A linear mixed model with temporal covariance structures in modelling catch per unit effort of Baltic herring

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Changes in the structure and attributes of a fleet over time will break down the proportionality of catch per unit effort (cpue) and stock biomass. Moreover, logbook data from commercial fisheries are hierarchical and autocorrelated. Such features not only complicate the analysis of cpue data but also seriously limit the application of a generalized linear model approach, which nevertheless is applied commonly. We demonstrate a linear mixed model application for a large hierarchical dataset containing autocorrelated observations. In the analysis, the key idea is to explore the properties of the error term of the model. We modified the residual covariance matrix, allowing the introduction of assumed fisher behaviour, influencing the catch rate. Fisher behaviour consists of accumulated knowledge and learning processes from their earlier area- and time-specific catch rates. Also, we investigated the effects of vessel-specific parameters by introducing random intercepts and slopes in the model. A model with the autoregressive moving average residual covariance matrix structure was superior over the block-diagonal and autoregressive (AR1) structure for the data, having a time-dependent correlation among trawl hauls. The results address the benefits of statistically advanced methods in obtaining precise and unbiased estimates from cpue data, to be used further in stock assessment. Fisheries agencies are encouraged to monitor the relevant vessel and gear attributes, including engine power and gear size, and the deployment practices of the gear.

Keywords: Baltic herring, catch per unit effort, hierarchical model, hyperdepletion, linear mixed model, longitudinal data.

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Introduction

Commercial catch per unit effort (cpue) data are used widely as an indicator of stock abundance. Generalized linear models are often applied to develop quantitative statement of fish stock status using cpue data (Large, 1992; Marchal *et al.*, 2001). A limitation of these models is their difficulty in accounting for the possible correlation of observations caused by the hierarchical structure of the data. A simplified assumption of uncorrelated observations is often made in a standard use of generalized linear models. Some writers recognize the restrictions of the generalized linear model approach (Hilborn and Walters, 1992; Marchal *et al.*, 2002; Maunder and Langley, 2004), but in applications, the consequences of ignoring the correlation of observations generally have not been considered with sufficient statistical rigour. Clearly, alternative models are needed for sound interpretation of commercial cpue data. We propose a mixed modelling approach for this purpose.

Observations from fisheries typically constitute several levels of hierarchy (Figure 1). In a hierarchical setting, the lowest (i.e. the gear haul) level observations are nested with the vessel level, constituting a two-level cross-sectional structure. This structure generates intra-cluster or intra-vessel correlation between observations, because trawl hauls are clustered by vessels. If repeated measurements are available for each vessel, the additional temporal level of hierarchy introduces autocorrelation of the observations. From a modeller's perspective, an exciting challenge with most commercial cpue datasets is the temporal dynamics in fishing power as the number and characteristics of vessels in the fleet change year on year. Typically, just a fraction of the vessels operate through the whole time-series being analysed, many vessels retiring or moving to another area, and new vessels entering the fishery.

Vessel and skipper characteristics (Hilborn and Ledbetter, 1985) contribute to an increase in the intra-vessel correlation, which tends to become stronger than the between-vessel correlation in cpue data. In fact, multiple correlations among location, time, and vessel attributes of basic observations are evident in any commercial fishery. For example, a vessel will likely not change the area of operation if the recent catch was as good as expected, or better. It is also possible that vessels learn from each other through communication systems. Mangel and Clark (1983) modelled the cooperation in a fleet and Little *et al.* (2004) modelled the learning process of individual vessels, i.e. how a fleet finds high densities of fish more effectively than a single vessel operating alone. However, Little *et al.* (2004) did not apply their model to a real dataset.

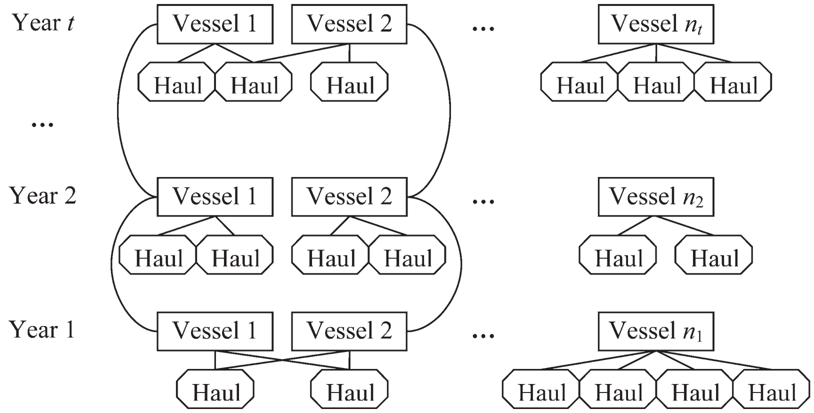

Figure 1. Levels of hierarchy in typical fisheries data. Note that some of the hauls by vessels 1 and 2 have been pairtrawled.

Bishop *et al*. (2004) compared three approaches in an earlier attempt to achieve statistically robust analysis of commercial cpue data. They recommended modelling approaches that allow alternative correlation and variance structures, such as generalized estimation equations (GEE; Diggle *et al*., 1994) and mixed models (Brown and Prescott, 1999; McCulloch and Searle, 2001). Linear mixed models in particular permit flexible modelling of complex intra-cluster and autocorrelation structures. Therefore, an assumption of homogeneity of variance, which limits the use of generalized linear models, can be relaxed (McCulloch and Searle, 2001). Modelling the correlation structure of observations rigorously will increase the precision of model parameter estimates (Brown and Prescott, 1999), manifest as decreased standard errors. In principle, this would reduce bias simultaneously.

