NOT TO BE CITED WITHOUT PRIOR
REFERENCE TO THE AUTHOR(S)

Northwest Atlantic Fisheries Organization

Serial No. N2690

NAFO SCR DOC. 96/17

SCIENTIFIC COUNCIL MEETING - JUNE 1996

Analysis of Catch-per-unit Effort Data for Scotian Shelf Silver Hake, 1977-95

by

Stephen J. Smith and Mark A. Showell
Department of Fisheries and Oceans, Marine Fish Division
P. O. Box 1006, Dartmouth, Nova Scotia, Canada B2Y 4A2

Introduction

At the June 1995 meeting of the NAFO Scientific Council, a paper was presented (Myers, Bowering & Power 1995) which explored potential problems in the standardization technique commonly applied to catch-per-unit effort (cpue) data. This technique, often referred to as Standar after the APL implementation of the method (Anonymous 1986), assumes a multiplicative model, applies a linear model fit to log transformed data and then uses retransformation methods discussed in Gavaris (1980). Using data from the Greenland Halibut fishery, Myers et al. (1995) examined the distribution of residuals from the multiplicative model to test the assumption of homogeneity (constant variance) and explored to see if unaccounted interaction effects in the model might be influencing the results. Their results showed that for Greenland Halibut, changes in the catch rate series were not artifacts related to the analytical technique.

In the assessment of the 4VWX silver hake resource, a similar standardized catch rate based on a multiplicative model has been used as a tuning index in calibration of the VPA since 1990. Discussion at last year's Scientific Council meeting raised the possibility that the analysis of catch and effort data presented in the 1995 4VWX silver hake assessment (Showell & Bourbonnais 1995) might be affected by problems similar those discussed for the Greenland halibut. As a result, a research recommendation was made as follows: "STACFIS expressed concern that for silver hake in Div. 4VWX the interaction effects between month and year in the silver hake cpue model may be influencing the results and recommended that these effects be investigated in future." In this paper we investigate the fit of the multiplicative model to the cpue data for silver hake and evaluate each of the main factors used in the model. Attention is also paid to the distributional assumptions of the model.

Material and Methods

As was the case in the 1995 assessment (Showell & Bourbonnais 1995), estimates of catch and effort were taken from Canadian observer data. Set-by-set observations were selected where silver hake was the main species caught, excluding tows where the trawl was damaged, during the core period of the fishery (April through July). Data were aggregated by year, country (Cuba, Russia), month and area (4W, 4X). In the aggregated data set, observations with less than 30 tons of catch were removed.

The standard application of the catch-rate (cpue) standardization method proceeds as follows (Gavaris 1980, Gavaris 1988). First truncate the catch and effort data for some lower limit of each. This catch and effort data will have been aggregated by time period (e.g., month), country, gear type, etc. Log transform the cpue data and fit a linear model using the categorizations of country, month, area, year, etc. as factors and assuming that the residuals have a normal distribution. This form of the linear model is often referred to as an ANOVA model (ANalysis Of VAriance, Cochran & Cox 1957, Hicks 1982). For each factor, one level (e.g., a specific month) is declared to be the **standard** against which all other levels are to be compared. Operationally, something like this has to be done to ensure that the design matrix is full rank and can be inverted to estimate the parameters. Once the model has been fitted, predicted values in the log scale are obtained for each year for some preselected level of each factor. These predicted values are retransformed according to the methods given in Gavaris (1980) to the original scale of measurement (e.g., tonnes per hour) with associated standard errors. This so-called **standardized** cpue series is then used for tuning sequential population analyses, etc.

In this paper we will concentrate on the linear model fit aspect of the standardization process. We use standard tools (see for example material in McCullagh & Nelder 1989) associated with linear models such as residual plots and hypothesis testing to evaluate fit.

Results

The ANOVA table for the standard application of the multiplicative model to silver hake data for the terms Country, Month and Year give significant F-statistics, while Area does not seem to be significant term (Table 1a). However, if the order of entry of the terms is changed by exchanging Year for Country, Area becomes significant (Table 1b). This behaviour suggests that the differences accounted for by Area are really a function of the differences between countries. Indeed the mean log(cpue) for Cuba and Russia in Area 4W and 4X are respectively, 0.54 and 0.67, and 0.50 and 0.63. These means are very similar to those for each country when calculated over both areas (Cuba — 0.53, Russia — 0.66) and implies that area differences may simply be due to how much each country fished in each area.

