Modelling Western Australian Fisheries with Techniques of Time Series Analysis: Examining Data from a Different Perspective

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1999/155 Modelling Western Australian fisheries with techniques of time series analysis: examining data from a different perspective

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OBJECTIVES:

1. To develop time series models to predict the future catches, efforts and CPUEs for selected Western Australian fisheries.
2. To investigate the application of time series techniques to catch-effort relationships, catch-environment relationships, stock-recruitment-environment relationships, and catch-puerulus settlement relationships.
3. To investigate the application of time series modelling techniques in the understanding of historical data on product values and to predict the future product values for the western rock lobster fishery.
4. Develop statistical quality control techniques (moving average and autoregressive control charts) to assess the impact of annual catch and effort on the environmental sustainability of some fisheries, so as to aid industry and biologists in managing these stocks.

NON-TECHNICAL SUMMARY:

OUTCOMES ACHIEVED:

Time series techniques provide new ways of stock assessment for a wide variety of fisheries in Western Australia. The models are straightforward, generally requiring only few parameters to be estimated. The methods are particularly beneficial for commercial or recreational fisheries where there are few existing stock assessment techniques and/or limited available data (for example, only catch and fishing effort). Time series models are applicable as simpler alternatives for fisheries where some biological properties are known. Seasonal and spatial patterns and recruitment and environmental effects on catch and catch-per-unit-effort have been studied from the perspective of time series analysis for the purposes of improving the management of WA fisheries. Fisheries for which time series models improve stock assessment techniques include western and southern rock lobsters, tiger and king prawns in Shark Bay, Australian herring, Australian salmon, pilchards, Spanish mackerel, dhufish, red emperor, sea mullet and yellow-eye mullet. Moreover, time series models are also being used as a new statistical quality control technique to produce improved acceptable catch ranges used in the annual Western Australian *State of the Fisheries Report*.

The management of fisheries in Western Australia requires an understanding of the status of the fisheries stocks. For many species, the only available data are catch, effort and CPUE history. For these and other fisheries, time series methods may improve the stock assessment methods. Biological information is expensive to collect, and much of the information required for stock assessment methods such as age-structured models is simply unavailable, especially for low value fisheries. Time series analysis or control charting methods comprise a select few statistical techniques available for the purpose of stock assessment in these cases. Prediction may be improved using time series methods on catch and effort data with or without external data such as biological or environmental variables. Even when biological parameters can be estimated for a given model, time series methods may be superior as prediction tools.

The aim of this research was to apply time series methods on the western rock lobster fishery, several commercial finfish fisheries and the major tiger and king prawn fisheries, and determine how useful these techniques are for fisheries assessment and management. The following table classifies appropriate models according to the temporal structure and properties of the data sets. The ARIMA(X), seasonal ARIMA(X) and GARCH classes of models are explained in chapter 2; SQCC = statistical quality control charting; NLR = nonlinear regression.

Data set type	Annual	Seasonal	Monthly	Comments
Independently distributed	SQCC	N/A	N/A	
Autocorrelated or trending	ARIMA, SQCC	ARIMA or SARIMA	SARIMA	SQCC requires specific methods (see Ch 3).
Exogenous explanatory variables	NLR, ARIMAX, SQCC	ARIMAX or SARIMAX	SARIMAX	SQCC methods may also be adapted for regression terms. Nonlinear relationships require specific techniques if data are autocorrelated.
Interventions or large-scale shifts	ARIMAX, SQCC	ARIMAX or SARIMAX	SARIMAX	Use exogenous techniques with dummy variables.
Volatile	ARIMA-GARCH	ARIMA-GARCH or SARIMA-GARCH	SARIMA-GARCH	Conditional hetero-skedasticity models required.

The following is a summary by fishery of the methods included in this report.

Western rock lobster fishery: Annual forecasts of western rock lobster catches were calculated in each zone by using puerulus data collected three to four years prior. Two types of seasonal catch data were analyzed. Firstly, monthly catches over zones A, B and C were fitted using univariate seasonal ARIMA transfer function models. Methods were developed to incorporate the annual puerulus information into the seasonal models for each zone. These models provided reliable predictions for monthly catches in zones A and B, but catches taken from zone C were less predictable.

Another seasonal ARIMA transfer function model was used to analyze the “whites” and “reds” catches in zones B and C, where the “whites” season extended from mid November to the end of January, and the "reds" season followed from February to June. The objective was to predict the proportions of whites to reds catches for each fishing season. These seasonal catches were known to be correlated, so there was interest in obtaining better catch estimates for management purposes. The 1993/94 management changes affected the catches and fishing effort during the whites and reds seasons in different ways. These effects were quantified using a time series intervention analysis. While the fishing effort decreased by an average of 18-24% in all zones during the whites season, the average decrease of only 8-10% during the reds season showed that there was still latent fishing effort during the reds season prior to the pot reduction.

Southern rock lobster fishery: A model describing the dynamics of the southern rock lobster fishery in the Esperance area was tested. It was discovered that Esperance CPUE correlated highly with an interaction of May catch rates in the central northern zone of the South Australian lobster fishery lagged 5 to 6 years prior together with the Fremantle Sea Level indicator of the Leeuwin Current. This knowledge has generated an approach to forecasting catches in a similar way to the western rock lobster fishery. A significant increase in variance of monthly catches was noted as a result of the increased live tank storage facilities from 1990 onwards.

Finfish fisheries: Time series methods are particularly useful for many finfish fisheries, especially those that are smaller or less valuable. The time series methods are used as refinements to the knowledge of many finfish fisheries. Many finfish fisheries have only catch and effort data (over approximately 25 years) available for analysis. In the past, managers of these fisheries would use catch range or annual CPUE prognoses to measure performance. The results of this project indicate that some simple quality control methods and simple time series models provide more insight to the dynamics of the fisheries. Consideration of fishing effort as a regulating tool for a variety of finfish fisheries has been included in this project.

There are some finfish fisheries for which time series methods could not improve the knowledge of the fisheries. The age structure of these fish were typically highly variable from year to year. In these cases, other modelling tools such as age-structured techniques are more appropriate.

A summary of the results for finfish fisheries is presented.

- Univariate statistical control charts of catches were computed for over 12 finfish species. Catches outside a range of the mean ± 2 standard deviations may be interpreted as warning signals to respective managers.
- Effects of environmental variables such as the Leeuwin Current are of interest to managers of relevant fisheries. There is substantial literature on the importance of the Leeuwin Current on fish stocks in Western Australia. However, this project demonstrates the importance of the Southern Oscillation Index (SOI) indicator on Western Australian stocks also. The Leeuwin Current or SOI have a positive effect on catches taken from Western Australian waters, and a negative effect on others. For five key commercial fisheries, selected monthly catch rate/environmental interactions were shown to be more influential than environmental variables alone. Fishing effort was a significant factor in explaining catches for four out of five fisheries. The five selected WA fisheries were Australian herring, western Australian salmon, pilchards, Spanish mackerel and westralian dhufish.

- Volatility models for four fisheries were tested (King George whiting, red emperor, sea mullet and yellow-eye mullet). Generalized autoregressive conditional heteroscedasticity (GARCH) effects were detected for the latter three fisheries. GARCH models are a family of nonlinear time series models which estimate variances (e.g. from the residuals of an ARIMA model) over time. Monthly catch predictions (both point estimates and variance estimates) were significantly improved for these fisheries using GARCH models, especially for the sea mullet and yellow-eye mullet fisheries.

- A comparison of twelve fisheries was made over two main spatial fishing areas, namely the west coast and the south coast of WA. The seasonal behaviour was similar for all fisheries. However, there were large differences in management implications between the west and south coast fisheries. It was verified that most of the west coast fisheries could be effort controlled, but many of the south coast fisheries could not. The south coast fisheries were generally more unpredictable than the west coast fisheries.

- A unique estuarine recruitment relationship was discovered for Swan River tailor. Catches of 0^+ and 1^+ year old fish from Point Walter during the months of February through April were used to form a recruitment index. Commercial catches of tailor in the Swan River were shown to correlate highly with the recruitment index for 8 years, with the exception of one outlier. Both the Point Walter index and the commercial Swan River catches of tailor are trending downwards, indicating possible decreases in stocks. This trend may be persisting in nearby oceanic waters, as a nonlinear relationship exists between annual catches taken from the Swan River and annual catches taken from the ocean adjacent to the Perth Metro area (block 32150) early in the same year.

Prawn fisheries: A spatial time series study of Shark Bay king and tiger prawn catches over 30 years was undertaken. A time series model was advantageous for several reasons. Firstly, the predictions are competitive with state space models that use biological parameters. Secondly, unbiased spatial correlations among the different fishing regions were computed using time series analysis. This has enabled a quantitative conclusion that the lower southwestern areas (G1+G2+G3) form a separate sub-fishery to the remainder of the fishery (A through F). Thirdly, the time series models account for the missing data in 1981 for Shark Bay prawn fisheries. Efficiency estimates were computed for each area, alerting managers to the less efficient areas that may warrant a revision of allowable fishing days in Shark Bay.

KEYWORDS:
Fisheries management, time series, stock assessment, recruitment relationships, control charts, western rock lobster, southern rock lobster, finfish, prawns.

1.0 General Introduction

1.1 Background

For the large number of small low value fisheries in Western Australia and across Australia generally there is a need for alternative low cost stock assessment and catch forecasting tools to enable fisheries management performance indicators to be developed. Most traditional stock assessment models require significant knowledge of stock biology and need ongoing data collection. The data are generally expensive to collect and often beyond the financial capacity of the fisheries concerned.

Time series based modelling methods are likely to provide a more cost effective approach, but are reliant on a sufficient number of years of data. In Western Australia where the major fisheries such as the rock lobster fishery have comprehensive databases extending over 30 years or more and most minor fisheries now have data in excess of 20 years, time series modelling can now be explored and developed. This model development will be timely for use in other parts of Australia, where comprehensive databases were instigated more recently, that is, sufficient long time series will become available for time series modelling in the next 5 years, for most small-scale fisheries in Australia.

Time series data can provide the essential and direct information to understand natural resource systems. Better understanding of these data can lead to the development of better management strategies. In many Western Australian fisheries, there are long run detailed data records on commercial catches and fishing effort but limited data on individual stock biology. In many cases, records of related environmental variables are also available. For some fisheries, other relevant data may have been recorded, for example, puerulus settlement data are available for western rock lobster in Western Australia since 1968. Up to now, these data have been utilized in mechanistic models to understand the behaviour and the dynamics of fisheries such as western rock lobster fishery.

Methods of time series analysis have been identified as providing a new approach to fisheries modelling and stock assessment (e.g., Saila et al. 1980; Mendelssohn 1981; Noakes et al. 1987; Freeman and Kirkwood 1995; Stergiou et al. 1997). The aim of time series methods is to extract the hidden rules of the underlying systems directly from time series data. Time series methods are well developed in mathematical statistics. Several new methods of time series analysis (e.g., state-space reconstruction and time delay embedding) from nonlinear dynamical system theory have also been developed in the last decade, and their applications have been seen in many scientific fields.

The time series methods demand fewer biological assumptions than the traditional fisheries models, however, the results of the time series methods may allow identification of the nature of some biological processes. The methods also allow existence of correlations among the historical data over the time. Therefore, the time series methods are more general and flexible than the traditional methods that rely on biological assumptions and assume independent errors.

In addition, time series models are comparatively simple. With simple mathematical forms and few assumptions, time series methods may significantly reduce the modelling costs including research costs and computing costs; and may contain less uncertainty than the conventional methods. For some fisheries (e.g., some finfish fisheries), conventional mathematical modelling is rather difficult or may require resources that are not justified by the values of the fisheries. In these instances, time series modeling offers a feasible way to examine the time series data and to provide predictions of future catches. Research (e.g., Noakes et al. 1990; Stocker and Noakes 1988; Roff 1983) has demonstrated that simple time series models may provide more accurate forecasts than the relevant biological models. Little research work has been undertaken in the application of time series techniques to Western Australian fisheries and across Australia generally.

1.2 Need

1. Responsible management of fisheries requires an assessment of the success of the management plan in achieving its objectives, together with an assessment of the state of the fish stock and likely consequences of the current and alternative management strategies. In many cases, the management plan is intended to maintain the status quo. Trends in time series of data, or values that fall outside the range of predicted outcomes, may indicate that the status quo is not being maintained, or that significant change has occurred within the system. Cost effective methods are required to provide rapid feedback to fisheries managers that a major perturbation has occurred, or that the system is changing, in order that appropriate management action may be implemented.
2. Need to produce low-cost effective models for stock assessment and catch prediction of Western Australian fisheries, especially those low-value fisheries (eg. some finfish fisheries). With few biological assumptions and simple mathematical forms, time series modelling may significantly reduce modelling costs including research costs and computing costs. Time series approaches may also significantly reduce model uncertainty, and therefore may provide more reliable prediction results.
3. Need to reduce the risk of model failure through inadequate assumptions regarding biological processes. Models currently used by Fisheries WA involve often untenable biological assumptions, with the result that predictions are conditional on the accuracy of the assumptions. To reduce the risk of model failure through inadequate assumptions, it is highly desirable to supplement the current models by applying techniques such as time series methods that make few assumptions regarding the biological processes and to compare predictions from the two modelling approaches.

Given the above, time series modelling is seen as a highly valuable and strategic element of the research programme for Western Australian fisheries; the benefits of this project could be transferred Australia-wide to fisheries researchers allowing improved management advice.

2.0 General Methods

Documentation of time series models and statistical quality control charts applied to WA fisheries completed. There are 11 major sections on modelling of WA fisheries that are to be included in this report. The 11 sections and their content are as follows.

1. General introduction to definitions and methods of time series analysis and statistical quality control charts. Background material, literature research and application to fisheries. Description of the various methods and why they were chosen, also discussion on technicalities and problems encountered when modelling.
2. Use and analysis of statistical quality control charts for a variety of WA fisheries. How to empirically choose the upper and lower warning and control limits. Which data to analyze. How management policies affect the analysis.
3. Time series analysis of seasonal western rock lobster catches taken from three main fishing zones off WA. Use of puerulus collector information as a forecasting tool for seasonal catches, involving nonlinear estimation procedures. Analysis of the forecasts using existing data.
4. Analysis of the proportions of “whites” and “reds” catches for western rock lobsters over a 30-year period. Effects of management intervention package on the inter-annual proportions of “whites” and “reds” catches.
5. Time series analysis of the Esperance southern rock lobster fishery. Use of catch rates from South Australia and environmental information as a forecasting tool for the fishery. Forecasts made for the three most recent seasons, and compared with the actual data. Effects on data of increased live storage facilities introduced in the early 1990s.
6. Multivariate time series analysis of 30 years of tiger and king prawn catches in Shark Bay. Contemporaneous spatial analysis carried out across the whole fishery. Model prediction compared with other existing models. Uncorrelated sub-fishery found in the southwest. Fishing efficiency estimates calculated for each zone.
7. Regional comparison between the western and southern waters of twelve finfish fisheries. Fishing effort significant for the west but not significant for the south. Seasonal time series models fitted to each region of each fishery. Model consistency appeared for the western sub-fisheries. Consequences for management of these fisheries discussed.
8. Seasonal ARIMA-GARCH models fitted to a selection of volatile seasonal finfish fisheries. Improvements found for forecasts using seasonal ARIMA-GARCH models rather than seasonal ARIMA models.
9. Seasonal catch rate-environment time series models used to aid the prediction and forecasting ability of several key commercial finfish species for which relatively little biological information is known. Use of Fremantle Sea Level and Southern Oscillation Index.
10. Documentation of an annual Point Walter juvenile tailor catch rate index as a tool to forecast commercial catches of tailor in the Swan River. The Swan River has historically proven to be conducive to the study of finfish populations. There is evidence of a rare estuarine recruitment relationship for tailor in the Swan River. Juvenile indices from other sites investigated. Environmental effects on tailor in the Swan estuary analyzed. Annual commercial catches in the Swan River and nearby sea catches compared. Time series

models fitted to commercial Swan tailor catches. Relevance of the impact of the recreational sector on commercial tailor catches in the Swan discussed.

The report follows the above format, listing each result as a chapter in the report. Chapters 3-11 have been arranged in research publication format, namely in sections including Abstract, Introduction, Methods, Results, Discussion.

2.1 Introduction to time series methods and preliminary definitions

Time series analysis is a well-developed scientific method of analysis that has been extensively and successfully used in fisheries studies around the world as well as other fields such as economics and meteorology. A time series is a set of data that has been collected at equally spaced time intervals. A time series model describes how the historical records and modelling errors determine the future values of the time series. The research in this project will involve identification of necessary lags which represent at what time historical records are needed to predict the future, identification of the mathematical functions which represent the relationship between the past values and the future values, and dealing with noise or uncertainty.