The main task in parameterizing linear mixed models is to develop a parsimonious but well-fitting correlation structure of the observations. This is executed by parameterizing models with alternative correlation structures. We propose an efficient and statistically sound approach to develop parameter estimates, their standard errors, and evaluation criteria to choose between alternative models. For practical application, it is useful to consider the implications of changes in the estimated quantities along with changes of the assumed correlation structures. This we establish for the northern Baltic Sea herring (*Clupea harengus*) fishery, for which tuning of the sequential population analysis (XSA; Shepherd, 1999), is exclusively based on commercial catch and effort data (ICES, 2004). Therefore, cpue information standardized for changes in fishing power in the fleet is vital for quantitative stock assessment. We estimate also the relationship between stock abundance and cpue, because strict proportionality has been assumed between them for most age groups in the population analysis (ICES, 2004), owing to software limitations (Darby and Flatman, 1994). Overall, we demonstrate the utility of analysing detailed vessel, gear, and catch data in improving interpretations of the factors controlling cpue. This improvement in knowledge is gained by rigorous modelling of the error term.

Material and methods

Fishery data

The data were retrieved from the register of the Finnish Game and Fisheries Research Institute containing logbook data of catch and effort for the Finnish herring trawl fishery. The dataset contains 53 227 trawl hauls by 190 herring trawlers in ICES Subdivision 30 (the Bothnian Sea) between 1990 and 2003. A map of fishing rectangles is presented in the Appendix (Figure A1). The number of operating vessels decreased, and the average cpue increased towards the end of the period. Logbook data include also conventional temporal and spatial (in 50 × 50 km rectangles) information on trawl hauls and the trawling method (single or pairtrawling). The data were assigned with information on vessel length and engine power obtained from the vessel registry by the national maritime administration. It is known *a priori* that the average area of the capture opening of the gear has increased considerably in the herring trawling fleet (Rahikainen and Kuikka, 2002). Those authors modelled average gear size in the fleet using information on the sale of new herring trawls and their sizes, and about the service life of trawls. Therefore, an index of the annual average trawl size was used as an explanatory variable in the analyses.

The estimate for ICES Subdivision 30 herring stock biomass is derived by virtual population analysis tuned with XSA, using commercial cpue as an index of stock abundance. The estimates were taken from ICES (2004). As we studied the relationship between total herring biomass and cpue, the fact that tuning data influence the estimated biomass raises the danger of circular argument. To avoid this, data for the year 2003 were excluded from the analyses of catch rate. With this removal, the estimation and testing results clearly changed from the results analysing all data. It appeared unnecessary to exclude more data, because changes remained slight with further removals. It is important to ensure that tuning impacts directly the fish stock estimates for the terminal year only. The impact of tuning decreases swiftly for earlier years, mainly because tri-cubic time weighting has been applied for this particular fish stock in the XSA (ICES, 2004), and because the tuning information does not extend to the earliest years of data. ICES (2004) applied cpue data for three tuning fleets with equal weights, commercial trapnets, and pelagic and demersal trawls, to calibrate the XSA, but we analysed partially different datasets from the trawl fleets only. Further, the annual biomass used in our analysis is highly aggregated, with little variation, but the unit of analysis is a low-level entity with large variation in cpue, so giving additional protection against possible technical problems in the estimation procedure. Hence, we consider the biomass estimate used in the analysis to be valid.

The distribution of cpue showed a clear skewness (Figure 2), violating the normality assumption needed for rigorous modelling using linear models (McCulloch and Searle, 2001). A logarithmic

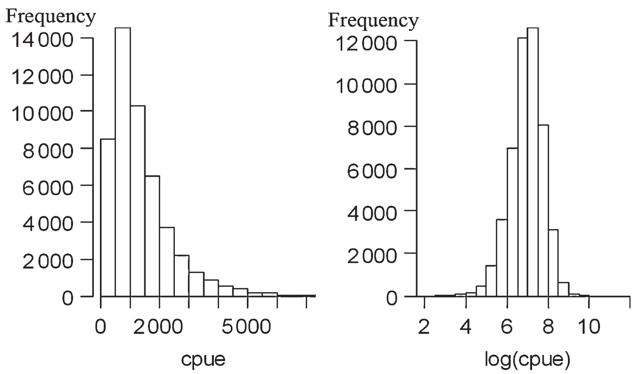

Figure 2. Distribution of the average and logarithmic cpue. The unit of cpue is kilogramme of herring per actual hour trawled.

transformation was used such that the distribution of the logarithmic cpue fulfils the normality assumption reasonably well. Some of the explanatory variables were also log-transformed to investigate their linear relationship with the logarithmized cpue.

Basic linear mixed model

Mixed models are extensions of general (or generalized) linear models (GLMs; McCulloch and Searle, 2001). A mixed model is constructed by incorporating a random component, denoted Zu, into the conventional formula of a linear model, given by $y = X\beta + \varepsilon$. The random component is needed in the analysis of hierarchical data where the independence and homogeneity assumptions of standard linear models are not met. This is invariably true regarding commercial fisheries data. With good choices of the matrix Z, different covariance structures $\mathrm{Cov}(u)$ and $\mathrm{Cov}(\varepsilon)$ can be defined and fitted. Successful modelling of variances and covariances of the observations provides valid statistical inference for the fixed effects (β) of the mixed model.

Using matrix notation, a linear mixed model can be written as follows:

$$y = X\beta + Zu + \varepsilon, \qquad (1)$$

where y is the vector of measurements of the study variable, $X\beta$ the fixed part of the model (similar to standard linear models) such that X denotes the $(n \times p)$ observation or design matrix, and β denotes the unknown $(p \times 1)$ vector of fixed intercept and slope effects of the model. $Zu + \varepsilon$ is the random part, where u is a $(q \times 1)$ vector of random intercept and slope effects, with an assumed q-dimensional normal distribution with zero expectation and $(q \times q)$ covariance matrix denoted by G, and Z is the $(n \times q)$ design matrix of the random effects. Note that the structure of the covariance matrix G is not specified. The residuals ε can be correlated, and the possibly non-diagonal covariance matrix of the residuals is denoted by R. A multivariate normal distribution can be assumed for the observations with expectation $X\beta$ and covariance matrix V, which is given by $V = ZGZ + R$.

