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THE IMPLICATIONS OF USING THE FREQUENCY OF ZERO CATCHES AND OTHER MEASURES AS INDICES OF ABUNDANCE

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SUMMARY

It has been suggested that the distribution properties of within-cell CPUE are much more sensitive to changes in abundance than average CPUE. Bannerot and Austin (1983) suggested that the frequency of zero catches and certain transformations thereof would be useful alternatives. This paper re-analyzes Bannerot and Austin's data to further elucidate the implications of using these alternative indices of abundance. The implied relationship between average CPUE and abundance is deduced from the alternative indices assuming CPUE is negative-binomial distributed. Finally, an additional alternative, the catch-per-unit-search effort, is proposed and applied to Bannerot and Austin's data.

RÉSUMÉ

On a suggéré que les propriétés distributives de la CPUE intracellulaire étaient beaucoup plus sensibles aux changements d'abondance que la CPUE moyenne. Bannerot et Austin (1983) ont suggéré que la fréquence des captures nulles et certaines des transformations qui en découlent seraient des alternatives utiles. On a analysé de nouveau les données de Bannerot et Austin pour rechercher les implications de l'emploi de ces indices alternatifs d'abondance. La relation présumée entre la CPUE moyenne et l'abondance est dérivée des indices alternatifs qui supposent que la CPUE est distribuée selon le modèle binomial négatif. On propose également une autre alternative - la capture par unité d'effort de recherche - que l'on applique aux données de Bannerot et Austin.

RESUMEN

Se ha sugerido que las propiedades distributivas de la CPUE dentro de una célula son mucho mas sensibles a los cambios en la abundancia que la CPUE media. Bannerot y Austin (1983) sugirieron que la frecuencias de capturas cero y algunas transformaciones relacionadas serían alternativas útiles. Este documento analiza de nuevo los datos de Bannerot y Austin con el fin de seguir dilucidando lo que implica usar estos índices de abundancia alternativos. La relación implícita entre la CPUE media y la abundancia se deduce de los índices alternativos que asumen que la CPUE tiene una distribución binomial negativa. Finalmente, se propone, y se aplica a los datos de Bannerot y Austin, la captura por unidad de esfuerzo de búsqueda como alternativa adicional.

The indices of abundance used by the SCRS have been standardized assuming the catch per unit effort (CPUE) is linearly related to the abundance of the stock being fished:

$$CPUE_{ijy} = Q_j N_y \Psi_i \tag{1}$$

i	index of an observation in strata j of year y
N_y	stock abundance in year y
Q_j	catchability/availability coefficient in strata j
Ψ	function describing the error structure.

To date, most of the SCRS' attention has centered on the choice of strata and the most appropriate form of Ψ. Several studies, however, have shown that average CPUE is relatively insensitive to changes in abundance (Peterman and Steer, 1981; Bannerot and Austin, 1983; NMFS, 1984). Numerous authors have demonstrated an asymptotic relationship between average CPUE and N. Fox (1974) and others have suggested expressing CPUE as a power function of N. The standardized CPUE series could be regarded as an index of N^b, and b could be estimated along with the proportionality factor q within the VPA (as suggested by Parrack, 1986)

Bannerot and Austin (1983) suggested that a more practical solution may be to replace the mean CPUE with a less-biased index of abundance. They were able to show that the relative frequency of zero CPUE (P_0), and various transformations thereof, was a better indicator of yellowtail snapper abundances than the mean CPUE. They argued that P_0 is likely to be useful for many other fisheries as well, particularly those with a large proportion of zero catches. While P_0 may be less useful for fisheries where zero catches are infrequent, the general principle of increasing rightward skew with decreasing abundance should still hold.

In a review of Atlantic bluefin tuna data, NMFS (1984) noted that the frequency distributions of bluefin tuna catches by Japanese longliners in the Gulf of Mexico became increasingly right-skewed from 1978-79 to 1980-81 whereas the mean CPUE showed no change. Simulation analyses indicated that mean CPUE estimates were biased upwards by about 5 percent. However, the bias would increase substantially as the stock declined--potentially preventing the actual declining trend from being detected (NMFS, 1984).

