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PREDICTING YEAR CLASS STRENGTH FROM THE ABUNDANCE OF AGE-0 ROCKFISH: PROJECTIONS OF STATISTICAL POWER

By

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Predicting year-class strength from the

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Summary

The Groundfish Analysis Investigation of the Tiburon Laboratory conducts an annual survey of age-0 rockfish (Genus *Sebastes*). A major long-term goal of these surveys is to estimate the strength of a year class based on their abundance at age 0. This requires that a positive relationship between recruitment to the fishery and age-0 abundance be established. In this report we examined the statistical power for establishing such a relationship. This was done for a range of specified assumptions. The first case we considered was when expected recruitment to the fishery is directly proportional to the abundance at age-0. We found that high power could be achieved with ten or more years of data provided the standard deviation of recruitment to the fishery, given a particular value of the age-0 abundance index, is not too large (on the order of several to ten times the standard error associated of the index of age-0 abundance.) This allows below or above average year classes to be distinguished from average ones with high probability.

We then considered the effect of compensatory mortality, occurring between the age-0 stage sampled by our juvenile surveys and recruitment to the fishery, on our estimates of power. In the face of moderate compensation our ability to establish a relationship between recruitment to the fishery and age-0 abundance was not compromised, and we also had moderately high power to detect the existence of the compensation. In the face of very strong compensation, the statistical power for detecting a relationship between recruitment to the fishery and age-0 abundance was much lower. In this latter situation a recruitment index is needed to a lessor degree since recruitment

is relatively constant.

Although 10 years of data should be adequate, under a range of assumed conditions, for establishing a relationship between recruitment to the fishery and age-0 abundance, we note that there is a substantial time lag between the time the survey estimate of age-0 abundance is made and the time that a reliable independent estimate of recruitment to the fishery becomes available. This time lag can approach ten years in length for some species of rockfish.

Introduction

An estimate of current stock size is an important ingredient in the management of most groundfish stocks. In many cases these estimates are based largely on catch-at-age data from the fishery, using methods such as cohort and virtual population analysis, or more recently the stock-synthesis model. A number of workers have noted that the estimates of the size of the more recently recruited year classes based solely on catch-at-age data are generally not reliable (e.g. Deriso *et al.* 1983, Methot in press). Recent modelling work has shown that reliable real-time estimates of recruitment to a fishery can increase the range of viable management approaches, and ultimately increase yields or decrease risk (Lenarz, in prep.). Auxiliary, fishery-independent data can improve estimates of recent recruitment and current stock size substantially (e.g. Deriso *et al.* 1983). Surveys of juvenile abundance can potentially provide such auxiliary data, and can readily be incorporated into assessments using methodology like the stock synthesis model (Methot in press). Such data also provide some potential for predicting recruitment to the fishery several years in the future (but see Walters 1989, see Discussion). Data from juvenile surveys have played an important role in assessments of stock size by the Northeast Fisheries Center (e.g. Clark 1981).

The Groundfish Analysis Investigation at the Tiburon Laboratory has conducted an annual survey off the central California coast each year since 1983. These surveys use mid-water trawls and are designed to yield an index of the abundance of age-0 rockfish (genus *Sebastes*) during their pelagic phase. A major goal of these surveys is to estimate year-class strength, thereby predicting future recruitment into the fishery. Surveys of juveniles were chosen over surveys of larvae because recruitment strength into a fishery is often not well correlated with larval abundance due to high and variable mortality during the larval stage (e.g. Hjort 1914, Gulland 1965, Houde 1987). By sampling after the larval stage, the variability associated with mortality of that stage is removed and statistical power should be increased. Thus, our attempts to relate recruitment to the fishery to juvenile abundance might avoid the chronically low power that may often play a role in preventing the detection of a stock - recruit relationship (Walters and Ludwig 1981, Goodyear and Christensen 1984, Overholtz *et al.* 1985), or a time trend in recruitment (Peterman and Bradford 1987).

Before using data from the juvenile survey in stock assessments and projections we need to establish that a positive correlation exists between recruitment into the fishery and the earlier survey-determined age-0 abundance of that year class. The purpose of this report is to estimate the number of years of survey data required to establish with high probability the relationship, given that such a relationship exists. However, the probability of detecting a significant relationship (power) depends upon the form of the underlying relationship, and statistical errors about that relationship, in addition to the number of years of data that are available. Unfortunately, neither the magnitude of the statistical errors nor the form of the underlying relationship is known. The approach adopted here is to estimate statistical power under a range of assumptions about the variability around the underlying relationship, and for two types of relationships between recruitment into the fishery and abundance at age-0.

