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A NUMERICAL EVALUATION OF LOGNORMAL, DELTA-LOGNORMAL AND POISSON MODELS FOR STANDARDIZING INDICES OF ABUNDANCE FROM WEST ATLANTIC BLUEFIN TUNA CATCH PER UNIT EFFORT DATA (PRELIMINARY RESULTS)

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SUMMARY

In 1994, the SCRS conducted VPA assessments of west Atlantic bluefin tuna using both log-normal and Poisson models to standardize the CPUE indices of abundance. The VPA using the Poisson-standardized CPUE series was adopted as the base case because it returned a substantially lower residual sum of squares than did the VPA using the log-normal-standardized CPUE. The SCRS stressed, however, that their decision was not a judgement in favor of the Poisson model as the most appropriate. They pointed out that there have been few studies on this topic. This paper uses artificial data with known population statistics to examine the efficacy of the log-normal, delta-log-normal and Poisson models when the data are Bernoulli distributed.

RÉSUMÉ

En 1994, le SCRS a évalué la VPA du thon rouge de l'Atlantique Ouest avec les modèles lognormal et Poisson pour standardiser les indices d'abondance de la CPUE. La VPA dérivée de la série CPUE standardisée par le modèle Poisson a été retenue comme cas de base car elle donne une somme résiduelle des carrés substantiellement inférieure à celle que donne la VPA dérivée de la CPUE standardisée avec le modèle lognormal. Toutefois, le SCRS a insisté sur le fait que cette décision ne signifiait pas que le modèle Poisson est le plus adéquat. Le SCRS a rappelé que peu d'études avaient été entreprises sur ce sujet. Ce document utilise des données artificielles avec des statistiques connues de population pour examiner l'efficacité des modèles lognormal, delta-lognormal et Poisson lorsque les données sont distribuées selon Bernoulli.

RESUMEN

En 1994, el SCRS realizó evaluaciones por VPA del atún rojo del Atlántico oeste, aplicando modelos lognormales y modelos Poisson para estandarizar la CPUE de los índices de abundancia. El VPA que aplicaba series de CPUE estandarizadas con el modelo Poisson se adoptó como caso base, debido a que daba una suma residual de cuadrados mucho mas baja que el VPA que aplicaba la CPUE lognormal estandarizada. No obstante, el SCRS subrayó que esta decisión no era un juicio a favor del modelo Poisson como el mas adecuado. Señaló que se habían hecho pocos estudios al respecto. Este documento emplea datos artificiales con estadísticas de población conocidas para examinar la eficacia de los modelos lognormales, delta lognormales y Poisson cuando los datos están distribuidos según Bernoulli.

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INTRODUCTION

In 1994, ICCAT's Standing Committee on Research and Statistics (SCRS) conducted VPA assessments of West Atlantic bluefin tuna using both lognormal and Poisson models to standardize the CPUE indices of abundance (Brown 1995). The VPA using the Poisson-standardized CPUE series was adopted as the base case. The SCRS stressed, however, that their decision was not a judgement in favor of the Poisson model as the most appropriate approach in general. They pointed out that there have been few studies on this topic.

Porch and Scott (1994) used a Monte-Carlo approach to examine the ability of general linear models (GLMs) of catch per trip to index the interannual trends in the abundance of West Atlantic **small** bluefin tuna. They found that the delta-lognormal model of Lo et al. (1992) best reproduced the true trends. The index adopted by the SCRS in their 1993 assessments, however, was based on the average catch per line-hour, pooled across five different trips, rather than the catch on a single trip (Brown and Browder 1994). Porch (1994) therefore evaluated the relative performance of the different GLM methods using Brown and Browder's aggregated data set as the template for generating artificial data sets. He found that the choice of GLM model (delta-lognormal or lognormal using a variety of additive constants) was unimportant when the data are aggregated. Dong and Restrepo (1996) fit negative binomial and Poisson models to the (U.S. rod and reel) large fish CPUE data and found that both models similarly satisfied the variance-mean expectations. This is in contrast to their findings for the (U.S. rod and reel) small fish data, for which the negative binomial distribution was found to be a much better choice than the Poisson model.

This study essentially repeats Porch's (1994) analysis, excepting that data from the **large** bluefin tuna fishery are used as a template for generating artificial data which are Bernoulli distributed. Furthermore, the efficacy of the Poisson model in addition to the lognormal and delta-lognormal are examined using the artificial data, which have known population statistics.

METHODS

Model Evaluation

Three types of GLM models were studied: ln(CPUE+c), the delta-lognormal and Poisson. The mathematical details of these models are explained fully in Porch and Scott (1994). The constants used in the ln(CPUE+c), or lognormal, GLMs was an arbitrary small value-- 0.001 (Note: The SCRS has used various additive constants in past analyses, including values up to 10X the maximum observed CPUE; the present study considers only the small constant case). Effort units in each case were line-hours (number of lines * number of hours fishing).