The recommendation from NAFO suggested that the Month-Year interaction term be investigated and indeed such a term is significant when added to the model ($p < 0.0001$). However, before any interaction terms can be blindly added to the model, two aspects need to be investigated further. The residual plot from the multiplicative model used in last year's assessment (Table 6: Showell & Bourbonnais 1995) indicated that problems may exist in the normality assumption or assumption of common variance or both. Secondly, the behaviour exhibited in Table 1 suggests that we have some aliasing between main effects which needs further attention.

The implications of the first problem is that the results of the F tests in Table 1 may not be reliable for judging the significance of any of the factors including interaction terms added to the model. The residuals corresponding to the models in Table 1 are presented in Fig. 1. Note the larger scatter of points for the lower range of predicted values as well as the trend in the local mean residuals above the zero line as indicated by the fitted Lowess line (Cleveland & Devlin 1988). The pattern in the scatter of the residual points suggests that the variance of the residuals is not constant over the range of predicted values. Additionally, there appears to be a trend towards underestimation by the model as the predicted values increase.

Constant variance is required for the normal distribution and the log transform was applied to the original data assuming that this assumption would be met. Assumptions concerning constant variance can be investigated for the original data by looking for mean/variance (or standard deviation) relationships over the factor groupings. Mean cpue and standard deviations for the original data and log transformed data for each year are presented in Fig. 2. The pattern in Fig. 2a suggests a constant coefficient of variation which is characteristic of the gamma distribution (McCullagh & Nelder 1989). If the log transform to normality had worked for these data the expected pattern for Fig. 2b would have been a horizontal band of points. Instead, the data seems to be more variable at the lower range of the means, the same pattern noted for the residuals in Fig. 1.

If a constant coefficient of variation is appropriate for these data then, we may be better served by fitting a gamma distribution to the original data instead of using the log transform. The results of fitting such a generalized linear model (McCullagh & Nelder 1989) are presented in Table 2. A log link functio was used to correspond to a multiplicative model. The theory of generalized linear models refers to the measure of the discrepancy between the observed and fitted values from a model, formed from the logarithm of the ratio of the respective likelihoods as deviance. The deviance is defined with respect to the probability distribution used. Evaluation of whether or not factors/covariates explain significant portions of the total deviance is generally done for nested models using a χ^2-test (page 119, McCullagh & Nelder 1989). The χ^2-test was used here to evaluate the fit of the factors. The results in Table 2a differ from those in Table 1a by showing that only Month and Year were significant when entered in the standard way. However, when Year is entered first Month becomes less significant (Table 2b).

The difference between Table 2a and Table 2b brings us back to the second point to be investigated. That is, if the significance of a factor is dependent upon its order of entry in the model, indicating aliasing between factors, then how can we determine which factors are important? One very useful way of doing this is to use what has been called the all-subset model building approach (Lawless & Singhal 1978). This approach proceeds as follows. First fit all of four of the factors to the data. Then compare the fits via change in deviance for all possible models with three of the factors with the full model. The three factor model with the smallest change in deviance (and non-significant χ^2) would be chosen as a equivalent model in terms in explanatory power. Further, compare all possible models with two of the terms chosen for the three factor model against the full model in a similar manner. Finally, from the best two factor model test the fit for each of the two factors to determine the best one factor model.

The results of applying the above procedure to the full model in Table 2a is presented in Table 3. The conclusion from this table is that a model with just Year in it has as much explanatory power as that with all four factors included. Month is a best a marginal effect. Given that we only have a one factor model then interaction terms are no longer an issue.

The residuals from the model cpue=1+Year are plotted against the fitted values transformed to the constant-information scale for the gamma distribution (page 398, McCullagh & Nelder 1989) in Fig. 3. Residual plots for generalized linear models can be interpreted in the similar manner to that for normal models when presented in this way. Overall, there do not appear to be any problems concerning non-constant variance or tendency to over or underestimation for this model.