If we assume large enough variation about an underlying relationship, we would estimate nearly infinite sample sizes would be required to detect the relationship. However, establishing the existence of such a relationship would be of little use as a management tool since a given estimate of age-0 abundance would be a poor predictor of recruitment into the fishery. Thus we restrict our attention to cases where if the underlying relationship were known, age-0 abundance might provide a useful tool for estimating recruitment into the fishery.

We assume that attempts to verify a relationship between recruitment into the fishery and age-0 abundance will be based on a regression of estimates of the former on the latter, with both being natural log-transformed. The statistical power of this procedure is estimated for (a) direct proportionality between recruitment into the fishery and age-0 abundance, and (b) a Beverton-Holt relationship representing compensatory mortality following high levels of recruitment at age 0. The expected source of information on recruitment into the fishery is from methods making use of a time series of catch-at-age data such as the stock synthesis model (Methot in press). Such estimates are now available for widow rockfish (Hightower and Lenarz 1989), and we use estimates of the variation in recruitment into the widow rockfish fishery in our power calculations. Thus we are using widow rockfish as a model species. The collation of appropriate data and calculations are underway by the Groundfish Analysis Investigation at the Tiburon Laboratory to generate time series of recruitment into the fisheries for other rockfish species that are common in the juvenile surveys.

Methods

Case One: Directly Proportional Recruitment

The first case we consider is that where expected recruitment into the fishery is directly proportional to estimated abundance at age-0. In this case we invoke the model:

$$R_{i+\tau} = aJ_i\epsilon_i, \tag{1}$$

where J_i is an index of the abundance of age-0 fish (juveniles) in year i, $R_{i+\tau}$ is the estimated recruitment of these same fish into the fishery τ years in the future, a is a proportionality constant, and ϵ_i is the multiplicative error about the assumed relationship (which is due both to variability in survival, and estimation error and is assumed to have a log normal distribution). Taking natural logs of both sides yields:

$$\ln(R_{i+\tau}) = \ln(a) + \ln(J_i) + \ln(\epsilon_i), \tag{2}$$

which has the form assumed in simple linear regression

$$r_i = c_1 + c_2 I_i + \varepsilon_i \quad (3),$$

with $c_1 = \ln(a)$, $c_2 = 1$, $\varepsilon_i = \ln(\epsilon_i)$, $r_i = \ln(R_{i+\tau})$, and the transformed index $I_i = \ln(J_i)$.

Our procedure then is to assume that a set of r_i values (representing ln-transformed recruitment to the fishery) is generated from a set of I values (representing ln-transformed indices of age-0 abundance), based on equation 3, and then calculate the statistical power for rejecting the null hypothesis $c_2=0$. Power depends not only upon the number of years of data available, the variance of the errors, ε_i, but also on the particular I values available for use in the regression. The abundance of age-0 fish is of course not under our control, and thus until all the samples are collected and data are processed the set of I values that will be available for a regression will remain unknown. We deal with this problem by estimating power for a number of sets of I values (the ln-transformed age-0 abundances) generated randomly from an assumed normal distribution. Because we are assuming that expected recruitment into the fishery is directly proportional to age-0 abundance, we estimate the variance of I from the observed variability in recruitment (R) seen for widow rockfish. Given the assumed log-normal distribution of R, the variance of I, σ^2_I, is given by:

$$\sigma^2_I=\ln((\sigma^2_R + \mu_R^2)/\mu_R^2) \qquad (4),$$

where σ^2_R and μ_R are the variance and mean of R (Law and Kelton 1982). The mean of I is irrelevant to our calculation of power.