This paper reanalyzes Bannerot and Austin's data to further elucidate the implications of using P_0 and its transforms as indices of abundance. The relationship between average CPUE and abundance is deduced from the alternative indices assuming CPUE is negative-binomial distributed. Finally, an additional alternative, the catch per unit search effort, is proposed and applied to Bannerot and Austin's data.

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REANALYSIS OF YELLOWTAIL SNAPPER CPUE

Bannerot and Austin (1983) found that the apparent catchability coefficient of yellowtail snapper decreased with abundance such that the power function $0.2731N^{0.4935}$ provided a much more acceptable fit to the CPUE data than the conventional linear model (Figure 1a). While the power function approach has been popular in the literature, it lacks some appeal in that it is entirely empirical with no theoretical justification. Beddington (1979) and Cooke (1985) developed an equation relating CPUE to abundance when the effort spent handling the catch is proportional to the number of fish caught:

$$CPUE = \frac{qN}{1+hqN} \tag{2}$$

q	catchability/availability coefficient
h	number of effort units spent handling one fish.

This model seems especially appropriate for fisheries such as yellowtail snapper (and perhaps bluefin tuna) where fish are caught individually. Indeed, it fit the yellowtail data even better than the power function (Figure 1b).

Bannerot and Austin (1983) also showed that the relative frequency of zero catches P_0, the square root of P_0, and $\log_e(P_0)$ were all much better correlated with the observed abundance of yellowtail snapper than was the mean CPUE. Moreover, the percent change in P_0 was much better correlated with the percent change in N than was the percent change in the mean CPUE. The correlation coefficient however, measures only the extent to which two variables are linearly correlated. It is therefore instructive to plot the data so that any departures from linearity may be examined visually. Bannerot and Austin (1983) did not publish their raw data, however they did present graphs of fits of the negative binomial distribution to pooled catch per unit effort frequency distributions as well as the corresponding negative binomial parameters (mean CPUE and dispersion coefficient k) and local abundance.

The number of observations (effort) for each distribution was reconstructed by dividing the expected frequency of zeroes read from the graph by the expected relative frequency of zeroes computed from the negative binomial parameters. The observed relative frequency of zeroes could then be computed by dividing the observed frequency of zeroes read from the graph by the computed total effort. The total catch associated with each frequency distribution was then computed as the mean CPUE multiplied by the total effort.

Fits of P_0 and the transformations of P_0 mentioned above are shown in Figure 2. A linear correlation between P_0 and N implies the relationship

$$P_0 = b - aN \quad . \tag{3}$$

Since $P_0 = 1$ when $N = 0$ we can deduce that $b = 1$. Equation 3 was fitted to the data by use of linear regression where b was both estimated as a free parameter and fixed to 1.0 (Figure 2a). The regression that estimated b did fit the data fairly well, however it was unrealistic at low levels of abundance. The regression conditioned on $b = 1.0$ performed very poorly.

A linear correlation between the square-root of P_0 and N implies the relationship

$$P_0 = (b - aN)^2 \quad , \tag{4}$$

where again one would expect $b = 1$. The linear regression with b as a free parameter (Figure 2b) performed slightly better than that of equation 3. The regression with b fixed to 1.0 was much less efficient, but still much better than the corresponding regression of equation 3.

The best fit to the data was provided by regressing $\log_e(P_0)$ against N, which corresponds to the model

$$P_0 = e^{(b-aN)} \quad . \tag{5}$$

Solving for $P_0 = 1$ when $N = 0$ yields a value of 0 for b. The regressions with b as a free parameter and fixed to zero are shown in Figure 2c. In this case the estimated value of b is fairly close to zero and the two curves are quite similar.

The last linear correlation examined was the percent change in P_0 against the percent change in N:

$$\frac{P_{0,i} - P_{0,k}}{P_{0,k}} = -a\frac{N_i - N_k}{N_k} \quad .$$

For very small changes in N this is approximately equivalent to

$$\frac{dP_0}{P_0} = -a\frac{dN}{N} \quad ,$$

which has solution

$$P_0 = bN^{-a} \quad . \tag{6}$$

This function is undefined for $N = 0$ when a is positive, but we observe that P_0 ought to be close to 1 when $N = 1$ so that

$$b \equiv \frac{P_0(N{=}1)}{1} \approx 1 \quad .$$

The regressions of equation (6) are shown in Figure 2d. When b was allowed to be a free parameter the power function fitted the data fairly well except that P_0 was much greater than 1.0 for small N. When the more realistic requirement of $P_0(N{=}1) = 1$ was imposed the flexibility of the power function was greatly curtailed, resulting in a very poor fit.