The methods of univariate time series analysis identify trends, seasonal cycles and autocorrelation patterns for each time series, while multivariate time series analysis identifies input-output relationships and cross-correlations among many processes that are available to us such as catch, effort, spatial zones, price markets and environmental factors. The aims of time series analysis in fisheries are to fit appropriate models to data, to provide reliable forecasts over the short term, and to explore the consequences of changes in regulations. Time series analysis in fisheries gives management cost effective, relevant and up-to-date information at any point in time to regulate as appropriate if trends or observations deviate too far from predictions.

Forecasting ability depends on various errors made from:

- the choice of model used;
- parameter estimation; and
- residual noise in the data that is unaccounted for by the selected model.

In general, the more control we have over the errors listed above, the better our forecasts are. Thus, a wide range of models and several measures of model appropriateness need to be developed to compare predictive capacities. We have reviewed seven texts and over twenty scientific papers describing applicable time series models in fish industries around the world. The literature review that follows in the next section is an introduction to a broad range of the terminology and modelling techniques and methodologies associated with time series modelling techniques that are relevant to this project.

The analysis will be divided into four main sections, namely,

- statistical quality control charts;
- univariate time series analysis;
- multivariate time series analysis including transfer function models and dynamic regression; and
- nonlinear time series models.

We shall introduce some elementary definitions, simple control charting techniques and univariate models such as Box-Jenkins (1976) ARIMA and seasonal ARIMA models, which are the basic building blocks of time series analysis. We perform elementary and advanced time series analyses using SPLUS software and develop some SPLUS scripts where the existing functions do not exist. A preliminary analysis will show that seasonal ARIMA models can identify some of the biological dynamics that occur in the western and southern rock lobster fisheries, several finfish fisheries and prawn fisheries but are not appropriate or flexible when actually making predictions. For many fisheries, however, the addition of exogenous variables, such as fishing effort, recruitment and environmental variables, management intervention and technological factors allow the models to produce better predictions. For example, puerulus settlement indices can be used in time series models to predict recruitment into the western rock lobster fishery. Advanced models such as the ARCH/GARCH family, intervention methods and multivariate analysis can handle the more challenging dynamics involving volatility in time series, changes in management controls and spatial dynamics, respectively.

A series of definitions is given below. These terms and concepts are used throughout the remainder of this section and the following sections of this report.

Definition 2.1 A time series is a sequence of observations x_t, each one being recorded at time *t*. ◊

Definition 2.2 A sequence of observations $\{X_t\}$ is said to be IID noise if $X_1, X_2, \ldots$ are independently and identically distributed random variables with zero mean. ◊

This is rarely the case with practical data. Even when an analysis has been performed, the errors may be uncorrelated but not independent.

Definition 2.3 A sequence of observations $\{\varepsilon_t\}$ is said to be **white noise** if $\varepsilon_1, \varepsilon_2, \ldots$ are random variables which have mean zero and variance σ^2, and the ε_t's are uncorrelated across time, viz.

$$E(\varepsilon_t) = 0 \qquad [2.1]$$

$$Cov(\varepsilon_s, \varepsilon_t) = \begin{cases} \sigma^2 & \text{for } s = t \\ 0 & \text{for } s \neq t. \end{cases} \qquad [2.2]$$

We denote a white noise process by $\{\varepsilon_t\} \sim WN(0, \sigma^2)$. If, in addition, the ε_t's are independent, viz.

$$\varepsilon_s, \varepsilon_t \text{ independent for } s \neq t, \qquad [2.3]$$

then we refer to the sequence as **independent white noise**. Finally, if [2.1] through [2.3] hold and

$$\varepsilon_t \sim N(0, \sigma^2), \qquad [2.4]$$

then we have Gaussian white noise. ◊

The aim of time series analysis is to filter one or more data streams to reduce the residuals to white noise. If the white noise is not Gaussian, then the residuals may be further analyzed using nonlinear models such as GARCH models or bootstrapping methods.

The autocovariance and autocorrelation functions

Definition 2.4 Denote the **autocovariance function** (ACVF) between X_t and its *k*th time lag X_{t-j} as follows:

$$\gamma_k = Cov(X_t, X_{t-j}) = E[(X_t - \mu_t)(X_{t-j} - \mu_{t-j})]. \qquad [2.5]$$

Then the theoretical **autocorrelation function** (ACF) is defined as

$$\rho_j = \frac{\gamma_j}{\gamma_0}. \qquad [2.6]$$

The **partial autocorrelation function** (PACF) is defined by $\phi_{hh}, h \geq 1$ from

$$\begin{bmatrix} \phi_{11} \\ \phi_{2h} \\ \vdots \\ \phi_{hh} \end{bmatrix} = \Gamma_h^{-1} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_h \end{bmatrix}, \qquad [2.7]$$

where $\Gamma_h = [\gamma_{i-j}]_{i,j=1}^h$ is the variance-covariance matrix of the process $\{X_t\}$. ◊

The autocorrelation and partial autocorrelation functions provide a “signature” of the time series. These functions are viewed graphically at consecutive time lags. For example, white noise occurs when the ACF at all lags $j = 1,2,\ldots$ are insignificant. The partial autocorrelation function ϕ_{hh} is the conditional correlation of X_t and X_{t-h} given that mutual linear dependencies on $X_{t-1}, X_{t-2}, \ldots, X_{t-h+1}$ have been removed.

Stationarity

Definition 2.5 A process $\{X_t\}$ is said to be **weakly stationary** if there exist μ, γ_j for any *j* such that

$$\begin{aligned} E(X_t) &= \mu && \text{for all } t \\ Cov(X_t, X_{t-j}) &= \gamma_j && \text{for all } t \text{ and any } j. \Diamond \end{aligned} \qquad [2.8]$$

Definition 2.6 A process $\{X_t\}$ is said to be **strictly stationary** if, for any $j_1, j_2, \ldots, j_n$, the joint distribution of $(X_t, X_{t+j_1}, X_{t+j_2}, \ldots, X_{t+j_n})$ depends only on the time intervals separating the dates $(j_1, j_2, \ldots, j_n)$. ◊

Unless specifically stated otherwise, a stationary time series will refer to a weakly stationary time series. There are theoretical reasons why a time series should be de-trended to a weakly stationary process. Any trend should be accounted for before reliable forecasts can be made.

Linear processes
Definition 2.7 A time series $\{X_t\}$ is a **linear process** if it has the representation

$$X_t = \sum_{j=-\infty}^{\infty} \psi_j \varepsilon_{t-j} \qquad [2.9]$$

for all *t*, where $\{\varepsilon_t\} \sim WN(0, \sigma^2)$ and $\{\psi_j\}$ is a sequence of constants satisfying $\sum_{j=-\infty}^{\infty} |\psi_j| < \infty$. ◊

The bulk of the modelling procedures consist of linear models. More advanced nonlinear models are used when there is conditional heteroscedasticity.

Short and long memory processes

Definition 2.8 A stationary process is said to be **summable** or possesses a **short memory** if it satisfies

$$M = \sum_{j=0}^{\infty} |\rho_j| < \infty . \qquad [2.10]$$

If the process is not summable, we say it possesses a **long memory**. ◊

For the purposes of this project, we only analyze short memory processes.

2.2 Statistical control charting methods in fisheries

Statistical control charting was invented by Walter A. Shewart of Bell Telephone Labs in the 1920s. They were used for continuous monitoring of manufacturing process variation for the purposes of improving economic effectiveness. A control chart is a quality characteristic of a sample measured over time. The chart contains a center line measuring the average of the process when under control, an upper control limit and a lower control limit. The control limits are chosen such that nearly all the sample points lie between them. Provided the points are within the control limits, the process is assumed to be in control. Points exceeding the control limits may indicate evidence of a process that is out of control. In terms of a fishery, this may mean that fishing pressure is too high, or that stock levels are dangerously low.

The univariate methods of control charting used for Western Australian fisheries can involve attribute-type charts or variable-type charts. A control chart for an attribute maps data of interest generally over annual periods, together with control limits and warning limits if required. A control chart for a variable is a time progression of a variable, such as mean, range or variance, calculated from sub-samples of the data, together with a centre line and associated control limits. A control chart for a Western Australian fisheries variable would typically use monthly data, calculating the variable over each fishing season, since an annual data set of 25-30 years is too short for sub-sampling. Control charts for variables increase the power of quality control charting methods, but rely on sufficiently long time series.

The aim of the statistical control chart analysis in this project is to determine for which fisheries the methods work well, and the reasons why they don't for other fisheries. Setting the control limits for fisheries data will also be a discussion point in the analysis.

2.3 History of time series modelling and review of literature in fisheries

Box and Jenkins (1976) are considered the founders of modern time series modelling by introducing the **autoregressive integrated moving average** (ARIMA) family of statistical models. ARIMA models were introduced to primarily handle non-independent data streams. For example, significantly autocorrelated residuals from a regression analysis may give biased parameter estimates and therefore need to be filtered by a time series model such as ARIMA. Useful forecasts can then be made for the non-independent data stream. An **autoregressive** model of a time series $\{X_t\}$ is a regression model of that time series on its previous history. For example, a linear autoregression model with a finite number *p* of lag terms, denoted by $\mathrm{AR}(p)$, is expressed as

$$X_t = \sum_{j=1}^{p} \phi_j X_{t-j} + \varepsilon_t , \qquad [2.11]$$

where $\{\varepsilon_t\} \sim WN(0, \sigma_1^2)$ is a white noise process. A **moving average** model of a time series aims to average out previous error steps of a time series $\{X_t\}$ to attempt to smooth the process. For example, a linear moving average model with a finite number *q* of lag terms, denoted by $\mathrm{MA}(q)$, is expressed as

$$X_t = \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t , \qquad [2.12]$$

where $\{\varepsilon_t\} \sim WN(0, \sigma_2^2)$. Combining the linear autoregressive and moving average properties gives the **autoregressive moving average** (ARMA) family of models, denoted by $\mathrm{ARMA}(p, q)$, and expressed as

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t . \qquad [2.13]$$

The analyses of autoregressive and moving average processes are based on a stationarity assumption of the time series. If the time series possesses what is known as homogeneous nonstationarity (see section 2.5), an **integrated** component of an ARIMA model is used. By differencing the process a finite number of times *d*, a stationary process may result. A combination of autoregressive, moving average and integrated components make up the specifications for the ARIMA models. ARIMA models are a historical generalization of the exponential, double exponential, etc. smoothing methods of the 1950s and 1960s (see Brown 1960, Gilchrist 1976). Technological advances have enabled ease of estimation of ARIMA models, following the precursory "pen-and-paper" style smoothers. Exponential smoothing is equivalent to an $\mathrm{ARIMA}(0,1,1)$ filter, while double exponential smoothing is a special case of an $\mathrm{ARIMA}(0,2,2)$ filter (see Chapter 3).

Seasonal ARIMA (SARIMA) models can often be used in fisheries data since monthly data is available. Catches at a given time depend on catches for the previous months and the previous seasons. Exogenous variables may be included in the ARIMA or SARIMA models, from which the equivalent terms ARIMAX (SARIMAX) or (seasonal) transfer function noise (TFN) models arise. Exogenous variables in fisheries include biological and population information, environmental data and intervention variables.

Saila, Wigbout and Lermit (1980) demonstrated that ARIMA models are useful statistical tools for modelling and predicting monthly data of the average catch (kg) per day fished of rock lobster, *Jasus edwardsii*, from the Gisborne area, New Zealand between the years 1963 and 1974. They compared the predictive performance for 1975 and 1976 of two optimal ARIMA models fitted from 1963 to 1974 with two simple forecasting techniques, namely, monthly averages and harmonic regression analysis. The forecast values for the two ARIMA models used were shown to be far superior to the forecasts given by the other two methods. However, there were no seasonality factors incorporated into their model. A seasonal ARIMA model would be expected to give better forecasts again.

Stocker and Noakes (1988) and Noakes (1990) compared preseason forecasts of various methods for Pacific herring and sockeye salmon stocks in British Columbia. Their results indicated that simple time series models outperformed other competing fisheries models such as Ricker-type recruitment models.

Mendelssohn (1981) investigated the uses of some elementary seasonal ARIMA models and TFN models to forecast the monthly catch, effort and catch-effort of skipjack tuna, *Katsuwonus pelamis*, near Hawaii from 1964 to 1978. A seasonal differencing of 12 months was carried out on both catch and effort data sets, and then appropriate seasonal moving average models were fitted. Overfitting was carried out ensuring reasonably optimal models were found. Transfer function models were also introduced, comparing both catch and effort time series, to improve on the forecasts. The SARIMA and TFN models performed reasonably well on forecasts for 1979. However, the authors suggest that variables involving the fishermen's behaviour and thus the fishery and not just the behaviour of the fish would better the forecasts. Finally, a disaggregated intervention model is also suggested by the author as an improvement, as the effect of an intervention in 1973 changed the distribution of the model variables. We will frequently encounter changes of regime when studying our data, including the southern and western rock lobster data.

Stergiou, Christou and Petrakis (1997) compared seven different well-established techniques of time series modelling on sixteen species in the Hellenic marine waters. Their results led them to believe that ARIMA models and dynamic regression models outperformed other techniques such as monthly averages, harmonic regression, linear multiple regression and vector autoregression. Mendelssohn and Curry (1987) successfully analyzed time series of catch per unit effort from 1966 to 1982 of a small pelagic species off the Ivory Coast using sea temperature data. Therefore, it is in our interest to carefully study ARIMAX models and multivariate time series models, attempting to build in other important factors such as changes in regime and environmental variables.

2.4 Building blocks for time series models: The ARIMA models

2.4.1 ARMA processes, stationarity and invertibility

Autoregressive moving average (ARMA) processes form the fundamental family of time series model since they were developed and used by Box and Jenkins (1976). Many stationary processes can be successfully modelled by the ARMA class of models. Throughout this literature review, we will make use of the backward shift operator *B*, which is defined as $B(\cdot_t) = \cdot_{t-1}$, and thus $B^j(\cdot_t) = \cdot_{t-j}$, $j = 0, \pm 1, \ldots$. If $j = 0$, then $B^0 = I$, the identity operator.

Definition 2.9 $\{X_t\}$ is an **ARMA** (p,q) **process** if $\{X_t\}$ is stationary and if for every *t*,

$$X_t - \phi_1 X_{t-1} - \ldots - \phi_p X_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}, \qquad [2.14]$$

or, equivalently,

$$\left(I - \phi_1 B - \ldots - \phi_p B^p\right) X_t = \left(I + \theta_1 B + \ldots + \theta_q B^q\right) \varepsilon_t, \qquad [2.15]$$

where $\{\varepsilon_t\} \sim WN(0, \sigma^2)$ and the polynomials $\left(1 - \phi_1 z - \ldots - \phi_p z^p\right)$ and $\left(1 + \theta_1 z + \ldots + \theta_q z^q\right)$ have no common factors. The process $\{X_t\}$ is an **ARMA** (p,q) **process with mean** μ if $\{X_t - \mu\}$ is an ARMA (p,q) process. ◊

We assert that $\left(1 - \phi_1 z - \ldots - \phi_p z^p\right)$ and $\left(1 + \theta_1 z + \ldots + \theta_q z^q\right)$ have no common factors for redundancy reasons in the parameterization process. For example, it is possible to fit a white noise process $X_t = \varepsilon_t$ with an ARMA $(1,1)$ model such as $(1 - kB) X_t = (1 - kB) \varepsilon_t$, where $|k| > 1$. But it would obviously be problematic to estimate *k* in the specified ARMA model.

The following theorem serves as the main condition for stationarity of an ARMA process.

Theorem 2.1 (Existence and Uniqueness)

A stationary solution $\{X_t\}$ of equations [5.1] and [5.2] exists and is also unique iff

$$\phi(z) = 1 - \phi_1 z - \ldots - \phi_p z^p \neq 0 \; \forall \; |z| = 1 \,.\, ◊ \qquad [2.16]$$

Thus, a sufficient condition for stationarity of an ARMA process is that none of the zeros of the autoregressive polynomial lies on the unit circle. It is important that the data be stationary when fitting ARMA models by finding the complex roots of the autoregressive polynomial and demonstrating that they lie significantly inside or significantly outside the unit circle. We can use the `polyroot` function in SPLUS to find the complex roots of a polynomial (up to machine precision) to check the stationarity of the data.

