

Abstract.—Rock lobster, *Jasus verreauxi*, have been fished off New South Wales, Australia, since the late nineteenth century. Since 1994–95 (1 July 1994 to 30 June 1995) the fishery has been managed under an output-control scheme with an annual total allowable catch (TAC) of 106 metric tons (t). Estimates of catch and catch per unit of effort (CPUE) have been developed from data collected from the commercial fishery for the period 1903–1936 and the period from 1969–70 to 1993–94. A production model was fitted to these data by using a robust observation-error estimator that minimizes the median of squared differences between log-observed and predicted CPUEs. A bootstrap resampling procedure was incorporated into this robust estimation method to estimate stock parameters and their uncertainties. The virgin biomass of the rock lobster was 4084 t (its 5th and 95th percentiles being 2553 and 6400 t). The stock biomass decreased substantially until 1990–91. Since 1992–93, it has stabilized and has probably increased owing to the large decrease in the allowable catch after 1988–89. The stock biomass in year 1995–96 was likely to have been between 15% and 30% of the virgin biomass (75% confidence interval). The implications from using different estimation methods on assessing this lobster stock are discussed.

Modeling the dynamics of eastern rock lobster, *Jasus verreauxi*, stock in New South Wales, Australia

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The eastern rock lobster, *Jasus verreauxi*, reportedly is the largest spiny rock lobster in the world (Philips et al., 1980). It occurs in waters off the coast of New South Wales (NSW), Australia, around the coast of Tasmania, and as far west as South Australia (Montgomery, 1995). It is also found off New Zealand, predominantly around the North Island (Kensler, 1967a).

Limited information on the life history of *J. verreauxi* in waters off NSW is available (McWilliam and Philips, 1987; Montgomery, 1992, 1995; Montgomery and Kittaka, 1994; Montgomery¹). Most information comes from studies of the species in waters off New Zealand (Kensler 1967a, 1967b, 1967c; Booth, 1984a, 1984b, 1986). However, comparisons of mitochondrial DNA from juvenile rock lobsters from NSW and New Zealand waters have suggested that the populations are genetically distinct (Brasher et al., 1992).

The distribution of rock lobsters across habitat is patchy. From the puerulus to early juvenile stages of their life cycle, lobsters are probably asocial and thought to occur principally within the complex structure of forests of macroalgae or within beds of seagrass in waters from the intertidal zone to 30 m. During the older stages of the juvenile phase,

the animal may begin to aggregate and migrate en masse to the habitat of adults. Adult rock lobsters live in aggregations from depths of around 10 m to those of the continental slope (Montgomery, 1995; Montgomery¹). From the older juvenile stage onward, lobsters aggregate by day, and at night they roam alone. Information on the movements of tagged rock lobsters off New Zealand (Booth, 1984b) and spatial patterns in the length composition of rock lobsters in waters off NSW (Montgomery¹) suggest that for management purposes the entire NSW population of rock lobsters should be considered as a unit stock. These studies indicate that older juveniles and adults move in an inshore–offshore direction and along the coast. The movement along the coast is thought to be associated with breeding (Booth, 1984b).

Rock lobsters have been fished off the east coast of Australia since the late nineteenth century. It is an important fishery in NSW, with an annual output of over 5 million US dollars. Since the 1994–95 fishing

¹ Montgomery, S. S. 1990. Preliminary study of the fishery for rock lobsters off the coast of New South Wales. Final Report, grant no. 86/64. Fisheries Research and Development Corporation, Canberra, Australia, 166 p.

year (i.e. from July 1 1994 to June 30 1995), this fishery has been managed under an output-control scheme with an annual total allowable catch (TAC) of 106 t. No attempt has been made previously to quantify the dynamics of this fishery.

Abundance indices, catch per unit of effort (CPUE), have been developed by Montgomery (1995) from data collected in the commercial fishery for the period of 1903–36 and that from 1969–70 (i.e. 1 July 1969 to 30 June 1970) to 1993–94. Because data are mainly collected and derived from the NSW commercial fishery, large errors are likely to exist in the catch and CPUE data, and there is a concern that the quality of the data is perhaps not good for the purpose of modeling.

Production models are fitted to catch and CPUE data by using an observation-error estimator that minimizes the sum of squared differences between log-observed and predicted CPUEs (Hilborn and Walters, 1992). This estimator assumes that there is only error in the observed abundance index and that there are no observation errors in catch or process errors in the dynamics of the stock biomass. Because the least-squares method is sensitive to the assumption on the error structure in the model (Rousseeuw and Leroy, 1987), the unrealistic error assumption associated with the observation-error estimator tends to result in large errors in estimated parameters when models are fitted to data (Schnute, 1989; Chen and Andrew, 1998).

A more realistic error structure should include process error in the dynamics of the stock biomass and observation errors in both CPUE and catch. In our case, if the distribution of all error terms can be fully defined, we can apply the Kalman filter to generate a likelihood function and then maximize this likelihood function to yield parameter estimates (Sullivan, 1992), or we can define an appropriate variance-covariance matrix based on the defined error structure and then apply a generalized least-squares method to estimate parameters in the model (Paloheimo and Chen, 1996). However, the former approach is rather complicated because the dynamic model is nonlinear and there are two observation models (i.e. one for CPUE and the other for catch; Reed and Simons, 1996). The latter approach needs information on process and observation errors (Paloheimo and Chen, 1996). Such information is probably nonexistent in most fisheries. Moreover, the parametric assumption on error distribution (e.g. normal, log-normal, etc) may not be true.

Because of all these difficulties with the error structure for production models, it is desirable to have an estimation method that is robust with respect to assumptions concerning model error structure. Least median of squared errors (LMSE; Rousseeuw, 1984),

which minimizes the median of squared differences between predicted and observed log CPUEs, is such an estimator (Chen and Andrew, 1998). A bootstrap procedure (Efron, 1979) was incorporated into the LMSE estimator to estimate the parameters and their uncertainties in this study. The probability of short-term overexploitation, defined as a fishing mortality rate higher than the selected biological reference points, was estimated for the next fishing season with different levels of TAC.

Production models

Production models are the simplest stock assessment models that are commonly used in fisheries (Hilborn and Walters, 1992). The input data for these models are the time series of catch and associated abundance index. Several variants of production models have been proposed (e.g. Pella and Tomlinson, 1969; Walters and Hilborn, 1976; Schnute, 1977, 1989; Punt, 1993). Without considering the structure of observation and process errors, the deterministic production model that is most commonly used can be written as

$$B_{i+1} = B_i + g_i - C_i \quad (1)$$

where B_i = the stock biomass;
 C_i = the catch; and
 g_i = the growth of population in biomass, all in year i .

The g_i is often referred to as surplus production and often described by the logistic or Schaefer function written as $g(B_i) = rB_i(1 - B_i/K)$, where r is a parameter describing the intrinsic rate of population growth in biomass and K is a parameter corresponding to the unfished equilibrium stock size (often referred to as the carrying capacity or virgin biomass). The stock biomass in year i is often assumed to be directly related to a relative abundance index that can be observed in fisheries. This assumption can be written as

$$I_i = qB_i$$

where q = the catchability coefficient; and
 I_i = the abundance index in year i (Hilborn and Walters, 1992).

Methods for the parameter estimation

The use of an appropriate method to fit a production model to the observed data has been shown to be as

important in terms of the reliability of estimated parameters as the specification of the algebraic form of the underlying population dynamic model (Punt, 1988, 1993; Polacheck et al., 1993). Several approaches have been proposed to estimate parameters in production models when only indices of abundance and catch are available (Hilborn and Walters, 1992). The four most commonly used approaches are equilibrium estimators (Gulland, 1961), effort-averaging estimators (Fox, 1975), process-error estimators (Walters and Hilborn, 1976; Schnute, 1977), and observation-error estimators (Butterworth and Andrew, 1984; Ludwig and Walters, 1985). These approaches differ in how observation and process errors are introduced into the models that describe the dynamics of populations.