IMPLICATIONS OF P_0 MODELS IN TERMS OF MEAN CPUE

The fits of equations 3-6 to the P_0 data are as good or better than the fits of equations 1 and 2 to the CPUE data. Inasmuch as most of us are accustomed to thinking in terms of CPUE, it is useful to consider the implications of equations 3-6 to the relationship between CPUE and N. To do this, however, it is necessary to select a probability density function. Bannerot and Austin (1983) used the negative binomial distribution to model their yellowtail snapper data, so for consistency it will be used here as well.

The formula for P_0 according to the negative binomial distribution is

$$P_0 = (1+m/K)^{-K} \quad .$$

In the limit as K goes to infinity this expression is equivalent to the Poisson model

$$P_0 = e^{-m}$$

(in practice for K > 10). Solving these equations for the mean CPUE (m) yields

$$\begin{aligned} m &= K(P_0^{-1/K}-1) \quad [\textit{negative binomial}] \\ m &= -\log_e(P_0) \quad [\textit{Poisson}] \quad . \end{aligned} \tag{7}$$

Substituting equations 3-6 into equation 7 yields expressions relating the mean CPUE (m) to abundance. Bannerot and Austin (1983), however, demonstrated that the dispersion coefficient K was positively correlated with abundance. This possibility was accommodated by allowing K to vary in proportion to N.

The general shapes of the resulting curves are depicted in Figure 3. The models expressing P_0 and its square root as a linear function of N both indicate that, if CPUE is negative binomial or Poisson distributed, the mean catch per trip ought to increase with N at an increasing rate. Allowing K to increase with N dampens the rate of increase but does not change its fundamental nature. The model $\log_e(P_0) = 1 - aN$ also implies that the mean CPUE will increase with N at an increasing rate except when K is very large (Poisson) or when K increases linearly with abundance (both exceptions imply the mean CPUE is proportional to abundance). Only the power function $P_0 = bN^{-a}$ implies that the mean CPUE will increase at a decreasing rate.

DISCUSSION

An asymptotic relationship between the mean CPUE and abundance of yellowtail snapper is apparent. The handling-time model fits the data slightly better than a power function of abundance and much better than the conventional linear model. The success of the handling time model suggests that the nonlinear trend in the data is largely attributable to the time required to land a fish that has been hooked (including those too small to keep) and redeploy the gear. Handling-time is likely to be even more important in the US rod and reel fishery for bluefin tuna because, on average, bluefin tuna require much more time to land than yellowtail snapper. This implies that the apparent decline in West Atlantic bluefin tuna abundances may have been greater than indicated by the current CPUE indices (which were standardized under a linear model assumption).

The amount of effort spent handling each fish could in theory be estimated via direct observations of the fishing process, but otherwise would be difficult to estimate directly because the local abundance of bluefin tuna is hard to observe directly. Another option would be to use handling-time or power function models rather than the canonical catch equation in the SCRS assessments (for example Parrack, 1986). Finally, there is Bannerot and Austin's (1983) suggestion of using a replacement index such as the relative frequency of zero catches.

The replacement indices suggested by Bannerot and Austin do appear to correlate well with the abundance data. As they point out, however, the value of these replacement indices over expressing catchability q as a power function of N (or over using the handling time model) cannot be determined until similar studies have been conducted on other fisheries. Moreover, this study has shown that linear correlations between P_0, the square-root of P_0 and $\log_e(P_0)$ all imply that CPUE should increase with N at an increasing rate (i.e., q increases with N) whereas yellowtail snapper CPUE clearly increases with N at a decreasing rate. Only the power function $P_0 = N^{-a}$ allows for CPUE to increase at a decreasing rate, but this function behaves relatively poorly as an index.

