ISSN 1175-1584

MINISTRY OF FISHERIES
Te Tautiaki i nga tini a Tangaroa

Models for southern bluefin tuna in the New Zealand EEZ, 1998–99

K. M. Richardson
T. Murray
H. Dean

New Zealand Fisheries Assessment Report 2001/18
April 2001

Models for southern bluefin tuna in the New Zealand EEZ, 1998–99

K. M. Richardson
T. Murray
H. Dean

New Zealand Fisheries Assessment Report 2001/18
April 2001

Published by Ministry of Fisheries
Wellington
2001

ISSN 1175-1584

Citation:
Richardson, K.M.; Murray, T.; Dean, H. (2001).
Models for southern bluefin tuna in the New Zealand EEZ, 1998–99.
New Zealand Fisheries Assessment Report 2001/18. 21 p.

This series continues the informal
New Zealand Fisheries Assessment Research Document series
which ceased at the end of 1999.

EXECUTIVE SUMMARY

Richardson, K.M.; Murray, T.; Dean, H. (2001). Models for southern bluefin tuna in the New Zealand EEZ, 1998–99.

New Zealand Fisheries Assessment Report 2001/18. **21 p.**

Longline fishing effort has declined steadily within the New Zealand Exclusive Economic Zone coincident with a contraction of the southern bluefin tuna (SBT) fishing season and the reduction in Japanese longline vessels taking up SBT licences. This trend has been partially offset by a growth in domestic longline effort during the 1990s.

Nominal SBT CPUE declined between 1980 and 1986, fluctuated around 30% of the 1980 level between 1986 and 1993, and increased thereafter to vary around 60% of the 1980 level.

A number of generalised linear and additive CPUE standardisation models are investigated in an effort to better match model properties with those of longline SBT data. An iterative maximum likelihood power transformation approach is developed that reduces evidence for model lack-of-fit relative to log-normal and Poisson models. The relative abundance of SBT has been estimated using this method.

Spatio-temporal changes in fishing patterns required that the fishery be split into distinct fishing areas (East Cape, West Coast, and Chatham Rise) for this analysis and separate indices were estimated for each. The trend in these indices for the East Cape region generally follows that of nominal CPUE suggesting an increase in abundance after 1994, whereas West Coast abundance indices are roughly constant over this period. Since most effort after 1990 in the New Zealand SBT fishery has been in these two areas, the models suggest an increase in abundance for New Zealand SBT.

However, this conclusion should be regarded as preliminary since the models do not account for the spatio-temporal complexities of the fishery. In addition, evidence for model lack-of-fit remains, although significantly reduced. Suggestions for further model development to deal with these issues are provided.

1. INTRODUCTION

The southern bluefin tuna (SBT) caught in the New Zealand EEZ are part of a single Southern Hemisphere stock that occurs in the Pacific, Indian, and Atlantic Oceans, mostly south of 30° S. New Zealand appears to be the easternmost extent of the range of this species, although there have been unconfirmed reports of fishing in some years by Japanese longliners on the high seas southeast of Chatham Islands.

The fishery for SBT has been in existence for at least 50 years. Fishing has caused abundance to decline sharply during that time, particularly in the 1970s and 1980s, and there is concern about the potential for recovery of the stock (Anon. 1998).

In New Zealand waters, SBT have been caught by handline and trolling during winter months off the west coast of the South Island from small vessels. These methods are still occasionally used. Most SBT, however, are caught by medium to large (20–50 m) longline vessels in autumn and winter. Southern bluefin catches, restricted to a national competitive catch limit of 420 t since 1989, have usually been below this limit.

Fishing effort by Japanese longliners has been declining since 1979–80. In contrast, fishing effort by New Zealand vessels for SBT increased rapidly from 1989–90 to a peak of 0.9 million hooks in 1994–95 before declining to less than 0.4 million hooks in 1996–97.

Generalised linear models are often used to account (standardise) for systematic changes in catchability, fishing power, etc, while estimating trends in abundance (e.g., Punt et al. 2000). Generalised Linear Models (GLMs) have three main components: A linear predictor describing the systematic component of the data, a member of the exponential class of distributions describing the random component, and a link function relating the linear predictor to the mean of the distribution. Generalised Additive Models (GAMs), which are extensions of GLMs allowing the non-linear effects of covariates on the response to be estimated from the data, are also now being used (e.g., Bigelow et al. 1999, Daskalov 1999). In both model types, response variables are assumed independent, i.e., the data arise from a random sampling process.

The systematic component is specified by an assumed relationship between mean catch rate and stock density. Predictors of catch rates are assumed to be without error (fixed effects), and multiplicative so that a logarithmic transformation of the relationship yields a linear sum of terms of which only the spatial density is of interest. This fixes the link function required by generalised linear or additive models. Quinn & Deriso (1999), Hilborn & Walters (1992), and Richardson et al. (1998) discuss the method in detail.

There is a growing recognition of the need to develop an understanding of the underlying statistical distribution of catch rates (see Quinn & Deriso 1999, Richardson et al. 1998, Dong & Restrepo 1996, Power & Moser 1999) so that catch rate analyses can be put on a more solid statistical foundation. In the analysis of SBT longline catch and effort data, log-normal response models have been favoured (see, e.g., Anon. 1996). However, zero catches (common in SBT fisheries) present a difficulty for the log-normal model. This is usually resolved by adding a small constant to the Catch per Unit Effort (CPUE, defined here as number of fish per thousand hooks) before fitting the model. The arbitrary constant can, if required, be removed from the constant term computed using the model. Other approaches have been proposed. Vignaux (1994) suggested that combining a binomial model (of the probability of zero catch) with a log-normal model of positive CPUE might be more appropriate. A variety of statistical models has been applied to catch-rate data precisely because of the uncertainty about which response model to use (e.g., Punt et al. 2000).

