fish sampled in area 2 during the whole year, in area 3 during January–May, or in area 4 during January–April, were assumed to have spent the juvenile stage in the west coast area; fish sampled in any other area/time combination were considered of questionable origin, and were not included in the study.

Using these criteria, the data-set used in the analysis included 1676 individuals from the Barents Sea component, and 5019 from the Norwegian west coast component.

Calculation of classification variables

The basic variables used for the analysis were the radii of the annuli on the herring scales (Fig. 2). The annuli radii were standardised to compensate for not always using a corresponding scale from all individuals and for individual variability in the scale radius/fish length ratio. A plot of scale radius vs. fish length for the data in the IMR database showed evidence of a non-linear relationship, so we used an exponential model:

$$SR = ae^{bL}$$

where SR is the total scale radius (in mm), L is total fish length (in cm) and a and b are constants.

This model was fitted to the over 50 000 pairs of scale radius-fish length measurements available in the IMR database. The fitted model was then used to compute the expected scale radius for each scale as:

$$SR_x = 2.056e^{0.032L}$$

and the standardised annuli radii R_x were calculated by multiplying the observed radii R by the ratio between the expected and the observed scale radii as

$$R_x = R\,\frac{SR_x}{SR}.$$

It was shown by Runnstrøm (1936) that adolescent herring migrating into the Norwegian Sea from the Barents Sea increase their growth rate, which is reflected in the radius of the corresponding annulus. Barents Sea herring are not expected to start migrating into the Norwegian Sea before the age of 3, so this growth difference will only be apparent in the scales of herring originating from the Norwegian west coast area. Since these fish also tend to have an overall higher growth rate (Runnstrøm, 1936), both the actual growth increments and the ratios between consecutive growth increments may be used to discriminate between fish of the two components. The following variables were therefore computed:

- R1 Radius of first ring;
- R2 Radius of second ring;
- R3 Radius of third ring;
- I2 Growth increment corresponding to second growth season (I2=R2 − R1);
- I3 Growth increment corresponding to third growth season (I3=R3 − R2);
- I2R1 Ratio between growth increment during the second growth season and the radius of the first ring (I2R1=I2/R1);
- I3R2 Ratio between growth increment during the third growth season and the radius of the second ring (I3R2=I3/R2);
- I3I2 Ratio between growth increments during the third and the second growth seasons (I3I2=I3/I2);
- RMAX Largest ratio between two consecutive growth increments (Largest of I3I2 and I2R1);
- LI Position of the largest ratio between two consecutive growth increments (1 or 2);
- NGIL1 Number of times a growth increment is larger than the previous one;
- LII Position of the last increment increase (3 if I3I2>1, 2 if I3I2$\leqslant$1, I2R1>1);
- IIL1 Indicator variable: 1 if either I2R1 or I3I2 are larger than 1, otherwise 0.

Estimators

Linear or quadratic discriminant analyses (Johnson and Wichern, 1988) are the two methods generally used for classification of mixed groups of fish (e.g. Cook, 1982; Pontual and Prouzet, 1988; Barlow and Gregg, 1991). Given multinormally distributed data, these methods are optimal in the sense that no other method will give better results (Johnson and Wichern, 1988). Logistic regression (Cox and Snell, 1989) is an alternative and preferable method when the explanatory variables are not multivariate normal (Press and Wilson, 1978). In a comparative study of logistic regression vs. discriminant analysis, Prager and Fabrizio (1990) concluded that logistic regression provided slightly better results on their test data-sets. In our case, it was difficult to justify the multinormality assumption for the predictor variables, and logistic regression was thus used to derive the classification rule. Component (B or W, where B=Barents Sea, W=West coast) is considered as the dependent variable, and is assumed to be binomially distributed. The covariates are the different quantities computed from the scale radius measurements.