Recently, it has been suggested in some studies that observation-error estimators tend to perform better than others in parameter estimation (Punt, 1988, 1993; Hilborn and Walters, 1992; Polacheck et al., 1993). These estimators are constructed by assuming that the population dynamic equations are deterministic (thus there is no process error) and that all of the error occurs in the relationship between stock biomass and relative abundance index. This assumption can be written as

$$\log(I_t) = \log(qB_t) + e_t$$

With the assumption that the e_t are independent, normally distributed variates, the estimates of the model parameters ($B_{initial}$, q , r , and K) are obtained by maximizing the appropriate likelihood function (Polacheck et al., 1993) or by minimizing the sum of squared e_t (Hilborn and Walters, 1992). The time series of stock biomass are estimated by projecting the biomass at the start of the catch series forward by using the historical annual catches. Because the estimation methods for observation-error estimators are least-squares types, they are sensitive to the assumption about the error structure of the model. Thus, parameter estimates tend to be unreliable if the specification of error structure (i.e. no process error, no error in observed catch, and log-normal error in observed abundance index) is not correct. However, in practice, it is almost impossible to know the true error structure. It is therefore desirable to use an estimation approach that is robust to the assumption about the model error structure for observation-error estimators.

An observation-error estimator, which minimizes the median of squared differences between observed and predicted log CPUEs, has been found to be robust with respect to incorrect specification of error structure (Chen and Andrew, 1998). This estimator can be written as

$$\text{Minimize } \frac{\text{median}}{i=1, \dots, N} \left[\log(I_i) - \log(\hat{I}_i) \right]^2.$$

It is an extension of the linear robust regression method used by Chen and Paloheimo (1994) and Chen et al. (1994) for nonlinear parameter estimation. It should be noted that the algorithm developed for the linear parameter estimation (Rousseeuw, 1984) can not be used for the above estimator. The simplex method of Nelder and Mead (1965) was used to conduct the nonlinear parameter estimation for the above estimator (Press et al., 1992; Chen and Andrew, 1998).

Estimation of stock parameters for eastern rock lobster

Catch and CPUE data were available for two time periods. The first period (hereafter referred to as period I) was from 1903 to 1936, and the second (period II) from 1969–70 to 1993–94. The fishery was confined to grounds close to shore in period I, whereas from the beginning of period II, the fishery expanded to the continental slope. Therefore, it is highly likely that large differences in catchability existed between these two periods. Both the size and structure of the rock lobster stock on the NSW coast may have changed greatly over the two periods (Montgomery, 1995), and it is likely that the growth rate of the NSW rock lobster stock differed between these two periods of time. Parameters r and q were thus assumed to be different in these two time periods. Parameter K was assumed to be the same for these two time periods. This assumption was considered to be reasonable because the harvesting on the expanded fishing grounds at the beginning of period II was not from an unexploited portion of the stock. It is thought that eastern rock lobsters along the NSW coast display a movement that is typical of several other species of rock lobster, moving between inshore and offshore grounds and along the coast (see Herrnkind et al., 1994). Hence, lobsters on the grounds on the continental slope likely had been exposed to fishing on more traditional shallower grounds at other times.

The LMSE method was applied to fit the model to data observed in period I and estimate parameters B_{1903} , r_I , q_I , and K_I , where subscript I refers to period I. Because the year 1903 was early in the development of the fishery, it is reasonable to assume that B_{1903} is the same as K_I in parameter estimation (Hilborn and Walters, 1992). Thus, there are only three parameters to be estimated with data observed in the first time period.

An algorithm that incorporates a bootstrap approach into the LMSE method was developed to es-

timate the sampling distribution for model parameters. This approach is referred to as the bootstrapped LMSE method and its procedure follows:

- 1 estimate the model parameters using the LMSE method;
- 2 calculate the predicted CPUEs using the LMSE-estimated parameters;
- 3 calculate the residuals between observed and predicted log CPUEs;
- 4 randomly sample the residuals with replacement to add to the predicted logarithm CPUEs to yield pseudo observed CPUEs;
- 5 apply the LMSE algorithm to the pseudo observed CPUEs to estimate bootstrapped estimates;
- 6 repeat steps 4 to 5 100 times to simulate 100 sets of pseudo CPUE data and to estimate subsequently the corresponding 100 sets of bootstrapped parameters; and
- 7 calculate the median value and 90% confidence intervals for each parameter using the 100 bootstrapped estimates.

Following Efron and Tibshirani (1985) and Manly (1991), the median values and 90% confidence intervals derived from the 100 sets of bootstrapped parameters were used as the parameter estimates and their associated uncertainties. The 100 bootstrap runs were considered sufficient for the LMSE method in this study because a preliminary analysis indicated that differences in the distributions of estimated parameters derived from 100 and 2000 bootstrap runs were small.

Since K_{II} was assumed to be the same as K_I , there were three parameters, r_{II} , q_{II} , and B_{69-70} , to be estimated in modelling CPUE and catch data observed in period II. Although CPUE for period II was derived from accurate records of catch and effort associated with part of the commercial fishery, under-reporting of total catch occurred to a significant extent during period II (Montgomery and Chen, 1996). The extent of under-reporting in different fishing seasons was estimated on the basis of a survey of fishermen (Table 1; Montgomery¹; Montgomery, unpubl. data). Thus, catch in fishing year j was adjusted from the reported catch (Fig. 1) as

$$(\text{Adjusted catch})_j = \frac{(\text{reported catch})_j}{1 - (\text{adjustment coefficient})_j},$$

where adjustment coefficient = the proportion of under-reporting estimated.

The seven-step procedure described above was modified to include the uncertainties in K_I in estimating the parameters and associated uncertainties in period II. The modification was accomplished by using values of K_I randomly sampled from the bootstrapped samples generated in the bootstrapped LMSE analysis for period I. Such a modification takes into consideration the variation in K_I (thus K_{II}) when estimating q_{II} , r_{II} , and $B_{1969-70}$ and their variabilities.