The implications of the preceding paragraph probably hinge in part on the choice of the negative binomial and Poisson models for the frequency distribution of CPUE. None of the pooled frequency distributions of yellowtail snapper CPUE were significantly different from the negative binomial at the five percent level (Bannerot and Austin, 1983). Nevertheless, it is evident by inspection that the negative binomial distribution severely overestimates P_0 when N exceeds 180. Therefore, the negative binomial appears incapable of capturing the dynamics of P_0 and leads to misleading conclusions regarding the relationship of yellowtail snapper CPUE and abundance. To date, however, there have been few examples of successful applications of distributions other than the negative binomial and Poisson to CPUE data with zero catches.

Taken together, the results of this study indicate that replacements for the mean CPUE based on the relative frequency of zeroes should be approached with caution, but not abandoned. The value of replacement indices notwithstanding, it would seem prudent to subtract handling time from the effort data so that less-biased catch per unit search-effort indices may be constructed. It may also be instructive to consider the use of a catch equation that accounts for handling time in the assessment models.

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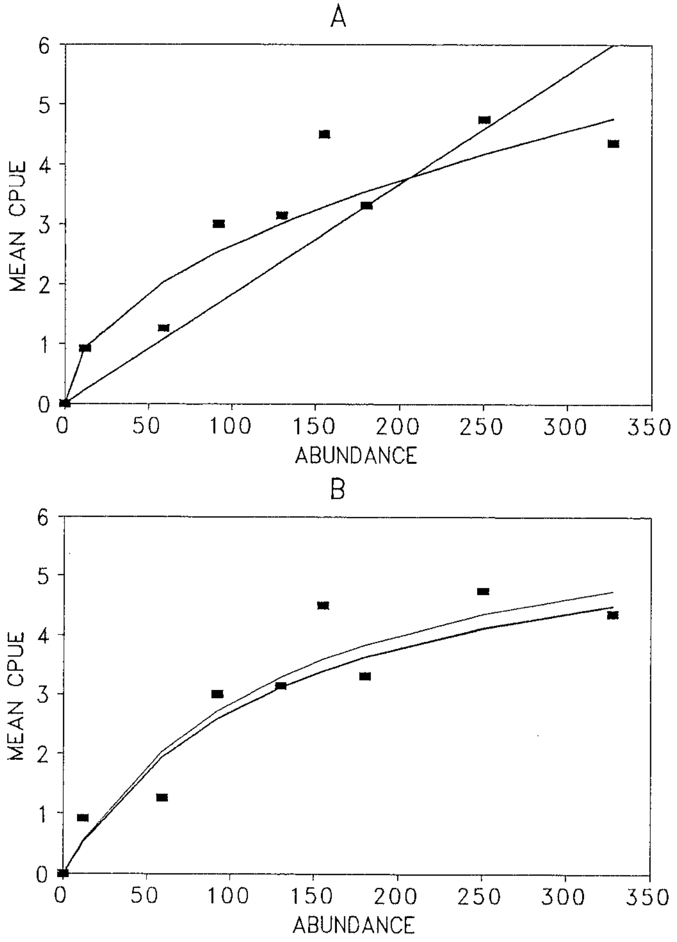

Figure 1. The average CPUE and abundance of yellowtail snapper (Bannerot and Austin, 1983) fitted by A) the conventional linear and power function models and B) the handling time model. The two curves in panel B represent the fits of the handling-time model assuming the data were identically normal distributed (uppermost curve) and normally-distributed with the variance in CPUE proportional to the mean CPUE (lowermost curve).