Representing the dependent or classification variable by Y (taking the values 0 or 1 according to whether it is W or B) and the different k covariates by $X_0, X_1, \ldots, X_k$, the probability of observation i coming from the Barents Sea is given by

$$P(Y_i=1) = \frac{\exp(Z_i)}{1+\exp(Z_i)},\ Z_i = \sum_{j=0}^{k} \beta_j x_{ij}$$

where the β_j are the parameters (coefficients) of the model and $X_0=1$, so that β_0 represents the constant term in the model.

The predicted probability of this observation coming from the Norwegian west coast area is $P(Y_i=0) = 1 - P(Y_i=1)$. Observation i is assigned to the Barents Sea area if $P(Y_i=1) \geqslant 0.5$, and to the Norwegian west coast component otherwise.

The parameters of the model were estimated by fitting it to observations of known origin using SAS PROC LOGISTIC (SAS, 1990). The classification rule was implemented in a simple SAS program.

The classification matrix $C=\{c_{ij}\}$, where c_{ij} denotes the probability that an observation from class i will be classified into class

$$j\left(\sum_{j=1}^{k} c_{ij}=1\right),$$

was used to represent the properties of this classification rule (Johnson and Wichern, 1989). The error rate of the rule, E, defined as the probability of wrongly classifying an observation, and given by

$$E=\frac{1}{k}\sum_{i=1}^{k} 1-c_{ii},$$

was used to get an overall measure of the performance of the classification scheme.

To estimate C and E, we used the bootstrap method proposed by Efron (1982), as modified by Chatergee and Chatergee (1983). To obtain a good fit of the model, it is convenient that the data be at least approximately balanced, that is, comprising approximately equal numbers of observations from both components. Since the data-set used here includes fewer observations from the Barents Sea component than from the Norwegian west coast one, the construction of the learning and test sets had to be adjusted to the number of observations from the Barents Sea component. Denoting by N_B the total number of observations from the Barents Sea component, the learning set was constructed by randomly drawing, with replacement, N_B observations from each of the components. The test set then comprised all observations from the Barents Sea component not included in the learning set, plus an equal number of observations from the Norwegian west coast component, randomly drawn, without replacement, from those not included in the learning set. The classification rule was estimated by fitting the logistic regression model to the learning set, and it was applied to classify the observations in the test set. The elements of the classification matrix were estimated as $\hat{c}_{ij}=n_{ij}/n_i$, where n_i is the number of observations in the test set which belong to component i, and n_{ij} is the number of these which are classified into component j. Having the $\hat{c}_{ij}$, E is estimated by

$$\hat{E}=\sum_{i=1}^{k} w_i(1-\hat{c}_{ii}), \quad w_i=\frac{n_i}{\sum_{i=1}^{k} n_i}.$$

The procedure was repeated B times, and the final estimate of the classification matrix was computed as the weighted average of the B classification matrices derived from this procedure,

$$\overline{C}=\{\overline{c}_{ij}\}, \quad \overline{c}_{ij}=\sum_{l=1}^{B}\frac{n_{il}}{\sum_{l=1}^{B} n_{il}}\hat{c}_{ijl}$$

where n_{il} is the number of observations actually belonging to class i in the bootstrap test sample l.

The final estimate for E, $\overline{E}$, was then computed from $\overline{C}$ in the standard way.

To estimate the proportions of the observations from the two components in a mixed sample, we used Cook's (1983) constrained corrected classification estimator. This estimator is based on Cook's and Lord's (1978) corrected classification estimator,

$$\hat{U}=\hat{R}\hat{C}^{-1},$$

where $\hat{U}=\{u_i\}$ is the vector of estimated proportions,

$$\hat{R}=\{\hat{R}_i\}=\left\{n_i/\sum_{i=1}^{k} n_i\right\}$$

(n_i=number of observations classified into component i), and $\hat{C}^{-1}$ is the inverse of the estimated classification matrix.

