

## Sensitivity of the F35% Target Fishing Rate to Variation in the Maturity Schedule

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**Abstract:** Monte Carlo simulation experiments were conducted to explore how variability in the maturity schedule for English sole *Pleuronectes vetulus* is transformed into variability in estimates of F35%. Random values were generated for age at 50% maturity and the maturity slope coefficient for each of 10935 combinations of 8 factors. From these simulated data F<sub>35%</sub> values were derived and summarized for each experimental treatment as an average F<sub>35%</sub> value and coefficient of variation. The summary statistics were then transformed and analyzed using forward stepwise linear regression to determine the relative importance of different factors plus a quadratic term were required to account for 90% of the variability in the data, whereas in the model for coefficient of variation in F<sub>35%</sub>, all eight factors, plus interaction term and a quadratic term, were required to account for 90% of the variability in the data. In both models the age at 50% maturity and the age at 50% selection were the two most important explanatory variables.

**Key words:** F<sub>35%</sub>, English sole, Monte Carlo, maturity schedule, fishing rate

### INTRODUCTION

Most fish stocks experience large year to year variations in recruitment, which are due either to changes in fishery removals or to changing environmental conditions. Because of recruitment variability, as well as the large geographic range and inaccessibility of most fish stocks, it is difficult to measure accurately the vital characteristics of any given stock, particularly the stock's size and growth rate. Success in managing a fishery will depend in large part on the stability of the stocks supporting the fishery (Gulland, 1983). Many fisheries are managed using annual quotas that are designed to produce target fishing rates that will provide a high yield without causing the stock to be overfished.

These target fishing rates may not be easy to measure with a high degree of accuracy.

Various methods have been used for calculating target fishing rates; each has advantages and disadvantages. The goal is to catch a reasonable amount of fish from the stock but without causing any loss in the stock's long-term productivity. The instantaneous rate of fishing mortality that produces the maximum average yield in the long term is often described as F<sub>MSY</sub> (Clark, 1991). F<sub>MSY</sub> depends very much on the relationship between spawning stock size and the recruitment produced by this spawning stock, the so-called spawner-recruit relationship (Beverton and Holt, 1957; Ricker, 1958). For most fish stocks this relationship has proven to be very difficult to measure. If recruitment is relatively independent of spawning stock, then the target fishing rate can be based

on a yield-per-recruit analysis (Beverton and Holt, 1957). F<sub>max</sub> is the fishing mortality coefficient that produces maximum yield per recruit for a given fixed age-at-entry. Due to its independence from a spawner-recruit relationship, F<sub>max</sub> in many cases can be larger than F<sub>MSY</sub> (Deriso, 1982; Clark, 1991). As an alternative to F<sub>MSY</sub> and F<sub>max</sub>, Gulland and Boerema proposed F<sub>0.1</sub>, which is defined as the fishing mortality rate for which the slope of the yield-per-recruit versus fishing mortality curve falls to 10% of its value at the origin. A drawback of F<sub>0.1</sub> is that it can cause depletion of the spawning portion of the stock if the fish recruit to the fishery before they attain maturity (Clark, 1991; PFMC, 1994).

Clark (1991) proposed a target fishing rate that overcomes the problems of F<sub>max</sub> and F<sub>0.1</sub> and behaves much better than those targets over a wide range of circumstances. Clark used simulation models with life history parameters typical of groundfish species to determine a target fishing rate that would result in yields close to the MSY level without depleting the stock or threatening the spawning biomass. He found that 75% of the F<sub>MSY</sub> could be achieved if the equilibrium spawning biomass was maintained in the range of 20-60% of the unfished level and he concluded that in general it was appropriate to try and maintain the spawning biomass at 35% of the unfished level. He defined F<sub>35%</sub> as the instantaneous fishing mortality rate that reduces the spawning potential per female to 35% of its virgin or unexploited level. The calculation of F<sub>35%</sub> depends on the age-specific schedules for growth, maturity and recruitment to the fishery.