The models were built in a stepwise manner by incorporating the explanatory x-variables one-by-one into the model. At each step, we examined the change in model characteristics. In addition to the fixed effects, statistically significant random intercept and slope effects were incorporated into the models to allow vessel-specific variation in the model coefficients. The fit of the models was improved by postulating powerful structures for the residual covariance matrix R. In addition to a block-diagonal structure (referring to Model 1 below), we introduced an autoregressive structure (Model 2) and an ARMA (autoregressive moving average) structure (Model 3) for the residual covariance matrix.

In selecting a realistic model for the data, we did not look for the best fit, but for a parsimonious and sufficiently well fitting model. The significance of model terms was tested with a t-test for single fixed effects and with a large-sample Wald test for single random effects.

We used the SAS procedure MIXED (SAS Institute Inc., 1999) and the R function lme (R Development Core Team, 2005) in fitting the models. Restricted or residual maximum likelihood and generalized least squares were used in parameter estimation (McCulloch and Searle, 2001). A "sandwich" estimator (Diggle *et al.*, 1994; Lehtonen and Pahkinen, 2004) of the covariance matrix of the estimated fixed effects coefficients was used (corresponding to the EMPIRICAL option of the SAS procedure MIXED). In computation, we used the services of CSC (www.csc.fi), a State IT centre for scientific research. CSC servers were used because computing the correlation structures used in our model needs large memory capacity. The latest desk computers are, however, capable of similar analysis. A more technical description of mixed modelling can be found, for example, in Pinheiro and Bates (2000) and McCulloch and Searle (2001).

Model evolution

At the unit level, Model (1) can be rewritten as

$$y_{ijt} = (\beta_0 + u_i) + (\beta_1 + v_{1i})x_{1ijt} + (\beta_2 + v_{2i})x_{2ijt} + \cdots + (\beta_m + v_{mi})x_{mijt} + \varepsilon_{ijt}, \qquad (2)$$

where y_{ijt} refers to the log-transformed cpue assigned to trawl haul j by vessel i at point in time t (a given month of a given year), x_{kijt} $(k = 1,\ldots, m)$ constitute the measured quantities (log-transformed in some cases) of the continuous predictor variables and the values of the constructed indicator variables, β_0 is the fixed intercept common to all vessels, β_k are the fixed slope effects also common to all vessels, u_i are the random, vessel-specific, intercepts, and v_{ki} are the random slope effects. It is customary for all possible random effects not to be included, but some of these effects are set to zero in advance or based on empirical evidence. In contrast, a random effect can appear in a model with the corresponding fixed effect set to zero.

The mixed models constructed are special cases of the basic model [Equation (2)]. For all models, we used the following explanatory variables (or variable groups) for the fixed effects: annual log-estimate of the biomass, trawl size index, engine power (logarithmic), indicator of pairtrawling, type of gear (pelagic or bottom trawl), year, and month. An interaction between engine power and the indicator of pairtrawling was included in the models.

In addition to the fixed intercept effect β_0 common to all vessels, vessel-specific random intercepts u_i were included in all models, allowing variation in the vessel-wise levels of log cpue. If a variable had a significant effect on the variance of the log cpue, then a random effect v_{ki} was assigned. The effects of the trawl size index, the type of trawl, and the month-effect were specified as vessel-specific random effects, but all other effects are common to all vessels. For example, the average trawl size of the

Finnish herring fleet, measured as the mouth area of the trawl, more than doubled (increment 135%) between 1990 and 2002 (Rahikainen and Kuikka, 2002). Applying trawl size as a random effect is reasonable because there are major differences in trawl size among vessels, but vessel-specific data on trawl size are lacking. The random effects had to be assumed to be mutually independent, because modelling the dependence structure was not possible with the computation capacity to which we had access.

Alternative methods are available in a model selection procedure for linear mixed models. We used a likelihood ratio test for nested models, a new model being obtained by adding new parameters into the current model. If the models to be compared were not nested, for example, because of different covariance-structure, the comparison was made with information criteria. Akaike's Information Criterion (AIC) and Schwarz's Bayesian Criterion (BIC, SBS) were used. In addition, statistical measures used for choosing the effects include the multiple correlation coefficient r^2 and an adjusted r-statistic of goodness-of-fit proposed for mixed models by Vonesh *et al.* (1996).

The basic model formulation is

$$\begin{aligned} y_{ijkv} = {} & (\beta_0 + u_i) + \beta_1 x_{1v} + (\beta_2 + v_{1i}) x_{2iv} + \beta_3 x_{3i} + \beta_4 x_{4ijkv} \\ & + \beta_5 x_{5ijkv} + (\alpha_k + v_{ik}) + \delta_v + \gamma_{ijkv} + v_{2i} x_{6ijkv} + \varepsilon_{ijkv}, \end{aligned} \quad (3)$$

where y_{ijkv} is the logarithmic cpue of trawl haul j made by vessel i in month k of year v, $i = 1, \ldots, n$, where n is the number of vessels, $j = 1, \ldots, m_i$, where m_i is the number of trawl hauls made by vessel i, $k = 1, \ldots, 12$, and $v = 1990, \ldots, 2002$; $(\beta_0 + u_i)$ is a fixed intercept effect common for all vessels plus a random, vessel-specific intercept effect for vessel i; x_{1v} is the logarithmic biomass for year v; x_{2iv} is the trawl size index for vessel i in year v; x_{3i} is the logarithmic engine power for vessel i; x_{4ijkv} is the indicator of pairtrawling (1, pair; 0, single) for haul j of vessel i in month k and year v; x_{5ijkv} is an interaction of engine power and the indicator of pairtrawling for haul j of vessel i in month k and year v; x_{6ijkv} is an indicator of trawl type (pelagic or bottom trawl) for haul j of vessel i in month k and year v; $(\alpha_k + v_{ik})$ is a fixed intercept effect for month k plus a vessel-specific random month effect for vessel i in month k; δ_v is a fixed intercept effect for year v; γ_{ijkv} is a fixed intercept effect of location of haul j of vessel i in month k and year v; β_1, β_2, β_3, β_4, and β_5 are fixed effects common for all vessels; v_{1i} and v_{2i} are the vessel-specific random effects; and ε_{ijkv} is the residual term.