Expected power is estimated by the average power for 2000 randomly generated sets of I values for each combination of parameters. For each I sample we estimated power for rejecting the null hypothesis under the alternative given by equation 3. In our calculations of power, we assume that for a given set of data the estimated slope divided by its standard error is a random variable from a non-central t distribution, $T(\eta,\nu)$, with non-centrality parameter η, and degrees of freedom ν. Power for rejecting the null hypothesis at level α then is 100 x the probability that the absolute value of such a random variable will exceed the α level critical value of the usual t-test with ν degrees of freedom. ν is the number of paired observations - 2 (the usual degrees of freedom associated with the slope in a linear regression), and in our calculations $\alpha = 0.05$ for two-tailed tests. η is the slope under the alternative hypothesis (unity here), divided by the true standard deviation of estimated slopes:

$$\sigma_{c2} = \sigma_\varepsilon \; / \; [\Sigma(I_i - \bar{I})^2\,]^{1/2} \,.$$

The probability that the noncentral t random variable would exceed a specified value was found by using a built in routine in the Gauss[tm] software package for finding the CDF of a noncentral t-distribution. Note that the calculation of power for a given set of I values does not require the generation of r_i values, nor the calculation of a regression; power depends only upon α, ν, and η. It is only because the I values are not under our control and power depends upon them through their influence on η, that simulations are needed to calculate average power over all possible sets of I.

The detection of a statistically significant relationship between recruitment into the fishery and age-0 abundance does not demonstrate that the relationship is useful in managing the fishery. We would also like an idea of the average size of the error in our predictions based on the regression. For large sample sizes this is given by the standard deviation of the assumed errors about the true relationship (σ_ε). Simply put, if many years of data were available the usefulness of the regression depends only on how noisy the true relationship is. However, for more modest sample sizes, the magnitude of errors will also depend both on the number of years of data and upon the amount of recruitment to age-0 that occurred during a given year. This is true because our regression line is not equal to the true relationship. On average deviations will be greater when the regression is based on smaller sample sizes, or when we are predicting far away from the mean of the I values. This is of particular interest because of the wide range of recruitment seen in a number of rockfish species. We have therefore also estimated the standard deviation of the prediction errors, when recruitment is one third the mean level, a value which is well within the range of observed recruitment for widow rockfish. This is a measure of our ability to distinguish between a poor recruitment year and an average recruitment year (because of symmetry, it also measures our ability to distinguish between an average and good recruitment year in the simulation). For a given set of I values, the standard deviation of the prediction error is given by:

$$\sigma_p = \sigma_\varepsilon\{1 + 1/n + (I_o - \bar{I})^2/\sum_{i=1}^{n}(I_i-\bar{I})^2\} \quad (5),$$

where σ_ε is the standard deviation of the errors about the underlying model, and I_o is the I value corresponding to a recruitment of 1/3 the average (See for example Draper and Smith 1981). To estimate prediction error for other levels of recruitment we would use different values for I_o.

In the above discussion of prediction errors we made the implicit assumption that differences between observed and predicted recruitment were entirely due to differences between actual and predicted recruitment. This may not approximate the actual situation since observed recruitment is an estimate of actual recruitment, and error associated with the estimation process could be substantial. At the opposite extreme we could assume that actual recruitment is perfectly proportional to age-0 abundance, and that the errors ε_i are entirely a consequence of estimation errors. If this were the case, our concern would be with the differences between our predictions and actual ln(recruitment). The standard deviation of these differences is given by:

$$\sigma_\delta = \sigma_\varepsilon\{1/n + (I_o - \bar{I})^2/\Sigma(I_i-\bar{I})^2\} \qquad (6),$$

which differs from σ_p (equation 5) by a constant equal to σ_ε. This shows that a regression prediction of recruitment will be more useful, for a given level of error about the underlying model (σ_ε), when the error is dominated by estimation error and not by departures of actual recruitment from the expected recruitment$|I_i$.

Case two: a Beverton-Holt relationship

When a year-class is strong there may be compensation so that a smaller proportion survive to recruit into the fishery than would recruit from a weaker year-class. The result is that we will see less variation in recruitment into the fishery in response to variation in the abundance of the age-0 fish, and detecting the relationship between recruitment into the fishery and abundance at age-0 will be more difficult. We explore quantitatively how such compensation might influence our statistical power by assuming that there is a Beverton-Holt type relationship, i.e.

$$R_{i+T} = [aJ_i \,/\, \{1 + cJ_i\}]\varepsilon_i \qquad (7),$$

where R_{i+T} and J_i are recruitment of a year class into the fishery and at age 0 respectively, c is a parameter that determines the degree of compensation, and the ε_i is the multiplicative error (assumed to be normally distributed), and a is a scaling factor which for our purposes can be ignored. Asymptotic recruitment is equal to a/c. Thus, for a fixed a, the choice of asymptotic recruitment determines the extent of compensation. We have estimated power for two levels of compensation. In the first we assumed that asymptotic recruitment was 37.5 x 10^6, 10% above the maximum observed recruitment. However, with this asymptote, compensation is not especially strong; more than half the observed values for widow rockfish are below 50% of the asymptote (Table 1). For this reason we calculated power using a second asymptote equal to 20 x 10^6. Note that it is possible for recruitment into the fishery to be above the asymptote because we are allowing error about the underlying relationship.