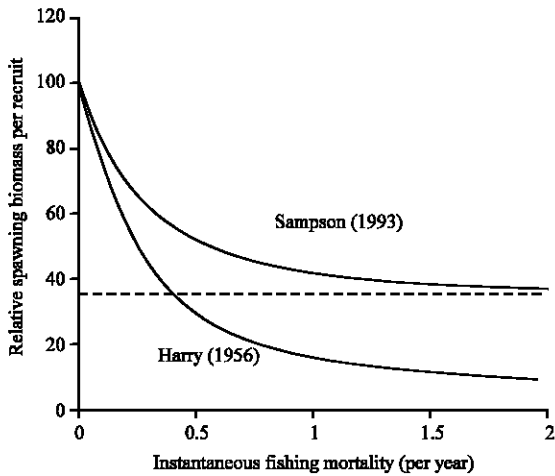


Fig. 1:  $F_{35\%}$  is the instantaneous rate of fishing mortality that reduces the spawning potential to 35% of the unexploited level. It can be greatly influenced by the maturity schedule

The Pacific Fishery Management Council (PFMC) uses the  $F_{35\%}$  target fishing rate to derive annual catch quotas for most of the groundfish stocks along the U.S. Pacific coast (PFMC, 1994). Many of the groundfish species in this region are long lived and  $F_{35\%}$  values are typically in the range of 0.1-0.3 per year. In a recent assessment of the stock of English sole *Pleuronectes vetulus* off Oregon and Washington, Sampson (1993) estimated the  $F_{35\%}$  value to be more than 2.0 year<sup>-1</sup>. He attributed this very large  $F_{35\%}$  value to the presence of unusually large numbers of small females that were mature but unfished. For any given stock the value of  $F_{35\%}$  depends on the maturity schedule, which is often estimated from a limited number of samples. An apparent shift in the maturity schedule in the fish can cause a big shift in the estimated relationship between spawning biomass and fishing mortality. This leads to an  $F_{35\%}$  (Fig. 1) with a larger  $F_{35\%}$  level associated with earlier maturation.

Sampson estimated a maturity schedule for female English sole based on data collected from the commercial fishery by port agents from the Oregon Department of Fish and Wildlife. He noted that there had been a large shift in the maturity schedule compared to data reported in Harry (1956). Sampson estimated the length at 50% maturity for English sole to be 23 cm, whereas the data reported by Harry indicated it to be 30 cm. Maturity is not the only potential source of variability in calculations of  $F_{35\%}$ . Weight at age and availability to the fishery are also important factors. In this study, for simplicity, variability in the maturity schedule for English sole is assumed the

primary source of variability in the  $F_{35\%}$  target fishing rate and Monte Carlo simulation techniques were used to examine the relationship between uncertainty in the maturity schedule and uncertainty in  $F_{35\%}$  but these do not appear to any published investigations on the sensitivity of the  $F_{35\%}$  target fishing rate to variability in the input parameters that determine  $F_{35\%}$ . The objective of the current study is to examine how variability in the maturity schedule for English sole is transformed into variability in estimated values for  $F_{35\%}$ .

## MATERIALS AND METHODS

**Mathematical model for spawning biomass and  $F_{35\%}$ :** The main independent variables involved in the calculation of  $F_{35\%}$  are the population numbers at age, the maturity at age and the weight at age. Each variable has its own set of input parameters. For convenience the variables and parameters and the symbols used to denote them, are listed in Table 1. English sole *Pleuronectes vetulus* data collected in 1986-1990 by the Oregon Department of Fisheries and Wildlife (ODFW) were used to achieve the objective.

The total spawning biomass was calculated by summing the spawning biomass component for each age-class. The spawning biomass for each age group was calculated using Eq. 1 (Appendix A). For a given instantaneous rate of fishing mortality ( $F$ ), the spawning biomass relative to an unexploited stock is given by the ratio of the exploited total spawning biomass over the unexploited total spawning biomass. The  $F_{35\%}$  fishing rate target is the value of  $F$  that reduces the relative spawning biomass to 35%.

The population size at age was modeled as a function of the instantaneous rate of fishing mortality Eq. 2 (Appendix A). Selectivity was modeled as a logistic function of age Eq. 3 (Appendix A).