Definition 2.10 An ARMA (p,q) process $\{X_t\}$ is **invertible** if there are constants $\{\pi_j\}$ such that $\sum_{j=0}^{\infty} |\pi_j| < \infty$ and

$$X_t = \sum_{j=0}^{\infty} \pi_j X_{t-j} \text{ for all } t. \quad [2.17]$$

Invertibility is equivalent to the condition

$$\theta(z) = 1 + \theta_1 z + \ldots + \theta_p z^p \neq 0 \, \forall |z| \leq 1. \lozenge \quad [2.18]$$

Real-world data that is not invertible typically has a conditioning problem at the beginning of the series. It is best to select representations that are invertible, since forecasts based on noninvertible representations depend on future values of the data!

2.4.2 Order selection

Observation of the ACF and PACF functions can often indicate how p and q are to be chosen to obtain a model that is a good representation of the data. The general characterization of an ARMA(p,q) process is an exponentially decaying ACF and a truncated PACF up to standard error fluctuations. Deviations from this characterization indicate the time series may be nonstationary, the errors may have nonconstant variance, a Gaussianity assumption has been broken, and/or the process is nonlinear.

What is meant by standard error of the ACF and PACF? One needs a sample estimate of such parameters. The maximum likelihood estimator of the ACVF at lag h, denoted $\hat{\gamma}_h$, can be shown to be approximately

$$\hat{\gamma}_h = \frac{1}{n} \sum_{t=1}^{n-|h|} \left(X_t - \overline{X}\right)\left(X_{t+|h|} - \overline{X}\right). \quad [2.19]$$

The estimator is approximate in the sense that maximization of the log-likelihood function leads to a linear system only in the limit where the number of data points $n \to \infty$. Likewise, the maximum likelihood estimator of the ACF at lag h is approximately

$$\hat{\rho}_h = \frac{\hat{\gamma}_h}{\hat{\gamma}_0} \quad [2.20]$$

The graphs of the sample ACF and PACF of a time series indicate approximate 95% confidence interval bounds based on Gaussian white noise as horizontal dotted lines. Any autocorrelation coefficient that exceeds these bounds may be deemed significantly nonzero. For instance, the ACF and PACF of a realization of a Gaussian white noise process of length n reveal autocorrelations and partial autocorrelations that fall within the specified bounds with 5% error, on average.

For short memory processes such as the ARMA(p,q) models, the approximate distribution of the sample ACF is normal. If, in addition, we assume that $\rho_h = 0$ for $h > q$, the variance is approximately

$$Var(\hat{\rho}_h) = \frac{1 + 2\sum_{j=1}^{q} \rho_j^2}{n} \qquad [2.21]$$

for $h > q$. Thus, for an ARMA(p,q) process, the approximate 95% confidence limits of the sample ACF are given by

$$\pm 1.96 n^{-\frac{1}{2}} \left(1 + 2\sum_{j=1}^{q} \rho_j^2\right)^{\frac{1}{2}}. \qquad [2.22]$$

Similarly, the approximate 95% confidence limits of the sample PACF are given by

$$\pm 1.96 n^{-\frac{1}{2}}. \qquad [2.23]$$

Suppose that the ACF does decay exponentially and the PACF truncates subject to random error, so that an ARMA model is appropriate. We need to find an optimum pair (p,q). A rough guide is the following visual analysis. Presence of the first p significant partial autocorrelations generally indicates that an autoregressive process of order p is evident in the ARMA process. Larger than otherwise expected individual autocorrelations from an autoregressive process indicate the presence of significant moving average components.

The AIC and AICc criteria

While observations of the sample ACF and PACF can be a helpful guide or checking device, minimization of the AICc log-likelihood criterion of Hurvich and Tsai (1989) based on the AIC criterion of Akaike (1973) is possibly the best statistical measure to determine an optimum pair (p,q) for an ARMA(p,q) process. The AIC criterion is defined by choosing $p, q, \boldsymbol{\beta}$ that minimizes the following expression:

$$\text{AIC} = -2 \ln L(\boldsymbol{\beta}, S(\boldsymbol{\beta})/n) + 2(p+q), \qquad [2.24]$$

where

$$\boldsymbol{\beta} = (\phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q) \qquad [2.25]$$

$$S(\boldsymbol{\beta}) = \sum_{j=1}^{n} \frac{\left(X_j - \hat{X}_j\right)^2}{r_{j-1}} \qquad [2.26]$$

$$L(\boldsymbol{\beta}, \sigma^2) = \frac{1}{\sqrt{\left(2\pi\sigma^2\right)^n \prod_{j=1}^{n} r_{j-1}}} \exp\left\{-\frac{1}{2\sigma^2} \sum_{j=1}^{n} \frac{\left(X_j - \hat{X}_j\right)^2}{r_{j-1}}\right\}, \qquad [2.27]$$

and $\hat{X}_j, r_{j-1}$ for $j = 1,2,\ldots,n$ are derived from the innovations algorithm. Estimation errors arising from overly high values chosen for p and q is reflected by a penalization of the AICc statistic, since the $2(p+q+1)$ term approaches zero as p and q grow. This agrees with the parsimony philosophy of parameter selection. The AIC criterion is considered valid for $n \geq 30 + p + q$. For smaller samples, the AICc criterion is valid. It is defined by choosing $p, q, \boldsymbol{\beta}$ that minimizes

$$\mathrm{AICc} = -2\ln L(\boldsymbol{\beta}, S(\boldsymbol{\beta})/n) + 2(p+q)\frac{n}{n-p-q-1}. \qquad [2.28]$$

The $n/(n-p-q-1)$ term corrects for the small sample bias in the AIC.

Remark 1. It is important that the AIC or AICc for one data set is *not* compared with the AICc for another data set. Even the same data set with different autoregressive parameters (*p*) cannot be compared unless the data subset used after conditioning is the same. For example, the AIC or AICc of an $\mathrm{AR}(3)$ model can be compared with an $\mathrm{AR}(1)$ model for a given data set only if the data used to fit the $\mathrm{AR}(1)$ model is truncated by two points at the beginning of the time series.

Remark 2. Minimization of the AIC or AICc statistic that involves a large number of parameters as compared to the number of data points probably indicates that the data do not represent an $\mathrm{ARMA}(p,q)$ process.

Remark 3. The penalization factors for the AIC and AICc depend on the magnitude of the data. Thus, non-negative data should be divided by its mean before computing these order selection statistics.

The BIC criterion
Sometimes, Schwarz' (1978) Bayes information criterion (BIC) is used to select a model. It is defined as

$$\mathrm{BIC} = -2\ln L(\boldsymbol{\beta}, S(\boldsymbol{\beta})/n) + (p+q)\ln n. \qquad [2.29]$$

2.4.3 Parameter estimation

Mendelssohn (1981) used backforecasting methods to estimate his parameters. The techniques used in SPLUS for estimation of parameters will involve maximum likelihood functions. For ARMA models, there are basically two ways to approach the estimation problem. Minimization of the logarithm of the **exact likelihood function** leads to a nonlinear system of equations to be solved for optimal estimators. A simpler approximation of the exact likelihood function is the **conditional likelihood function**, which conditions the exact likelihood function on a subset of data points at the beginning of the time series. Minimization of the logarithm of the conditional likelihood function becomes a linear system of equations to be solved for asymptotically optimal estimators. Conditional likelihood estimators are consistent for invertible ARMA processes and can be found by numerical optimization, in general.

Freeman and Kirkwood (1995) claim that state-space time series methods are well suited to stock assessment. They estimate biomass population and recruitment indices using maximum likelihood methods and the Kalman filter. The Kalman filter is an algorithm that incorporates maximum likelihood estimation for a wide class of models known as state-space models. The Kalman filter has two very useful properties. Firstly, it can account for missing values in the data, treating them as predicted values. Secondly, the Kalman filter enables estimates to be continually updated as new incoming data becomes available over time.

2.4.4 Nonstationary time series and ARIMA models

Many observed time series are not stationary. There are two types of nonstationarity, namely explosive stationarity and homogeneous stationarity. **Explosive nonstationarity** occurs when there is a root greater than unity for the characteristic polynomial $\phi(z) = 0$. When one or more roots of $\phi(z) = 0$ are on the unit circle and all others are inside the unit circle, a weaker type of nonstationarity occurs, called **homogeneous nonstationarity**. For the homogeneous cases of nonstationarity, autoregressive integrated moving average (ARIMA) models are appropriate.

Denote the (backward) difference operator $\nabla = 1 - B$, where B is the backward shift operator. In other words, ∇ is defined as

$$\begin{aligned} \nabla X_t &= X_t - X_{t-1} \\ \nabla^2 X_t &= X_t - 2X_{t-1} + X_{t-2} \\ &\vdots \end{aligned} \qquad [2.30]$$

Definition 2.11 $\{X_t\}$ is an **ARIMA**(p,d,q) **process** if there is a nonnegative integer d such that the process $\{\nabla^d X_t\}$ is a causal ARMA(p,q) process.

It is clear from the definition of ∇ that $\{\nabla^d X_t\}$ being a stationary ARMA process implies that $\{X_t\}$ is homogeneously nonstationary. Therefore, ARIMA processes are applicable in the case of homogeneous nonstationary time series.

Order estimation for ARIMA models

We can roughly deduce the number of differences d required by consideration of the ACFs and PACFs of the original process and its d-differenced processes. Also, the presence of one or more unit roots of the characteristic polynomial of an autoregressive process indicates further differencing is required, while the presence of one or more unit roots of the characteristic polynomial of a moving average process indicates the process has been overdifferenced. Our approach is to select d to be the minimum non-negative integer required to achieve stationarity (i.e. no unit roots).

2.5 Seasonal ARIMA time series models

Many environmental time series involve a seasonal component. Seasonal ARIMA models involve a further differencing to account for a seasonal component of period *s*. Define the seasonal difference operator $\nabla_s = 1 - B^s$. The definition of a seasonal autoregressive integrated moving average (SARIMA) process is as follows:

Definition 2.12 $\{X_t\}$ is a **SARIMA**$(p,d,q)\times(P,D,Q)_s$ **process with period** *s* if there are nonnegative integers d, D such that the process $\{Y_t\} = \{\nabla^d \nabla_s^D X_t\}$ is an ARMA process defined by

$$\phi(B)\Phi(B^s)Y_t = \theta(B)\Theta(B^s)\varepsilon_t, \qquad [2.31]$$

where $\{\varepsilon_t\} \sim WN(0,\sigma^2), \phi(z) = 1 - \sum_{j=1}^{p} \phi_p z^p$, $\Phi(z) = 1 - \sum_{j=1}^{P} \Phi_j z^j$, $\theta(z) = 1 + \sum_{j=1}^{q} \theta_j z^j$ and $\Theta(z) = 1 + \sum_{j=1}^{Q} \Theta_j z^j$.

In the definition, *p*, *d* and *q* are nonseasonal parameters while *P*, *D* and *Q* are seasonal parameters. The time series $\{X_t\}$ can be nonstationary either nonseasonally or seasonally. Monthly time series data is generally seasonally nonstationary only.

Order selection for SARIMA processes
Ozaki's (1977) adjusted AIC criterion is set out in Hipel and McLeod (1994, p.434) as:

$$\mathrm{AIC} = \frac{n}{n'}\left(-2\ln L(\boldsymbol{\beta}, S(\boldsymbol{\beta})/n') + 2(p+q+P+Q)\right), \qquad [2.32]$$

where $n' = n - d - sD$. The adjusted AICc criterion is based on the adjusted AIC criterion as follows:

$$\mathrm{AICc} = \frac{n}{n'}\left(-2\ln L(\boldsymbol{\beta}, S(\boldsymbol{\beta})/n') + 2(p+q+P+Q)\frac{n'}{n'-p-q-P-Q-1}\right). \qquad [2.33]$$

2.6 Transfer function models

When analyzing a time series, there maybe interest in incorporating other independent time series into the model. For example, fishing effort, environmental variables and biological data might help to describe a catch time series for a fishery. Transfer function (TFN) models, equivalently known as SARIMAX models, are used for this purpose. They resemble regression models, for example, an ARMAX model would be written

$$\phi(B)\left(Y_t - \sum_{i=1}^{k} \delta_i X_{it}\right) = \theta(B)\varepsilon_t, \qquad [2.34]$$

where $\{Y_t\}$ is the dependent time series and $\{X_{it}\}_{i=1}^{k}$ are the independent time series. $\delta_i \; (i = 1,\ldots,k)$ are the transfer function coefficients.

2.6.1 Testing the significance of the transfer function coefficients

Similar to regression, it is important to know which independent variables are significant in a time series model. They can be tested as follows, since the parameters of the ARIMA process and the transfer function coefficients are asymptotically uncorrelated. Let **W** be the filtered matrix of the covariate matrix **X** according to the ARIMA process. We define **W** mathematically. The model is

$$\mathbf{Y} = \mathbf{X}\delta + \mathbf{Z}, \qquad [2.35]$$

where **Y** is the observed data, δ is the vector of regression coefficients and **Z** is an unobserved ARIMA process with ARIMA parameters. Define **G** to be the linear transformation (i.e. filter) such that

$$\mathbf{GY} = \mathbf{GX}\delta + \varepsilon, \qquad [2.36]$$

where $\mathbf{GZ} = \varepsilon \sim WN(0, \sigma^2)$. Then we define $\mathbf{W} = \mathbf{GX}$. **G** can be expressed in Splus as

$$\text{arima.filt}(data, model)\text{\$filt - arima.filt}(data, model)\text{\$pred}.$$

Then the variance-covariance matrix of the transfer function coefficients is given by

$$\mathbf{H} = \text{cov}(\delta) = \sigma^2 \left(\mathbf{W}^{\mathbf{T}}\mathbf{W}\right)^{-1}. \qquad [2.37]$$

The standard errors of the transfer function coefficients are thus the square roots of the diagonal elements of **H**. A *t*-test may then be applied to each transfer function coefficient.

2.7 Multivariate ARIMA models

In certain circumstances, a set of time series variables cannot be described as **independent** predictors of a given time series. They may instead be correlated. We are no longer interested in a single parameter σ^2 that describes the predictor capacity of the variables, rather a variance-covariance matrix describing the relationship among all the variables. For this situation, a multivariate analysis is required. We define what is meant by a multivariate ARIMA model. Let

$$\mathbf{Z}_t = (Z_{t1}, Z_{t2}, \ldots, Z_{tk})^T$$

be a vector of *k* time series, where the vector of means for $\mathbf{Z}_t$ is given by

$$\mu = (\mu_1, \mu_2, \ldots, \mu_k)^T.$$

Then a *k*-dimensional ARMA(p, q) process can be written as

$$\begin{aligned}&(\mathbf{Z}_t - \mu) - \mathbf{\Phi}_1(\mathbf{Z}_{t-1} - \mu) - \mathbf{\Phi}_2(\mathbf{Z}_{t-2} - \mu) - \ldots \mathbf{\Phi}_p(\mathbf{Z}_{t-p} - \mu)\\ &= \varepsilon_t + \mathbf{\Theta}_1\varepsilon_{t-1} + \mathbf{\Theta}_2\varepsilon_{t-2} + \ldots + \mathbf{\Theta}_q\varepsilon_{t-q},\end{aligned} \qquad [2.38]$$

where $\mathbf{\Phi}_i$ is the ith parameter matrix of order $k \times k$ for $i = 1,2,\ldots, p$, $\mathbf{\Theta}_i$ is the ith parameter matrix of order $k \times k$ for $i = 1,2,\ldots,q$, and $\varepsilon_t \sim NID(0, \mathbf{\Delta})$. Stationarity and invertibility conditions require that the zeros of the determinant equations $|\mathbf{\Phi}(B)| = 0$ and $|\mathbf{\Theta}(B)| = 0$, respectively, must lie outside the unit complex circle.

The multivariate ARIMA model given by [2.37] is very general. There is no set model building technique, nor is there a general estimation procedure for such a model. Moreover, the number of parameters that are required to be estimated increases exponentially with respect to the number of time series included in the model. Therefore, simpler multivariate models such as transfer function noise (TFN) models and contemporaneous ARMA (CARMA) models are used. TFN models require that the $\mathbf{\Phi}_i$ and $\mathbf{\Theta}_i$ matrices are lower diagonal for all i. That is, variable i can only be described in terms of present and previous values of itself and the other $1,\ldots(i-1)$ time series variables and associated errors. CARMA models are even more restrictive, by requiring that all $\mathbf{\Phi}_i$ and $\mathbf{\Theta}_i$ are diagonal. That is, variable i can only be described by previous values of itself and its errors. These models can be extended to include integrated and seasonal terms. The study of interest in this project will use contemporaneous seasonal ARIMA (CSARIMA) models to analyze Shark Bay tiger and king prawn catches and catch rates over the different areas. The main interest is in the contemporaneous variance-covariance matrix $\mathbf{\Delta}$ of the innovations ε_t.