Power was calculated by Monte-Carlo simulations. J and R data were generated, natural logarithms were taken to produce a set of r and l data, a regression was done, and the standard test for significance of a regression at the $\alpha=0.05$ level was done. This was repeated 2000 times, and the percentage of tests yielding significant results was the estimated power of the test. J was assumed to have a log normal distribution with specified variance. R is generated from J by equation 6. The variance of J was set by first transforming estimated values of R for widow rockfish into values of J using an inverse of equation 6, and then calculating the variance of the resulting J values. In the case where the asymptote was set at 20 x 10^6, values exceeding this asymptote were first made equal to 90% of the asymptote because the inverse transform does not exist for R greater than the asymptote.

Results

Case one: directly proportional recruitment

Power was calculated for a range of sample sizes, i.e. number of years of data, (5, 7, 10, 15, 25) and for each sample size σ_ε was varied from 0.1 to 0.5. (A standard deviation for the errors of 0.5 on a ln-scale means that roughly two-thirds of the values of recruitment into the fishery (R) will be between 0.61 and 1.65 times the expected recruitment, given the observed abundance at age 0 (J).)

As is necessarily the case, power increases when more years of data are available, and decreases as σ_ε increases. Reasonably high power (greater than 80%) was achieved for all levels of σ_ε when 15 or more years of data were available, and for all but the highest level of σ_ε for 10 years of data (Table 2). With less than 10 years of data power fell off more sharply as σ_ε increased (Table 2). The generally high power reported in Table 2 stems from the fact that the assumed variation in I is based on observed variation in recruitment of widow rockfish to the fishery, and this ranged over nearly an order of magnitude in 10 years (Table 1). Thus, with ten or more years of data we would expect to obtain a wide range of recruitment levels, ranging from very good to very poor.

In addition to power, prediction error (σ_p) is of interest. For a large number of years of data (n=25) this approaches σ_ε. When fewer years of data are available prediction error is larger, but the relative size of the prediction error across levels of σ_ε remains the same. For example, the prediction error for σ_ε=0.5 is approximately five times the prediction error for σ_ε=0.1 for all values of n. For a given level of $\sigma_{\varepsilon,}$ prediction error is nearly three times higher when n=5 than when n=25. Most of the reduction in prediction error is achieved by the time n has been increased from 5 to 10. Prediction error was reduced by 50% of its initial value (for n=5) by an increase in years of data to 10. A further increase in n to 25 results in less than a 15 % further reduction.

To put these prediction errors in context, it is useful to consider how often we are able to distinguish between a poor year-class and an average one, when our prediction errors are dominated by differences between actual and expected recruitment. If we predicted that recruitment would be one third average, and this underestimated recruitment to the fishery by 1.1 units or more on a natural log scale, we would have identified an average or better year-class as a moderately poor one. For the largest σ_ε we considered, with n=10, then σ_p = 0.78 and we would make this kind of mistake roughly 8.5% of the time. (The 8.5% is rough because the prediction error is generated for J equal to one third its average, but is applied to a predicted R at one third its average.) Likewise, we would expect that year-classes we expected to be three times average to actually be average or below when we observe them recruit to the fishery about 8.5% of the time. The above results are a worst case scenario because they depend upon σ_ε being dominated by differences between actual recruitment and expected recruitment given J_i. When error in estimating actual recruitment is an important component of the ε_is, the regressions will generally be better predictors of actual recruitment (see Methods).

Thus with ten years or more of data, for the σ_ε we considered, we can distinguish between moderately poor and average, or moderately good and average, most (>90%) of the time. The power for detecting a positive relationship between recruitment to the fishery and age 0 abundance in this situation exceeds 70%. Although the relationship between power and prediction error is not one-to-one, it is generally the case that higher power means smaller prediction errors. For all cases reported in Table 2, when power exceeds 70%, prediction error is less than 0.8.