The key difference between the specific models was in the assumed structure of the residual covariance matrix, which explicitly models the dependence of cpue on past catch rates. We interpret this dependence as fishers' behaviour related to the use of information of past cpue in decisions on their spatial and temporal allocation of fishing effort, i.e. where and when to fish. We selected three different structures with increasing complexity, referred to here as Models 1, 2, and 3. We describe the covariance structures of the residuals applied for the three models below.

Model 1

In Model 1, the covariance matrix of residuals R was postulated as a block-diagonal containing vessel-specific diagonal (co-)variance matrices R_i. For example, for vessel i with four trawl hauls, the structure of R_i is given by

$$R_i = \begin{bmatrix} \sigma_i^2 & 0 & 0 & 0 \\ 0 & \sigma_i^2 & 0 & 0 \\ 0 & 0 & \sigma_i^2 & 0 \\ 0 & 0 & 0 & \sigma_i^2 \end{bmatrix}.$$

This residual covariance structure implies that information on catch rates received via the preceding fishing trips is not utilized at all in decisions concerning the next trip. The covariance matrix G of the random effects is also block-diagonal, with vessel-specific covariance matrices G_i as its elements.

Model 2

In developing the more complex Model 2, we assumed that fishers make decisions about future fishing strategy using information from the most recent fishing trips, so that the latest ones have the greatest influence on decisions, and the significance of previous trips vanishes quickly.

This suggests an autocorrelative covariance structure between successive trawl hauls, where the correlation declines with increasing time-lag. For this model, we postulated an autoregressive AR(1) structure for the residuals, which gives the vessel-specific covariance matrices R_i. The matrices are of the form

$$R_i = \sigma^2 \begin{bmatrix} 1 & \rho & \rho^2 & \rho^3 \\ \rho & 1 & \rho & \rho^2 \\ \rho^2 & \rho & 1 & \rho \\ \rho^3 & \rho^2 & \rho & 1 \end{bmatrix},$$

where ρ denotes the autocorrelation coefficient. The structure assumes an equal residual variance σ^2 for all vessels.

Model 3

In the most complex Model 3, the residuals were assumed to follow an ARMA(1,1) structure. In addition to the autocorrelation coefficient ρ, a moving-average parameter γ was included. The MA structure makes the correlation between observations decline at different rates compared with the pure AR structure. In this model, past observations contribute to the autoregressive structure of successive hauls more strongly than in Model 2. This modification is based on the assumption that fishers use long-term experience in planning their next fishing trip, not only the recent catches. In the model, this experience is allowed to extend over years and even decades, because the moving-average parameter is constant for all observations for a vessel.

In Model 3, vessel-specific residual covariance matrices R_i are of the form

$$R_i = \sigma^2 \begin{bmatrix} 1 & \gamma & \gamma\rho & \gamma\rho^2 \\ \gamma & 1 & \gamma & \gamma\rho \\ \gamma\rho & \gamma & 1 & \gamma \\ \gamma\rho^2 & \gamma\rho & \gamma & 1 \end{bmatrix}.$$

For simplicity and computational reasons, equivalence of the residual variances for all the vessels was again assumed.

Results

The major difference among Models 1, 2, and 3 is in the assumed covariance structure of the residuals. The choice of a specific

Table 1. Comparison of information criteria for Models 1, 2, and 3.

Criterion	Residual covariance structure		
	Model 1 Variance components	Model 2 AR(1)	Model 3 ARMA(1,1)
$-2 \times$ residual log-likelihood	95 660.3	87 848.6	84 684.6
AIC	95 686.3	87 876.6	84 714.6
Bayesian information criterion (BIC)	95 728.5	87 876.7	84 763.3

The fixed and vessel-specific random parameters are the same for all models, and only the covariance structures vary.

Table 2. Estimates of variance component parameters for Model 3.

Covariance parameter	Subject	Estimate	Standard error	Z-value	Probability Z
Intercept	id	0.019	0.012	1.51	0.0659
Type of trawl	id	0.041	0.007	5.59	<0.0001
Trawl size index	id	0.011	0.003	3.28	0.0005
January	id	0.036	0.012	2.88	0.0020
May	id	0.060	0.012	4.75	<0.0001
June	id	0.018	0.007	2.40	0.0083
July	id	0.182	0.037	4.81	<0.0001
August	id	0.244	0.043	5.68	<0.0001
September	id	0.157	0.028	5.58	<0.0001
October	id	0.018	0.008	2.12	0.0169
November	id	0.026	0.008	3.00	0.0014
December	id	0.020	0.009	2.20	0.0137
ρ	id	0.872	0.004	189.99	<0.0001
γ	id	0.419	0.006	65.79	<0.0001
Residual	–	0.365	0.003	92.95	<0.0001

structure reflects to some extent the analyst's understanding and interpretation of the data-generating process and the fishers' behaviour in the herring fishery. We first compare the fit of the models. Model 1, with the simplest covariance structure for the residuals, acts as a reference model.

Comparison of the information criteria (Table 1) shows that Model 3 with the ARMA(1,1) covariance structure for the residuals is clearly the best. Compared with Models 1 and 2, both the AIC and the BIC are at their minimum for Model 3. Moving from Model 2 to Model 3, the likelihood ratio test of model improvement gives an observed value of $2\ (\log(L_2) - \log(L_3)) = 3164$. This indicates strong statistical significance when referring to the χ^2 distribution with 1 d.f. For Models 1 and 3, we obtain $2\ (\log(L_1) - \log(L_3)) = 10\,975.7$, which is very large and indicates a substantial model improvement in favour of Model 3 (in this case, though, the likelihood ratio test is not completely valid, because Models 1 and 3 are not nested and the degrees of freedom cannot be defined uniquely).