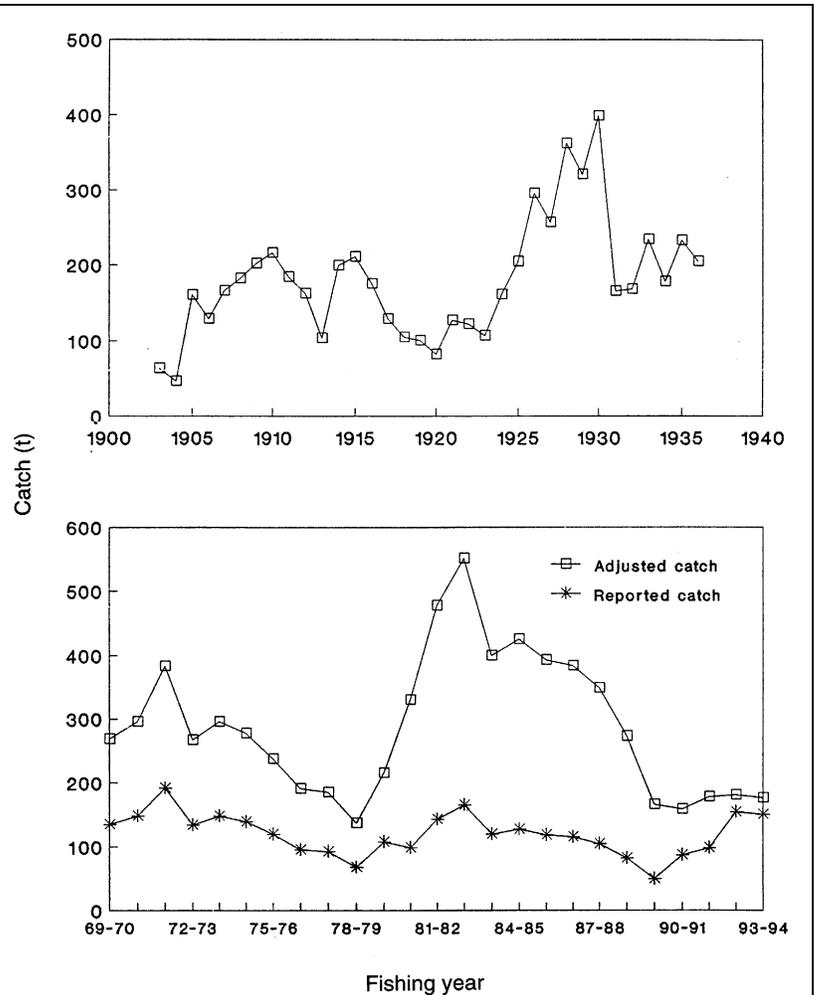


Figure 1

The landed catch of eastern rock lobsters in New South Wales (NSW), Australia, during the period of 1903-36, and from 1969-70 (i.e. 1 July 1969 to 30 June 1970) to 1993-94.

Table 1

Coefficients used to adjust reported catch data in the period of 1969–70 to 1993–94.

| Year | Adjustment coefficient |
|--------------------|------------------------|
| 1969–70 to 1979–80 | 0.5 |
| 1980–81 to 1989–90 | 0.7 |
| 1990–91 to 1991–92 | 0.45 |
| 1992–93 to 1993–94 | 0.15 |

Evaluation of probability of overexploitation for next fishing season

The probability of short-term overexploitation (i.e. the probability of the fishing mortality rate being higher than defined biological reference points) was defined with respect to different levels of catch for the 1996–97 fishing season. The two biological reference points used in our study were $f_{0.1}$ and f_{MSY} . The $f_{0.1}$ is equivalent to the more commonly used $F_{0.1}$ (Hilborn and Walters, 1992) and is defined by the equation

$$\left. \frac{\partial C(E)}{\partial E} \right|_{E=f_{0.1}q} = 0.1 \left. \frac{\partial C(E)}{\partial E} \right|_{E=0},$$

where $C(E)$ = the equilibrium yield corresponding to effort E (Punt, 1993).

From the above equation and Equation 1, $f_{0.1}$ can be calculated as $f_{0.1} = 0.45r$. The TAC in year j based on the $f_{0.1}$ can be calculated as $TAC_{0.1}(j) = 0.45rB_j$, where B_j is the estimate of stock biomass in year j . The rate of fishing mortality (f_{MSY}) producing maximum sustainable yield (MSY) can be calculated as $f_{MSY} = 0.5r$. The TAC in year j , based on f_{MSY} , can be calculated as $TAC_{MSY}(j) = 0.5rB_j$. It should be noted that the $TAC_{MSY}(j)$ calculated above changes with the current stock biomass and is thus dynamic over time. It differs from the commonly used equilibrium maximum sustainable yield (EMSY) calculated as $rK/4$ (Hilborn and Walters, 1992). The use of $TAC_{MSY}(j)$ is more robust with respect to interannual variability in the biomass of the stock than is a TAC based on the more commonly used EMSY.

Results

Parameters r_I , q_I , and K_I estimated with the LMSE method were 0.203, 1.76×10^{-6} (per vessel), and 3208 t, respectively. This results in an EMSY of 163 t. The predicted CPUEs tended to follow the CPUEs ob-

Table 2

Summary of the estimates of parameters with the bootstrapped LMSE method from 100 runs of bootstrap simulation for CPUE and catch data observed during 1903 to 1936.

| Statistic | Parameter | | | |
|-----------|-----------|--------------------------------------|-------|------------|
| | r_I | $q_I \times 10^{-6}$ (per vessel) | K_I | σ^I |
| Median | 0.155 | 1.20 | 4084 | 0.428 |
| Mean | 0.149 | 1.26 | 4269 | 0.497 |
| CV | 48.6% | 28.0% | 26.0% | 53.1% |
| 5th% | 0.045 | 0.79 | 2554 | 0.187 |
| 95th% | 0.292 | 1.94 | 6400 | 1.058 |

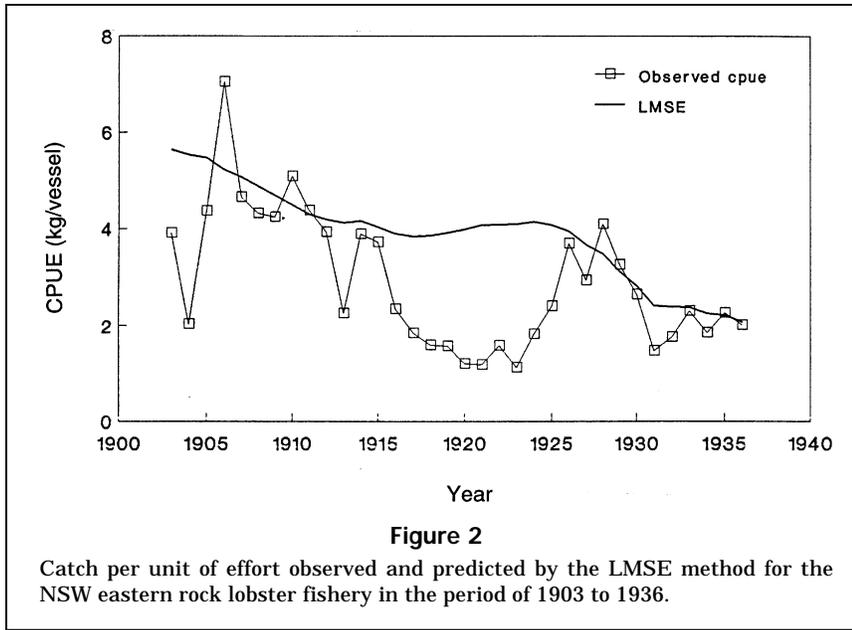
^I For each bootstrap run, σ is calculated as

$$\sigma = \sqrt{\frac{\sum_{j=1}^n (CPUE_j - CP\hat{U}E_j)^2}{n}},$$

where CPUE and $CP\hat{U}E$ are observed and predicted catch per unit of effort, respectively, and n is the number of years.