The widespread use of the log-normal response model in fisheries is probably due to familiarity with the method and the availability of software packages. Rarely are the consequences of using this model considered, and a more detailed analysis of the properties of longline CPUE data is warranted.

In the present study, the properties of catch and effort data in the New Zealand SBT fishery are investigated from which a natural interpretation of CPUE as frequency data emerges. However, a Poisson GLM is not the most appropriate response model, since the data are found to be significantly over-dispersed. Several linear response models that can better handle this property of the data are investigated and a significant improvement in model fit over log-normal and Poisson models is found.

A generalised additive extension of one such linear model is used to standardise CPUE for SBT in the New Zealand EEZ and is compared with results from the more conventional log-normal model.

This report satisfies Objective 2 of Project TUN1999-02: *To produce a standardised CPUE analysis and report for CCSBT on southern bluefin tuna for the 1999 and 2000 fishing years respectively.*

2. METHOD

The positions of all SBT longline operations used for this analysis are shown in Figure 1. Catch (number of fish) and effort (number of hooks set) data for target and bycatch species, longline set position, date, start and finish times, sea surface temperature, vessel specifications, and other fisheries information were obtained from the Ministry of Fisheries for 1980–1998.

These data originate from forms filled out by commercial fishers on each operation directed at catching SBT by longline and provide information on catch in number and weight by species for each fishing operation. Other details, such as position, effort, vessel specifications, and environmental factors that might affect fishing, are also given. Only data from the Tuna Longlining Catch, Effort and Landing Return (TLCER) forms were used in this study.

A number of criteria were used to identify errors in catch, effort, and position. Position errors were detected by both graphical and analytical methods that identify unlikely sequential fishing positions. Range checks on position, effort, number of sets per day, average weight of fish, amount of catch, sea surface temperature, and operational details were used to identify such data. All probable errors detected were then checked against the original form or, more usually, against a number of fishing operations by the vessel in question that immediately precede or follow the given operation. Where there was clear evidence of error in recording or data entry, records are replaced with values used elsewhere in the trip (if constant), or by the mean of adjacent values.

Errors that pass these tests include wrongly assigned fishing method codes, target species, and catch that appears to be wrongly identified. The effect of these errors on the analysis is considered slight.

The spatio-temporal complexity of the fishery, particularly during the 1990s, motivated the division into three regions (East Cape, West Coast, and Chatham Rise) (Figure 1) for this analysis. In the Chatham Rise region, 1992–1996 were combined since there was very little fishing in that period. All three areas have contracted in extent since the 1980s.

Moon phase calculations were based on algorithms given by Duffet-Smith (1990).

2.1 Models for the random component

McCullagh & Nelder (1989) emphasised that it is important to choose the class of statistical model carefully, paying attention to the type and structure of the data. In that spirit, Figure 2 presents a histogram of log(CPUE) data from the East Cape region for Japanese vessels in the years 1980–1998. The log transformation is used partly for convenience in plotting the data, but also because this transformation is often used in linear models for longline CPUE. A small constant, chosen to be one-tenth of the smallest positive CPUE value, has been added to all CPUE values to enable plotting of zero catch rates. It is apparent that the distribution of these data has identifiable peaks at several distinct values of CPUE. When the histograms are plotted separately by year, there are noticeable temporal variations, but the presence of distinct peaks at "small" CPUE values appears to be present in all years.

There is a separate "spike" for each unit of catch until they coalesce at larger catches. Furthermore, at a given value of catch, different levels of effort contribute to the variability in CPUE which is why there is a narrow spike at zero catch, but broader spikes at non-zero catches. A reasonable conclusion from this view of the longline fishing operation is that catch can be considered as a counting process so that longline CPUE can be viewed as proportions (of successes) where the total of successes and failures (i.e., effort) can vary. These data do not appear to be from a log-normal distribution, and other models are likely to be more appropriate.

One approach would be to treat both catch and effort as random variables. The distribution of CPUE conditional on effort certainly appears to have simpler distributional properties (Figure 3). By making assumptions about the statistical properties of both catch and effort it is possible, in principle, to derive the distributional form of CPUE. However, there are problems with this approach. For example, the distribution of effort depends on both time (e.g., year) and nation. Even if the problem was tractable, there is no guarantee that the results would be particularly useful within a linear model. The approach taken here is to adopt the 'counting process' view and deal separately with other characteristics that can be expected or shown to be important for longline data.

If the probability of catching a fish on any hook was constant and independent of catching a fish on other hooks, then CPUE could be regarded as samples of various size from a binomial population. A binomial GLM might then be a reasonable model for the random component of CPUE data in a given year, provided that SBT were distributed uniformly across a given area. In fact, since the probability of catching an SBT on a given hook can be considered small, a Poisson model could be used as a limiting form for the binomial distribution.

The spatial distribution of SBT is heterogeneous, and fishers have imperfect knowledge of where to find them. Once a school is located, however, it can to some extent be 'tracked'. Guesswork is involved even then, and serial correlation is likely to exist in the catch rate data. Over-dispersion, where the data display more variability than is allowed for in the mean-variance relationship of the assumed response model, is to be expected in tuna longline CPUE data. In fact, it is often argued that over-dispersion is the rule rather than the exception in frequency data (Fitzmaurice 1997, McCullagh & Nelder 1989). Over-dispersion must be accounted for in a response model if incorrect inferences about the fitted parameters are to be avoided (Fitzmaurice 1997). This is not a matter of theoretical importance only. For example, Richardson et al. (1998) argued that it is necessary to estimate yearly spatial effects in order to derive abundance indices for the SBT fishery.