In the most recent stock assessment for U.S. west coast English sole (Sampson, 1993), the fishery selectivity curve was dome-shaped rather than S-shaped because the older fish did not appear to be fully vulnerable to the fishery. In this study, I elected to use the simpler logistic model for selectivity because older fish make a relatively small contribution to the spawning biomass. For example, based on the demographic parameters used by Sampson (1993), an unexploited cohort of English sole reaches its peak spawning biomass at around four years of age and spawning biomass declines rapidly with age thereafter.

Weight at age was modeled by a von Bertalanffy growth equation with weight proportional to the cube of length (Eq. 4, Appendix A), while the proportion mature at age was modeled as a logistic function (Eq. 4,

**Table 1: Definition of variables and parameters**

a	Age
m <sub>a</sub>	Proportion mature at age
n <sub>a</sub>	Population number at age
w <sub>a</sub>	Weight at age
sb	Spawning biomass
M	Instantaneous rate of natural mortality
s <sub>a</sub>	Selectivity coefficient, relative vulnerability to fishing
F	Instantaneous fishing mortality for fully vulnerable age-classes
A	Age at 50% maturity
B	Slope coefficient for the logistic maturity schedule
C	Slope coefficient for logistic selectivity schedule
D	Age at 50% selection
R	Number of fish recruiting to the fishery
K	Growth rate coefficient
W <sub>∞</sub>	Average maximum weight
cvA	Coefficient of variation for parameter A, expressed as a percentage
cvB	Coefficient of variation for parameter B, expressed as a percentage

**Table 2: Experimental design**

Variables	Levels	Values
A	5	1 2 3 4 5
cvA	3	10% 25% 50%
B	3	0.5 1 2
cvB	3	10% 25% 50%
K	3	0.2 0.25 0.3
C	3	0.5 1 2
D	3	3 5 7
M	3	0.2 0.25 0.3

Appendix A). The total spawning biomass is a function of the instantaneous rate of fishing mortality obtained by Eq. 5 (Appendix A).

The F<sub>35%</sub> target fishing rate satisfies the following equations,

$$sb(F_{35\%}) = 0.35 \times sb(0)$$

$$\sum_a \{R \times \exp[-(M + F_{35\%} \times s_a) \times a] \times W_{\infty} \times [1 - \exp(-K \times a)]^3 \times m_a\} = 0.35 \times \sum_a \{R \times \exp(-M \times a) \times W_{\infty} \times [1 - \exp(-K \times a)]^3 \times m_a\}$$

The parameters R and W<sub>∞</sub> canceled from each side to leave:

$$\sum_a \{ \exp[-(M + F_{35\%} \times s_a) \times a] \times [1 - \exp(-K \times a)]^3 \times m_a \} = 0.35 \times \sum_a \{ \exp(-M \times a) \times [1 - \exp(-K \times a)]^3 \times m_a \}$$

Because F<sub>35%</sub> occurs in the summation of several exponential terms, it is impossible to solve the above equation directly for F<sub>35%</sub>. However, F<sub>35%</sub> can be determined using numerical techniques, given values for the parameters (M, A, B, C, D, K).

Variability in any of these input parameters will propagate into variability in F<sub>35%</sub>. The focus of this study was the relationship between variability in F<sub>35%</sub> and variability in the maturity schedule, which is controlled by the parameters A and B.

**Monte Carlo experimental design:** Monte Carlo procedures were used to examine the influence on F<sub>35%</sub> of variability in the maturity parameters (A, B). Monte Carlo methods are general techniques for analyzing the statistical properties of functions of random variables (Rubinstein, 1981).

For each of the parameters involved in the calculation of F<sub>35%</sub> (M, A, B, C, D, K), a range of values was chosen that would likely encompass ones that would apply to the English sole fishery off Oregon and Washington. For example, Sampson (1993) used a value of 0.24 per year for the growth parameter (K) for this stock and I tried these values for K: 0.02, 0.25, 0.30 per year (Table 2). Parameters M, C, D and K were treated as fixed (non-random), but Parameters A and B were random variables, each with three levels of relative variability (coefficients of variation). Parameter A, which represents the age at 50% maturity, had five levels of expected values. Parameter B, which controls the slope of the maturity schedule, had three levels of expected values. The remaining Parameters each had three levels. In the Monte Carlo experiment, I examined the influence of 8 factors with a total of 10,935 different combinations (Table 2).