If all elements of $\hat{U}$ are non-negative, the final estimate is just $\hat{U}$. Otherwise, a constrained estimate $\overline{U}$ is recomputed as shown by Cook (1983)

$$U_i=A_i\hat{U}_i-A_i\frac{\left(\sum_i A_i\hat{U}_i\right)-1}{\sum_i A_i},$$

$$A_i=\begin{cases}1, & \hat{U}_i>0\\ 0, & \hat{U}_i\leq 0\end{cases}$$

and this correction is applied iteratively, until all estimated proportions are non-negative.

Estimation of the classification rule and the associated errors

The first step in the estimation of the classification rule was to select the subset of the variables to include in the model. A two-step procedure was used. In the first step, 100 bootstrap samples were taken, with replacement, from the original data-set. Given the requirement that the data should be balanced, the bootstrap samples were constructed in such a way that each sample had 1676 observations from each of the two components.

Logistic regression with forward variable selection procedure (PROC LOGISTIC from SAS) was then applied to each of the samples. The significance level for inclusion of the variables was set to 0.25. For each new variable included in the model, the reduction in the Akaike Information Criterion (AIC) and in the Schwartz Criterion (SC) (Kotz *et al.*, 1988) were calculated. When the inclusion of a new variable caused an increase in these criteria, the procedure was stopped, and the variable was not included in the model.

After this procedure had been applied to all 100 samples, the frequency with which each variable was included in the model was computed. To take account of the association between variables, the frequencies were taken pairwise (that is, the frequencies computed were the frequencies of different pairs of variables). Those variables that occurred in pairs with a frequency of occurrence of at least 10% were kept for further analysis, the others were eliminated from the procedure.

In the second step, all models consisting of the variables selected previously were evaluated separately. A set of 50 bootstrap training and test samples was generated. Each learning sample included 1676 observations from each component. The test sets included all observations from the Barents Sea component not included in the corresponding learning sample, and the same number of observations from the Norwegian west coast area, drawn randomly without replacement from the set of all the observations from this nursery which had not been included in the learning sample. The expected error rate of each model and its standard error were estimated using the procedures above and the same 50 bootstrap samples for all models.

The model with the lowest and least variable overall classification error was selected as the "best" model. If several models resulted in very similar average overall error rates (differing by less than twice their standard errors) and similar standard errors, the simplest one (with fewest variables) was selected as the "best" model.

Having selected the "best" model, it was necessary to estimate its parameters. A balanced data-set was created, including all available observations from the Barents Sea area and the same number of observations from the Norwegian west coast area, drawn randomly, without replacement, from the original data-set. The model selected in the previous step was then fitted to these data, using the methods described above, and the estimated parameters were taken as the best possible estimates for this model.

The classification matrix associated with this model was estimated by using the bootstrap procedure on 100 bootstrap learning and test sets with the same properties as those taken earlier.

To obtain estimates of the errors associated with the estimates of stock composition a Monte Carlo approach was used. To take account of the possibility that these estimates may depend on the true proportions of the different classes in the population, 21 simulated populations, of known composition and with 3352 observations each, were constructed by resampling with replacement and unequal probabilities from the original data-set. The proportion of Barents Sea fish in these populations varied from 0–100%, by steps of 5%.

From each of these artificial populations 50 simple random samples, of 1500 observations each, were drawn with replacement. For each sample j taken from population i, the proportion of Barents Sea observations $\hat{B}_{ij}$ was estimated, and the absolute error $e_{ij} = \hat{B}_{ij} - B_i$, where B_i is the true percentage of Barents Sea observations in population i, was computed.

These errors were then plotted against the true percentages, to evaluate whether a pattern was apparent. If no pattern could be identified, then all the error estimates were pooled, to provide a single estimate of the distribution of these errors. If a pattern was apparent, on the other hand, the errors were kept separate, and their distributions were estimated separately for each value of the true proportions.