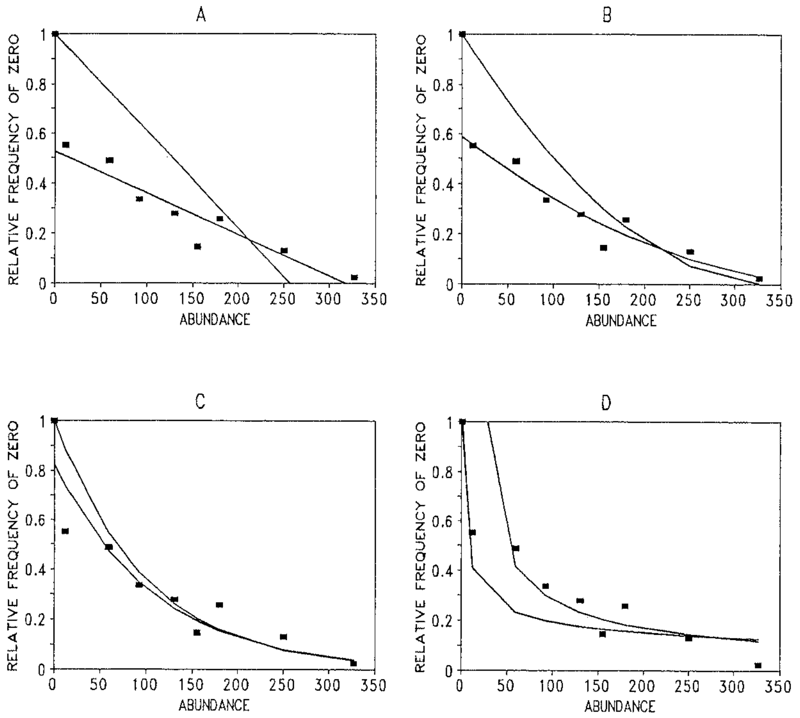

Figure 2. The relative frequency of zero CPUE and abundance of yellowtail snapper (Bannerot and Austin, 1983) fitted by A) linear regression of P_0 on N, B) regression of the square-root of P_0 on N, C) regression of $\log_e(P_0)$ on N and D) regression of $\log_e(P_0)$ on $\log_e(N)$. The two curves in each panel represent the regressions resulting when the intercept parameter was allowed to be a free parameter and when it was forced to equal 1.

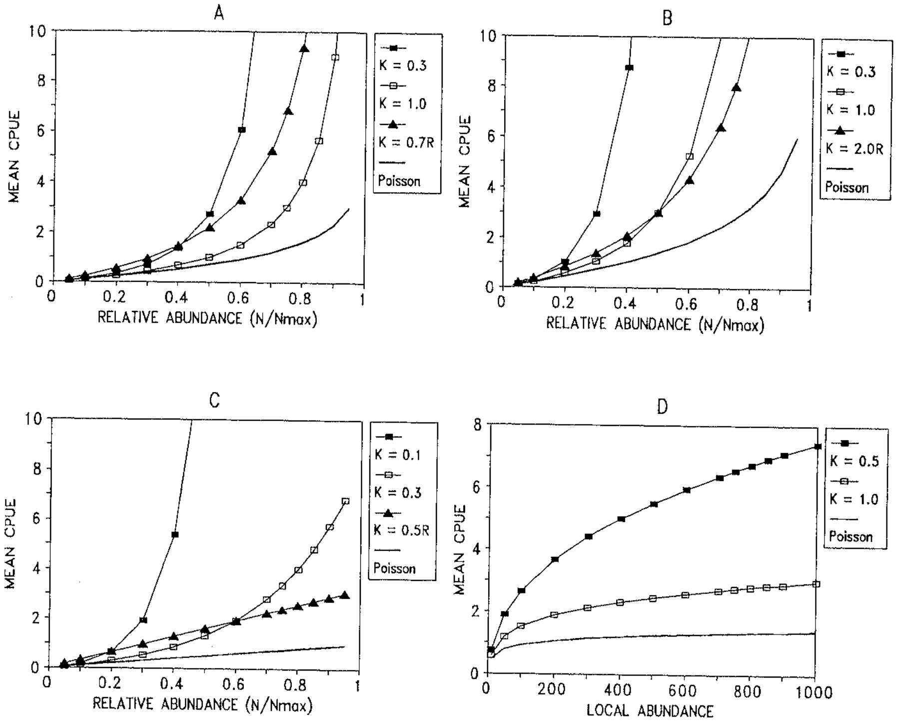

Figure 3. Implied relationships of average CPUE to abundance when CPUE is negative binomial distributed and abundance is indexed by A) P_0, B) square-root of P_0, C) $\log_e(P_0)$ and D) P_0^a (where a = 0.2). The legends indicate the magnitude of the dispersion coefficient K either as a constant or as a function of the relative abundance R. For models A, B and C the x-axis is expressed in terms of relative abundance to generalize the presentation (since in these models the theoretical maximum value of the regression parameter, a, is $1/N_{MAX}$).