For each of the combinations of factors, I generated 100 pairs of normally distributed random values for the maturity Parameters A and B and then calculated the 100 corresponding values for F<sub>35%</sub>. The values for A and B were generated independently of each other. To summarize the data for each experimental treatment I, calculated the average and coefficient of variation of the 100 values for F<sub>35%</sub>. The coefficients of variation were expressed as percentages rather than fractions.

Because negative values for either A or B would not be realistic on biological grounds, any negative values that appeared during the generation process were discarded and replacement values were produced. The tail area of the normal distribution is roughly proportional to the standard deviation (Neter and Kutner, 1989), hence negative values for A and B were observed mostly when one or both coefficients of variation (cvA, cvB) were large (50%). However, the total number of negative numbers that were regenerated to positive values was negligible; less than 1%.

**Data analysis:** Stepwise linear regression techniques were used to find relatively simple combinations of factors that would account for most of the variability in the independent variables; the average F<sub>35%</sub> (denoted simply as F<sub>35%</sub>) and coefficient variation for F<sub>35%</sub> (denoted as cvF<sub>35%</sub>). However, preliminary examination of the F<sub>35%</sub> and cvF<sub>35%</sub> data indicated that they were not normally distributed as assumed in standard linear regression. As a consequence, the F<sub>35%</sub> and cvF<sub>35%</sub> data were transformed

Table 3: Summary of results from the regression models with all the basic variables

Dependent variables	Independent variables treated as					
	Continuous			Discrete		
	d.f	1 / F <sub>35%</sub> R <sup>2</sup>	log (cvF <sub>35%</sub> ) R <sup>2</sup>	d.f	1 / F <sub>35%</sub> R <sup>2</sup>	log (cvF <sub>35%</sub> ) R <sup>2</sup>
Basic terms	8	0.90	0.86	18	0.93	0.89
+2 Level interaction	36	0.96	0.86	18	0.93	0.89
+Quadratic terms	44	0.98	0.96	-	-	-

prior to the linear regression analyses. Routines from the Statistical Analysis System (SAS, 1989) were used to analyze the data.

**Model selection:** Forward stepwise selection procedures (Ramsey and Schafer, 1996) were used to determine the sequence of models of increasing complexity that, for a given degree of complexity best accounted for the variability in each of the dependent variables. The complexity of a model was measured by the coefficient of determination (R<sup>2</sup>). Initially the eight factors were treated as continuous variables. At the first step of the selection process the factor that produced the largest R<sup>2</sup> value was selected. At the second step of the process each of the remaining seven factors, plus the square of the factor selected at the first step, were added to the model and the new factor (or quadratic term) that produced the largest increase in R<sup>2</sup> was selected. Interactions between two factors were not added to the model at later steps unless both factors were already in the model as main effects. This process continued until overall R<sup>2</sup> values of at least 90% were obtained.

After the last step of the selection process, I reanalyzed the data with the factors treated as discrete variables rather than as continuous variables, thereby relaxing the assumption that the dependent variables were linear functions of the independent variables. The difference in R<sup>2</sup> values between a model with continuous variables versus the same model with class variables is a measure of the nonlinearity in the relationship between the dependent and independent variables.

To explore more fully the relationship between model complexity and explanatory power, models were also fitted to the two independent variables containing all eight of the basic independent variables. I then added all pair-wise interactions of the basic variables and then added quadratic terms for all the basic variables (Table 3). I also reanalyzed these same sets of models with the independent variables treated as discrete variables.

Appendix A: Mathematical model for spawning biomass and F<sub>35%</sub>

- 1- Obtaining the spawning biomass (sb) for each age group  

$$sb_a = n_a \times w_a \times m_a$$
- 2- Obtaining the population size at age  

$$n_{a+1} = n_a \times \exp [ - ( M + F \times s_a ) ]$$
- 3- Obtaining the selectivity  

$$s_a = 1 / \{ 1 + \exp [ - C \times ( a - D ) ] \}$$
- 4- Obtaining weight age relation by the von Bertalanffy growth equation  

$$w_a = W_{\infty} \times \{ 1 - \exp ( - K \times a ) \}^3$$
- 5- Obtaining the proportion mature at age  