Each of the above models were applied, in manners consistent with what had been done in previous SCRS assessments, to 500 different artificially-generated data sets. Thus, the lognormal GLMs were applied to artificial data sets which were aggregated across 15 different trips; the delta-lognormal and Poisson GLMs were applied to artificial data representing single trips. For the purposes of the simulations, the abundance trends were assumed to be known and were determined from the most recent VPA results. The estimated indices (standardized CPUE) for each year y in data set k (I_{yk}) were normalized by their mean ($R_{yk}=I_{yk}/I_{k}$) and compared to the normalized vector of "known" abundance ($A_y=N_y/N$). The error was calculated as $E_{yk}=R_{yk}-A_y$

The accuracy and precision of the GLM outputs were evaluated by examining the average error over all data sets ($E_{y.}$) and the coefficient of error:

$$CE_y = \frac{\sqrt{\langle E_{yk}^2 \rangle}}{A_y} \quad .$$

The angle brackets denote the ensemble average. The coefficient of error is essentially the coefficient of variation with the sample mean replaced by the known value.

Data generation

The 500 artificial data sets were created assuming catch per trip was Bernoulli distributed; that is, on any given trip there are two possible outcomes-- zero or one fish. The Bernoulli approach was taken because catches larger than one were rarely observed, due to a variety of factors including: 1) bag limits, 2) the financial incentive to rush each fish to market as quickly as possible and 3) the basic rare event nature of the catches.

The Bernoulli distribution has a single parameter, P_{jk}, which is the probability of catching a fish on the k'th trip within strata j. Artificial observations were drawn from the Bernoulli distributions by equating the catch to one if a uniform random number generator produced a value less than or equal to the expected value of P_{jk}. Otherwise, the catch was set to zero. The number of observations belonging to each strata of each artificial data set was the same as in the real data set.

The strata chosen were year, month of the year and region as described in Brown (1995). Within each strata the probability of catching a fish during any given line-hour, p_j, was held constant. The P_{jk}'s were defined as

$$P_{jk} = f_{jk} p_j \quad , \tag{1}$$

where f_{jk} is the observed number of line-hours associated with the k'th trip in strata j. Strictly speaking, the appropriate formula is

$$P_{jk} = 1 - (1 - p_j)^{n_{jk}} \quad ,$$

where n_{jk} is the potential number of line-hours the k'th trip in strata j would be willing to exert. In practice, n is not known for those trips which caught a fish since they normally return to port immediately thereafter. However, it can be shown that for small p, equation (1) will suffice.

The probability of catching a fish during a given line-hour is the same as the expected catch for that line-hour (CPLH) inasmuch as it is only possible to catch a single fish. Accordingly, the expected value of p for a given strata was computed from the model

$$p_{mry} = q_0 M_m R_r N_y \tag{2}$$

q_0	=	reference catchability
M_m	=	month effect on q and N
R_r	=	regional effect on q
N_y	=	abundance in year y.

The month and region effects were obtained by running a Poisson GLM on the real data. The month effects for July, August and September were 0.644, 0.599 and 1.000, respectively. The regional effects were 0.833 and 1.000. The reference catchability (1.53×10^{-7}) was obtained by regressing the Poisson GLM estimates of standardized CPLH on VPA estimates of stock abundance for age 8 and older large bluefin tuna. The VPA estimates of abundance were obtained from the latest SCRS assessments (ICCAT, 1995). The abundances used for 1994 and 1995 were arbitrarily set to 30,000 and 40,000 fish, respectively. Note that the use of GLM and VPA estimates to generate parameter values for equation (2) was intended to capture the scale of the variations one might expect for large bluefin tuna rod and reel CPUE.

RESULTS

The delta-lognormal and Poisson models estimated very similar patterns that generally reflected the underlying abundance and artificially generated catch rate trends (Figure 1). However, the lognormal model tended to overestimate relative abundance during the earlier years and to underestimate relative abundance during the more recent years, with the exception of the final year. Overall, the most accurate estimates were obtained using the GLMs employing the Poisson model, but the GLMs using the delta-lognormal model also performed well (Figures 3 and 4).

CONCLUSIONS

The results of this study indicate that, in terms of predicting abundance trends accurately, the choice of GLM model may be important when the catch rate data have characteristics similar to those of the artificially generated data used for this study. Although both the delta-lognormal and particularly the Poisson model produced fairly accurate estimates of the underlying abundance trends, the lognormal model appeared to exaggerate the "known" abundance trends. When the "known" population trend showed moderate declines, the lognormal GLMs estimated much larger declines; similarly, the lognormal model tended to show large increases when the underlying trend experienced modest increases.

The lognormal model was the only model tested using aggregated data and only one additive constant was evaluated. The results presented here do not provide any indication as to whether the inaccuracies are the result of the lognormal distribution assumptions, the aggregation effects, or a combination of the two. The decision to use aggregated data when applying the lognormal model in past SCRS assessments was based upon the extremely high proportion of zeros in the raw data. Lognormal GLMs generally provide very poor fits, in terms of variability explained and residual distributions, to the single trip data from the large bluefin tuna fishery; aggregated data appear to be more lognormally distributed and the lognormal models have provided better fits when applied to such data.