The goodness-of-fit statistics also show that Model 3 fits the data well. The multiple correlation coefficient r^2 for Model 3 is 0.425, and the observed value of the adjusted r-statistic is 0.597. Both statistics indicate that the model explains a large proportion of the total variation.

We now need to evaluate in more detail the results for the covariance structures of Models 2 and 3. In Model 2, an autoregressive structure was assumed for the residuals. The estimated AR(1) parameter was positive and highly significant, indicating strong positive autocorrelation ($\hat{\rho} = 0.3895$) between consecutive trawl hauls. The correlation decreased with increasing temporal difference between hauls. This type of correlation structure seems realistic, because stronger correlation can be expected for trawl hauls with a small temporal difference than for hauls that are more separated.

In Model 3, both residual covariance parameter estimates of the ARMA model, $\hat{\rho}$ and $\hat{\gamma}$, are positive and highly significant (Table 2). This indicates a strong autoregressive structure (parameter ρ), supplemented with a strong moving average structure (parameter γ). The estimates of the statistically significant covariance parameters in Table 2 are variance components which describe the additional variance within vessels. For example, vessel-specific variation in cpue is larger in August than in October. These estimates varied only little between Models 1, 2, and 3.

In Model 1, covariances between successive hauls are assumed to remain equal, which is unrealistic. In Model 2 with its more realistic AR(1) structure, covariances decline quickly with increasing time-lag between hauls. Model 3 with the ARMA(1,1) structure provides a compromise between the equal covariances assumption and the AR(1) covariance structure. In Model 3, covariances tend to decline with increasing time difference, but the moving average parameter flattens the rate of decline.

Estimates of fixed effects for Model 3 are displayed in Table 3. The cpue increases with engine power. For example, if engine power increases by 50 kW, cpue increases in pairtrawling by $\exp(0.691 \log(50)) = 14.9\ \text{kg h}^{-1}$ and in single trawling by $\exp(0.691 \log(50) - 0.209 \log(50)) = 6.6\ \text{kg h}^{-1}$. In North Sea bottom-trawl fisheries, fishing power increased with horsepower too (Marchal *et al.*, 2002).

Cpue increases with stock abundance (Table 3). The relationship between the two is not strictly proportional (Figure 3), but of the type referred to as "hyperdepletion" by Hilborn and Walters (1992). In this type of relationship, the cpue drops much faster than abundance at virgin stock size, whereas the change in cpue will be smaller than the change in abundance when stock size is considerably reduced from its original level. As a diagnostic check for Model 3, the boxplots of residuals (Figure 4) show that when plotted against biomass, the residuals do not indicate any trend. This confirms that it is safe to use a logarithmized linear predictor model in this case.

The cpue of the herring trawl fishery varies seasonally (Table 3). Using August as the reference, because the average cpue in August was nearest to the median of the monthly unit effort, the greatest positive effects are during the spawning season of Baltic herring, in May and June. The clearest negative effects are for September and October. The effects of January, November, and December were not statistically significant. Significant positive effects were also noted for February, March, and April. The number of levels of the month-effect, as well as the levels of year and location effects, was reduced in a stepwise manner to ease the computation of the models. Only the statistically significant levels of the variables were included in the final model.

ICES Subdivision 30 is divided into 27 geographic rectangles to specify the location of trawl hauls. Only five rectangles had a significant effect on cpue (Table 3), and these were used in the final analysis, whereas the effects of the other rectangles were fixed to

Table 3. Estimates of fixed effects and their significance for Model 3.

Effect	Estimate	Standard error	d.f.	*t*-value	Probability > |*t*|
Intercept	−15.922	3.216	135	−4.95	<0.0001
Logarithmic engine power	0.691	0.092	52E3	7.47	<0.0001
Logarithmic total biomass	1.403	0.238	52E3	5.89	<0.0001
Pairtrawling (0)	1.076	0.468	52E3	2.30	0.0216
Log engine power × pairtrawling (0)	−0.209	0.080	52E3	−2.59	0.0097
Trawl size index	0.318	0.051	156	6.23	<0.0001
February	0.172	0.021	52E3	8.08	<0.0001
March	0.162	0.024	52E3	6.69	<0.0001
April	0.182	0.023	52E3	7.69	<0.0001
May	0.268	0.032	137	8.32	<0.0001
June	0.435	0.028	114	15.22	<0.0001
July	0.148	0.051	101	2.91	0.0044
September	−0.106	0.044	115	−2.38	0.0189
October	−0.228	0.024	113	−9.34	<0.0001
Rectangle 22	−0.102	0.028	52E3	−3.60	0.0003
Rectangle 31	−0.063	0.017	52E3	−3.54	0.0004
Rectangle 34	−0.125	0.031	52E3	−4.00	<0.0001
Rectangle 36	−0.183	0.018	52E3	−9.71	<0.0001
Rectangle 37	−0.203	0.045	52E3	−4.42	<0.0001
Year 1990	0.342	0.053	52E3	6.42	<0.0001
Year 1993	−0.171	0.029	52E3	−5.84	<0.0001
Year 1998	−0.132	0.032	52E3	−4.02	<0.0001
Year 2000	−0.155	0.025	52E3	−6.05	<0.0001

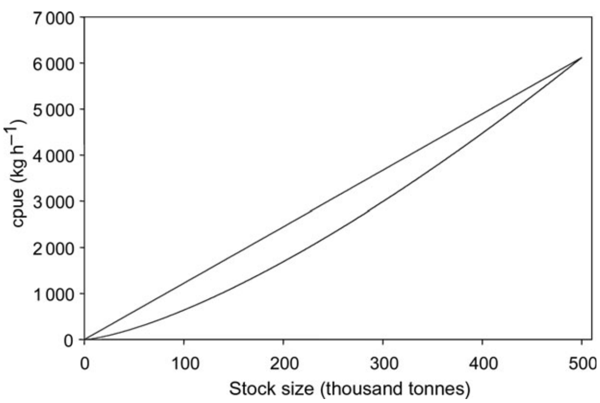

Figure 3. Relationship between cpue and stock size estimated with Model 3 (curved line), and strictly proportional dependence (straight line).

zero to reduce the number of estimated parameters. The effects were negative, indicating that in these rectangles, cpue tends to be lower than on average, although in these rectangles the total catches are quite high, signifying high fishing effort too. Most of these rectangles are near main fishing ports and/or have trawling areas which are either traditional or pose low risk of trawl damage through unfavourable seabed structure. A shorter time spent steaming to fishing areas decreases costs and may well compensate for the lower catch rate.