Case two: Beverton-Holt Recruitment

Again we consider a range of sample sizes (n = 5, 7, 10, 15, and 25) and let σ_ε range from 0.1 to 0.5 for each sample size. It is worth noting that σ_ε has been defined differently in case two than it was in case one: in case one it was the additive error on a natural log scale, here it is the multiplicative error on an arithmetic scale. Thus, for example, an error of 0.5 leads to an overestimation of 65% in case one and of 50% here. For this reason we have added an additional level of σ_ε, 0.65, here. Note, however, that the distinction between the two different definitions of σ_ε is more than a simple scaling issue, which complicates our comparison of power between case one and case two.

With asymptotic recruitment at 37.5 x 10^6 there is some deterioration in our ability to detect a relationship between recruitment into the fishery and age-0 abundance (i.e. to reject H1: slope=0) in comparison with case one (Table 3). Because σ_ε is defined differently in case one and two, the somewhat lower power reported in Table 3 in comparison with that in Table 2 should not be over-interpreted. It is also of interest that our power for rejecting the null hypothesis of direct proportionality (H2: slope=1) is about the same as our power for rejecting H1. Thus with moderate levels of compensation we still have a reasonable chance both of establishing the existence of this compensation and for establishing a positive relationship between recruitment to the fishery and age-0 abundance.

The power for establishing a relationship between recruitment to the fishery and abundance at age-0 is much poorer when stronger compensation is assumed (Table 4). With asymptotic recruitment is assumed to be 20 x 10^6, more than 10 years of data are required to achieve power of 70% for H1 except at the lowest level of σ_ε. At the two highest levels of σ_ε power never exceeds 50% even with 25 years of data. In contrast with the large decline in power for H1, increases in power to detect compensation (i.e. to reject H2) are only modest.

We illustrate why the decline in power occurs when compensation is strong in Fig. 1. There we give an example of the data generated when $\sigma_\varepsilon=0.3$ and $n=15$ for asymptotic recruitment of 20 x 10^6 and 37.5 x 10^6. When asymptotic recruitment is 20 x 10^6 most of the data points occur over a range for which most of the variation in age-0 abundances is removed in recruitment to the fishery by compensation. Thus variation in recruitment to the fishery is dominated by error about the underlying relationship. In contrast, when asymptotic recruitment is 37.5 x 10^6 many data points occur over the range where recruitment to the fishery shows a substantial response to variations in age-0 abundance. There are also some data points near the asymptote in this case, and that is why we also had good power to detect compensation in this case.

Discussion

In this report we have calculated power for detecting a relationship between recruitment to the fishery and age-0 abundance under specified assumptions. We found that if recruitment to the fishery were directly proportional to age-0 abundance we would achieve moderately high power with ten years of data, unless error about the true relationship were higher than the highest we assumed. The resulting errors are such that we can usually distinguish moderately good or poor year-classes from average ones, even when all the assumed error is due to differences between actual and expected recruitment to the fishery. In the face of moderate compensation (based on the assumption that the observed maximum recruitment into the widow rockfish fishery is 10% below the asymptote of a Beverton-Holt age-0 abundance - fishery recruit relationship) power is only slightly lower. However, in the face of stronger compensation power falls off sharply so that moderately high power was often not achieved even with 25 years of data. It is worth emphasizing that the compensation of interest here occurs between the stage sampled by the juvenile rockfish surveys and recruitment into the fishery. The occurrence of compensation elsewhere in the life-history is not relevant to the issue at hand.

A dilemma we are faced with is that our answers depend entirely upon the assumptions we have made. It is possible that compensation is strong enough, or the age-0 abundance - fishery recruit relationship is noisy enough, so that the probability of detecting a relationship between recruitment to the fishery and age-0 abundance is low for data collected over a reasonable time horizon. The calculations in this report suggest some partial solutions to the dilemma.

First, if low power is primarily the result of strong compensation, power to detect this compensation itself should be quite high. The existence of compensation over a broad range of age-0 abundances would suggest that there is a bottleneck at an older age prior to recruitment to the fishery, and that variation in recruitment to the fishery stems largely from variations in mortality after this bottleneck. For example mortality could be high and variable during the process of settlement from the pelagic to bottom habitat. This information would aid in the management of the rockfish fisheries.