Results

Selection of the explanatory variables

The first phase of the variable selection procedure indicated that only 7 of the 14 variables considered initially were included in pairs of variables selected more than 10% of the time (Table 1). Of these 7 variables, R3 and I3I2 were always selected, LI was selected together with the two first in 98% of the cases, and IIL1, I3R2, LII, and NGIL1 appeared in, respectively, 37%, 27%, 18%, and 14% of the cases. R3 was always the first variable to be included in the model, I3I2 was always the second, and LI showed up in either the third (79% of the trials) or fourth (19% of the trials) position. The other variables did not have such stable positions.

Since R3 and I3I2 were included in the model in all trials, all subsequent analyses considered these two variables as a necessary component of the models to be tried. In addition, the inclusion of LI in 98% of the trials was taken as an indication that the only 3-variables model worth considering would be the one including R3, I3I2, and LI.

The comparison of the error rates of the different models, including these variables estimated by the bootstrap procedure (Table 2), showed that the 3-variables model gave a significantly lower error rate than the two-variables model. None of the 4-variables models gave a clear improvement over the 3-variables model, since the difference in the average error rates between the 4-variables models and the simpler model was smaller than twice the asymptotic standard error of the estimates. The model including R3, I3I2, and LI was therefore selected as the best model for the classification rule.

The final model was therefore

$$P(\text{Barents Sea}) = P(Y_i = 1) = \frac{\exp(\beta_0 + \beta_1 R3_i + \beta_2 I3I2 + \beta_3 LI_i)}{1 + \exp(\beta_0 + \beta_1 R3_i + \beta_2 I3I2 + \beta_3 LI_i)}$$

The estimated values for the coefficients β_0 to β_3 are given in Table 3, together with the corresponding asymptotic 95% confidence intervals. The confidence intervals for all parameters were quite narrow, indicating good precision in their determination. The final average estimate of the classification matrix is presented in Table 4.

The matrix is reasonably symmetrical, since the estimated probability of correctly classifying a fish from the

Table 1. Frequency of occurrence of the different pairs of variables, in 100 applications of PROC LOGISTIC, with the forward variable selection procedure.

	R1	R2	**R3**	I2	I3	I2R1	I3R1	**I3R2**	**I3I2**	RMAX	**LI**	**NGIL1**	**LII**	**IIL1**
R1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R2		4	4	0	0	0	0	1	4	0	4	0	0	2
R3			**100**	0	2	0	1	**27**	**100**	0	**98**	**14**	**18**	**37**
I2				0	0	0	0	0	0	0	0	0	0	0
I3					2	0	0	4	2	0	2	0	0	2
I2R1						0	0	0	0	0	0	0	0	0
I3R1							1	1	1	0	0	0	0	0
I3R2								**27**	**27**	0	**27**	1	1	9
I3I2									**100**	0	**98**	**14**	**18**	**37**
RMAX										0	0	0	0	0
LI											**98**	**14**	**18**	**36**
NGIL1												**14**	0	0
LII													**18**	0
IIL1														**37**

Barents Sea area (89.47%) is almost the same as that of correctly classifying a Norwegian west coast fish (91.05%). The overall classification error rate of 9.74% is therefore a good summary of the classification matrix. The narrow distribution of the estimates of this error rate (Table 5) indicate that the estimated classification rule produced relatively stable and uniform results.

The errors in the estimates of stock composition derived from this classification rule do not show any trend with the true composition of the populations from which they are derived (Fig. 3). A single composite distribution for these errors was therefore computed (Fig. 4), 95% of this distribution being between -3.91% and 2.56%. This indicates that there is a probability of at least 95% that the true composition of the stock will be within $\pm 4\%$ of the composition estimated from applying this classification rule to a random sample taken from the stock.

Discussion

The procedure described in this paper eliminates the main problems associated with stock separation techniques used by earlier workers. All trained scale readers at IMR can identify and measure the first three scale annuli. Since the classification rule was developed on the basis of fish whose nursery area was known, the rule now corresponds directly to the areas of interest and its statistical properties can be evaluated.

The procedure is based on a number of explicit and implicit assumptions, of which the most important are:

Table 2. Classification error rates obtained under the different models considered.