2.8 Nonlinear time series models: the GARCH family

For some series, linear time series models such as ARIMA seem inflexible. One reason is that the data is volatile. A reliable family of models that treats data with high kurtosis $(>> 3)$ is the generalized autoregressive conditional heteroscedasticity (GARCH) models. These are models of changing variance, which arose from economic circles (Engle 1982, Bollerslev 1986). Suppose that u_t is a white noise process and is expressed as:

$$u_t = \sqrt{h_t} v_t, \qquad [2.39]$$

where v_t are independently and identically distributed with zero mean and unit variance. Then the GARCH specification is:

$$h_t = \kappa + \sum_{i=1}^{r} \delta_i h_{t-i} + \sum_{j=1}^{m} \alpha_j u_{t-j}^2 . \qquad [2.40]$$

The notation is $u_t \sim \text{GARCH}(r, m)$, and a non-negativity condition $\kappa \geq 0, \delta_i \geq 0 \; \forall \; i = 1,\ldots, r, \alpha_j \geq 0 \; \forall \; j = 1,\ldots, m$ is imposed. Stationarity of $\{u_t\}$ requires that

$$\sum_{k=1}^{\max(r,m)} (\delta_k + \alpha_k) < 1. \qquad [2.41]$$

If $\{u_t\}$ is the residual series of a data series y_t fitted with an ARIMA model with fitted values $\hat{y}_t$, then the fitted ARIMA-GARCH(r, m) model would be $\hat{y}_t - u_t + h_t$. The GARCH component has changed the fit of the data. In that sense, ARIMA-GARCH models can be considered nonlinear. However, ARIMA-GARCH models are reliable in the sense that the stationarity and invertibility conditions of the original data set may be verified. For the purposes of this project, we will consider only $\mathrm{GARCH}(1,1)$ components, which identify the major behaviour in volatility dynamics. We show that some finfish species exhibit volatile behaviour in the monthly catch time series.

2.8.1 Testing for a GARCH process

The main test that will be applied in this project is the McLeod-Li (1983) test for ARCH effects. If $\hat{r}_j$ is the autocorrelation at lag j for the square of the residuals ε_t, then for L sufficiently large the statistic

$$Q = n(n+2)\sum_{j=1}^{L}\frac{\hat{r}_j^2}{n-j} \qquad [2.42]$$

is asymptotically distributed χ_L^2 under the null hypothesis that the data is distributed linearly, where n is the number of data points and L is the number of lags (usually $L = 20$).

Another test for ARCH disturbances is Engle's (1982) LM test, which is based on the R^2 of an auxiliary regression, viz:

$$u_t^2 = \alpha_0 + \sum_{i=1}^{M}\alpha_i u_{t-i}^2 + \upsilon_t , \qquad [2.43]$$

where $\alpha_0, \ldots, \alpha_M$ are to be estimated, $\{u_t\}$ is the observed white noise process, $\{\upsilon_t\}$ is a white noise process and uncorrelated with any of the other explanatory variables, and it is assumed that $E(u_t^8)$ exists. If u_t is a linear process, then nR^2 is asymptotically distributed χ_M^2.

2.9 Summary of models used

Given the wide variety of Western Australian fisheries tested, certain models are more appropriate than other models for prediction of catches. Statistical quality control charts were valid for the majority of the fisheries that were tested (see Chapter 3). Below is a brief description of the types of variables and models fitted for each fishery.

2.9.1 Western rock lobster

Univariate ARIMA models were fitted to the annually aggregated catch data (1965/66 to 2001/02) for each of three zones A, B and C. Annual predictions from the puerulus collector/mortality nonlinear regression models are far superior to predictions from the ARIMA models, however ARIMA models may be of use if for some reason the puerulus data became unavailable in a particular zone.

Of more interest were univariate ARIMAX models of seasonal whites/reds catches in zones B and C when puerulus collector information and management intervention variables were included in the models. Proportions of whites to reds catches were studied, together with the effect the management intervention of 1993/94 had on the catch proportions.

Univariate seasonal models were fitted and used as forecasts for the monthly data. Estimation of the nonlinear transfer function, including fishing effort, puerulus collector information and Beverton-Holt mortality functions, were of theoretical value. There was evidence that catches from zone C may follow a nonlinear process such as GARCH.

2.9.2 Southern rock lobster

A SARIMAX model with a transfer function involving an interaction of May catch rates from the central region of the northern South Australian fishing zone and the Southern Oscillation Index (SOI) was fitted to describe the monthly catches from 1975/76 to 2001/02. The residuals exhibited a change in variance from 1990 onwards, indicating a SARIMAX model with two levels of variance would be superior. The complication arising from the estimation process left such an analysis outside the scope of this project.

2.9.3 Shark Bay prawns

A multivariate SARIMA approach to the prediction of the monthly catches from the seven main fishing areas of Shark Bay proved most useful. The predictions of the univariate SARIMA models for each area were comparable to more complicated age-structured seasonal models (Hall, 2000). Catches from neighbouring fishing areas were shown to be contemporaneously correlated, however, so a contemporaneous multivariate SARIMA approach was used. The correlation matrix revealed the lower western fishing areas (G1+G2, G3) comprised a separate sub-fishery from the rest of the fishery in terms of catch dynamics.

2.9.4 Finfish

Univariate SARIMA models were fitted to monthly catches for at least 12 finfish fisheries to ascertain the seasonal and nonseasonal behaviour of the fisheries. For the highly seasonal Australian herring and West Australian salmon fisheries, where there are high catches for a couple months of the year and very little catch in between, the low monthly catches needed to be aggregated in order for the SARIMA models to adequately fit the data. For at least 5 finfish fisheries, interactions involving monthly catch rates and environmental factors were successfully used in a nonlinear regression model to predict annual catches. These estimates were then used as annual transfer functions to improve the seasonal ARIMA models predicting monthly catches. Catches from three finfish fisheries were found to possess volatile behaviour from month to month. These fisheries were fitted using GARCH models. The forecasts were improved for two of these fisheries, and the conditional variance was improved for the three finfish fisheries.

For twelve finfish fisheries, the catch and fishing effort data was analyzed on the south coast region and the west coast region. SARIMA models were fitted to the data. It was found that the SARIMA model orders for most of the 12 fisheries on the west coast were consistent, and that the fishing effort data was a significant factor for explaining the catches when fitting the appropriate SARIMAX model. On the other hand, the behaviour of the catch data was more erratic off the south coast, and fishing effort was rarely significant in determining the south coast catches.

A time-delay linear regression model was used between mean monthly commercial Swan River tailor catch rates and mean juvenile Point Walter catch rates lagged approximately two years. There were six years of data used in the model. With the exception of an outlier, this relationship proved to be highly significant. The Point Walter juvenile tailor index was used as a transfer function in a SARIMAX model predicting monthly commercial Swan River tailor catches. There were significant correlations in the catch data from one month to the next, and from one year to the next. The transfer function component was significant. Juvenile catch rate indices from other areas were compared with the Point Walter index using linear regression. Eight years of annual commercial Perth sea catches in the immediate vicinity of the Swan River were compared with the mean monthly commercial Swan River catch rates at the same time using nonlinear regression.

2.10 References

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3.0 An exploratory study on statistical control charting for Western Australian fisheries management

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3.1 Abstract

A statistical quality control charting approach to stock assessment is investigated for many of the main Western Australian commercial species, including western rock lobster (*Panulirus cygnus*), Shark Bay and Exmouth Gulf tiger and king prawns, Australian herring, western Australian salmon, Spanish mackerel, pilchards, westralian dhufish and King George whiting. The control charting approach is also particularly useful for the more minor fisheries where there is limited biological knowledge. There are at least 25 years of annual catch and fishing effort data available for analysis for a wide range of Western Australian fisheries. A set of monitoring rules, designed to alert management to control aspects, is adapted to suit fisheries data. Acceptable catch ranges are calculated based on the history of catches in the fisheries. The quality control methods in this paper are closely aligned with the theory of control charting, placing emphasis on consistency and rigour across the fisheries. The analysis is compared with similar management techniques used for Western Australian fisheries in the past.

3.2 Introduction

Stock assessments for many fisheries rely only on catch range or catch rate forecasts. For some fisheries, there is insufficient research to enable more advanced modelling procedures such as age-structured models or yield per recruit models. Several reasons for this include lack of biological data, environmental effects and/or recruitment information on the fishery. For these situations, the more phenomenological models such as time series analysis or statistical quality control charting may explain the dynamics of the fishery. These simpler models directly identify trends, cycles and other repeated behaviour based on the given data rather than the biological estimates. When forecasting catches or catch-per-unit-effort (CPUE), the simpler models prove to be more reliable than the complex models (Noakes et al. 1990; Stocker and Noakes 1988; Roff 1983). We show that statistical quality control analysis utilizing easily obtainable Western Australian fisheries data such as catch and fishing effort provides quantitative insight into, and useful management advice for, many of the key Western Australian fisheries. Statistical quality control charts have been proven to enhance stock assessment methods (Okpanefe 1988). The research in Okpanefe (1988) has shown that quality control charting is a useful direct tool for monitoring average fish size and thus the status of some fisheries in Nigeria.

This paper is intended to provide an exploratory account of statistical quality control charting of catches and CPUE for a wide range of fisheries of Western Australia. The standard quality control rules for “alert” are investigated in a fisheries setting, and the upper and lower control and warning limits are adapted to suit fisheries data. Acceptable catch ranges are calculated to gauge sustainability limits on each fishery. The interpretation of a fishery’s status is enhanced by comparing quality control charts for the catch and CPUE series. The effects of management intervention on the data in some fisheries through quality control charting are also discussed.

3.3 Methods

Statistical quality control charts of the annual catch and annual CPUE were calculated for a variety of commercial Western Australian fisheries. Catch and CPUE data range from 1964/65 to 2000/01 for the three fishing zones of western rock lobster (*Panulirus cygnus*) and 1975/76 to 2001/02 for the Esperance southern rock lobster (*Jasus edwardsii*) fishery defined between the boundaries $120°\mathrm{E}$ and $125°\mathrm{E}$. For the Shark Bay and Exmouth Gulf, data is available from 1971 to 2001, however the 1981 data for Shark Bay is missing. Catch and CPUE data is available from July 1975 to June 2000 for many finfish fisheries. Included in this paper are Australian herring (*Arripis georgiana*), western Australian salmon (*Arripis truttacea*), Spanish mackerel (*Scomberomorus commerson*), pilchards (*Sardinops sagax*), westralian dhufish (*Glaucosoma hebraicum*), pink snapper (*Chrysophrys aurataus*), King George whiting (*Sillaginodes punctata*), tailor (*Pomatomus saltatrix*), baldchin groper (*Choerodon rubescens*), yellow-eye mullet (*Aldrichetta forsteri*) and sea mullet (*Mugil cephalus*). The finfish fisheries are year-round fisheries. The catch and fishing effort data is selected for each finfish species based on a financial year or a calendar year, depending on the seasonality of the fishery.

The upper and lower warning limits were set at $\bar{x} + t_{df,0.10}\, s$ and $\max\left(\bar{x} - t_{df,0.10}\, s, 0\right)$, where $\bar{x}$ and s are the sample mean and standard deviation, respectively, and *df* is the number of data points less one. The control limits were calculated from the warning limits and set at $\bar{x} + t_{df,0.02}\, s$ and $\max\left(\bar{x} - t_{df,0.02}\, s, 0\right)$. Variances of the series are assumed to be constant.

Based on a modified Shewart technique, the following rules are used to identify whether the process is out of control. When any of the following are observed, the process may be considered out of control:
A1: A point lies outside the control limits.
A2: Two consecutive points lie outside the warning limits.
A3: Seven consecutive points occur in either an upward or downward trend.
A4: Seven consecutive points occur on the same side of the centreline.

The control limits were calculated as 96% confidence intervals by setting the probability that a point falls outside the control limits to the probability of two consecutive points falling outside the 80% warning limits. A3 and A4 were set to seven points since fisheries time series are generally autocorrelated. If the observations were independent, the number of points required to trigger a warning would be five, since 2^{-N} becomes smaller than 0.04 when $N = 5$. The property of autocorrelation increases the conditional probabilities of consecutive points occurring in a trend or occurring on the same side of the centerline.

To calculate the acceptable catch range, we allow isolated points outside the warning limits, but inside the control limits. The sustainable catch period in a given fishery is determined subjectively as the catch range for which the fishery is considered sustainable over the long term. The sustainable catch period is maintained and affected by management intervention measures. For the purpose of this research, we assume that the sustainable catch period is the period available for the data set. The acceptable catch range is then given by $\left(1 - \text{probability of isolated point between warning and control limits}\right) \times 100\%$ confidence intervals. Given that a point is between the warning and control limits $\left(p = 0.16\right)$, the next point must be within the warning limits $\left(p = 0.8\right)$. Thus, the acceptable catch range is defined by the 87.2% confidence intervals for the sustainable catch period.

3.4 Results

Table 3.1 presents sample means, warning limits and control limits for the fisheries studied. An analysis of the control charts is studied below for each fishery.

Western rock lobster – Zone A

The 1998/99 catch exceeded the upper control limit. The 1998/99 and 1999/00 CPUEs exceeded the warning limits. Therefore, the catch for the 1998/99 season is not considered unreasonably high since there is an indication that abundance at that time was quite high. The implementation of the 1993/94 management package has not decreased catches in zone A, however the CPUE has been above the centreline for longer than the last seven seasons. The most likely interpretation of this result is that in this fishing zone there may have been competition among pots before 1993/94.

Western rock lobster – Zone B

Since the period from 1964/65 to 1976/77, catches have dramatically increased. Two consecutive catches were above the warning limits (1977/78 to 1978/79), commencing a consecutive seven point run above the mean. By contrast, the CPUEs have not increased. This points towards increasing fishing pressure over time, which may warrant a restraint in zone B in the future, such as a further pot reduction.

Western rock lobster – Zone C

Similarly to zone B, catches prior to 1976/77 were mostly below average. The catches during the period from 1977/78 to 1984/85 were above the overall mean, indicating the fishery may have experienced a period of good recruitment and/or higher exploitation. The 1999/00 catch was exceptionally high, significantly exceeding the upper control limit. Since the CPUE for that season also exceeded the upper control limit, the catch was most likely due to improvement in recruitment rather than the stock being subjected to increased exploitation.

Esperance southern rock lobster

Catches were below average from 1975/76 to 1990/91, however CPUE has not increased since this low-catch period. CPUEs exceeded the upper warning limit for three consecutive seasons (1991/92 to 1993/94), followed by a similar scenario for catches from 1993/94 to 1995/96. Increases in live storage capacity most likely led to the increased interest in the Esperance southern rock lobster fishery. Catches peaked above the upper control limit in 1998/99: a lower than expected CPUE for that season indicates the possibility of increased fishing pressure for that season. Catch rates have since declined to record low levels for the 27-year period, however catches remain average.

Shark Bay prawns

CPUEs were not included in the analysis, since it is very difficult to split the fishing effort over the multi-targeted fishery. Shark Bay tiger prawn catches were below average throughout the 1980s, however the king prawn fishery profited during that period. Shortly after, in 1990, the king prawn fishery suffered one of its worst years of catches, dropping below the lower control limit. In the same year, management implemented a buy-back of 8 vessels out of a prawn trawl fleet of 35 to reduce fishing effort. The tiger fishery seemed unsustainable throughout the 1970s and more recently from 1994 to 2000, however several complications arising from the use of GPS and year-to-year management changes make a conclusion regarding the state of the fishery difficult.

Exmouth Gulf prawns

CPUEs were not included in the analysis for the same reason as for Shark Bay prawns. The Exmouth Gulf prawn fishery is notoriously volatile so it is difficult to infer much from the control chart analysis. The only period where either fishery looked to be at dangerously low levels was from 1982 to 1984 when the tigers recorded very low catches and recruitment overfishing has been identified as the cause. Fishers appeared to be targeting tigers more than the kings in the 1970s. Management policies have implemented a shift in emphasis away from tiger catches and towards king catches since 1980.

Australian herring

Catches and CPUEs have shown a general increase from 1975/76 to 1991/92. The catch and CPUE for 1990/91 exceeded the respective upper control limits. Three out of four consecutive catches from 1988/89 to 1991/92 exceeded the upper warning limit. There was little concern from a management perspective, however, since environmental or biological effects most likely gave rise to high catch rates and thus attributed to the unusually high catches. The series was otherwise in control.