$$m_a = 1 / \{ 1 + \exp ( [ - B \times ( a - A ) ] ) \}$$

**RESULTS**

In 320 of the 10,935 experimental treatments (2.9%), the coefficient of variation for F<sub>35%</sub> was greater than 50%, which was the largest level of relative variability for A and B considered in the experiment (cvA, cvB). These unusually variable cases were almost always associated with the largest level for the age at 50% selection (D) and the largest slope coefficient for the logistic selection Curve (C). They were usually, but not always, associated with the largest level of the age at 50% maturity (A) and the two largest levels of relative variability in the age at 50% maturity. In general, larger values of F<sub>35%</sub> had larger relative variability, but the linear correlation of F<sub>35%</sub> and cvF<sub>35%</sub> was only 0.261, indicating that most of the variability in the values of cvF<sub>35%</sub> could not be accounted for by variation in F<sub>35%</sub>.

The raw data for F<sub>35%</sub> and cvF<sub>35%</sub> was highly skewed to the right (Fig. 2a and 3a). When the data was transformed using the natural logarithm function, the transformed data for cvF<sub>35%</sub> became symmetrically distributed (Fig. 3b), but the transformed data for F<sub>35%</sub> remained skewed to the right. The reciprocal transformation produced transformed values for F<sub>35%</sub> that appeared to be more symmetrically distributed (Fig. 2b) although they were somewhat skewed to the left. For the linear regression analyses, I decided to use the logarithmic transformed values of cvF<sub>35%</sub> and the reciprocal transformed values of F<sub>35%</sub>. Relatively few parameters and independent variables were needed to explain the variability in the reciprocal transformed values of F<sub>35%</sub> (Table 4). With the independent variables as continuous variables, a simple linear model with four terms (one for each of the factors D, A, M, K) explained almost 90% of the variability. By contrast it took a model

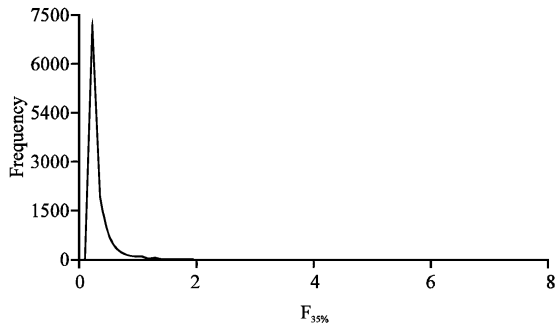


Fig. 2a: Average values of  $F_{35\%}$  obtained from 100 Monte Carlo replicates in each of 10,935 experimental treatments

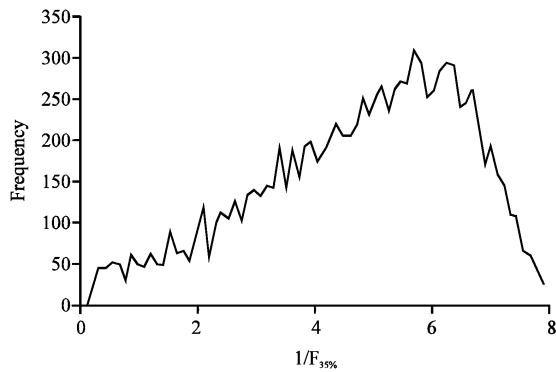


Fig. 2b: Reciprocal transformation of the  $F_{35\%}$  data

with 9 terms to account for the same amount of variability in the logarithmic transformed values of  $cvF_{35\%}$ . In general, much more complicated models were required to account for variability in the  $F_{35\%}$  data than to account for the variability in the  $cvF_{35\%}$  data. For both independent variables, the first two factors to enter during the forward stepwise model building were D and A, which are the parameters controlling the ages at 50% selection and 50% maturity.

When I fitted models to  $(1/F_{35\%})$  and  $\log(cvF_{35\%})$  in which all of the 8 basic dependent variables were included, the pattern of results was similar to the pattern in the stepwise analyses. For a given level of model complexity the model for  $F_{35\%}$  had greater predictive power than the model for  $cvF_{35\%}$ . Also, there were small differences in  $R^2$  value dependent variables that were not highly nonlinear functions of the basic independent variables.