Statistically significant year-effect estimates indicate differences in fishing power among years, caused by attributes other than trawl size and engine power in the fleet. The year term is used to eliminate the effects of unknown variables which might affect the catch rate, and we can only make educated guesses as to which factors might cause a significant year-effect. Possible reasons might be meteorological conditions: ice conditions in winter, warm/cold summers, or storm frequencies and intensities. In 1990, the cpue was higher than average, attributable to unknown factors included in the year term, whereas in 1993, 1998, and 2000, cpue was lower than the average and the effect could not be explained by other variables in the model, so the year term became significant. Observed and predicted cpue values are presented in Figure 5, with a trend line representing the increase in cpue. Clearly, variation in the monthly average cpue is considerable between and within years, but an increasing trend is still obvious. Even the high cpue values in 1990, discussed above, do not influence this trend line.

When the estimates of fixed effects derived by the three alternative models for logarithmic biomass, logarithmic engine power, and trawl size index are considered, they are similar only in terms of trawl size. Pivotally, interpretation of the results is influenced by the model structure in terms of the impact of logarithmic biomass and logarithmic engine power on cpue (Figure 6). The other difference among a simple model and more elaborate ones is in the improvement of the accuracy of the estimate. In Model 1, the estimated parameter for the stock response is only slightly greater than 1, i.e. the relationship between cpue and stock size is close to proportional. Note too that strict proportionality has been assumed between stock biomass and cpue in XSA. Non-linearity of the relationship becomes clearer with more sophisticated models, indicating that cpue decreases faster than stock abundance.

As a further diagnostic check, fitted values calculated for Model 3 predict quite well the annual and monthly variation at a unit

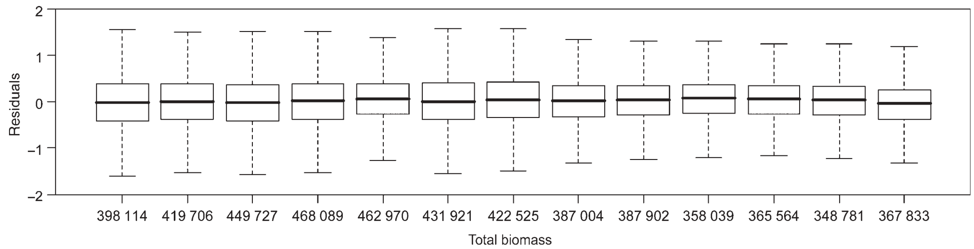

Figure 4. Boxplots of residuals against total biomass for Model 3.

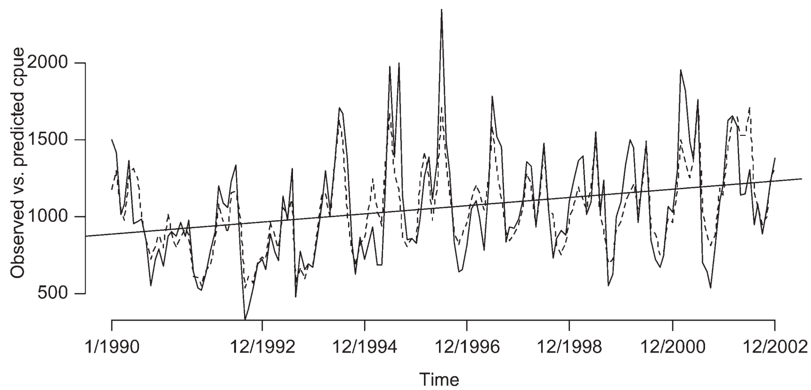

Figure 5. Observed (solid line) and predicted (dashed line) cpue values, with a trend line representing the increase over time of cpue.

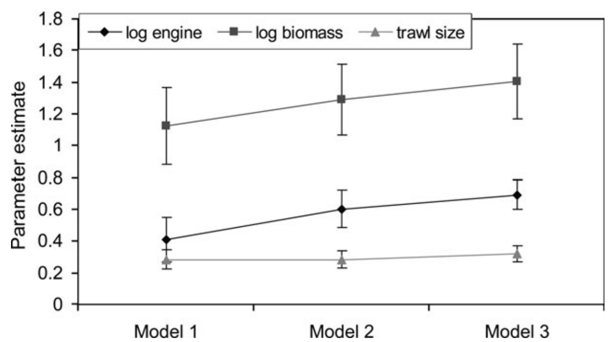

Figure 6. Estimates with their standard errors of three fixed parameters (log engine, log biomass, and trawl size) for Models 1, 2, and 3.