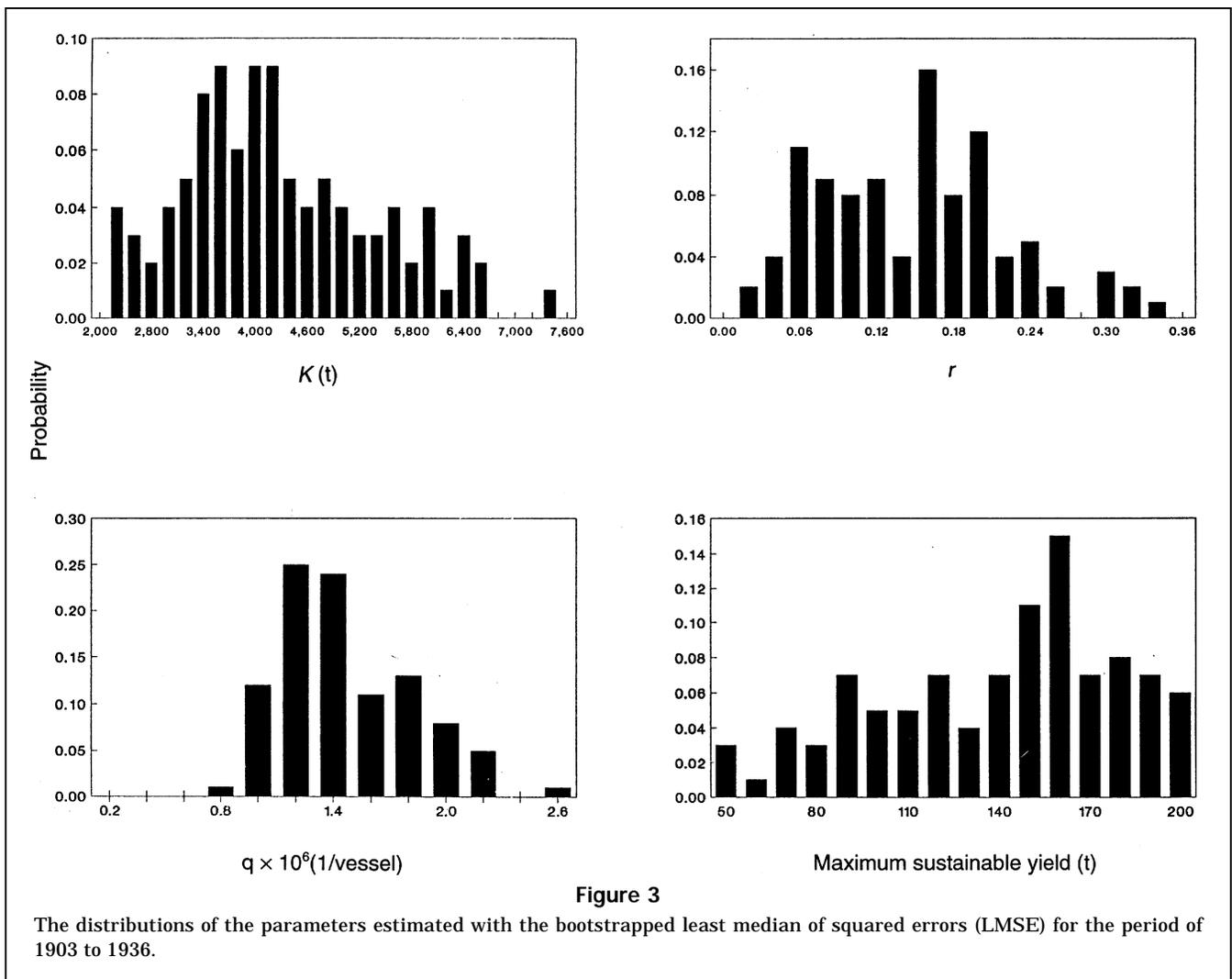
served in the majority of years in period I (Fig. 2). However, CPUEs observed in the years 1904 and 1917–24 differed considerably from the LMSE-predicted values, indicating that they virtually were ignored in the parameter estimation. The estimated stock size in year 1936 was 37.6% of the virgin biomass. The median value for K_I from the 100 bootstrapped LMSE estimates was 4084 t (Table 2), about 27% higher than the LMSE-estimated K_I . The coefficient of variation (CV) for the LMSE-estimated K_I was only 26%, indicating that the uncertainty associated with the LMSE-estimated K_I was small. The median values of bootstrapped r and q were 0.155 and 1.2×10^{-6} (per vessel) (Table 2), about 24% and 32% lower than the LMSE-estimated r and q , respectively. The higher CV for r , compared with the CVs for q and K_I , indicates that the estimate of r is more uncertain than the estimates of q and K_I . The distributions of all three parameters tended to be positively skewed (Fig. 3). The estimated EMSY ranged from 50 t to 200 t with the median value of 151 t (Fig. 3).

By assuming K_{II} to be the same as the median value of K_I estimated in the bootstrapped LMSE estimation, we estimated parameters r_{II} , q_{II} , and $B_{1969-70}$. The LMSE-estimated $B_{1969-70}$ was close to the value of K_I (4,365 t). The r_{II} was 0.218, about 7% higher than the LMSE-estimated r_I . The LMSE-estimated q_{II} was 0.15×10^{-6} (per trap-month). The model was fitted by means of the LMSE method by ignoring the data observed in the two fishing seasons 1971–72 and 1974–75 because



CPUEs in these two fishing seasons increased greatly and abruptly from the previous years, followed by an equally abrupt decrease (Fig. 4).

Distributions for parameters of the model estimated with the bootstrapped LMSE method for period II are presented in Figure 5. The median value of the stock biomass in year 1969–70 was 3808 t, 13% lower than the corresponding LMSE estimate. The estimated median value of r_{II} was 0.172 (Table 3), 22% lower than the LMSE-estimated r_{II} . The median value of q_{II} was only 10% of that estimated for q_I . This resulted from different units of fishing efforts used in calculating the abundance index (CPUE) in the two



time periods (per vessel versus per trap-month). The CVs and 90% confidence intervals for the parameters were small (Table 3), indicating that estimates of parameters for period II had small uncertainties. The estimated EMSY ranged from 80 t to over 200 t with a median value of 120 t (Fig. 5).

The median and 5th and 95th percentiles of the biomass of the stock for each year in period II are plotted in Figure 6. The calculation of total catches for 1994–95 and 1995–96 had not been completed when this study was conducted. However, the TAC of 106 t was likely to have been fully realized in each of these years. Thus, the biomasses of the stock for 1995–96 and 1996–97 were projected based upon the assumption that catches in 1994–95 and 1995–96 were 106 t. The 90% confidence intervals tended to increase from 1969–70 to 1994–95 (Fig. 6), indicating that estimates of the stock biomass in recent years were less precise than those in earlier years. The median value of the biomass of stock in the 1995–96 fishing year was 1420 t, and the 5th and 95th per-

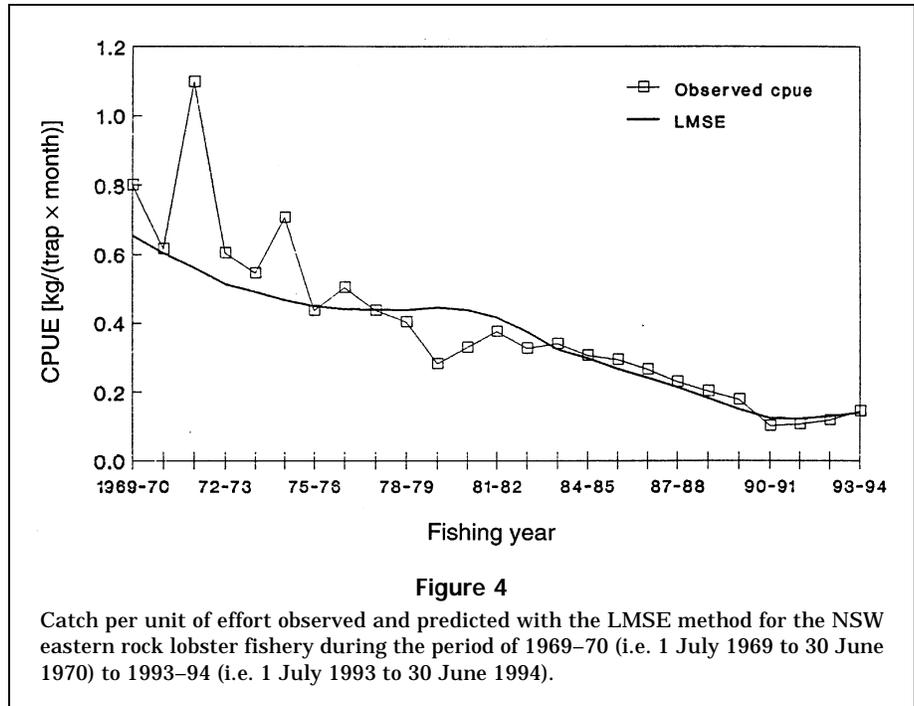


Figure 4
Catch per unit of effort observed and predicted with the LMSE method for the NSW eastern rock lobster fishery during the period of 1969–70 (i.e. 1 July 1969 to 30 June 1970) to 1993–94 (i.e. 1 July 1993 to 30 June 1994).

centiles were 710 and 2719 t (Fig. 6). Median values for the biomass of the stock fell until 1990–91 and then started to increase from 1992–93. The plot of the distribution of the ratio between biomass in year 1995–96 against the biomass of the virgin stock indicated that there was more than 75% chance that the biomass ranged between 15% and 30% of the virgin biomass (Fig. 7).