Western Australian salmon

While the high catch in 1983/84 was accompanied by an unusually high CPUE in the same year, this was not the case for the record catch in 1994/95. However, salmon stocks do not seem to have suffered since 1994/95.

Spanish mackerel

Catches and CPUE have experienced an upward trend from 1976 to the present day. The record catch in 1997 was accompanied by a series of three consecutive CPUE years (1997 to 1999) exceeding the upper warning limit. While the initial increase in CPUE and correspondingly catches from 1991 was probably a result of GPS technology, the recent high catches may have been recruitment driven or the result of coverage of new fishing grounds.

Pilchards

Catches dramatically increased during the 1970s and early 1980s, but then slumped from late 1998 into 1999 and 2000 due to mass mortality probably caused by herpesvirus (Gaughan et al. 2000). The record catch in 1996 was more a result of high abundance than any presence of fishing pressure, since the CPUE exceeded the upper warning level from 1995 to 1997.

Westralian dhufish

The catch and CPUE series were in control with the exception of a particularly high catch in 1986 but only an average CPUE. Thus, the 1986 catch level is considered unsustainable.

Pink snapper

The series were in control except for a record high catch in 1985, which can be partially explained by an above average CPUE in the same year.

King George whiting

CPUEs were particularly low from 1989 to 1997. However, the fishery made a remarkable recovery to post a record catch in 1999, with a corresponding record CPUE above the upper control limit signifying high abundance. King George whiting catches have otherwise remained in control.

Tailor
Tailor stock appeared to suffer in 1986, but catches have remained above average since 1992. The CPUE has remained in control except for 1986. More stringent management of the recreational fishing sector, which is larger in volume than the commercial sector, may have led to the higher than average commercial catches more recently. For example, the 1999 and 2000 catches both exceeded the upper warning limit, pushed up by the high CPUEs which were near the upper warning limit.

Baldchin groper
The baldchin groper fishery has experienced an increasing trend in catch through the 1970s and 1980s. Two consecutive seasons (1987/88 to 1988/89) of catches exceeded the upper warning limit. This was not accompanied by an increase in catch rates, so these catches were likely to be unsustainable. Since this period, catches of baldchin groper have been average.

Yellow-eye mullet
Catches in yellow-eye mullet have experienced a decrease since the mid-1970s. Catches have been below average from 1990. Stocks appear to be nearing a dangerously low level, with the CPUEs from 2000 to 2002 reported below the lower warning limit for the fishery.

Sea mullet
The 1979/80 and 1980/81 reported catches exceeded the upper warning limit. CPUE exceeded the upper control limit in 1982/83. Therefore, sea mullet was most likely highly abundant during this period. More recently, catches have been particularly low. Catch rates have held steady, however, indicating there is probably less demand for sea mullet in recent times.

3.5 Discussion

Acceptable catch range estimates for many fisheries have been estimated by calculating 80% confidence intervals about the historical mean of the double exponential smoothed data in the past. These estimates have been incorporated into the "State of the Fisheries Report" series since the 1990s. In some cases where there are trends in the fisheries data, 80% confidence intervals over the last 10 fishing seasons may best serve as the catch range estimate. Double exponential smoothing is known to be capable of forecasting data series with linear or sub-linear trends. Exponentially weighted moving average method (and consequently double exponential smoothing) is a useful approximate tool for independently, identically distributed data even when the parameter estimates are suboptimal. However, Muth (1960) pointed out that (single) exponential smoothing will only provide rational forecasts of future data if the data series follows an $\mathrm{ARIMA}(0,1,1)$ process. Similarly, we show in Appendix A that double exponential smoothing can provide rational forecasts only if the data series is an $\mathrm{ARIMA}(0,2,2)$ process. Such a process in fisheries exists but is scarce. As shown in Appendix A, a double exponential smoothing of the data is a sub-class of $\mathrm{ARIMA}(0,2,2)$ models. Optimizing the parameter for the double exponential method is not a trivial procedure.

One serious limitation of exponential or double exponential smoothing is the possibility of false alarm signals in the presence of autocorrelated data. Exponential moving average methods and CUSUM techniques have been shown to be sensitive to autocorrelated data (Bagshaw 1974; Bagshaw and Johnson 1975; Harris and Ross 1991; Alwan 1992; Woodall and Faltin 1993). The results in this paper show that the vast majority of annual fisheries catch data is autocorrelated. Therefore, the author suggests either calculating confidence intervals of the raw data series in the form of upper and lower warning limits to be used as the catch range estimate or, preferably, using a more sophisticated method such as ARMA charting (Jiang et al. 2000) to allow for autocorrelation.

In the present day, more reliable one-step ahead catch and CPUE forecasts may be estimated by maximum likelihood by fitting an $\text{ARIMA}(p,d,q)$ model, where p is the number of autoregressive parameters, d is the number of differences required to achieve stationarity and q is the number of moving average parameters. p and q are chosen by Hurvich and Tsai's (1989) small sample bias-corrected version of Akaike's (1974) AIC criterion. Exogenous variables such as recruitment and/or environmental information can be included in the form of transfer function(s) if there are significant relationships. Rarely would a series require 2 differences as the double exponential smoothing method suggests. Table 3.2 is a summary of the optimal ARIMA model for each fishery which has been analyzed by quality control charting. The AICc statistic has been included for the optimal ARIMA model, the optimal exponential smoothing, and the optimal double exponential smoothing. The only fishery where double exponential smoothing is superior to ARIMA is sea mullet, where there is a strong downward trend in the catch data.

Technological advances have changed the effectiveness of the fishing effort over the long term. However, there is no need to scale the nominal fishing effort data to effective fishing effort when calculating quality control charts. The technological knowledge of fishermen combined with management regulatory measures generally match the state of the fishery, keeping the CPUE series stationary in most cases.

3.6 Appendix A

We show that a double exponential smoothing of a data series is a special case of an $\text{ARIMA}(0,2,2)$ process. The double exponential smoothing method described by Brown (1963, pp. 128-132) and Gilchrist (1976, pp.72-74) is as follows. Let $\{\tilde{x}_t\}$ be the (single) exponential smoothing of a data series $\{x_t\}$, and $\{\tilde{x}_t^{(2)}\}$ be the double exponential smoothing of $\{x_t\}$. These series are defined for each t:

$$\begin{aligned} \tilde{x}_t &= (1-\alpha)x_t + \alpha\tilde{x}_{t-1} \\ \tilde{x}_t^{(2)} &= (1-\alpha)\tilde{x}_t + \alpha\tilde{x}_{t-1}^{(2)}. \end{aligned} \qquad (1)$$

Then the 1-step ahead forecast is given by

$$\hat{x}_t = \tilde{x}_{t-1} + \frac{1}{\alpha}\left(\tilde{x}_{t-1} - \tilde{x}_{t-1}^{(2)}\right). \qquad (2)$$

Thus, we can write

$$\begin{aligned} x_t &= \hat{x}_t + \varepsilon_t \\ &= \tilde{x}_{t-1} + \frac{1}{\alpha}\left(\tilde{x}_{t-1} - \tilde{x}_{t-1}^{(2)}\right) + \varepsilon_t, \end{aligned} \qquad (3)$$

where ε_t is the process error at time *t*. Lagging (3) one step and multiplying by α gives

$$\alpha x_{t-1} = (\alpha + 1)\tilde{x}_{t-2} - \tilde{x}^{(2)}_{t-2} + \alpha\varepsilon_{t-1} . \quad (4)$$

Subtracting (4) from (3), and using the second equation from (1),

$$x_t - \alpha x_{t-1} = 2\tilde{x}_{t-1} - (\alpha + 1)\tilde{x}_{t-2} + \varepsilon_t - \alpha\varepsilon_{t-1}. \quad (5)$$

Replacing $\tilde{x}_{t-2}$ using the first equation from (1) gives

$$x_t = \left(\frac{\alpha - 1}{\alpha}\right)\tilde{x}_{t-1} + \left(\frac{1}{\alpha}\right)x_{t-1} + \varepsilon_t - \alpha\varepsilon_{t-1} . \quad (6)$$

Again lagging (5) by one step and multiplying by α ,

$$\alpha x_{t-1} = (\alpha - 1)\tilde{x}_{t-2} + x_{t-2} + \alpha\varepsilon_{t-1} - \alpha^2\varepsilon_{t-2} . \quad (7)$$

Subtracting (6) from (5) gives the resulting equation:

$$x_t = 2x_{t-1} - x_{t-2} + \varepsilon_t - 2\alpha\varepsilon_{t-1} + \alpha^2\varepsilon_{t-2} , \quad (8)$$

which is an $\text{ARIMA}(0,2,2)$ process.

3.7 Further Developments

An ARMA(2,2) statistical quality control charting method has since been devised to account for the autocorrelation properties of fisheries catch data described in this chapter. The method is a generalization of the exponentially weighted moving average technique adjusted for catch series with the ARMA(1,1) property, and is defined as follows:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \theta_0 X_t - \theta X_{t-1} ,$$

where

$\{X_t\}$ is the original data, $\{Z_t\}$ is the monitoring process and $\theta_0 = 1 + \theta - \phi_1 - \phi_2$. These parameters are estimated by fitting an ARMA model to the original time series. The stationarity and invertibility conditions of the original process can therefore be checked. The ARMA(2,2) method is to be implemented to estimate acceptable catch ranges for many fisheries in WA. The range is calculated based on 87.2% confidence intervals, as outlined above, but adjusted for autocorrelation in the data. The method of adjustment involves an estimate of the variation of the observations compared with the variation of the predictions for a suitably relevant time period for each fishery. Where there are long-term trends in the catch data and the fishing effort correlates with the catches, a transfer function technique (see section 2.6) can be used to estimate an acceptable catch range based on historical catch and fishing effort data given an appropriate level of fishing effort.

3.8 References

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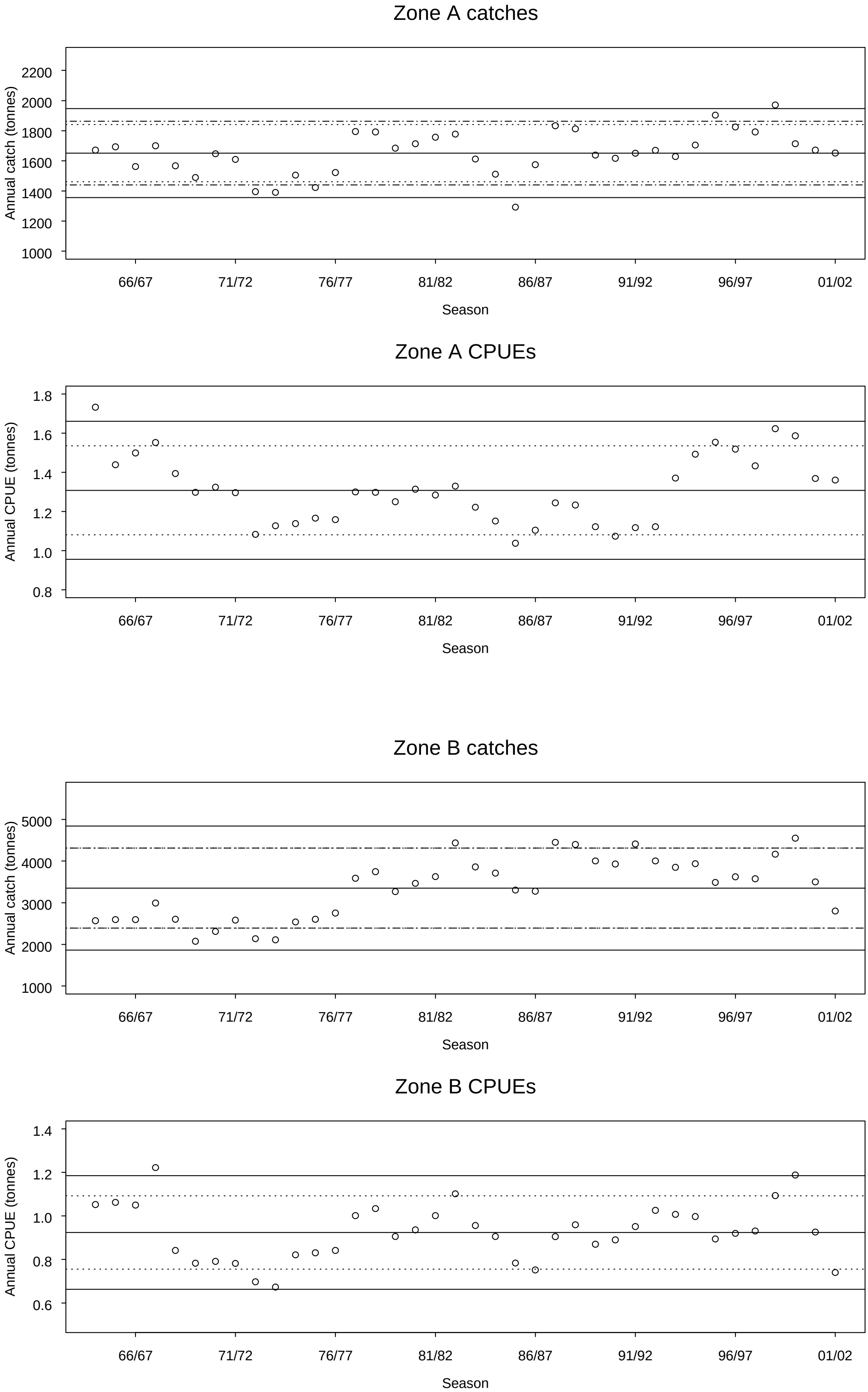
Table 3.1. Table of annual sample mean catches (tonnes) and CPUE (kg/pot lift for lobsters, kg/hour for prawns, kg/boat day for finfish), control limits and warning limits.

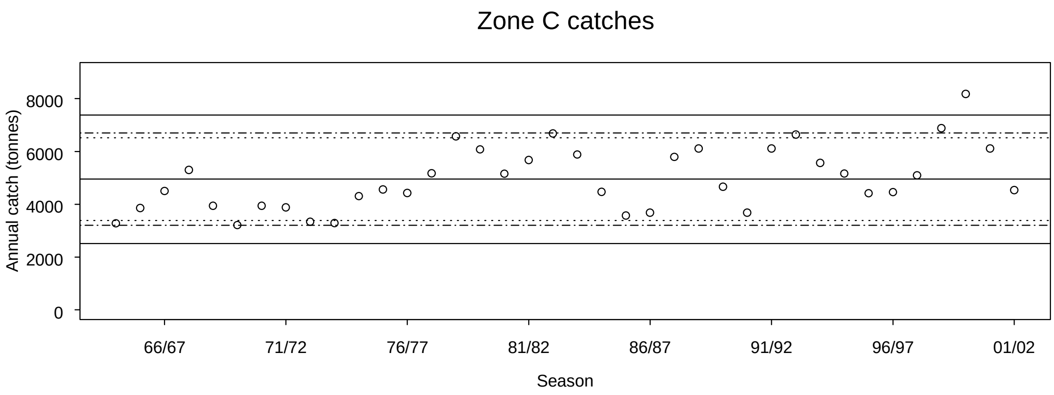
	Series	$\bar{x}$	c_u	c_l	w_u	w_l
Western rock lobster – Zone A	Catch	1651	1946	1357	1841	1461
	CPUE	1.31	1.66	0.96	1.53	1.08
Western rock lobster – Zone B	Catch	3351	4839	1863	4310	2393
	CPUE	0.92	1.18	0.66	1.09	0.76
Western rock lobster – Zone C	Catch	4949	7381	2518	6516	3383
	CPUE	0.95	1.35	0.55	1.21	0.70
Esperance southern rock lobster	Catch	33.6	78.3	0.0	62.2	4.9
	CPUE	0.82	1.20	0.44	1.06	0.58
Shark bay prawn – tiger	Catch	491	874	108	736	245
Shark Bay prawn – king	Catch	1309	1837	782	1648	971
Exmouth Gulf prawn – tiger	Catch	442	971	0	781	102
Exmouth Gulf prawn – king	Catch	364	567	162	494	234
Australian herring	Catch	938	1464	412	1274	601
	CPUE	143	220	66	192	94
Western Australian salmon	Catch	1985	3585	385	3008	961
	CPUE	756	1343	169	1131	381
Spanish mackerel	Catch	314	618	10	508	119
	CPUE	96	188	5	155	38
Pilchards	Catch	4881	12494	0	9751	10
	CPUE	999	2156	0	1739	259
Westralian dhufish	Catch	197	274	120	246	148
	CPUE	19	26	13	23	15
Pink snapper	Catch	825	1276	374	1114	536
	CPUE	65	87	43	79	51
King George whiting	Catch	37	69	4	57	16
	CPUE	9	15	3	13	5
Tailor	Catch	41	64	19	56	27
	CPUE	14	19	9	17	11
Baldchin groper	Catch	45	79	10	67	22
	CPUE	8	12	5	11	6
Yellow-eye mullet	Catch	342	782	0	623	61
	CPUE	47	77	16	66	27
Sea mullet	Catch	506	748	265	661	352
	CPUE	47	58	37	54	40

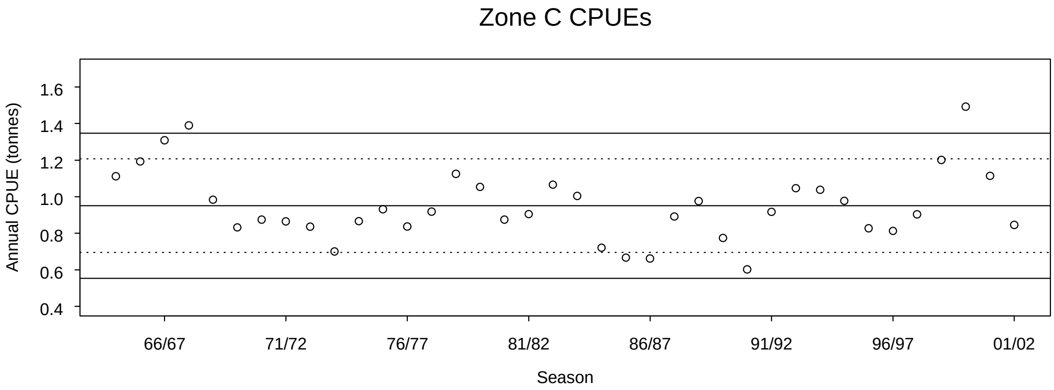
Table 3.2. Optimal ARIMA models for catch data.