The resultant predicted values for the original scale of measurement with limits indicated for approximate 95 percent confidence intervals are presented in Fig. 4. A big advantage of using the Gamma distribution in a generalized linear model is that no transformation of the observations is required to fit the model and hence the retransformation formulae given in Gavaris (1980) are unnecessary here.

Discussion

The usual application of the multiplicative model to standardize catch rates representing a number of different sources in a stock assessment generally concentrates on fitting the model and obtaining the standardized catch rate for use in calibrating sequential population analysis. While there are exceptions (e.g., Sinclair & Smith 1987, Myers et al. 1995), attention is rarely paid in assessment documents to investigating the actual fit of the model to the data. The main purpose of the multiplicative model is to try to objectively combine different cpue series which hopefully contain the same basic signal over time. As a general approach to this problem there is no requirement to stick to using the log transform and the normal distribution. In fact, Firth (1988) found that the gamma distribution was a more robust choice when comparing the performance of gamma and lognormal multiplicative models.

The results of our analysis showed that the lognormal was not a reasonable distribution for our data. When the gamma distribution had been used and all-subset model fitting was applied to remove the effect of order of entry of the covariates the only factor that remained in the model was Year. Interactions are no longer an issue because we only have one factor.

Our application of fitting a multiplicative model was meant to mimic, what may be considered by default, *standard procedure*. That is, catch and effort data was aggregated over the major categories of country/area/month for each year. When data aggregated in this way is then converted to catch rate we don't have any associated measure of the amount of information (i.e., number of records) that contributed to each observation. If we assume that the more catch/effort records that a catch rate is based on implies an increase in precision then we are not using this information when comparing catch rates across months, countries or areas. Instead the catch rate for each combination is treated equally. Therefore, while there may be more significant factors in our data, including interaction terms, we found no evidence for them at the current level of aggregation of the data.

References

Anonymous (1986). CAFSAC Assessment software catalogue, *CAFSAC Research Document* **86/96**: 24 p.

Cleveland, W. S. & 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. & Cox, G. (1957). *Experimental Designs*, Wiley, New York.

Firth, D. (1988). Multiplicative errors: Log-normal or gamma?, *Journal of the Royal Statistical Society, Series B* **50**: 266–268.

Gavaris, S. (1980). Use of a multiplicative model to estimate catch rate and effort from commercial data, *Canadian Journal of Fisheries and Aquatic Science* **37**: 2272–2275.

Gavaris, S. (1988). Abundance indices from commercial fishing, *in* D. Rivard (ed.), *Collected Papers on Stock Assessment Methods*, CAFSAC Research Document. 88/61., pp. 3–15.

Hicks, C. R. (1982). *Fundamental Concepts in the Design of Experiments*, third edn, Holt, Rinehart and Winston, New York.

Lawless, J. F. & Singhal, K. (1978). Efficient screening of non-normal regression models, *Biometrics* **34**: 318–328.

McCullagh, P. & Nelder, J. A. (1989). *Generalized Linear Models*, 2 edn, Chapman and Hall Ltd, London, England.

Myers, R. A., Bowering, W. R. & Power, D. (1995). An analysis of catch per unit effort for Greenland halibut off Newfoundland, *NAFO SRC Doc.* **95/65 N2580**: 8 p.

Showell, M. A. & Bourbonnais, M. C. (1995). Assessment of the 4VWX silver hake population in 1994, *NAFO SCR Doc.* **95/76 N2593**: 22 p.

Sinclair, A. & Smith, S. J. (1987). Assessment of 4VsW cod, *CAFSAC Research Document* **87/72**: 62 p.

Table 1. Comparison of analysis of variance results when the order of entry of the model terms are changed. Log transformed catch-per-unit effort data from silver hake on the Scotian Shelf, 1977–1995.

Terms	Df	Sum of Squares	Mean Square	*F*-Value	*p*-level
a) Standard order of entry					
COUNTRY	1	1.288	1.288	9.136	0.003
AREA	1	0.126	0.126	0.897	0.344
MONTH	3	6.954	2.318	16.446	<0.000
YEAR	18	55.402	3.078	21.839	<0.000
Residuals	299	42.140	0.141		
b) Altered order of entry					
YEAR	18	53.985	2.999	21.280	<0.000
AREA	1	0.903	0.903	6.410	0.012
MONTH	3	8.036	2.679	19.005	<0.000
COUNTRY	1	0.846	0.846	6.006	0.015
Residuals	299	42.140	0.141		

Table 2. Comparison of analysis of deviance results when the order of entry of the model terms are changed. Catch-per-unit effort data from silver hake on the Scotian Shelf, 1977–1995. Generalized linear model using a Gamma distribution with log link. The p-level refers to a χ^2 statistic.