The distribution of the biomass of the stock in 1996–97 is summarized in Figure 8. There was more than a 70% chance that the biomass of the stock ranged between 1000 to 1750 t. The probabilities of short-term overharvest (i.e. exceeding the selected biological reference points) were calculated for different levels of catch in 1996–97 on the basis of the distribution estimated for the biomass of the stock in 1996–97 (Fig. 9). For example, the TAC of 100 t would have a 30% chance of exceeding the reference point f_{MSY} and a 40% chance of exceeding $f_{0.1}$ (Fig. 9).

Discussion

The model used in this study is one of the simplest models commonly used in fish stock assessment (Hilborn and Walters, 1992). An essential assumption of this model, as with similar models, is that the relationship between CPUE and the biomass of the stock remains constant over time. Because of the use of the robust estimator, this assumption becomes the following: the proportional relationship between the

Table 3

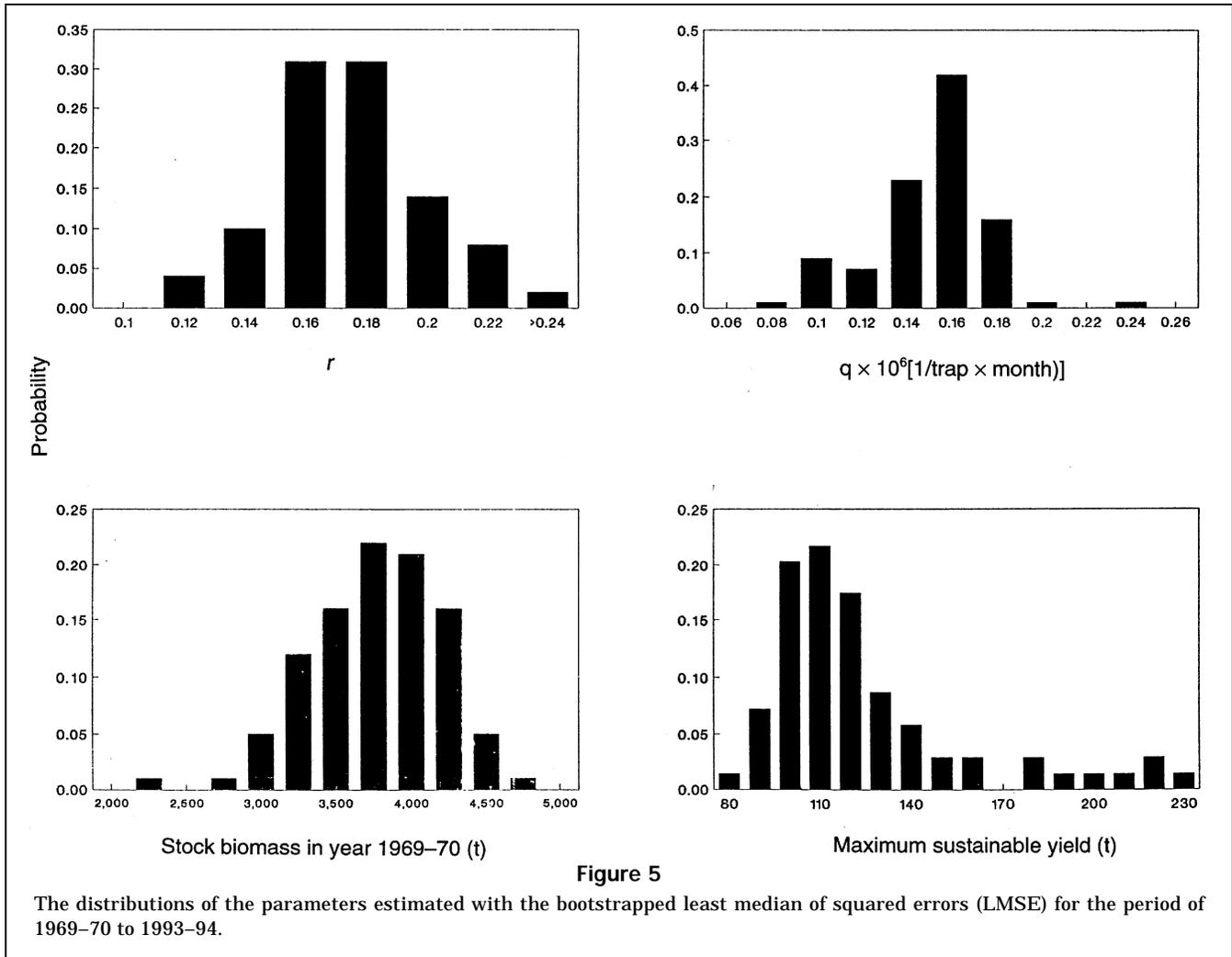
Summary of the estimates of parameters using the LMSE method from 100 runs of bootstrap simulation for CPUE and catch data observed from 1969–70 to 1993–94.

| Statistic | Parameter | | | |
|--------------------|-----------|---|------------------------|------------|
| | r_{II} | $q_{II} \times 10^{-6}$ (trap × month) ⁻¹ | $B_{1969-70}$ (ton) | σ^I |
| Median | 0.172 | 0.15 | 3808 | 0.237 |
| Mean | 0.177 | 0.15 | 3764 | 0.241 |
| CV | 19.4% | 16.2% | 11.5% | 360% |
| 5 th % | 0.132 | 0.11 | 3099 | 0.059 |
| 95 th % | 0.223 | 0.18 | 4418 | 1.098 |

^I For each bootstrap run, σ is calculated as

$$\sigma = \sqrt{\frac{\sum_{j=1}^n (CPUE_j - \hat{CPUE})^2}{n}}$$

where CPUE and \hat{CPUE} are observed and predicted catch per unit of effort, respectively, and n is the number of years.



stock biomass and CPUE is the same for the majority of years.