Variables in model	Average error rate (%)	Standard error of the average error rate (%)
R3+I3I2	10.06	0.090
R3+I3I2+LI	9.65	0.097
R3+I3I2+LI+IIL1	9.47	0.103
R3+I3R2+LI+I3R2	9.53	0.094
R3+I3R2+LI+LII	9.48	0.105
R3+I3R2+LI+NGIL1	9.48	0.107
R3+I3I2+LI+IIL1+I3R2	9.49	0.104
R3+I3I2+LI+IIL1+LII	9.51	0.106
R3+I3I2+LI+IIL1+NGIL1	9.50	0.108
R3+I3R2+LI+I3R2+LII	9.48	0.109
R3+I3R2+LI+I3R2+NGIL1	9.49	0.106
R3+I3R2+LI+LII+IIL1	9.49	0.106
R3+I3I2+LI+IIL1+I3R2+LII	9.46	0.107
R3+I3I2+LI+IIL1+I3R2+IIL1	9.47	0.106
R3+I3I2+LI+IIL1+I3R2+LII+NGIL1	9.45	0.106

Table 3. Point estimates and asymptotic (normal approximation) confidence interval for the parameters in the logistic classification model.

Coefficient	Estimate	95% confidence interval (asymptotic)
β_0 (Intercept)	33.42	33.12–33.72
β_1	−6.79	−6.85 to −6.73
β_2	−2.62	−2.74 to −2.50
β_3	−0.54	−0.57 to −0.51

Table 4. Estimate of classification matrix for the classification of herring by geographic origin.

	Percent classified as	
"True" origin	Barents Sea	Coastal
Barents Sea	89.47	10.53
Coastal	8.95	91.05

Table 5. Summary statistics for the distribution of the estimates of the classification error rate derived from 100 bootstrap samples.

Weighted average (%)	Extreme values (%)	95% confidence interval (asymptotic) (%)
9.74	8.22–11.17	9.60–9.86

(1) the samples used are pure samples, i.e. all fish considered as coming from one of the areas do indeed come from that area; (2) the samples used for developing the procedure are representative of the underlying population(s); and (3) the methodology used to develop the classification rule from the chosen predictor variables has adequate discriminating power. These assumptions are not completely fulfilled in all cases, and it is important to consider what might be the extent and relevance of the deviations from the assumed patterns.

Non-pure (contaminated) samples may arise from including in a sample from one of the components fish from the other component or from another stock. In this particular study, the arbitrary way used for defining the components adds an extra dimension to this question (since the components are not naturally isolated). We do not consider this to be a major source of error, however, since the location of the separation line was chosen such as to enclose the main distribution areas for young herring in the Barents Sea (Dragesund *et al.*, 1980; Toresen and Barros, 1995) and to be as close as possible to the border of the Barents Sea ecosystem (Dragesund and Gjøsæter, 1988). Contamination of the samples due to movements of fish between the two areas before age 3 or inclusion of herring from other stocks may still have occurred, but it is not likely that it will have been large enough to change our results appreciably. Although there are indications that some fast-growing fish may leave the Barents Sea at the age of 2+ (Dragesund *et al.*, 1980; Seliverstova, 1990), we found no reports of large-scale movements of herring younger than 3 years from the Norwegian west coast into the Barents Sea or vice versa, and the criteria used for selecting the samples were defined in such a way as to minimise the risk of obtaining very contaminated samples. The inclusion of significant numbers of herring from the North Sea or from local stocks is also unlikely. The patterns of occurrence of these fish are relatively well-known to IMR personnel, and they are also easy to detect by their markedly different growth pattern (Aasen, 1952; Hognestad, 1994), being routinely removed from the Norwegian spring-spawning herring samples once the age-length relationship has been determined.

The problem of the representativeness of the samples from each population/component, another recurring concern in this kind of study, is also unlikely to have flawed our results appreciably. Even if it is not possible to guarantee that all possible groups of fish are included in the samples used, the samples used were spread over most areas and a long period, and it is thus reasonable to assume that no major group will have been absent from the samples.