Figure 4 exhibits one possible empirical mean-variance relation for SBT CPUE:

$$V(\mu) \propto \mu^n, \tag{1}$$

with $n \approx 1.6$, providing support for the contention of over-dispersion relative to a Poisson model. This power law mean-variance form can be accommodated within a linear model through the concept of quasi-likelihood (McCullagh & Nelder 1989). However, this model has a deviance function that is not defined when the response is zero, at least for values of the power parameter (n) estimated in this study. Thus, to accommodate CPUE data in a power-variance response model, a 'small' constant (see below) must be added to the response variate when computing the deviance in much the same way as for log-normal models. A similar problem occurs when fitting a GLM for other commonly used exponential distributions (e.g., the gamma response model).

In contrast, negative binomial response models, which have the mean variance relation

$$V(\mu) \propto \mu(1+\frac{\mu}{\theta}), \tag{2}$$

where θ is the so-called shape parameter, are of exponential form (for fixed θ), have a known likelihood function, and are often used with over-dispersed Poisson data (Venables & Ripley 1999, White & Bennetts 1996), or for modelling a variety of clustered populations (Seber 1986). Furthermore the deviance function is defined when the response is zero.

It is possible to estimate θ from the data using an alternating maximum likelihood and GLM method (Venables & Ripley 1999). This iterative approach, which is used below, fits a negative binomial model with θ fixed at some value. Predicted values from this fit are used in the likelihood function to find a new estimate for θ, and the process is repeated until a convergence criterion is satisfied.

A similar approach is also possible for the power-variance model if the concept of extended quasi-likelihood, Q^+ (McCullagh & Nelder 1989), defined by

$$-2\phi Q^+ = \sum_i d_i + \phi \sum_i \log\{2\pi\phi V(y_i)\}, \tag{3}$$

is used. In this equation, d_i is the ith quasi-deviance component of the model, ϕ is the dispersion parameter, and $V(\cdot)$ is the variance function defined in Equation 1.

However, CPUE data often contain many zeroes and the extended quasi-likelihood function for a power variance model is not defined at zero CPUE. The usual practice of adding a small constant to the data (1/6 for counts with a power-variance function in Nelder & Lee 1992) to avoid zeroes appears to produce acceptable models for longline CPUE data. We use 1/6 of the minimum positive CPUE as the small constant, but there is some sensitivity to this value.

It is also possible to estimate the negative binomial shape parameter using the concept of extended quasi-likelihood (when the variance function in Equation 2 is used in Equation 3). However, results were very similar to the likelihood negative binomial model, and hence this method is not discussed further.

An alternative approach is to reduce the observed over-dispersion by using a suitable transformation of the original CPUE data and then to fit one of the standard GLMs. This is a variant of the method used in the classical log-normal model. In the standardisation analysis below, however, an iterative maximum likelihood power transformation is used to enhance the Poisson nature of the data, and a Poisson GLM with a logarithmic link function is then fitted. This is referred to as the modified response Poisson model. It must be borne in mind that the data have been suitably transformed before the final fit is carried out. A summary of assumptions for the different models discussed above is given in Table 1.

Model selection proceeded as follows. First, a negative binomial linear (Venables & Ripley 1999) model involving only the *year* predictor was used as the starting point. stepAIC was then used to select main effect predictor values using the AIC statistic (Aikaike 1974) to give an initial model. Next, since the AIC tends to over-fit, the effect of dropping or adding individual terms was tested at $p = 0.001$ and non-significant terms were discarded. The negative binomial shape (or aggregation) parameter is estimated at each step in both the above procedures, so likelihood ratio tests are used to compare the different negative binomial models.

The modified response Poisson model, with the explanatory variables selected above, was used in the following analyses because this model produced the least evidence of lack of fit. The result of this selection procedure is a main effects modified response Poisson model with an estimated power parameter (θ).

Finally, a GAM was fitted to the data under the assumption that the predictor variables selected as above (in the context of a linear model) would also be important in an additive model. Predictor variables in the additive model were the same as for the linear model, but interactions between longitude and latitude were allowed (i.e., using a two-dimensional smooth term in latitude and longitude) if these proved significant.

Predictor variables used were as follows.

1. Factors
   - *year*
   - *month* – February to August
   - *nation* – Japanese (foreign or charter), Domestic (N.Z. owned and operated).
2. Covariates
   - *moon phase* – fraction of illuminated lunar disc
   - *sea surface temperature*
   - *latitude* – set start position
   - *longitude* – set start position

- *effort* – hooks (thousands)
- *Southern Oscillation Index* (Troup's Index)
- *vessel length* (m)

For the linear models used, covariates were natural splines with up to 4 degrees of freedom. The number of degrees of freedom was chosen by stepAIC. For GAMs, a local regression smoother (Chambers & Hastie 1993) with the default smoothing parameter (½ for a one-predictor term). For a two-predictor term, a smoothing parameter of ¼ was used.
The standard error for the year coefficient on the scale of the response variable, $\exp(\hat{y})$, is calculated as

$$\text{var}[(\exp(\hat{y})] = \exp(2 * \hat{y}) e^{v} (e^{v} - 1)$$

with v the appropriate diagonal element of the covariance matrix, and $\hat{y}$ the value of the year linear predictor estimated during the fitting procedure.

3. RESULTS

For these data, all except the standard Poisson and log-normal response models produced similar residual plots and relative abundance indices. Comparison of deviance residual plots suggests that the modified response Poisson model provides the least evidence for lack of fit and this approach was used for the standardisation analysis that is reported here.

Figures 5 and 6 show fitted year factor levels and mean (unstandardised) CPUE in each of the East Cape, Chatham Rise, and West Coast SBT fishing areas for each fitted model. Figure 5 also contains selected (worst) residual plots for the East Cape model, and compares results with those from a logarithmic model. Data from each of these regions are given in Appendix 1 along with a plot of mean CPUE for the New Zealand EEZ (Figure A1).