Porch (1994), found that the choice between delta-lognormal GLMs and lognormal GLMs employing a variety of additive constants had little influence on the estimated CPUE indices and that all models generally reflected the underlying trends for data artificially generated to represent small bluefin catch rate information. This difference from the results presented in this paper is likely due to the difference in assumed catch distributions between small and large bluefin tuna. Trips targeting small bluefin have a lower proportion of zeros and there is a relatively wide range of numbers of fish caught per trip; large fish catches simulated for this paper were restricted to either 0 or 1 in the artificial data, similar to most of the fishery data.

How the underlying assumptions used to generate the simulated data sets influence the efficacy of the various models have yet to be evaluated. Thus, conclusions cannot yet be drawn as to which of the models examined is the most appropriate for fitting actual catch rate data.

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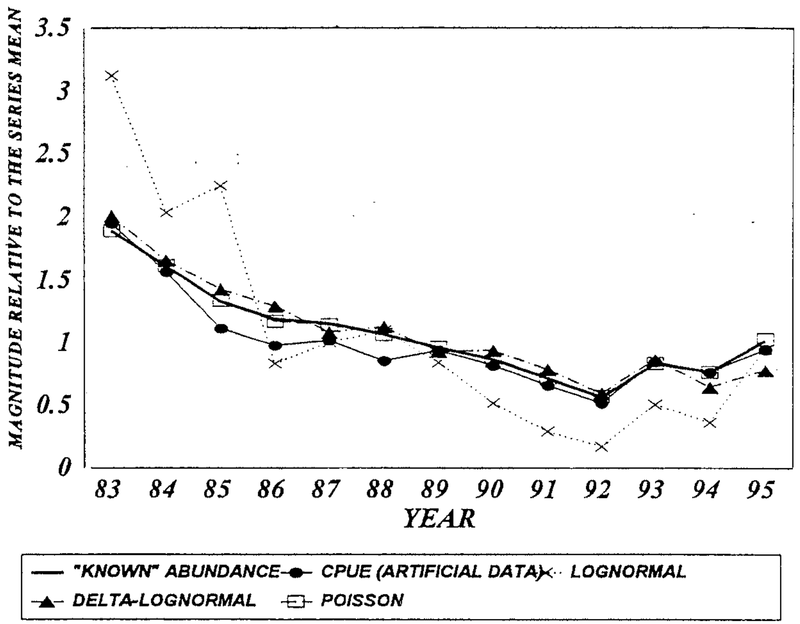

Figure 1. Average values of the estimated indices of relative abundance versus the known trends of [simulated] relative abundance and CPUE. Values for each series have been standardized relative to the series mean.

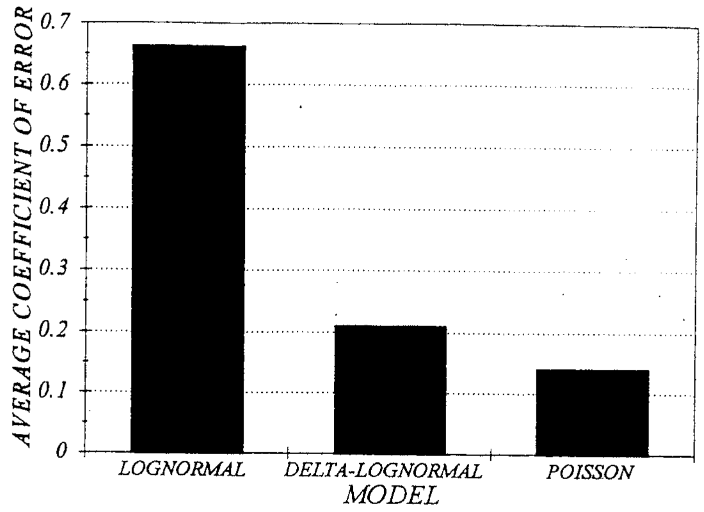

Figure 2. Average coefficient of error associated with each method.

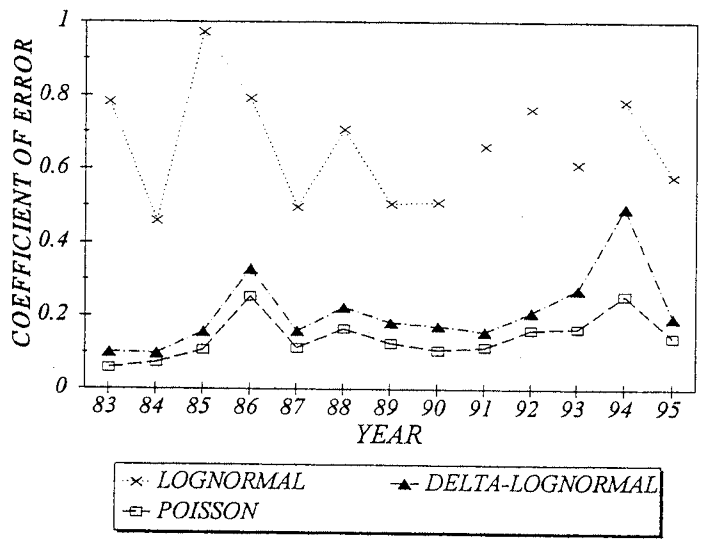

Figure 3. Coefficients of error by year.