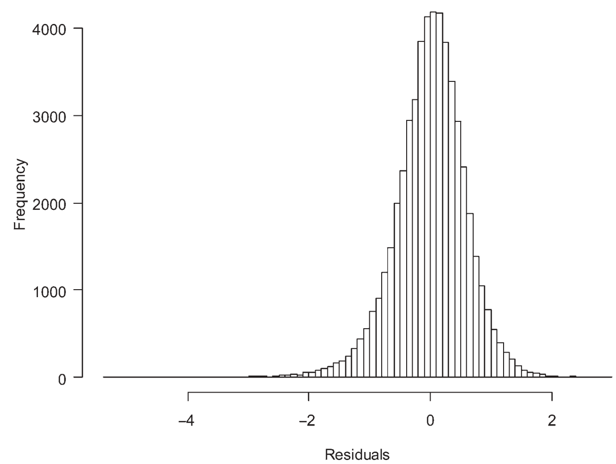

Figure 7. Distribution of residuals for Model 3.

level. Figure 7 shows that residuals of Model 3 are reasonably well distributed normally, even if there is a slight kurtosis. The few outliers in the scatterplot of residuals and predictions (Figure 8) can probably be explained by failures in gear setting. The normal probability plot of the residuals (Figure 9) also suggests that the residuals follow the normal distribution, except for a long tail at the lower end, which is also evident in Figure 7.

Discussion

The main practical goal of the analysis was to determine factors influencing the cpue of herring trawlers in the Bothnian Sea. This type of analysis is important when used in association with assessment procedures where commercial cpue data are applied as tuning series. The results indicate that linear mixed models provide powerful and flexible tools for analysing cpue data. We applied linear mixed models because the independence of trawl hauls cannot be assumed within vessels. Not only the correlation structure but also the vessel-specific variation among different factors could be taken into consideration with mixed models. It is naive to assume that fishing power would not increase over time (Branch *et al.*, 2006). Therefore, adjustment for changes in fleet and gear properties is essential to obtain a valid interpretation of commercial cpue data.

Several studies have used GLMs in cpue analysis (e.g. Large, 1992; Marchal *et al.*, 2001). In our opinion, a pure GLM is the wrong method for such data, because such models cannot take account of a possible correlation of observations caused by the hierarchical structure of the data. However, we made a few additional tests with a GLM, revealing that the models with covariance structures in the residuals were superior to GLMs. For

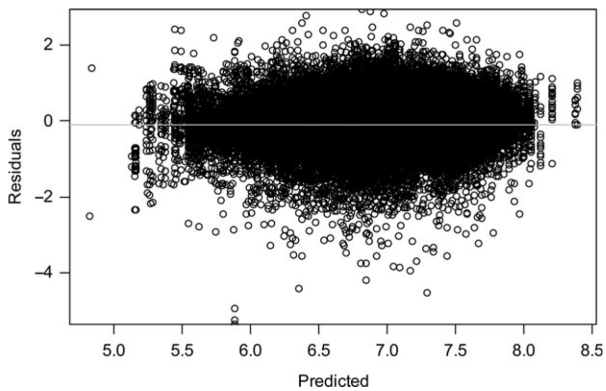

Figure 8. Scatterplot of residuals against predictions for Model 3, with a horizontal trend line.

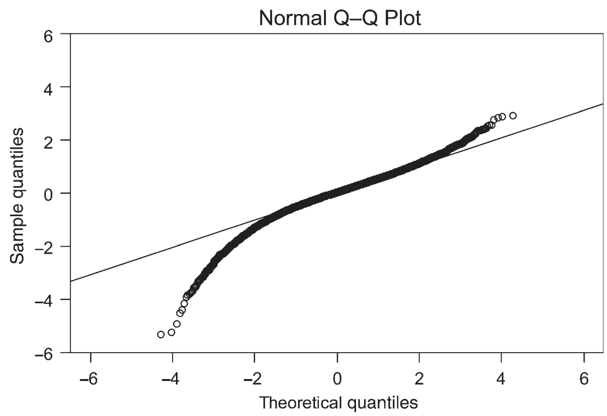

Figure 9. Normal probability plot for the residuals of the model.

example, the coefficients of determination for GLMs with the same set of variables were ~30%, whereas it was >40% for Model 3. Additionally, the residuals of the GLMs seemed to be autocorrelated, against the underlying assumptions of the model.

Here, the cpue data were tested using three models, starting with a simple one, including only the most important effects, and concluding with a model containing several fixed and vessel-specific effects in which the residuals were fitted by including an ARMA structure. Of the range of models tested, Model 3 was the best using standard information criteria. It explained >40% of the variability in the data, which is considered to be high taking into account the stochasticity of the fish capture process. The modelling assumptions between three models (use of autocorrelation) can be linked logically to the behaviour of fishers, i.e. the impact of the skippers' accumulated knowledge in decisions concerning spatial and seasonal distribution of fishing effort. In Model 3 with its ARMA(1,1) structure, covariances tended to decline with increasing time difference between the trawl hauls, but the moving average parameter reduces the rate of decline. This is a realistic assumption of the behaviour of fishers, who utilize knowledge accumulated during many years and even over generations to allocate their fishing effort. Previous research applying random utility models has confirmed that fishers have a great degree of fidelity to past fishing patterns (Holland and Sutinen, 1999; Hutton *et al.*, 2004). In those two analyses, the recent and previous year's catch rate appeared to be significant variables affecting location choice for fishing activity. Our results indicate that fishers integrate and utilize information on catch rate over much longer periods than just a few days or a year when making decisions about where and when to fish.

The most important effects that interact with the variation of cpue are the engine power, the estimated biomass of the herring stock, the trawling method (single vs. pairtrawling), the size of the trawl, and the time and the area of the fishing trip. The effects cannot be arranged according to their influence because they are not standardized effects. Moreover, the vessel-specific variation was explained by the trawling method, the size of the trawl, and the fishing month. A mixed model structure, used here, allows one to compute vessel-specific estimates of fishing power. By adding fishing area as a vessel-specific predictor, it would also be possible to analyse for instance the fishing power per area of individual vessels. Likewise, random effects provide estimates of the influence of trawl size, trawling method, and month on catch rate by each vessel. Consequently, it would be possible to identify vessels that are effective on just a few fishing grounds and vessels that are effective in several fishing areas.