There is evidence of lack of fit in most of the models in the above residual plots (see, e.g., Figure 5). The problem is considerably reduced compared with lognormal or Poisson models. Compare the linearity of the deviance residual quantile-quantile plot, the trend curves through the absolute deviance residuals in Figure 5. There is also a substantial reduction in estimated dispersion parameter for the modified response Poisson model (0.86) compared with the standard Poisson model (2.33). Nevertheless, caution is required when interpreting predictions from such models because assumptions about approximate normality of deviance residuals may not be valid.

The estimated SBT abundance indices for the East Cape area are, considering errors in the estimates, similar to or less than and the nominal (mean) CPUE values until 1994 (see Figure 5). There is a substantial increase in mean CPUE and abundance indices after 1995. In 1998, the estimated abundance index is about 80% of the 1980 value.

For the West Coast fishing area there appear to be significant differences between mean yearly CPUE values and estimated year coefficients (see Figure 3). However, there was a sharp reduction in effort after 1993 and this is reflected in the increase in the size of the confidence intervals over that period. There is no compelling evidence in the model for an increase in SBT abundance in this region after 1994, as is suggested by the mean CPUE time series, particularly since estimated confidence intervals probably under-estimate actual uncertainties.

Figure 3 also shows estimated abundance indices for the Chatham Rise fishing region when 1992 to 1996 are combined (aggregation of these years was required because there was little effort in this region during that time). Indices for the years 1997 and 1998 increased to about 35% of the 1980 value. The cautionary remarks above about model lack of fit also apply here. Only a small proportion of overall effort in the New Zealand SBT fishery has been expended in this region since 1992.

4. DISCUSSION

Unstandardised catch rates for the New Zealand EEZ increased after 1994. Longlining in the West Coast region has dominated during this period, though there is recent increased activity in East Cape, underlining the large spatial and temporal changes in the distribution of effort in the fishery.

Standardised indices are roughly constant in the West Coast over this period, but increase significantly in East Cape. It seems likely that fitted abundance trends from the three regions also suggest an increase in abundance for the New Zealand SBT fishery. However, since all models show evidence of residual model lack-of-fit, and spatio-temporal effects have been excluded, this conclusion should be regarded as preliminary.

Spatio-temporal effects can be accommodated by using the additional flexibility of additive models. Estimation of an overall index for the New Zealand SBT fishery while accounting for the observed spatio-temporal complexity should be possible using such a model. Even then, however, the hypotheses underlying catch-rate models may not adequately reflect the complexity of commercial SBT longline fishing. The problem of serial correlation in the data has not been addressed, and during this work we found that over-dispersion in the data often varied on a yearly basis. Further development of spatial models is definitely required. Other approaches, such as generalised linear mixed models, may also be useful.

5. ACKNOWLEDGMENTS

The research reported here was supported by the New Zealand Ministry of Fisheries under contract through NIWA Project TUN9902. We gratefully acknowledge this support.

6. REFERENCES

Aikaike, H. (1973). Information theory and an extension of the maximum likelihood principle. *In*: Second International Symposium on Information Theory (eds. B.N. Petrov & F. Csaki). Akademia Kiado, Budapest, Hungary. pp 267–281.

Anon. (1998). Report of the First CCSBT Stock Assessment Group, Shimizu, Japan, July 1998. (Draft report held by the CCSBT Secretariat, Canberra, Australia).

Anon. (1996). Report on the CCSBT Workshop on VPA and CPUE modelling (1996). 4–15 March, Hobart, Tasmania. (Draft report held by the CCSBT Secretariat, Canberra, Australia).

Bigelow, K. A.; Boggs, C. H.; He, X. (1999). Environmental effects on swordfish and blue shark catch rates in the US North Pacific longline fishery. *Fisheries Oceanography* 8(3): 178–198.

Chambers, J. M.; Hastie, T. J. (1993). Statistical models in S. Wadsworth and Brooks/Cole, Pacific Grove, California.

Daskalov, G. (1999). Relating fish recruitment to stock biomass and physical environment in the Black Sea using generalised additive models. *Fisheries Research 41*: 1–23.

Dong, Q.; Restrepo, V. R. (1996). Notes on the Poisson error assumption made to estimate relative abundance of West Atlantic bluefin tuna. *Collected Volumes of Scientific Papers of ICCAT 45*: 158–161.

Duffet-Smith, P. (1990). Astronomy with your PC. Cambridge University Press, Cambridge.

Fitzmaurice, G.M. (1997). Model selection with over-dispersed data. *Journal of the Royal Statistical Society D 46*: 81–91.

Hilborn, R.; Walters, C.J. (1992). Quantitative fisheries stock assessment. Chapman and Hall, New York.

McCullagh, P.; Nelder, J.A. (1989). Generalised linear models. Chapman and Hall, London, U.K.

Nelder, J.A.; Lee, Y. (1992). Likelihood, Quasi-likelihood and pseudo-likelihood: some comparisons. *Journal of the Royal Statistical Society* B *54*: 273-284.

Power, J.H.; Moser, E.B. (1999). Linear model analysis of net catch data using the negative binomial distribution. *Canadian Journal of Fisheries and Aquatic Sciences 56*: 191–200.

Punt, A. E., Walker, T.I., Taylor, B.L., Pribac, F. (2000). Standardisation of catch and effort in a spatially-structured shark fishery. *Fisheries Research 45*: 129–145.

Quinn, T.J.; Deriso, R.B. (1999). Quantitative fish dynamics. Oxford University Press, New York.

Richardson, K.; Murray, T.; Dean, H. (1998). Models for southern bluefin tuna in the New Zealand EEZ. *CCSBT-SC/9807/16*. (Draft report held by the CCSBT Secretariat, Canberra).

Seber, G.A.F. (1986). A review of estimating animal abundance. *Biometrics 42*: 267-292.

Venables, W. N.; Ripley, B. D. (1999). Modern applied statistics with S-Plus, 3rd ed. Springer-Verlag, New York.

Vignaux, M. (1994) CPUE analysis of West Coast South Island and Cook Strait spawning hoki fisheries 1987–93. New Zealand Fisheries Assessment Research Document 94/11. (Draft report held in NIWA library, Wellington).