Compared with traditional least-squares estimation methods, the LMSE method tends to fit the model to the majority of the data, and its estimates of parameters are not affected by atypical data observed in a few years (Chen et al., 1994). Thus, if atypical observations arise, parameter estimation with the LMSE will not be affected greatly. Because the LMSE is not sensitive to atypical data, these data tend to be far from the LMSE-estimated CPUEs (Figs. 2 and 3) and thus are readily detected. However, it is important to determine why an observed CPUE is far from the predicted CPUE. Such a practice requires extensive background information on the fishery. Apart from exceptionally large observation errors, atypical observations may arise from unusual environmental conditions and substantial changes in fishing methods and locations. The nature of atypical observations resulting from unusual

environmental conditions differs from those resulting from unusual observation errors. These atypical data should be considered separately from those observed under normal conditions in the stock assessment process because such unusual conditions last only for a short period of time in the development of the fishery (Chen et al., 1994). For example, the observed CPUE in 1971-72 was much higher than the LMSE-estimated CPUE (Fig. 4). This might result from the fishery being expanded in that year to include aggregations of lobsters on the previously unexploited slopes of the continental shelf. This would result in a high q for that year. Clearly, such a high level of CPUE cannot be sustained for long and should not be interpreted as an indicator of large stock biomass for that year. CPUEs observed from years 1917 to 1924 were much lower than the LMSE predicted (Fig. 2). This finding may be related to large observation errors in CPUEs. For this period, the number of fishing boats (other than trawlers or Dan-

ish seiners) that operated from lobster producing ports and in oceanic waters was used as an index of fishing effort for the lobster fishery. This was done because it was impossible to distinguish between vessels that were used for fishing lobsters and vessels that were used for fishing other species in the same area (Montgomery, 1995). During this period, annual landings of lobsters were probably under-reported because only lobsters sold at the main market centers were recorded. Such an over-estimation of efforts and under-estimation of catches would lead to under-estimation of CPUE for this period of time. It should be realized, however, that the above reasons for the large deviation of observed data from model estimates remain a working hypothesis.

Outliers can be identified in linear regression analyses by using criteria developed by Rousseeuw and Leroy (1987). However, the criteria developed through extensive simulations based on a linear regression model cannot be used in nonlinear regression analysis. An extensive simulation study is needed to develop suitable criteria to identify outliers in nonlinear regression analyses. Before this can be done, the LMSE-based re-weighted least squares, which has been shown to behave better than the least median of squares in linear regression analyses (Chen et al., 1994; Chen and Paloheimo, 1995), cannot be used in nonlinear regression analyses.

The results presented in our paper were based on catch data adjusted by using one set of adjustment coefficients. To test the sensitivity of the results to the adjustment coefficients, we also used two other sets of adjustment coefficients in the analysis (Table 4). These two sets of coefficients have more extreme values than the one presented in Table 1. The detailed

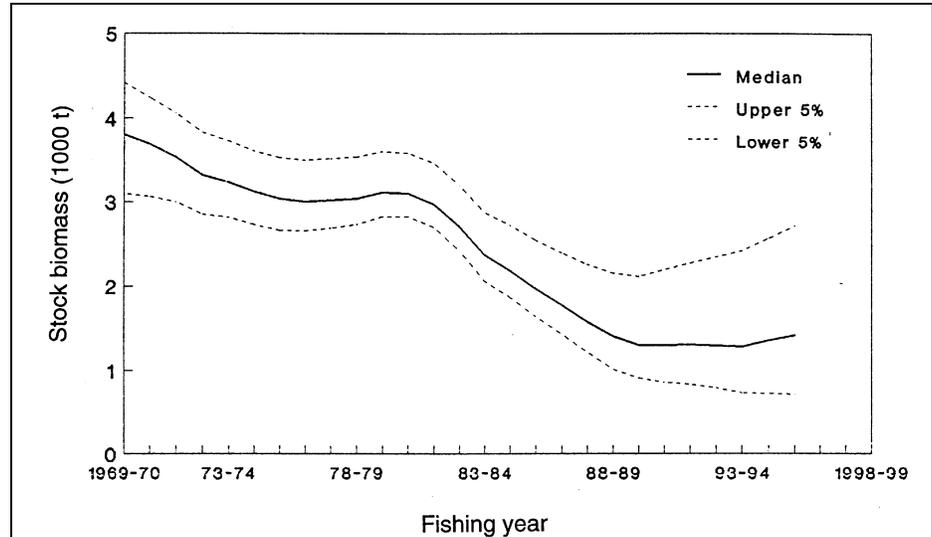


Figure 6

The median and 90% confidence intervals of stock biomass predicted with the bootstrapped LMSE method for the period of 1969–70 to 1995–96.

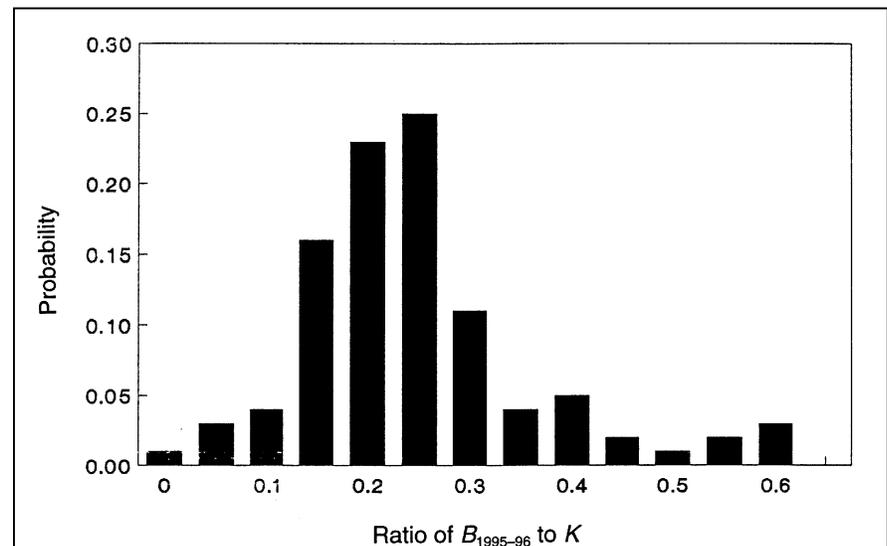


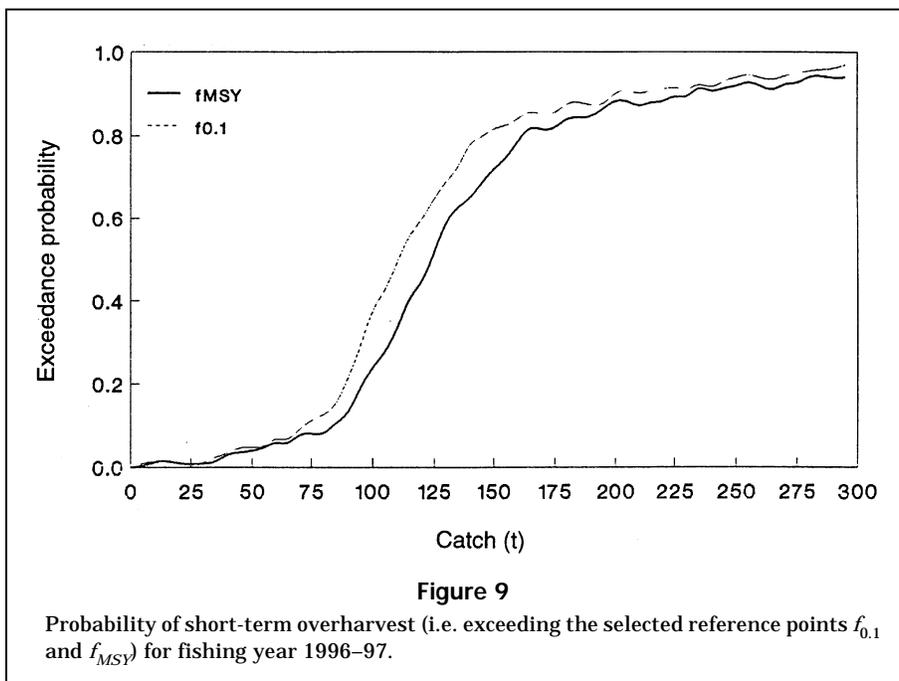
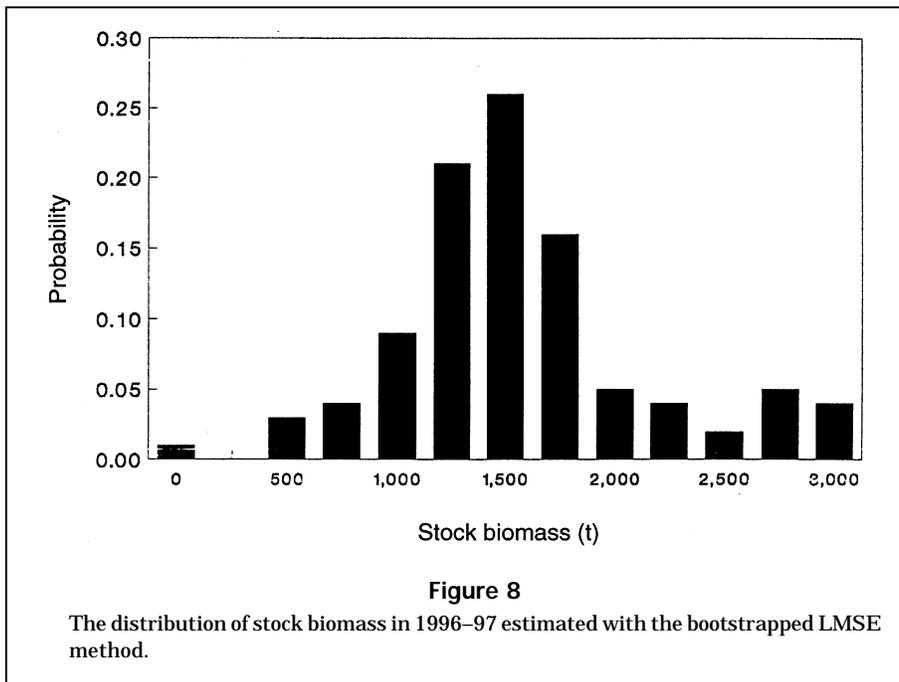
Figure 7