The choice of analytical procedure is another important aspect for the success of the classification. Even if the type of data available made logistic regression seem a more appropriate technique than linear or quadratic discriminant analysis, it could not be concluded *a priori* that the latter would still give better results. To investigate this, we performed a comparative study of the performance of the two procedures on our data. Logistic regression performed (marginally) better, with fewer variables, and we concluded that this latter method was to be preferred.

The classification success of 90% must be considered promising, taking into account that we are dealing with groups within a single stock. Typical classification success in comparable inter-stock separation studies in herring are typically in the range from 42%–96% (e.g. Côté *et al.*, 1980; Schweigert, 1981; Messieh *et al.*, 1989). Nevertheless, significant improvements in classification success could still be obtained by altering the procedures presented here. The most influential variable in the classification rule, R3, actually corresponds to the back-calculated length of the fish at age 3, and the high contribution of this variable clearly demonstrates the differences in growth between the two nursery areas. Since average growth may vary significantly among cohorts, and simultaneously in the two nursery areas, this also means that combining data for cohorts with

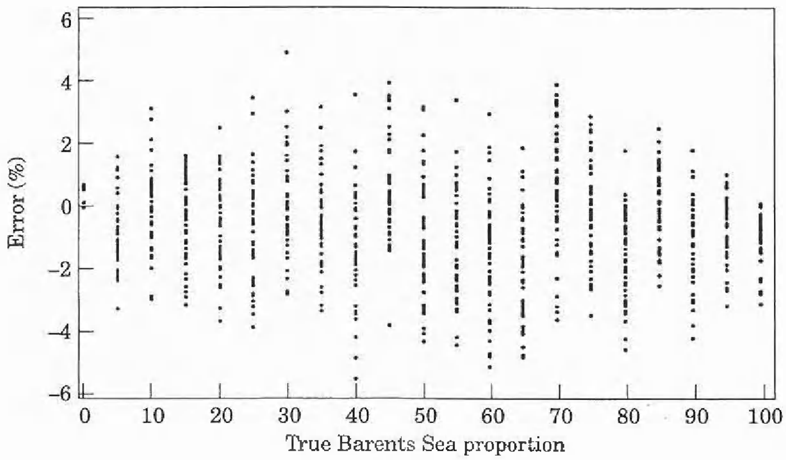

Figure 3. Distribution of errors in estimated proportion of Barents Sea fish related to true proportion in population. Derived from 50 bootstrap samples for each true proportion.

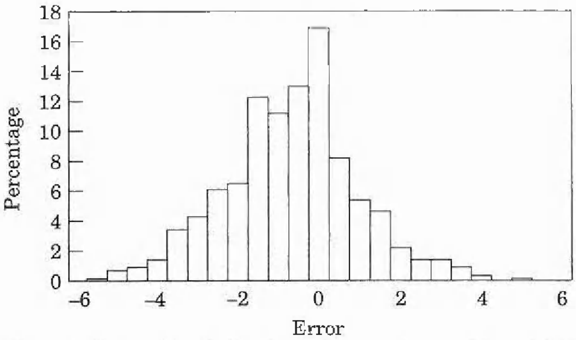

Figure 4. Composite distribution of errors. Derived from 1050 bootstrap simulations.

low and high growth reduces the power of the discriminating procedure. To explore this effect we split the data-set in two by extracting the 1973 cohort, which is known to have exhibited an unusually high growth and to have contributed a significant portion of the Barents Sea data-set (43%). We then repeated the analysis separately for each of the two data-sets arising from this splitting. The error rate was reduced from 10% in the combined data-set to 6.5% in the data-set without the 1973 cohort and to 5% on that containing only fish from this year-class. By separating the high-growth from the low-growth cohorts and estimating a distinct classification rule for each of these groups, the success of the classification procedure could therefore be significantly improved. Unfortunately, this can not easily be done on the data currently available in the IMR database, and thus the main procedure was not modified.

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