White, G.C.; Bennetts, R.E. (1996). Analysis of frequency count data using the negative binomial distribution. *Ecology 77*: 2549–2557.

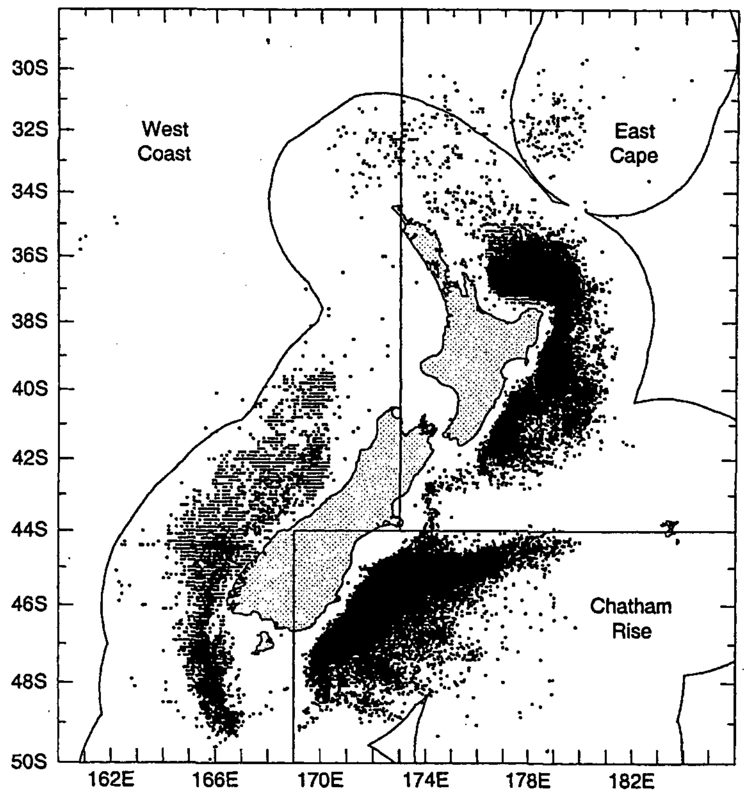

Figure 1: Longline start positions for sets targeting SBT (TLCER data only) for 1980–98 in the New Zealand EEZ. The three regions used in estimating relative abundance indices are shown.

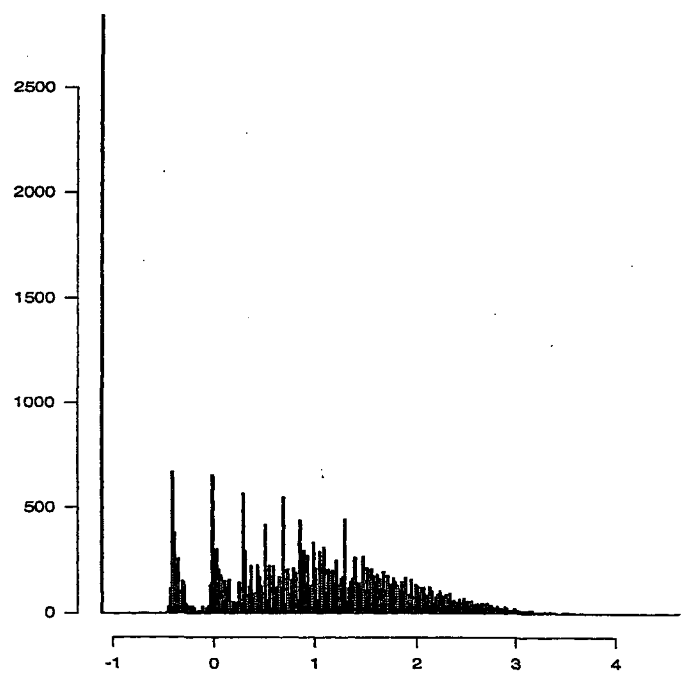

Figure 2: Histogram of log(CPUE) from the East Cape region, 1980–98. A small constant (see p.6) is added to plotted CPUE (number of fish per thousand hooks) values.

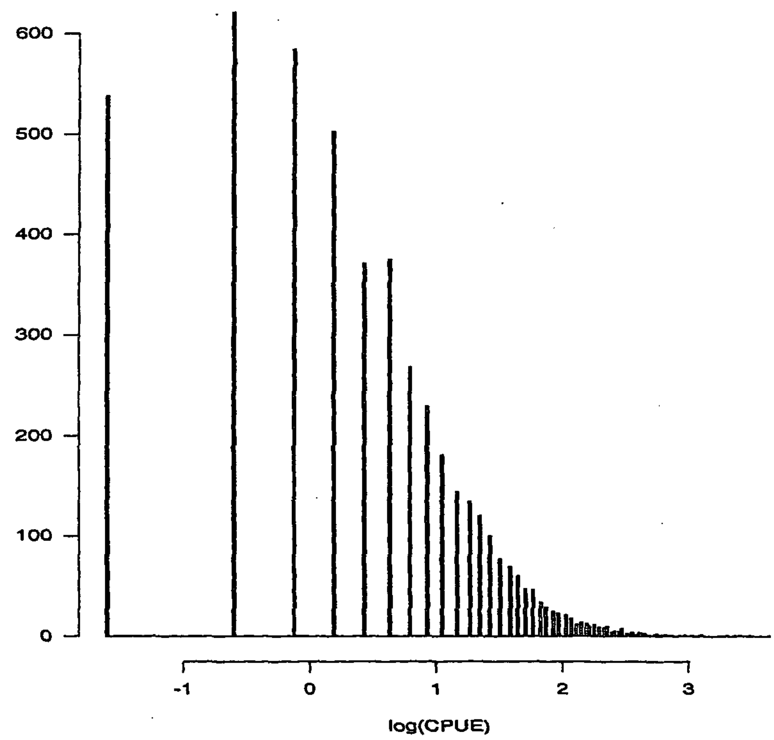

Figure 3: Histogram of log(CPUE) for vessels in the East Cape region from sets with a given effort (3000 hooks). A small constant is added to CPUE values for plotting purposes.