The distribution of the ratio between the biomass of the stock in 1995–96 ($B_{1995-96}$) and the biomass of the virgin stock (K) estimated with the bootstrapped LMSE method.

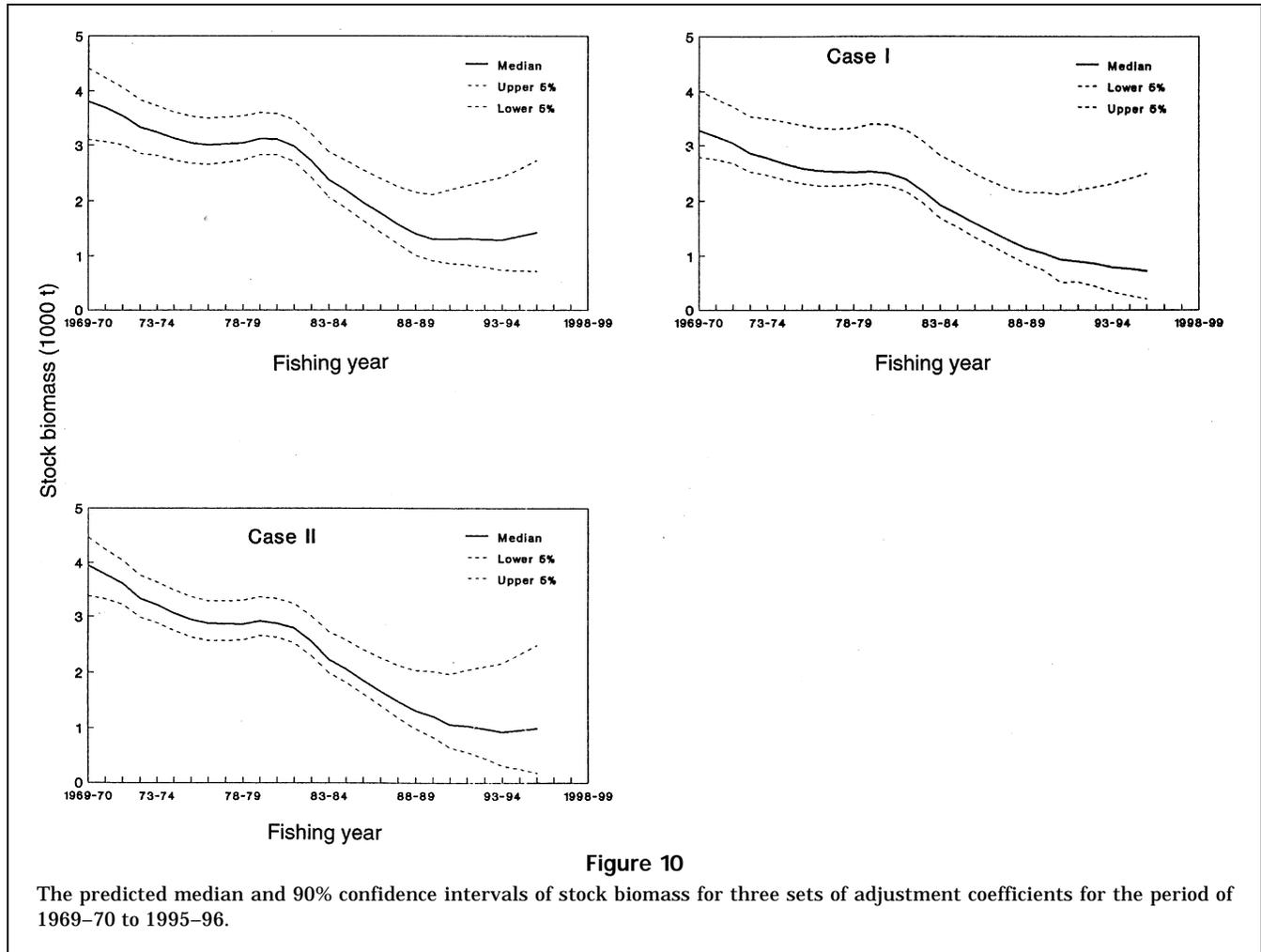
results for these two sets of data were reported in Montgomery and Chen (1996). We plotted the stock biomass estimated with these three sets of data (Fig. 10). Although there are differences, they are rather small considering the large differences in adjustment coefficients. This may indicate that the results presented in this paper tend not to be sensitive to small changes in catch adjustment coefficients used in period II.

It is clear that the size of the lobster stock off New South Wales was low, with respect to its virgin biomass, as was the 75% confidence. Recent stock biomass (i.e. in 1995–96) has been between 15% and slightly over 30% of the virgin biomass. However, it seems that the decline in the biomass of the stock has stopped in recent years, and that the stock is perhaps in a period of recovery.

Data observed in the two periods of time were modeled separately in our study. An alternative, perhaps better approach is to combine these two time periods with information on catches landed within the intervening period. This approach will be used in the next stock assessment when good estimates of catches from 1939 to 1968–69 become available.