Conversely, the failure to detect either a age-0 abundance - fishery recruit relationship, or compensation, would indicate that low power was primarily the result of large variance about the underlying relationship. This could be due to errors in estimating either the dependent or independent variables, or to relatively high temporal variations in survival rates of fish from age-0 until the time they recruit to the fishery. It will be important to determine the relative contribution of these two types of errors when a regression model is fit to the data. As we saw earlier in this report, the relative contribution of these two types of errors has important consequences. Previous calculations of a ln-transformed abundance index for age-0 widow rockfish reported standard errors on the order of 0.05 to 0.2 (Staff of the Tiburon Laboratory, 1989). If errors of similar magnitude are associated with relative estimates of recruitment to the fishery, these errors would not, alone, prevent us from detecting a relationship between recruitment to the fishery and age-0 abundance. Although we do not have direct estimates of error in the estimates of recruitment to the fishery, measurement error on the order of 0.2 is a reasonable expectation: Rivard (1981) used the delta method to estimate an average relative error (standard deviation/mean) of 24% in stock assessments of groundfish on the east coast. This relative error corresponds roughly to our σ_ε of 0.2.

We cannot, however, rule out the potential for measurement error to obscure a real relationship. The standard errors of our age-0 abundance index may not reflect all the uncertainty associated with the index. Catchability may vary from one survey to the next, either because the juvenile fish are different sizes or are distributed differently either in depth or in on-shore off-shore distribution. In principal, such variations can have large impacts on the magnitude of measurement error (e.g. Pennington 1986). One method that has been suggested for dealing with this "survey error" is to sample the entire study area several replicate times, and use the variability among these replicate surveys to estimate the measurement error associated with the survey. It is not possible to use this method for the juvenile rockfish surveys. This method requires that the replicate surveys have the same expectation and differ from one another because of random or unpredictable components. Although three replicate sweeps of the study area are now done during each May-June period, there is a systematic pattern of change in abundance and spatial distribution during the sweeps. The general pattern is for fish to move further inshore from the first to third sweep, and abundance of pelagic juveniles usually declines by the third sweep.

To this point we have acted as though we are faced with a fixed and well specified problem, and we attempt to solve it by a procedure that has been specified *a priori*. We are given a time series of recruitment to the fishery and abundance at age-0. We then linearly regress ln-transformed recruitment to the fishery against ln-transformed age-0 abundance using a conventional least-squares approach. Although such simplifications are appropriate for the calculations in this report, we stress that they are indeed simplifications. In fact the dependent and independent variables are not completely defined, and our procedure for establishing the relationship between the two is not fixed. For example, the index of age-0 abundance used in prior reports was calculated by first ln-transforming counts from individual hauls, using these ln-transformed counts to construct a stratified average for the study area for each replicate sweep within a year, and then taking the maximum value for a sweep within a year as the index of abundance. Currently we are exploring alternative procedures including estimating abundance based on an assumed delta distribution (Pennington 1983, 1986), and taking into account estimates of juvenile age since older fish will have experienced more mortality. We are also considering other ways to combine the data from different sweeps in addition to simply taking the maximum values, and this may reduce the "survey error" discussed above. When the time comes to construct the actual regression model between recruitment to the fishery and the age-0 abundance index it is very unlikely that we will restrict ourselves to simple linear regression on ln-transformed data. It probable that we will make adjustments to remove bias introduced by error in the independent variable. If evidence for compensation is present, various non-linear models will almost certainly be examined to see if they yield improved fits to the data.

In interpreting the results of the power analyses presented here, and judging how many years of data will need to be collected to evaluate the usefulness of the juvenile surveys, an additional fact needs to be kept in mind. There is lag between the time fish first recruit to a fishery and the time that an accurate estimate of recruitment to the fishery can be made using current methodology. This, after all, is one of the reasons why we want to develop a reliable predictor of recruitment. Thus, for example, although widow rockfish start recruiting to the fishery in large numbers at age 5 and estimates of recruitment are made at that age, it is not for another four years or so that the estimated relative strength of the year class stabilizes (Hightower pers. comm.). Thus if surveys were done for 15 years, at the end of that time we would have estimates of recruitment to the fishery for the first 10 years of data, but the last four of those ten recruitment estimates would be less reliable than the others. Given the power analyses presented here this implies that surveys will probably need to be done for 15 or more years before a reliable determination of their usefulness can be made, unless a striking relationship is apparent early on. Although one could conduct surveys for ten years, stop, and analyze the results nine years later, the initial surveys would then have little use in actually managing the stock, and there would be another of five or so years before data collected by reinitiated surveys would prove useful. Of course, for some species that recruit to the fishery at younger ages (for example Bocaccio) these time delays are not as much a problem.