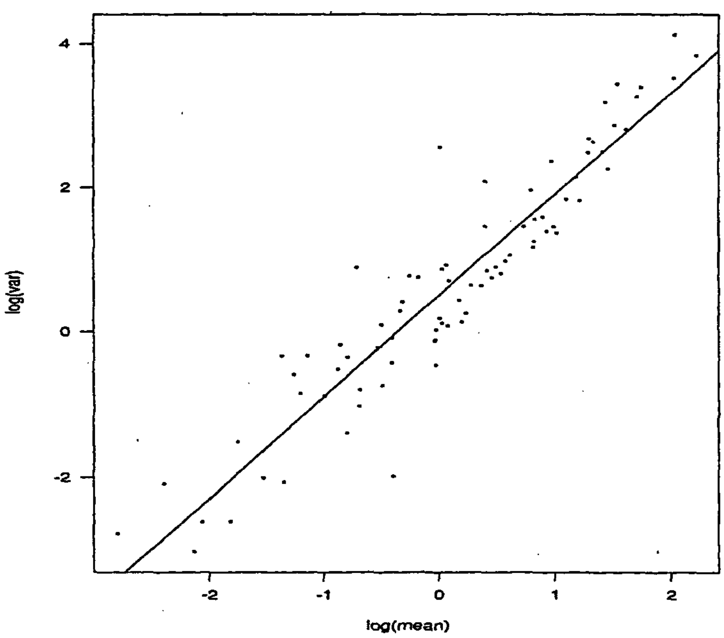

Figure 4: Regression to demonstrate an empirical power law mean-variance relation. Combined CPUE means and variances from Japanese and New Zealand vessels have been computed for each year:month stratum in the East Cape region.

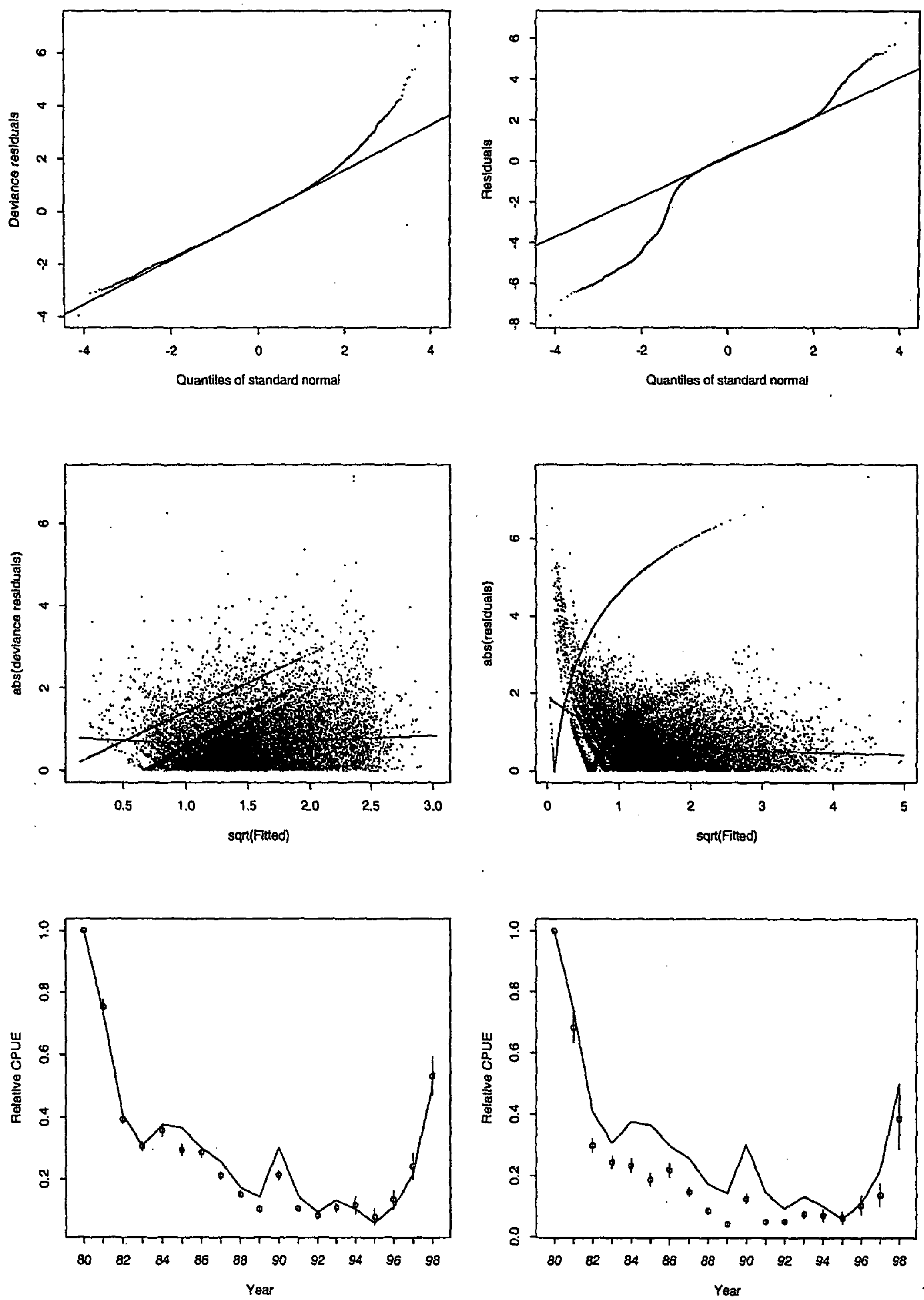

Figure 5: Residual plots and year coefficients for the modified response Poisson (left) and log-normal (right) models in the East Cape area. Smoothed curves through the residual scatter plots are drawn using a local regression algorithm. The index of the power transformation for the modified response Poisson model is estimated as n=0.733.