Species	ARIMA model	AICc (optimal model)	AICc (exp smooth)	AICc (double exp smooth)
W.r.lobster (Zone A)	$(0,0,1)$	-87.4	-75.5	-76.5
W.r.lobster (Zone B)	$(1,0,1)$	-41.6	-38.8	-38.5
W.r.lobster (Zone C)	$(1,0,1)$	-26.2	-13.9	-3.4
S.r.lobster (Esperance)	$(1,0,1)$	18.2	19.9	26.7
SB tiger prawn	$(1,0,1)$	11.9	17.6	22.3
SB king prawn	$(1,0,0)$	-22.1	-17.2	-14.8
EG tiger prawn	$(1,0,0)$	43.4	44.8	54.2
EG king prawn	$(0,0,1)$	-5.09	-1.27	2.68
A. Herring	$(1,0,0)$	-4.26	0.70	-0.10
WA Salmon	$(1,0,0)$	17.0	20.6	22.2
Sp. Mackerel	$(0,1,0)$	1.32	3.15	4.33
Pilchards	$(0,1,0)$	19.3	20.9	25.6
W. Dhufish	$(1,0,0)$	-23.5	-19.7	-19.7
Pink Snapper	$(1,0,0)$	-4.45	-0.16	0.96
KG Whiting	$(1,0,0)$	20.9	34.0	36.3
Tailor	$(1,0,0)$	-7.97	-3.50	0.72
Baldchin groper	$(1,0,0)$	-1.47	3.48	3.70
Yellow-eye mullet	$(0,1,1)$	20.9	20.9	22.9
Sea mullet	$(0,1,1)$	-19.1	-19.1	-21.4