In the forward stepwise regression analysis the following model was found to be the simplest combination of the independent variables that would account for at least 90% of the variability in the reciprocal transformed values of  $F_{35\%}$ :

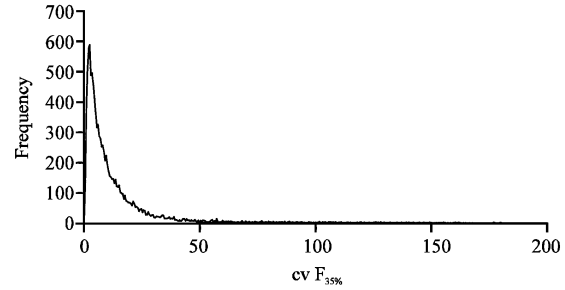


Fig. 3a: Coefficient of variation in  $F_{35\%}$  ( $cvF_{35\%}$ ) obtained from 100 Monte Carlo replicates in each of 10,935 experimental treatments.

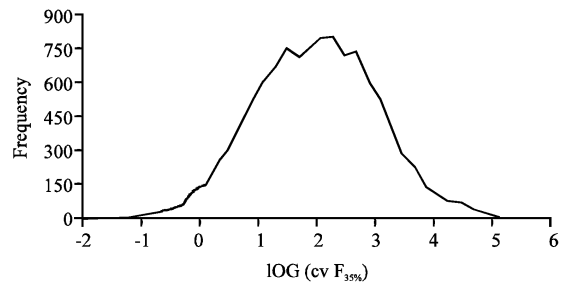


Fig. 3b: Logarithmic transformation of the  $cvF_{35\%}$  data.

Table 4: Summary of results from the forward stepwise regression analyses

Dependent variable: $(1 / F_{35\%})$			
	Independent variables	$R^2$	d.f.
Continuous	D	0.639	1
	D A	0.766	2
	D A M	0.857	3
	D A M K	0.899	4
	D A M K $D^2$	0.920	5
Discrete	D A M K	0.922	10
Dependent variable: $\log (cvF_{35\%})$			
	Independent variables	$R^2$	d.f.
Continuous	A	0.337	1
	A D	0.566	2
	A D $cvA$	0.740	3
	A D $cvA$ M	0.776	4
	A D $cvA$ M C	0.805	5
	A D $cvA$ M C $D^*C$	0.846	6
	A D $cvA$ M C $D^*C$ K	0.867	7
	A D $cvA$ M C $D^*C$ K $cvB$	0.888	8
	A D $cvA$ M C $D^*C$ K $cvB$ $A^2$	0.899	9
	A D $cvA$ M C $D^*C$ K $cvB$ $A^2$ B	0.909	10
Discrete	A D $cvA$ M C $D^*C$ K $cvB$	0.930	22

$$(1 / F_{35\%}) = \mu + \beta_A \times A + \beta_D \times D + \beta_M \times M + \beta_K \times K + \beta_{D^2} \times D^2 + \epsilon$$

Where  $\mu$  is the intercept, the coefficients ( $\beta_A, \beta_D, \dots, \beta_{D^2}$ ) are estimated parameter values (Table 5) associated with each of the independent variables, the independent variables were treated as continuous and  $\epsilon$  is approximately distributed as a normal random variant with a mean

Table 5: Estimates and standard errors for the selected models for  $F_{35\%}$  and the coefficient of variation in  $F_{35\%}$  ( $cvF_{35\%}$ )

Variable	Estimate	Standard error
Dep. Variable: $(1 / F_{35\%})$		
Intercept	10.154	0.073
$\beta_A$	0.444	0.003
$\beta_D$	0.493	0.0256
$\beta_M$	-13.045	0.117
$\beta_K$	-8.79	0.117
$\beta_{D^2}$	0.1357	0.0025
Dep. Variable: $\log (cvF_{35\%})$		
Intercept	-3.816	0.037
$\beta_A$	0.8223	0.011
$\beta_D$	0.0634	0.004
$\beta_{cvA}$	2.649	0.018
$\beta_M$	4.803	0.074
$\beta_C$	-0.751	0.016
$\beta_{D*C}$	0.208	0.003
$\beta_K$	3.68	0.074
$\beta_{cvB}$	0.907	0.018
$\beta_{A^2}$	-0.066	0.002
$\beta_B$	0.174	0.005

of zero and a variance of 0.2505. When the independent variables in the above model were treated as discrete (class) variables, the  $R^2$  value increased by only 0.002, which indicates that the dependent variable  $(1/F_{35\%})$  was essentially a linear function of the independent variables A, M and K and a quadratic function of D.