Terms	Df	Deviance	p-level
a) Standard order of entry			
COUNTRY	1	1.407	0.235
AREA	1	0.109	0.741
MONTH	3	12.143	0.007
YEAR	18	54.688	<0.000
b) Altered order of entry			
YEAR	18	58.518	<0.000
AREA	1	0.906	0.341
MONTH	3	8.148	0.043
COUNTRY	1	0.775	0.379

Table 3. Analysis of deviance results for all-subset model fitting for catch per unit effort data from silver hake fishery, 1977–1995. Gamma model with log link used. The p-level refers to a χ^2 statistic.

Terms	Change in Deviance	Df	p-level
1+Country+Area+Month+Year			
1+Area+Month+Year	-0.775	1	0.38
1+Month+Year	-3.071	2	0.22
1+Year	-9.830	5	0.08
1	-58.518	23	<0.000

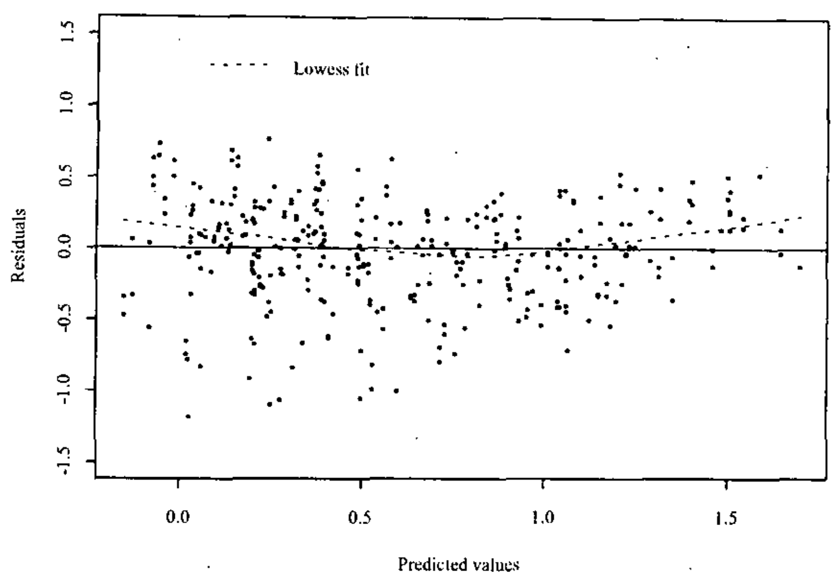

Figure 1. Residuals plotted against predicted values from the standard multiplicative model for Scotian Shelf silver hake cpue data assuming lognormal distribution with cpue=1+Country+Area+Month+Year.