The annual changes in catch rate and in the number of active vessels were notable during the observation period. Seasonal variation was considered by including a monthly effect in the models. The interaction between month and area factors was also tested, but it was not significant in the overall model and did not increase the explanation capability of the model significantly. Vessel-specific month effects take account of the seasonal differences in fishing areas, because skippers know where to go during different seasons. All the models we tested here used the vessels as a grouping factor, taking into account the dynamics in the structure of the fishing fleet as the number and the type of vessels participating in a fishery change over time. The effectiveness of the vessels generally increases over time owing to technical development, including improvements in gear and the hydraulics to manoeuvre the gear, and in electronic navigational aids (Robins *et al.*, 1998). Ignoring these factors may lead to a far too optimistic view about stock trends.

Our results confirm that unweighted cpue data are a biased estimator of stock abundance (Figure 3) and that stock size estimates will be biased when these data are used to tune a population analysis. The clear non-linear relationship between stock size and cpue suggests that changes in stock size have been overestimated in stock assessments. The hyperdepletion pattern may be caused by fisher behaviour if effort is allocated to the best areas in terms of catch rate (Hilborn and Walters, 1992). Also, fish concentration profiles may cause hyperdepletion (Clark, 1982).

The estimated effect of trawl size on the catch rate raises additional uncertainty in a stock assessment. Once the trend in trawl size in the Finnish herring fishery had been discovered (Rahikainen and Kuikka, 2002), the cpue time-series was adjusted by the estimated increase in the stock assessments (ICES, 2007). The adjustment was made in fishing effort data by multiplying the effort by the gear size index. Trawl size has a significant positive effect on the cpue (Table 3), as would be expected. The estimate is clearly below 1, denoting that a pay-off in terms of fishing power is smaller than the increase in the trawl size and that the average trawl size as such is not an adequate indicator of fishing power. The result is as anticipated, because the factors that determine the efficiency of a gear are complicated, and many details of gear technology, gear deployment, and fish behaviour have been omitted from our analysis. Clearly, alterations in the bridle path, i.e. the width swept by the otter boards, bridles, and sweeps, were not considered. Also the density of fish ahead of the trawl mouth and diel vertical migrations of the fish may affect swimming behaviour and catchability (Godø *et al*., 1999; Petrakis *et al*., 2001). The estimate we have now obtained suggests that the increase in fishing power is not strictly proportional to gear size, as has been assumed in the assessment process for this stock thus far (ICES, 2007).

We suggest that fisheries agencies be encouraged to assemble in-depth information on vessels and their gear. Obviously, engine power and trawl size contribute significantly to fishing power and catch rate. Detailed data on positioning systems and acoustic equipment on board would likely be of use in interpreting cpue data. Information on the time budget allocated to searching for herring aggregations and actually trawling was also an attractive explanatory variable, but logbooks of this fishery do not possess data on searching time. During the past 10 years, the Finnish herring fleet has polarized into vessels targeting herring for human consumption and for the fishmeal market (Salmi and Salmi, 1998; Stephenson *et al*., 2001; Rahikainen *et al*., 2004). This divergence in supply strategy implicates major differences in the fishing tactics and on-site dynamics of fishing vessels. Skippers fishing for the fishmeal market simply aim to maximize their catch rate, whereas skippers fishing for the human consumption market have to consider the size distribution of herring they intend to land, likely reducing their potential catch rates. Clearly, interpretations of cpue data may be misleading if the fishing strategy is not properly monitored. Unfortunately, cpue data cannot be assigned with information on fishing strategy currently. Indeed, past fishery evaluations of the ICES Subdivision 30 herring stock have had little predictive capability largely because of the impact of changing biological and industrial aspects of the fishery that have not been incorporated into stock assessments (Rahikainen, 2005).

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Appendix

Figure A1 presents a map of fishing rectangles in the Baltic Sea. Data from rectangles 21–47 are used in this study.

SAS syntax for Model 3 with the ARMA(1,1) structure

```
proc mixed covtest empirical lognote data=ices30;

class id pairtrawling trawltype;

model log_cpue=log_power log_totalbio pairtrawling log_power* pairtrawling sizeindex

month_signif_fixed rectangle_signif year_signif/s outp=d.predarma;

random int trawltype sizeindex month_signif_vessel/solution subject=id g v=7 vcorr=7;

repeated /subject=id type=arma(1,1) r=7 rcorr=7;

run;
```

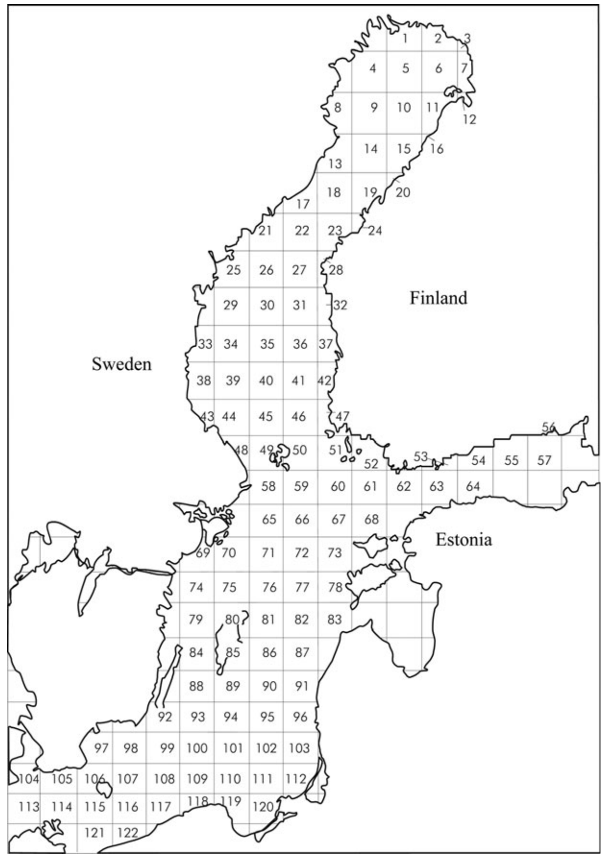

Figure A1. Fishing rectangles in the Baltic Sea. Data from rectangles 21–47 are used in this study.

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