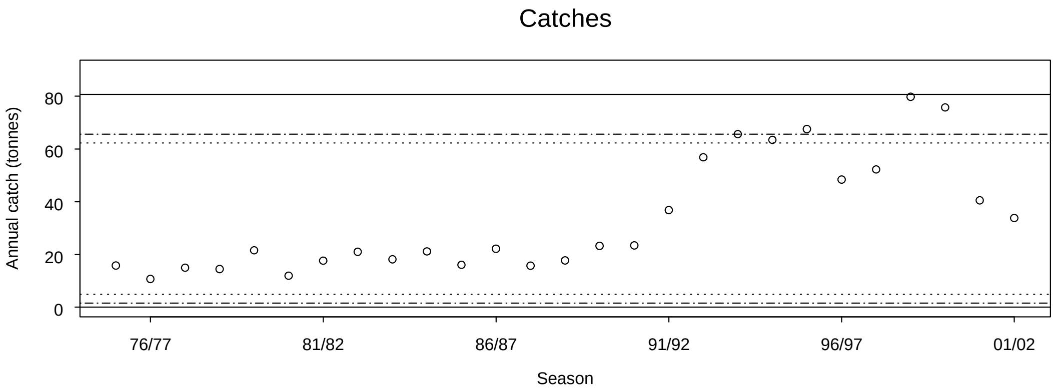
Western rock lobster

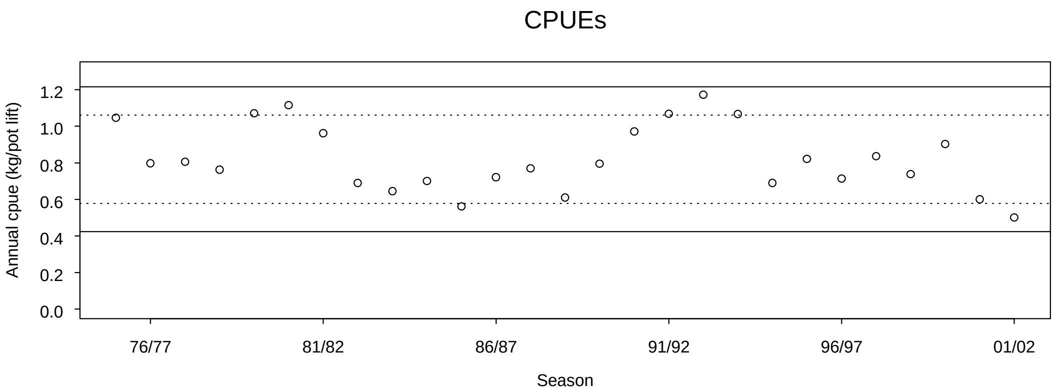






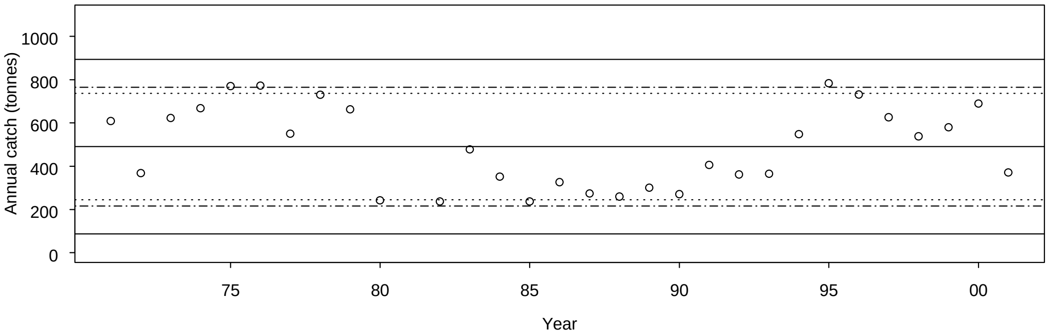
Southern rock lobster



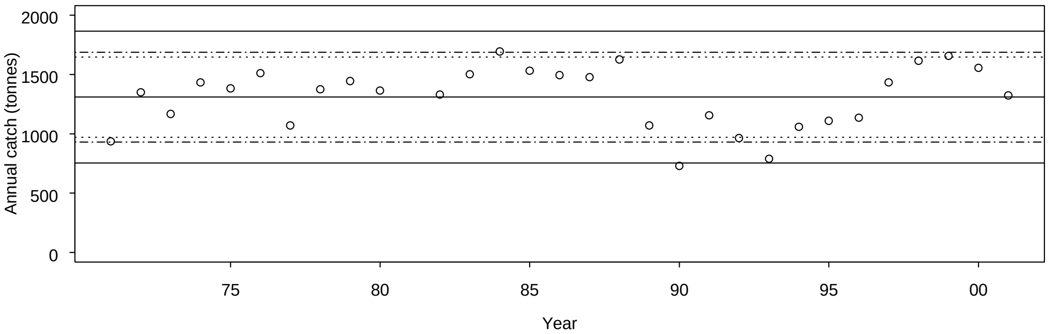


Shark Bay prawns

Shark Bay - Tiger catches

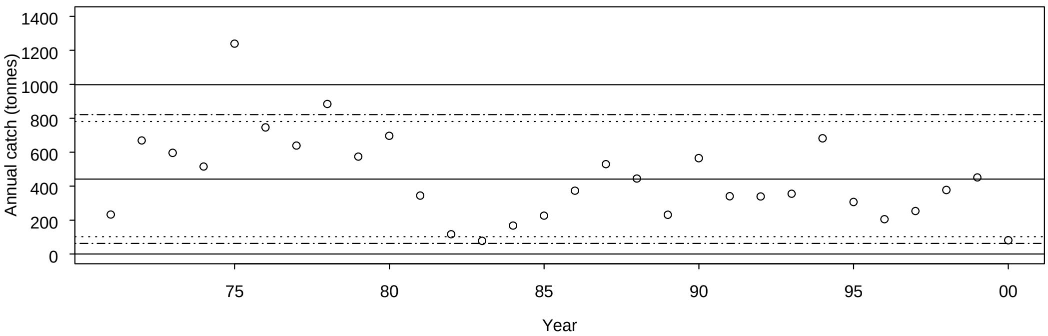


Shark Bay - King catches

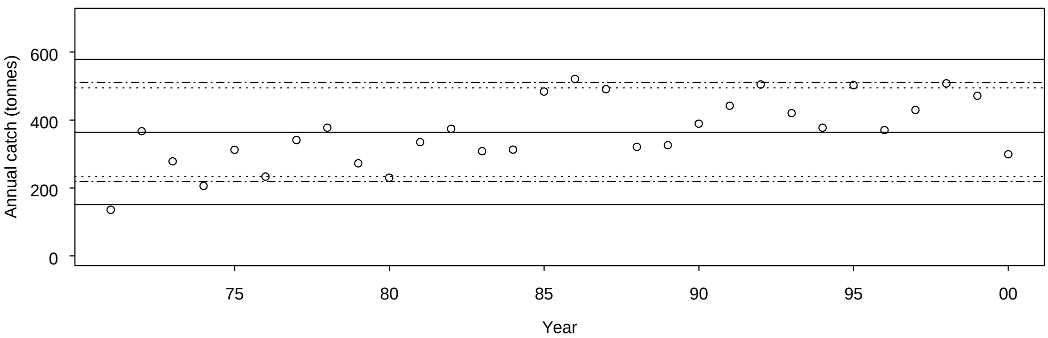


Exmouth Gulf prawns

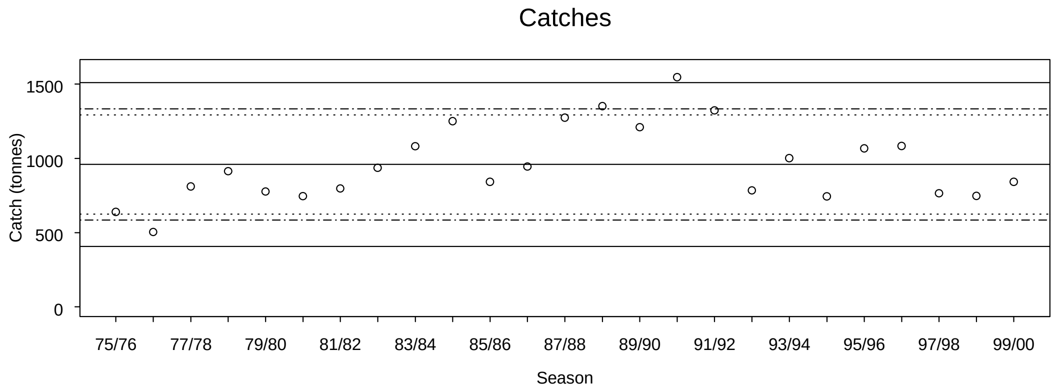
Exmouth Gulf - Tiger catches

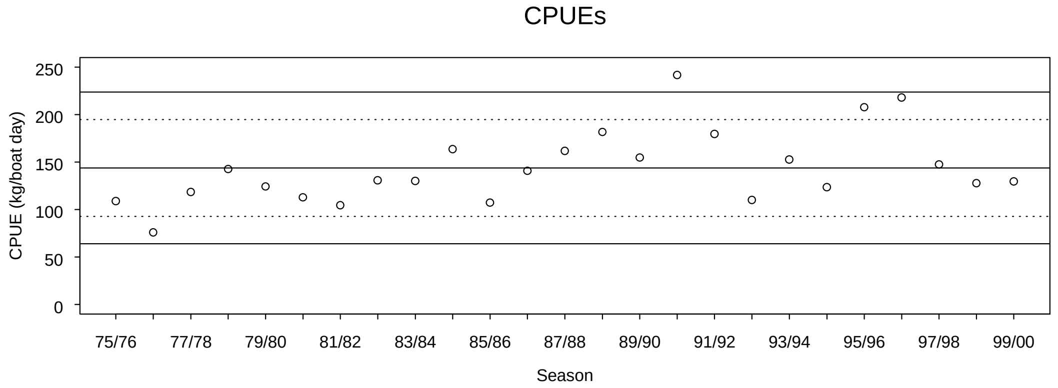


Exmouth Gulf - King catches

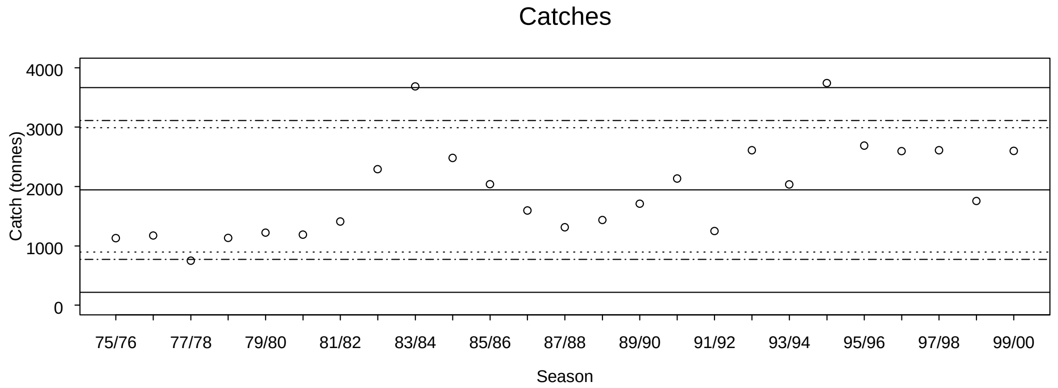


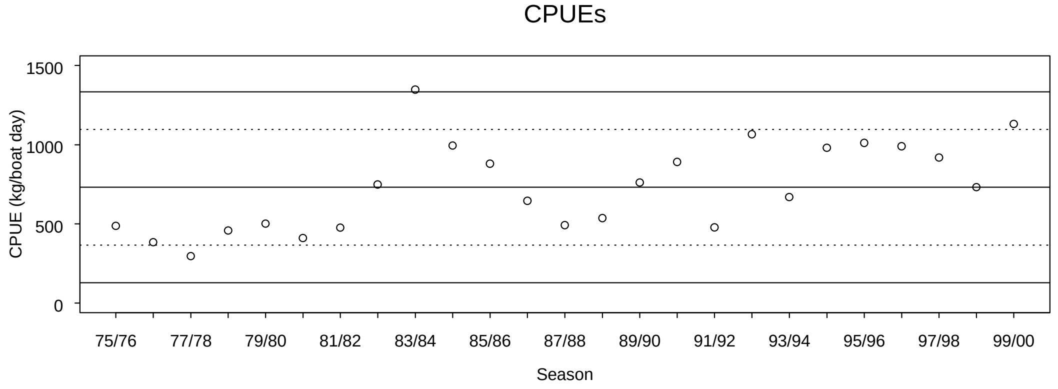
Australian herring





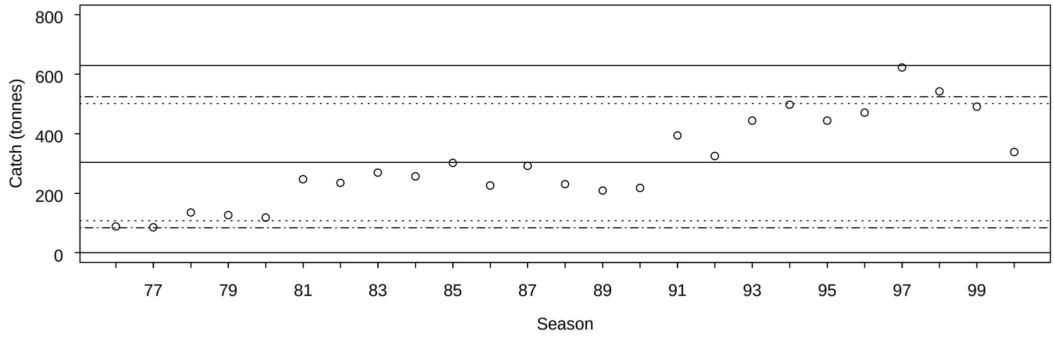
Western Australian salmon



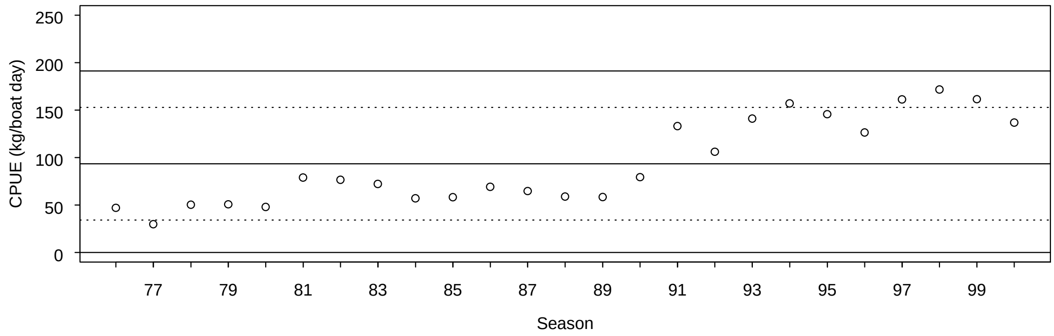


Spanish mackerel

Catches

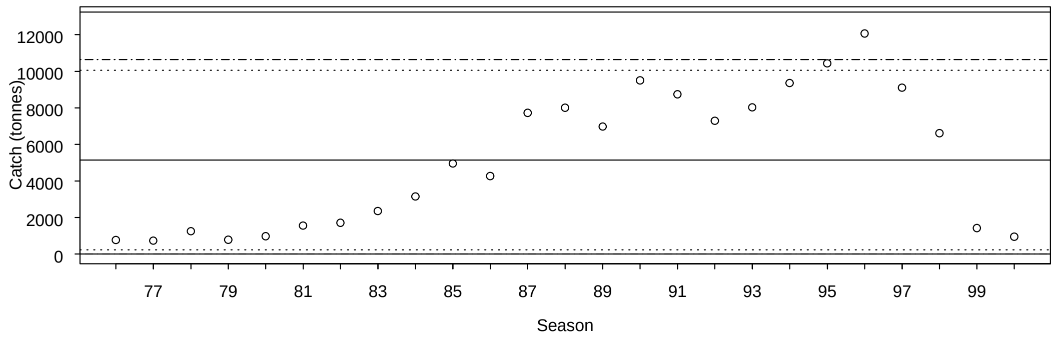


CPUEs

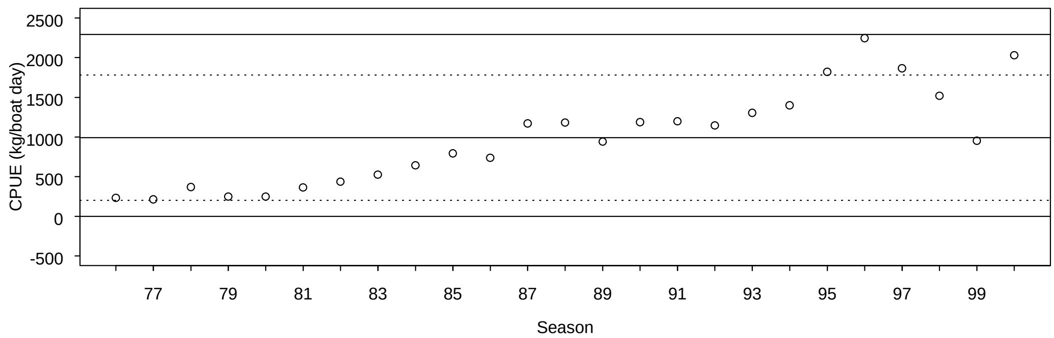


Pilchards

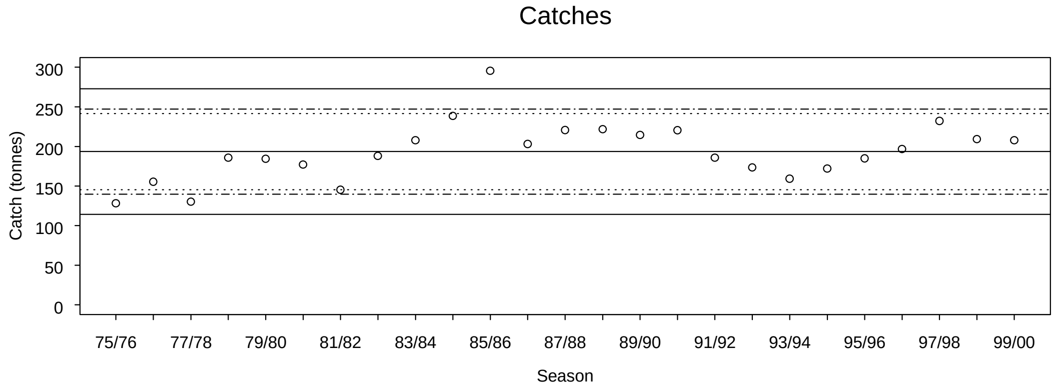
Catches

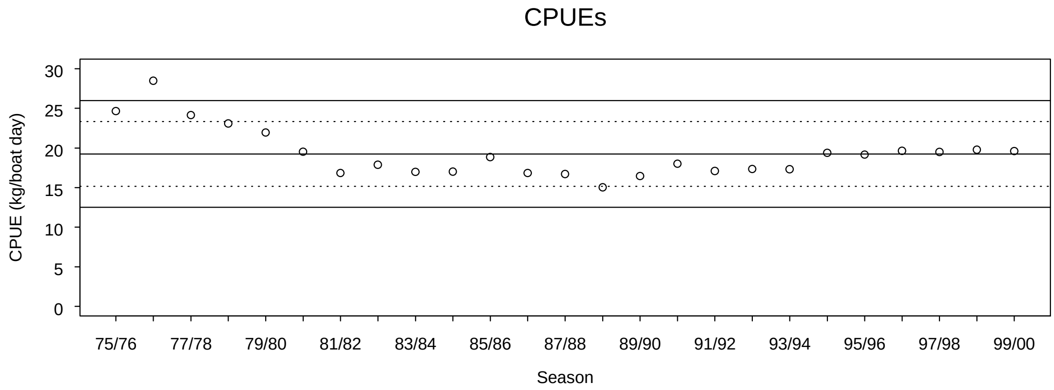


CPUEs

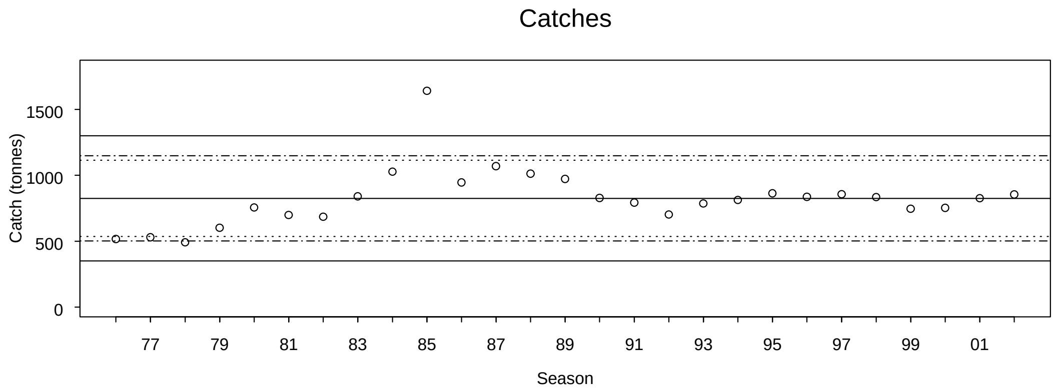


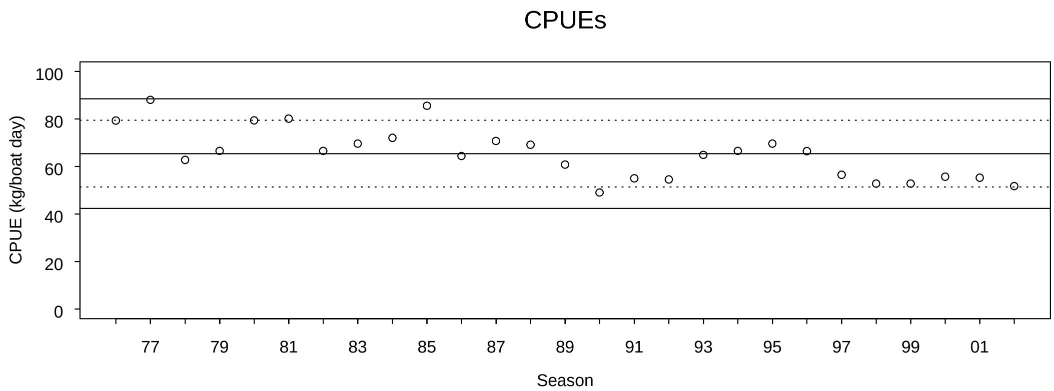
Westralian dhufish



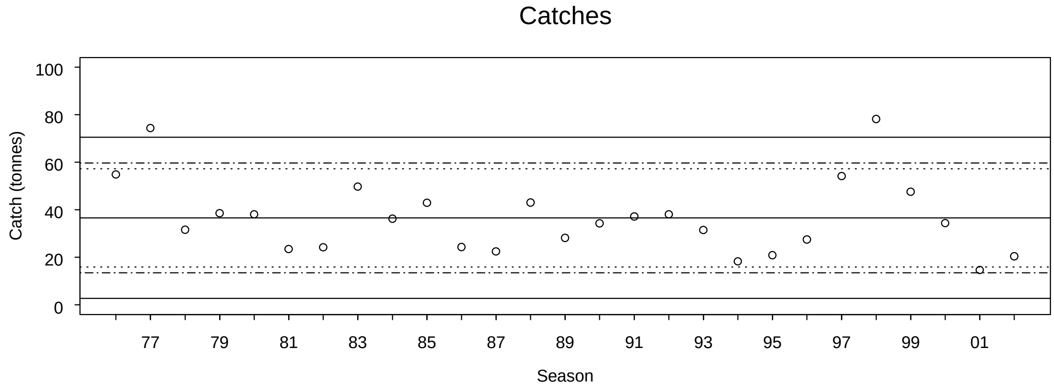


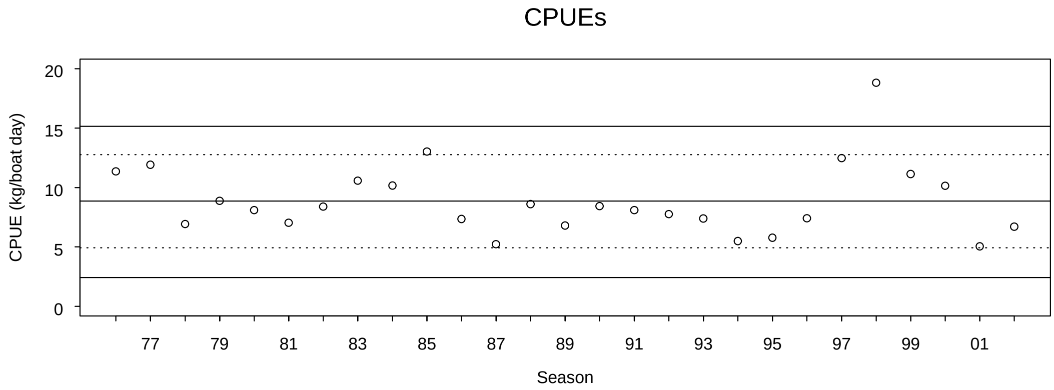
Pink snapper



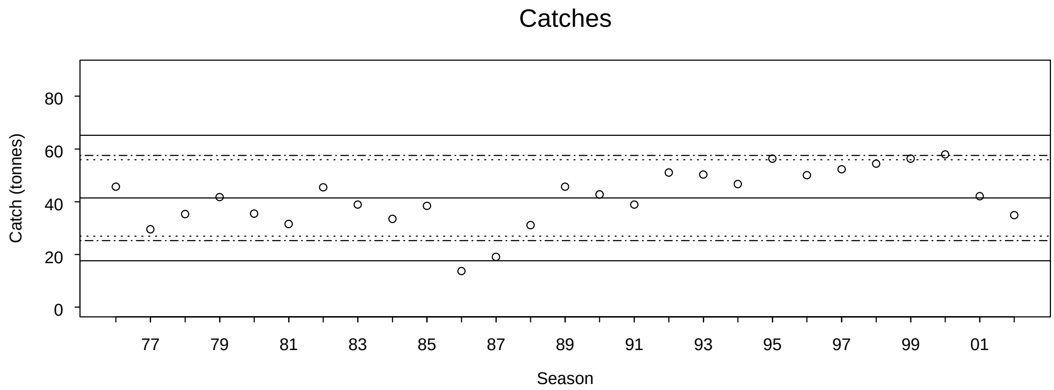


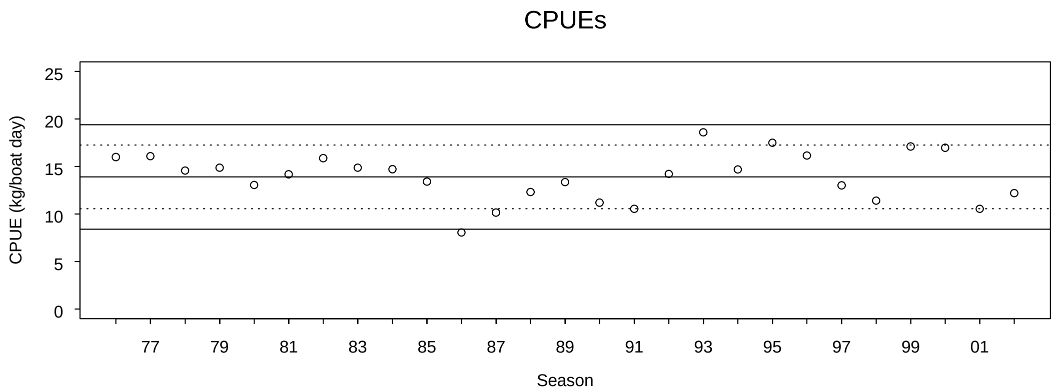
King George whiting



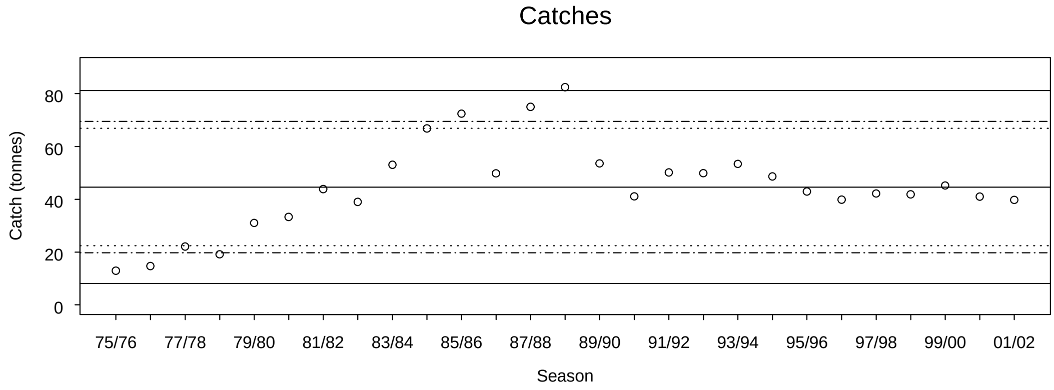


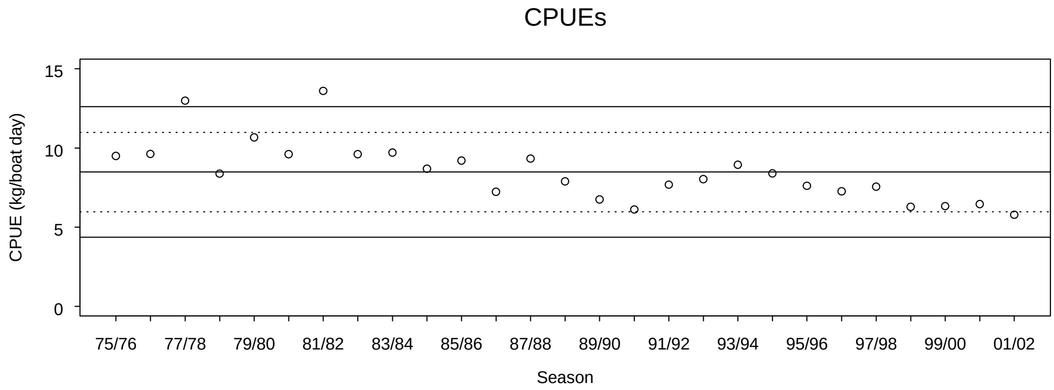
Tailor



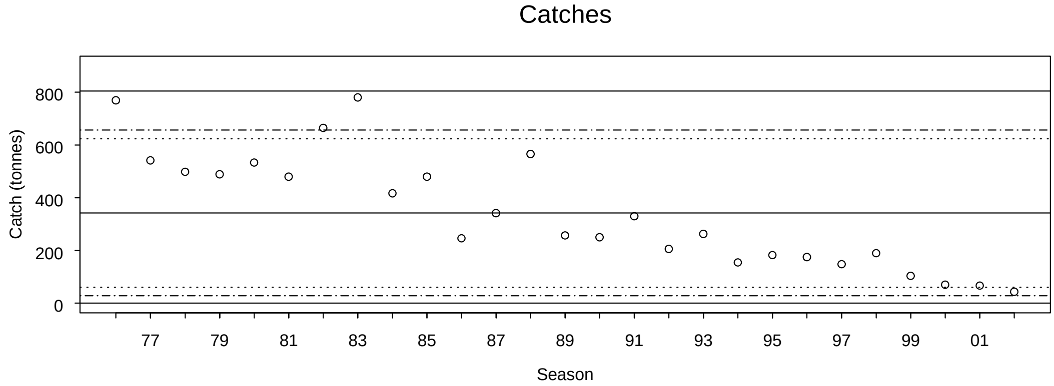


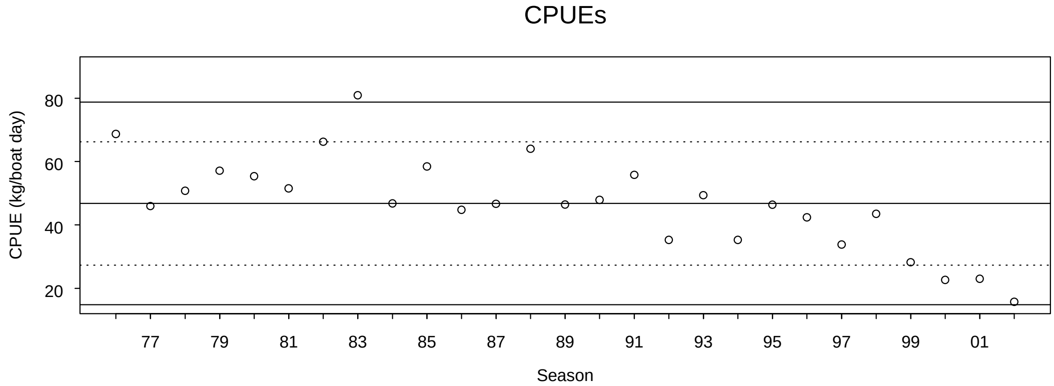
Baldchin groper



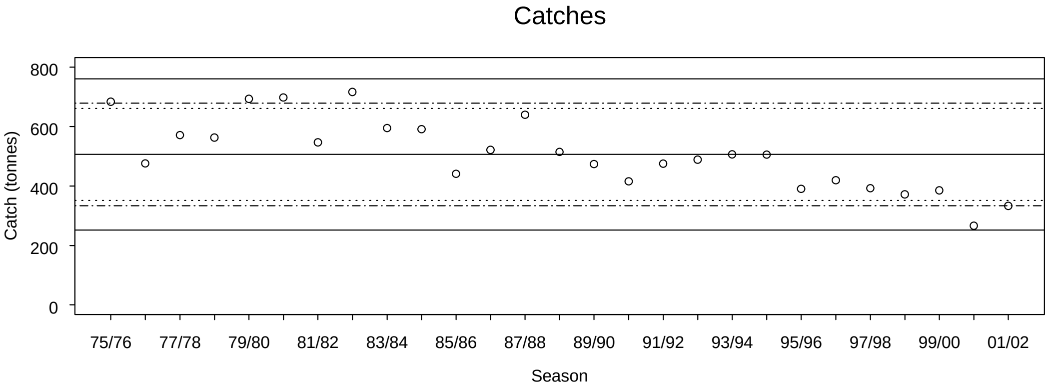


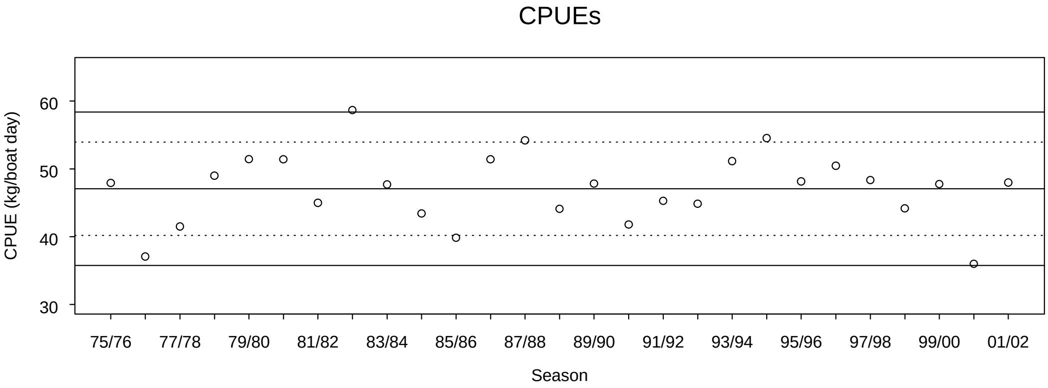
Yellow-eye mullet





Sea mullet


Catches
800
600
400
200
0
Catch (tonnes)
75/76
77/78
79/80
81/82
83/84
85/86
87/88
89/90
91/92
93/94
95/96
97/98
99/00
01/02
Season


CPUEs
60
50
40
30
CPUE (kg/boat day)
75/76
77/78
79/80
81/82
83/84
85/86
87/88
89/90
91/92
93/94
95/96
97/98
99/00
01/02
Season

4.0 Prediction of western rock lobster (*Panulirus cygnus*) monthly catches using seasonal ARIMA transfer function models with fishing effort and puerulus indices

M. D. Craine, Y. W. Cheng, N. Caputi, C. F. Chubb
WA Marine Research Laboratories, Department of Fisheries, Western Australia

4.1 Abstract

Time series methods are becoming increasingly popular for forecasting fisheries data. Four seasons (1996/97 to 1999/2000) of commercial western rock lobster monthly catches in each of three fishing zones are forecasted using seasonal ARIMA transfer function (SARIMAX) models based on historical data from 1976/77 to 1995/96. This paper suggests a general modelling procedure to treat nonlinear transfer components found in fisheries science theory. Piecewise-linear interpolations of the nonlinear catch-effort-puerulus (post-larval) settlement relationships are developed to easily validate the stationarity and invertibility conditions. Our results indicate that SARIMAX models describe the catch data well and give reliable predictions for each zone with the possible exception of zone C. The puerulus settlement and fishing effort variables are analyzed for significance in these time series models. The methodology developed in this paper is designed to provide an alternative for prediction of the likely range of future sustainable catches for fisheries management purposes, and will also be applicable to fisheries with limited biological data but a long time series of catch and fishing effort data.

4.2 Introduction

The western rock lobster (*Panulirus cygnus*) is the most valuable marine fishery in Australia comprising, on average, twenty percent of the total value of Australia's total fisheries production. The 1999/2000 western rock lobster catch was a record, posting a landed catch of over 14,000 tonnes and a landed revenue of A$390 million. To ensure that fishing pressure on this valuable fishery does not significantly deplete breeding stock levels, as occurred during the late 1980's, management adjusts fishing effort based on forecast catches (Chubb 2000). This ability to control annual catches is being further refined to keep breeding stocks within an acceptable range, above the biological reference point for this fishery of approximately 20-25% of the virgin biomass level (Hall and Brown 2000). This methodology has been possible for the western rock lobster fishery due to the successful annual recruitment forecasting system for this stock (Caputi et al. 1995a, 1995b), but would be very useful for many other fisheries without such forecasting systems. The purpose of this research is to develop alternative catch forecasting models using time series methods for a wide range of fisheries, and compare the methodology against "biological" forecasting systems where they exist.

There are three major zones in the fishery off the Western Australian coast (Figure 4.1). Zone A operates between Dongara and Kalbarri, and comprises fishing grounds adjacent to the offshore Abrolhos Islands. Zone B is situated to the north of latitude 30° S, excluding that area of the fishery designated as zone A. Zone C extends south of latitude 30° S to Cape Leeuwin. The fishing season since 1977/78 consists of 7.5 months, with the 'whites' fishing season operating from mid-November to January and the ‘reds’ fishing season operating from February to June. These names relate to the colour of the exoskeleton of the same population of lobsters. The lobsters moult in November and the whites moult again in February, changing colour to red. The fishing season for zone A only operates during the red season from mid-March to June. However, boats with a zone A licence are permitted to operate in zone B from November to mid-March.

Seasonal catch and effort data dates back to the 1964/65 season, while puerulus (post-larval) settlement information has been collected since the early 1970’s. However, historical management changes to the fishing season in the past only feasibly allow the use of seasonal catch and effort data sets from the 1977/78 season onwards. The 1976/77 season of data is used for conditioning purposes only when modelling.