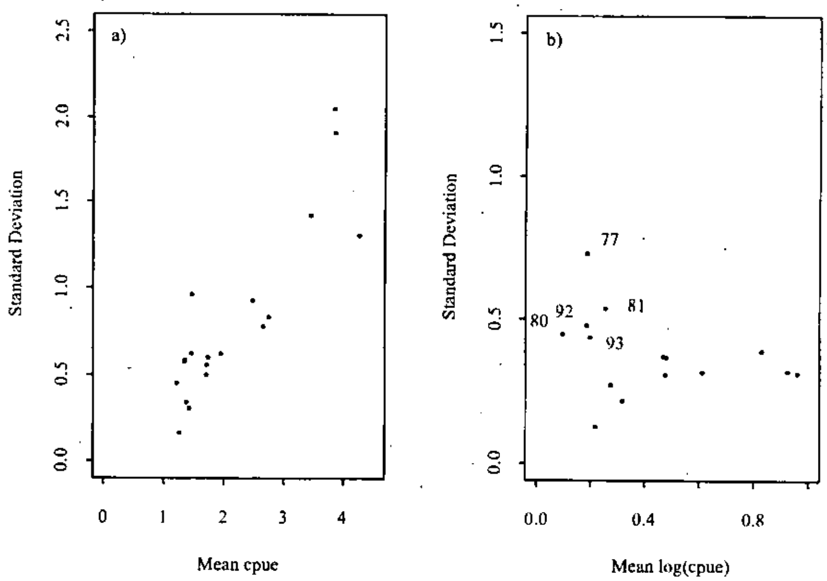

Figure 2. a) Mean cpue by year plotted against respective standard deviation, and b) mean log(cpue) by year plotted against respective standard deviation of cpue for Scotian Shelf silver hake cpue data.

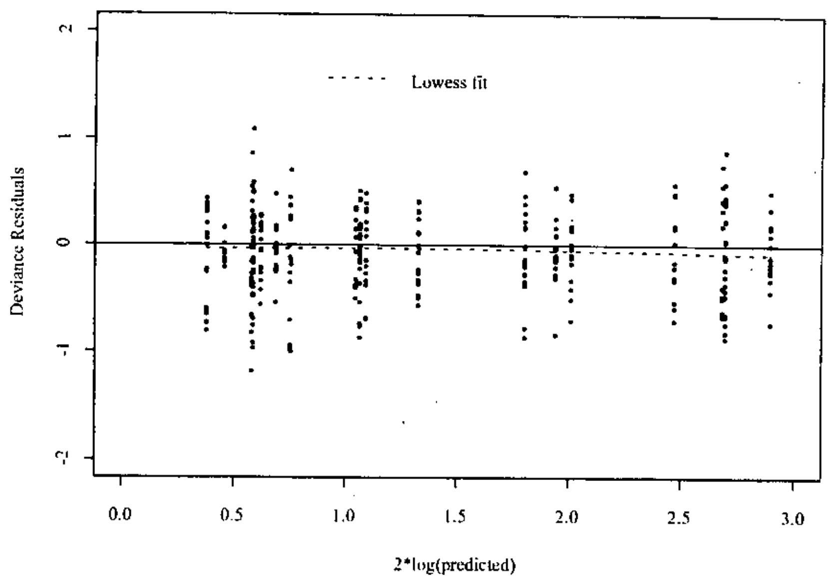

Figure 3. Deviance residuals plotted against scaled predicted value for Scotian Shelf silver hake cpue data. Model chosen was cpue=1+Year with Gamma distribution and log link.

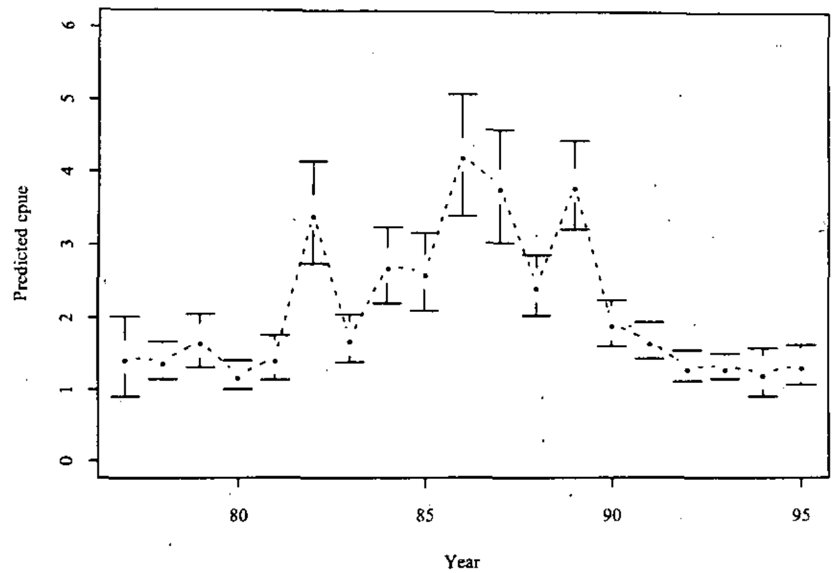

Figure 4. Predicted cpue from model cpue=1+Year assuming a Gamma distribution with log link. Upper and lower bounds represent approximate 95 percent confidence limits.