Because the data were limited, the choice of models that can be used to describe the dynamics of lobster stock in NSW is also limited. Two disadvantages of using the simple production models are 1) an inadequate representation of the fishery dynamics may result in large biases in estimates of parameters and biomasses, and 2) extra assumptions are needed about fisheries (e.g. CPUE is a good indicator of stock abundance). However, these simple models also have their advantages. If the model fails, this failure can be seen easily. Because of the simple mathematical structure and lack of constraints in the parameter estimation, estimates of parameters may not necessarily be biologically reasonable (e.g. as negative values), an indication of the failure of models or data (Hilborn and Walters, 1992). It is now fashionable to mimic biological and fisheries realism by setting up a model that is mathematically and statistically complicated. Although advantages are obvious, disadvantages associated with this type of models may not always be realized. In addition to the requirement of extra input data, such models tend to have some undesirable attributes in the estimation of parameters, such as overfitting and high correlations among estimates of parameters. Incorporation of different biological and fisheries processes (e.g. fishing and recruitment processes) into one model for parameter estimation can also create some



artificial links among parameters (e.g. between catchability coefficient and recruitment). A large number of built-in constraints (e.g. parameter A must have a value between A_1 and A_2) are often required to facilitate parameter estimation for such a model. This may artificially result in parameters having biologically reasonable estimates, even if the model fails. Such a feature also encourages the indiscriminate and uncritical use of stock assessment models, which leads to the misinterpretation of results. The extra biological or fisheries information (e.g. size structure, recruitment and spatial distribution) often incorporated into a dynamic model will certainly increase the accuracy and reliability in the estimation of parameters if the information is accurate. However, in practice, extra information is likely to be subject to large errors. In this case, a complicated model assimilating extra information will probably fail because its validation requires that each piece of information be true (Xiao²).

It is well known that the current biomass for a decreasing stock is often over-estimated when pro-

Table 4

Coefficients used to test the sensitivity of the stock assessment to adjustment coefficients used to adjust reported catch data in the period from 1969–70 to 1993–94.

| Year | Adjustment coefficient | |
|--------------------|------------------------|---------|
| | Case I | Case II |
| 1969–70 to 1979–80 | 0.4 | 0.6 |
| 1980–81 to 1989–90 | 0.6 | 0.7 |
| 1990–91 to 1991–92 | 0.3 | 0.5 |
| 1992–93 to 1993–94 | 0.1 | 0.2 |

duction models are used in assessment with the least squares method (e.g. Schnute, 1989; Hilborn and

² Xiao, Y. 1997. A theoretical consideration of subtleties in, and problems with, use of production models. Commonwealth Scientific and Industrial Research Organization (CSIRO) Marine Laboratory, Hobart, Australia. Unpubl. manuscript.

Walters, 1992; Polacheck et al., 1993; Chen and Andrew, 1998). In our study, when the maximum likelihood (ML) method was used, the r_I , q_I , and K_I had values of 0.041, 0.40×10^{-6} (per vessel), and 8,667 t, respectively. These are 20%, 23%, and 270% of the LMSE-estimated parameters, and 26%, 33%, and 213% of the median values of the bootstrapped LMSE estimates. According to the ML method, the eastern rock lobster stock had a large biomass with a low productivity rate. In contrast, the LMSE method predicted a smaller stock with a relatively high productivity rate. This difference arises from different methods used to fit the model to CPUE data. The ML was heavily influenced by the CPUEs observed from 1916 through 1924, whereas the LMSE virtu-

ally ignored these observations and tended to follow closely the CPUE in the majority of years (Fig. 11). Because of the high likelihood of under-estimation of CPUEs from 1916 through 1924, the LMSE method is probably more suitable. The estimates of r_{II} , q_{II} , and $B_{1969-70}$ by the ML method were 0.17, 0.13×10^{-6} (per trap-month) and 7174 t, differing from those estimated with the LMSE and bootstrapped LMSE methods (Table 3). This difference may result from different weightings of data for years 1971–72 and 1974–75. Fitting the model with the LMSE method virtually ignored the data observed in these years, which had much higher CPUEs than other years. However, fitting with the ML method was heavily influenced by these two years of high CPUEs (Fig. 11). Because

of the patchy distribution of lobsters in their habitat and the expansion of fishing grounds out to the continental slope off the NSW coast during the early 1970s, it is very likely that these two years of exceptionally high CPUEs resulted from high fishing efficiency (i.e. high q values), which should not be taken as an indicator of high biomass.

We suggest using the bootstrapped LMSE method as an alternative approach to fitting production models to catch-effort data. The results derived from such an analysis should be evaluated carefully with respect to the biology and ecology of the targeted fish species and with respect to how the catch-effort data were collected. Such an evaluation may shed some light on why some observations differ from the majority which the LMSE estimated line tends to follow. A comparison of results between robust and traditional least squares approaches may lead to a better understanding of the dynamics of the studied fish stock and identification of years in which atypical data are observed.

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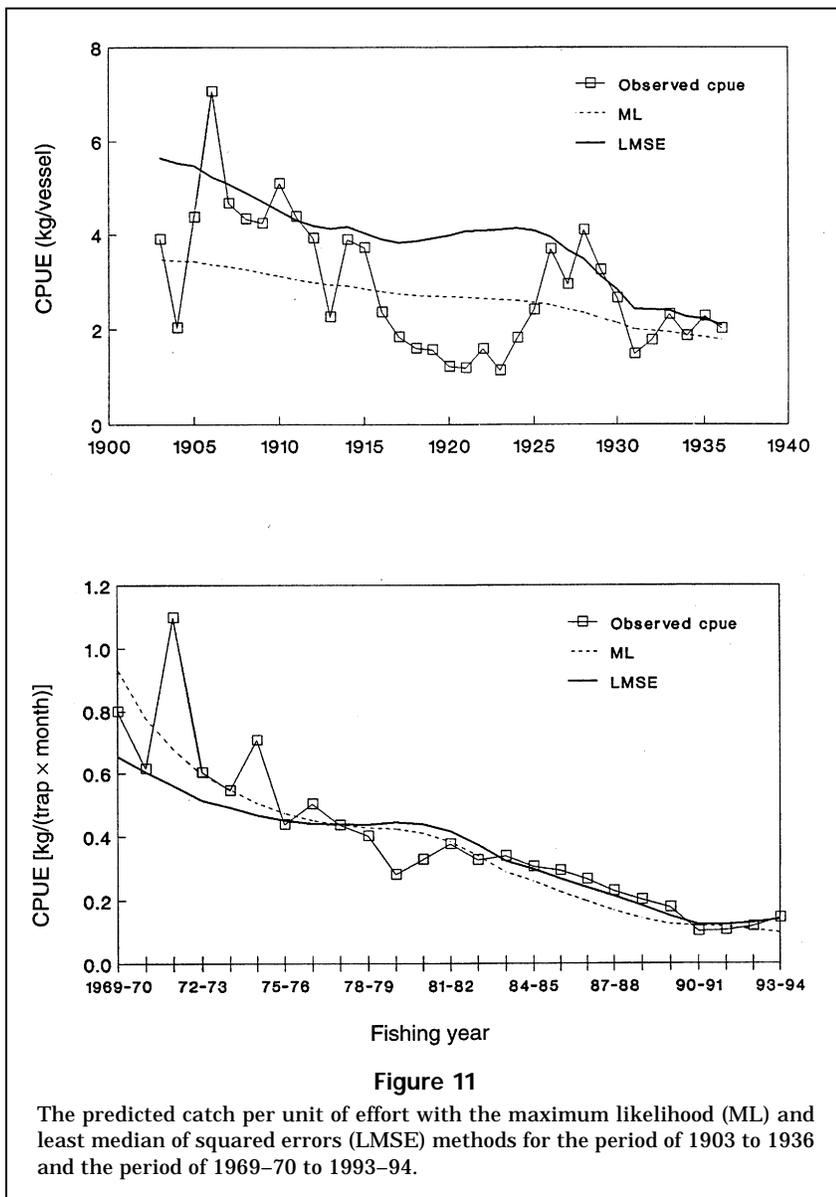


Figure 11

The predicted catch per unit of effort with the maximum likelihood (ML) and least median of squared errors (LMSE) methods for the period of 1903 to 1936 and the period of 1969–70 to 1993–94.

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