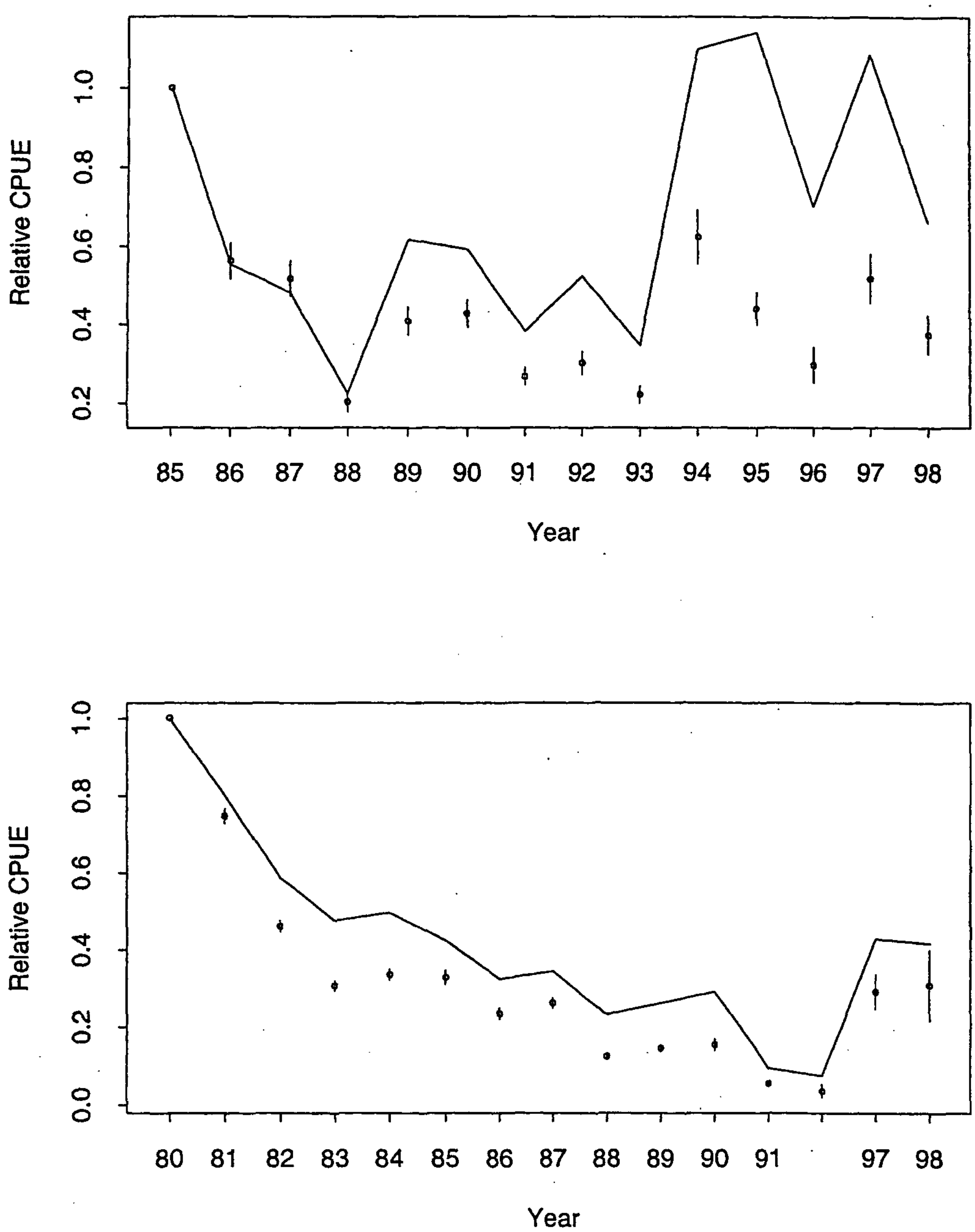

Figure 6: Estimated year coefficients from the modified response Poisson model for the West Coast (top) and Chatham Rise (bottom) regions. The line connects relative mean CPUE and bars represent 2σ errors.

Table 1: Some assumptions of the models investigated. Parameters estimated in the fitting procedure are indicated by a "hat". *NegBin* denotes the negative binomial, *Poi* the Poisson, and *Quasi* the quasi-likelihood models. The link function, relating the linear/additive predictor to the mean, is logarithmic in all models as discussed in the Introduction.

Model	Distributional form	Mean-variance relation
negative binomial	$CPUE \sim NegBin(\hat{\mu},\hat{\theta})$	$V(\mu)=\mu(1+\mu/\theta)$
Modified response Poisson	$CPUE^{\hat{\theta}} \sim Poi(\hat{\mu})$	$V(\mu)=\mu$
Power variance	$CPUE \sim Quasi(\hat{\mu},\hat{\theta})$	$V(\mu)=\mu^{\theta}$

APPENDIX 1: Summary of catch and effort data

East Cape.

Year	Sets	Hooks	Catch	CPUE[1]	Zero sets	% Zero sets
1980	3 541	8 200	61 719	7.5886	33	0.93
1981	3 693	9 002	50 116	5.5911	117	3.17
1982	3 307	8 608	26 445	3.0933	177	5.35
1983	2 438	6 504	15 245	2.3296	170	6.97
1984	1 495	4 134	11 757	2.8433	119	7.96
1985	1 101	3 197	8 968	2.7715	107	9.72
1986	1 427	4 088	9 448	2.2801	100	7.01
1987	1 810	5 363	10 531	1.9476	143	7.9
1988	1 724	4 932	6 363	1.3127	295	17.11
1989	891	2 536	2 788	1.0747	250	28.06
1990	810	2 299	5 276	2.2936	91	11.23
1991	1 331	3 876	4 314	1.1102	271	20.36
1992	1 187	3 417	2 431	0.7017	302	25.44
1993	394	886	970	1.0085	107	27.16
1994	192	185	113	0.7729	131	68.23
1995	155	137	63	0.4527	119	76.77
1996	212	190	167	0.8303	139	65.57
1997	196	269	718	1.6393	103	52.55
1998	232	383	1 745	3.7821	65	28.02

West Coast.