The results of the juvenile surveys done so far are encouraging in light of the results presented in this report. Very low numbers of juvenile widow rockfish were collected in 1983 (Staff of the Tiburon Laboratory, 1989), and preliminary indications are that this year class is also weak in the fishery (Hightower and Lenarz 1989). Since switching to the three sweep format for the juvenile cruises in 1986 a wide range in age-0 abundances have been observed in just three years: for example 1986 was a relatively poor year for widow rockfish, and more than ten times as juveniles per haul were collected in 1987 (Staff of the Tiburon Laboratory, 1989). This good contrast in age-0 abundances in the surveys done so far will act to enhance our ability to detect a relationship between recruitment to the fishery and age-0 abundance.

The primary goal in estimating recruitment based on the age-0 surveys is to use these estimates as auxiliary data in stock assessments. In the absence of such auxiliary information a very conservative management strategy needs to be adopted to prevent a high risk of recruitment over-fishing (Lenarz in prep.). In addition to their value as auxiliary data, the estimates of recruitment hold promise for providing better projections of future stock size than are currently available. Recently, however, Walters (1989) showed that for low productivity species like rockfish such projections are unlikely to produce substantial increases in long-term yield (provided an independent estimate of stock size is available). Often, however, we may want to manage stocks to maximize other functions of annual yields besides the long-term maximum (e.g. Deriso 1985, Hilborn 1985, Ruppert et al. 1985, Mendelssohn 1982, Walters and Hilborn 1976). For example, one might wish to have low among year variation in yields as well as a high long-term yield. One such risk adverse strategy is to maximize long-term log(yield) (Ruppert et al. 1985). Predictions of future recruitment may indeed increase the success of such management strategies, in addition to aiding in the assessment of current stock size.

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Table 1. Estimated recruitment to the widow rockfish fishery at age five in millions of fish. Estimates were obtained by Hightower and Lenarz (1989) using the stock synthesis model with M=0.15 and F[88]=0.25.

Year	Recruitment (in millions)
1979	8.51
1980	10.87
1981	7.49
1982	24.06
1983	29.36
1984	15.61
1985	34.07
1986	29.04
1987	13.62
1988	5.25

Table 2. Power and estimated prediction error when recruitment to age one was one third the mean (σ_p) for a range of sample sizes (n) and error about the underlying relationship (σ_ε). Results are for the alternative of directly proportional recruitment (case one).

		Sample size (number of years of data)				
σ_ε		n=5	n=7	n=10	n=15	n=25
0.1						
	power	97.6	99.9	100.0	100.0	100.0
	σ_p	0.29	0.19	0.16	0.13	0.12
0.2						
	power	81.6	96.5	99.7	100.0	100.0
	σ_p	0.57	0.39	0.31	0.27	0.24
0.3						
	power	58.2	84.8	96.7	99.7	100.0
	σ_p	0.84	0.58	0.46	0.40	0.35
0.4						
	power	42.6	68.3	87.9	97.8	99.9
	σ_p	1.16	0.77	0.62	0.53	0.47
0.5						
	power	31.6	52.5	75.0	92.0	99.4
	σ_p	1.40	0.98	0.78	0.67	0.59

Table 3. Power for rejecting H1: slope=0 and H2: slope=1 under the alternative described in case two with asymptotic recruitment=37.5 x 10^6.

σ_ε		n=5	n=7	n=10	n=15	n=25
		Sample size (number of years of data)				
0.1	power (H1)	92	99	100	100	100
	power(H2)	96	100	100	100	100
0.2	power (H1)	67	90	98	100	100
	power(H2)	78	96	99	100	100
0.3	power (H1)	49	74	91	99	100
	power(H2)	58	83	96	100	100
0.4	power (H1)	33	59	78	94	100
	power(H2)	44	69	88	98	100
0.5	power (H1)	28	47	66	86	98
	power(H2)	35	56	78	94	99
0.65	power(H1)	21	34	51	72	92
	power(H2)	25	44	64	83	97