The following model was found to be the simplest combination of the independent variables that would account for at least 90% of the variability in the logarithmic transformed values of  $cvF_{35\%}$  :

$$\begin{aligned} \text{Log}(cvF_{35\%}) = & \mu + \beta_A \times A + \beta_D \times D + \beta_{cvA} \times cvA + \beta_M \times \\ & M + \beta_C \times C + \beta_{D*C} \times D * C + \beta_K \times K + \beta_{cvB} \times \\ & cvB + \beta_{A^2} \times A^2 + \beta_B \times \beta + \epsilon \end{aligned}$$

Where  $\mu$  is the intercept, the coefficients ( $\beta_A, \beta_D, \dots, \beta_B$ ) are estimated parameter values (Table 5) associated with each of the independent variables, the independent variables were treated as continuous and  $\epsilon$  is approximately distributed as normal random variables with a mean of zero and a variance of 0.0992. When the independent variables in the above model were treated as discrete variables, the  $R^2$  value increased by 0.021 (Table 4), which indicates that the dependent variable  $(\log [cvF_{35\%}])$  was essentially a linear function of the independent variables, although the departure from linearity was ten times greater than the departure observed in the model for  $F_{35\%}$ .

The studentized residuals for the two selected models (Fig. 4 and 5) generally conformed to the pattern that one would expect to see if the underlying random errors in the models (the  $\epsilon$  values) were in fact normally distributed. These were unusual patterns, however, particularly for small predicted values of  $(1/F_{35\%})$  (Fig. 4).

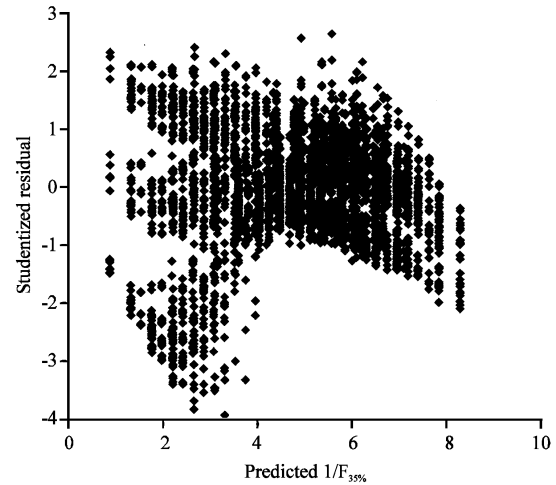


Fig. 4: Random sample of 30% of the standardized residuals from the regression model for  $(1/F_{35\%})$  with independent variables A, D, M, K and  $D^2$

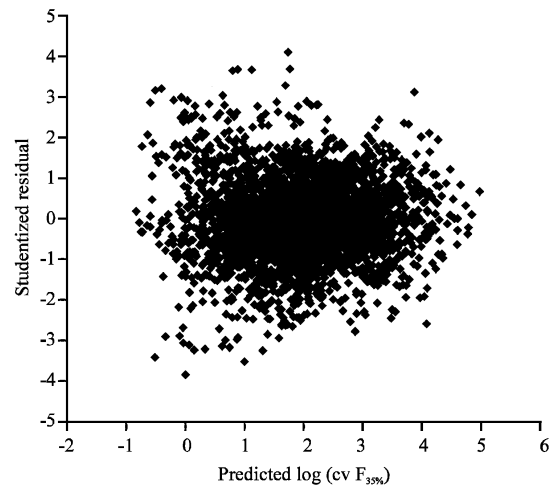


Fig. 5: Random sample of 30% of the standardized residuals from the regression model for  $\log (cvF_{35\%})$  with independent variables A, D,  $cvA$ , M, C,  $D*C$ , K,  $cvB$ ,  $A^2$  and B

The large positive residuals for small predicted values of  $(1 / F_{35\%})$  were generally associated with experimental combinations in which the age at 50% selection (D) was equal to 7 (its largest value) and the slope coefficient (C) was equal to 0.5 (its smallest value). The larger negative residuals for small predicted values of  $(1/F_{35\%})$  were also generally associated with combinations in which D was equal to 7, but in this case C was equal to 2, its largest value. The model for  $(1/F_{35\%})$  is not very accurate when the age at 50% selection is large and the slope coefficient is either very small or very large.