Year	Sets	Hooks	Catch	CPUE[1]	Zero sets	% Zero sets
1985	946	2 725	10 217	3.7115	9	0.95
1986	1 007	2 883	5 964	2.0588	39	3.87
1987	1 169	3 364	6 067	1.7874	91	7.78
1988	714	2 078	1 731	0.8309	164	22.97
1989	749	2 142	4 890	2.2916	62	8.28
1990	1 147	3 375	7 389	2.1976	40	3.49
1991	1 748	5 174	7 367	1.4217	152	8.7
1992	1 768	5 178	10 128	1.9463	124	7.01
1993	1 246	3 777	4 928	1.2882	159	12.76
1994	398	980	4 263	4.0797	38	9.55
1995	1 005	1 984	6 548	4.2391	112	11.14
1996	261	312	745	2.6012	61	23.37
1997	323	917	2 947	4.0284	23	7.12
1998	277	837	2 069	2.455	26	9.39

[1]Number of fish per thousand hooks

Chatham Rise.

Year	Sets	Hooks	Catch	CPUE[1]	Zero sets	% Zero sets
1980	6 630	16 353	56 745	3.4111	312	4.71
1981	5 512	14 417	39 753	2.7337	154	2.79
1982	3 344	9 247	18 800	2.0023	242	7.24
1983	2 215	6 266	10 207	1.6258	183	8.26
1984	1 981	5 892	10 001	1.6967	147	7.42
1985	1 232	3 613	5 255	1.4465	77	6.25
1986	906	2 722	3 014	1.1064	100	11.04
1987	1 394	4 109	4 842	1.174	148	10.62
1988	1 480	4 359	3 455	0.7914	331	22.36
1989	1 302	3 855	3 463	0.8949	208	15.98
1990	469	1 391	1 388	0.9949	95	20.26
1991	805	2 390	770	0.322	335	41.61
1992–96	53	149	29	0.1946	30	56.60
1997	133	394	569	1.4585	9	6.77
1998	36	99	144	1.4205	2	5.56

Whole EEZ.

Year	Sets	Hooks	Catch	CPUE[1]	Zero sets	% Zero sets
1980	10 171	24 553	118 464	4.8642	346	3.4
1981	9 205	23 419	89 869	3.8793	272	2.95
1982	6 651	17 855	45 245	2.5448	419	6.3
1983	4 653	12 770	25 452	1.9946	353	7.59
1984	3 476	10 025	21 758	2.1895	267	7.68
1985	3 279	9 535	24 440	2.5449	193	5.89
1986	3 340	9 694	18 426	1.8950	239	7.16
1987	4 373	12 837	21 440	1.6582	382	8.74
1988	3 918	11 369	11 549	1.0279	791	20.19
1989	2 942	8 533	11 141	1.3049	520	17.68
1990	2 426	7 064	14 053	1.996	227	9.36
1991	3 884	11 441	12 451	1.0868	759	19.54
1992	2 990	8 699	12 576	1.4315	448	14.98
1993	1 652	4 699	5 906	1.2135	272	16.46
1994	593	1 170	4 378	2.9895	171	28.84
1995	1 161	2 124	6 611	3.7274	233	20.07
1996	475	503	914	1.8076	200	42.11
1997	652	1 580	4 234	2.7860	135	20.71
1998	545	1 318	3 958	2.9516	93	17.06

[1]Number of fish per thousand hooks

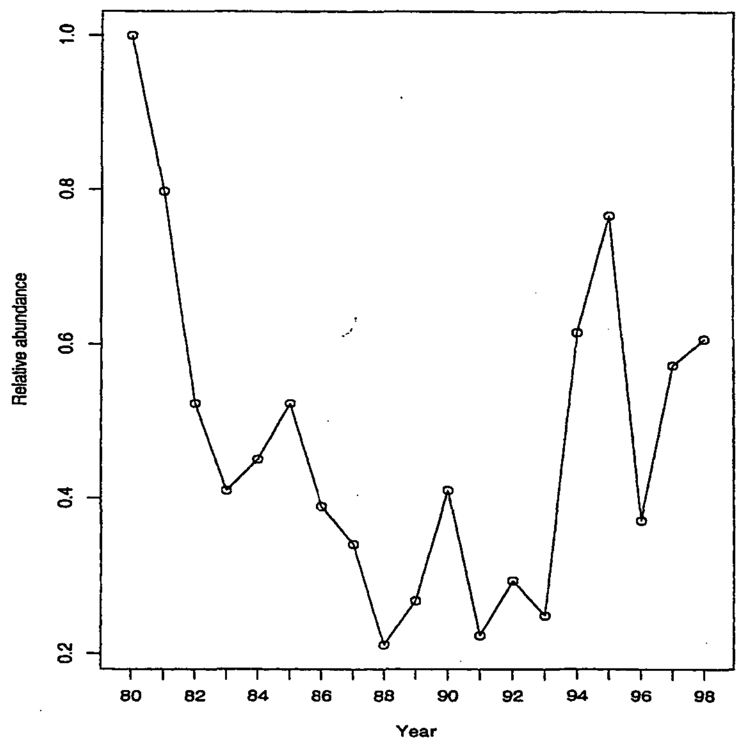

Figure A1: Nominal relative CPUE for the New Zealand EEZ.