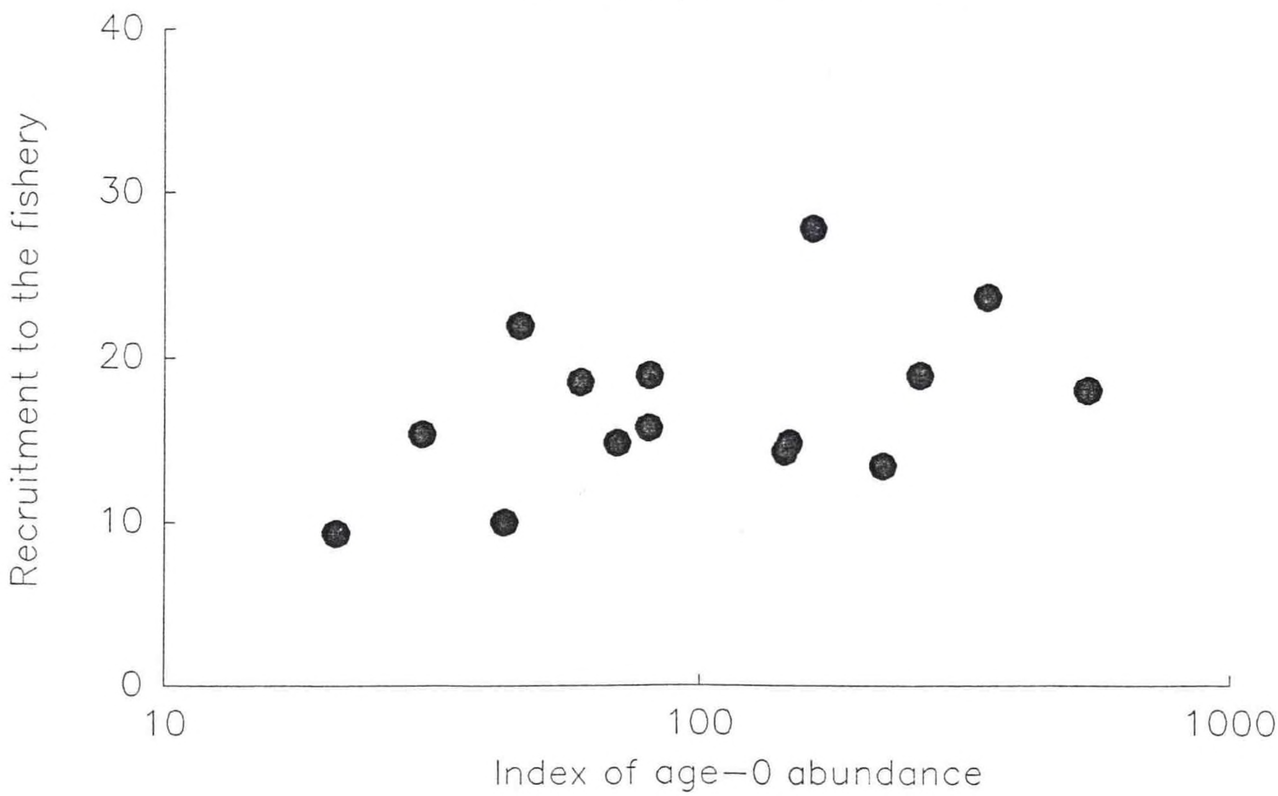
Table 4. Power for rejecting H1: slope=0 and H2: slope=1 under the alternative described in case two with asymptotic recruitment=20 x 10^6.

		Sample size (number of years of data)				
σ_ε		n=5	n=7	n=10	n=15	n=25
0.1						
	power (H1)	55	80	94	100	100
	power(H2)	98	100	100	100	100
0.2						
	power (H1)	28	44	62	83	97
	power(H2)	85	97	100	100	100
0.3						
	power (H1)	15	25	40	60	82
	power(H2)	64	88	97	100	100
0.4						
	power (H1)	10	18	27	41	63
	power(H2)	48	74	91	99	100
0.5						
	power (H1)	8	14	20	28	50
	power(H2)	37	58	83	95	100
0.65						
	power (H1)	6	9	14	21	34
	power(H2)	27	46	67	87	99

Figure Legends

Figure 1. Recruitment to the fishery versus abundance at age-0. Data were simulated assuming a Beverton-Holt relationship with σ_{ε} = 0.3. Top panel assumes asymptotic recruitment is 37.5 x 10^6 and bottom panel assumes asymptotic recruitment is 20 x 10^6.


Recruitment to the fishery
Index of age-0 abundance
0
10
20
30
40
1
10
100
1000


Recruitment to the fishery
Index of age-0 abundance
0
10
20
30
40
10
100
1000