## DISCUSSION

In the forward stepwise analyses, all of the explanatory variables entering the model for the average  $F_{35\%}$  also appeared in the model for the coefficient of variation in  $F_{35\%}$  ( $cvF_{35\%}$ ). But additional variables were required to account for the much greater variability in the  $cvF_{35\%}$  data. In both analyses the most powerful explanatory variables were the age at 50% maturity (A) and the age at 50% selection (D). Clark (1991) also found that the age at 50% maturity and selection were important determinants of  $F_{35\%}$ . He showed that  $F_{35\%}$  would be large if recruitment was delayed relative to maturation because the fish would then be given time to spawn before experiencing fishing mortality. However, if maturation occurred after recruitment, the fish would experience elevated mortality prior to first spawning so that  $F_{35\%}$  would be small.

In the model for  $(1/F_{35\%})$  the first variable to enter was the age at 50% selection, which alone accounted for 63% of the variability in  $(1/F_{35\%})$  and the second variable to enter the model was the age at 50% maturity, which accounted for 13% of the variability in the data. There was a substantial decrease in the predictive power associated with the variables entering the model after the first two. Four of the 8 primary explanatory variables never entered the model. Neither the slope coefficient for the logistic selectivity schedule (C) nor the slope coefficient for the logistic maturity schedule (B) had much influence on the value of  $F_{35\%}$ . Also, the relative variability in the maturity schedule parameters ( $cvA$  and  $cvB$ ) had little influence which suggests that  $F_{35\%}$  is essentially a linear function of the maturity parameters A and B.

In the model for  $\log(cvF_{35\%})$  all of the eight basic explanatory variables appeared in addition to an interaction term (C\*D) and a quadratic term ( $A^2$ ). The first explanatory variable to enter the model was the age at 50% maturity (A) which alone accounted for 34% of the variability in the  $\log(cvF_{35\%})$  data and the second variable to enter the model was the age at 50% selection, which accounted for 23% of the variability in the data. In contrast to the model for  $F_{35\%}$ , the relative variability in the age at 50% maturity ( $cvA$ ) had moderate influence on the value of  $cvF_{35\%}$ . The relative variability in the coefficient for the maturity schedule ( $cvB$ ) had only minor influence on  $cvF_{35\%}$  however.

In the Monte Carlo experiments the random values for A and B were chosen independently of one another, i.e., they were uncorrelated. In general, estimates of A and B would be derived from the same data and would tend to be correlated. Given that the selected model for  $F_{35\%}$  did not contain terms for B,  $cvA$ , or  $cvB$ , it seems likely that correlation between A and B would have little effect on

this model. In the selected model for  $cvF_{35\%}$ , the terms for B and  $cvB$  were of relatively minor importance, so that correlation between A and B would probably not have much effect on this model either.

For the  $F_{35\%}$  target fishing rate to be an effective tool in fisheries management, it should be robust to measurement errors in the data from which it is derived. For example, if measurement errors in the maturity schedule are amplified during the calculation of  $F_{35\%}$ , then catch quotas subsequently derived using an inaccurate  $F_{35\%}$  value might be so large that they would jeopardize the spawning potential of the fish stock, or they might be unnecessarily small and cause economic hardship to the fishermen. In the Monte Carlo experiments the coefficients of variation in  $F_{35\%}$  were generally smaller than the coefficients of variation in the maturity schedule parameters but there were instances in which the relative variation in the maturity parameters was greatly amplified. For example, 50% relative variability in A and B produced 179% relative variation in  $F_{35\%}$  for one of the experimental treatments observed in this study. It seems unlikely for this particular case that  $F_{35\%}$  would be an effective target for management. Before fishery managers routinely accept estimates of  $F_{35\%}$ , the estimates should be critically evaluated to establish that they are not overly sensitive to measurement errors.

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