Traditionally, linear regression models have been used to model catch predictions based on levels of puerulus settlement 3 to 4 years prior to the season (Phillips 1986, Caputi et al. 1995b). Catch predictions for western rock lobster are made using variations of an annual log-log puerulus-catch linear regression model (Caputi et al. 1995a, 1995b) defined by

(1) $$\log C_T = \log a + b_3 \log P_{T-3} + b_4 \log P_{T-4} + \varepsilon_T ,$$

where T is time in years, C_T is the yearly catch data, P_T is the mean of puerulus settlement data obtained from six collectors, b_3 and b_4 are parameters to be estimated and ε_T are normally and independently distributed with mean zero and constant variance, that is, $\varepsilon_T \sim NID\left(0, \sigma^2\right)$. Advantages in favour of this model are that any software package will quickly find the regression coefficients and that it has been reasonably reliable for annual catch predictions. However, the Gauss-Markov assumption of independence of the residuals is violated for (1) when fitting the annual white season catch series, annual red season catch series or the disaggregated catch series of the combined white and red seasons for each zone. For example, the Durbin-Watson (1950, 1951) statistic for the zone C log-log linear regression model (Caputi et al. 1995a, 1995b) with 10 observations taken from the white season using puerulus settlement information from 1986/87 to 1995/96 was 3.292, which is very close to the tabulated value $4 - d_l = 3.303$ at a 5% significance level (Greene 1993, p. 741). This result indicates that the residuals may be significantly negatively correlated for the annual white season regression model. A further problem with (1) is that the prediction estimates and confidence intervals of the predicted catches using log transformations are biased. The level of bias depends on the residual mean square error statistic.

A second model of interest is a delay-difference model (Hall 1997, Walters et al. 1993, Sullivan 1992, Schnute 1985, Deriso 1980). Length-age, weight-age relationships for differing sexes of the western rock lobster are estimated from this detailed model. One of the main disadvantages of this model is that the estimation process is very complex and time-consuming, involving at least 32 parameters (Sullivan 1992). It is also very difficult to estimate the standard errors associated with the estimated parameters.

The focus of this paper is on the application of seasonal autoregressive integrated moving average transfer function noise (SARIMAX) models with annual puerulus settlement information and annual fishing effort to predict seasonal catch data, and to examine the effect of these variables in the model. Transfer function models (TFMs), otherwise known as ARIMAX models, are appropriate modelling methods where the variables or the error terms under consideration are significantly serially correlated, since the models incorporate autoregressive and moving average terms (Box and Jenkins 1976). They can also handle time series with sub-exponential trends by the integrated process of differencing. The general form of these models is

$$\text{Output} \quad = \quad \text{Dynamics} \quad + \quad \text{Noise}\,,$$

where the dynamic component involves exogenous variables and the noise component is a seasonal ARIMA model in this paper.

4.3 Methods

The models used in this paper are defined as follows

$$C_{ti} = \frac{\theta_i(B)\Theta_i\left(B^{s_i}\right)}{\phi_i(B)\Phi_i\left(B^{s_i}\right)\nabla^d\nabla_{s_i}^D}\,\varepsilon_{ti}\,, \tag{2}$$

$$C_{ti} - f_i\left(\frac{\omega_{Ei}(B)}{\delta_{Ei}(B)}E_{ti}, \frac{\omega_{Pi}(B)}{\delta_{Pi}(B)}P_{ti}\right) = \frac{\theta_i(B)\Theta_i\left(B^{s_i}\right)}{\phi_i(B)\Phi_i\left(B^{s_i}\right)\nabla^d\nabla_{s_i}^D}\,\tilde{\varepsilon}_{ti}\,, \tag{3}$$

where C_{ti} is the monthly catch data over $i = \mathrm{A, B, C}$ zones, (2) is said to be a SARIMA model and (3) is a SARIMAX model. The left-hand dynamical component of (3) includes a continuous function f_i of the annual effort variables E_{ti} and the annual puerulus settlement variables P_{ti} calculated as a Winsorized mean (Kendall and Stuart p. 544, Phillips et al. 2000 chap. 1) of six collectors over respective zones. $\omega_{Ei}(B)$ and $\omega_{Pi}(B)$ are finite polynomials of the backward difference operator $B(\bullet_t) = \bullet_{t-1}$, and $\delta_{Ei}(B)$ and $\delta_{Pi}(B)$ are finite polynomials of B with identity constant term I. The seasonal ARIMA components in (2) and (3) are defined in terms of finite nonseasonal and seasonal autoregressive polynomials $\phi_i(B), \Phi_i\left(B^{s_i}\right)$ of degrees r_i and R_i, respectively, and finite nonseasonal and seasonal moving average polynomials $\theta_i(B), \Theta_i\left(B^{s_i}\right)$ of degrees z_i and Z_i, respectively, where the length of the season $s_\mathrm{A} = 4$ months for zone A and $s_\mathrm{B} = s_\mathrm{C} = 8$ months for zones B and C. $\nabla = I - B$ and $\nabla_s = I - B^{s_i}$ are nonseasonal and seasonal differencing operators, respectively. ε_{ti} and $\tilde{\varepsilon}_{ti}$ are white noise terms with mean zero and constant variance. The seasonal ARIMA modelling notation used in this paper is thus $\mathrm{SARIMA}(r_i, d_i, z_i) \times (R_i, D_i, Z_i)_{s_i}$.

For example, a $\mathrm{SARIMA}(3,0,0) \times (4,1,2)_8$ filter is later shown to be optimal for zone C. We will assume the catch for year T depends on effort in year T and a linear combination of the puerulus settlement information at annual time lags $(T-3)$ and $(T-4)$. Dropping the $i = \mathrm{C}$ subscript, the SARIMAX model is written and estimated in the form

$$\begin{aligned}
&\left(I - \phi_1 B - \phi_2 B^2 - \phi_3 B^3\right)\left(I - \Phi_1 B^8 - \Phi_2 B^{16} - \Phi_3 B^{24} - \Phi_4 B^{32}\right) \\
&\left(I - B^8\right)\left\{C_t - f\left[\omega_E E_t, \omega_P\left(\alpha B^{24} + (1-\alpha)B^{32}\right)P_t\right]\right\} \\
&= \left(I + \Theta_1 B^8 + \Theta_2 B^{16}\right)\varepsilon_t.
\end{aligned}$$

For the purposes of this paper, we put all $\delta_{\bullet i}(B) = I$ since causality is assumed for biological reasons. In other words, we assume that the catch at a given time is not affected by fishing effort nor puerulus settlement levels in future time.

To establish the significance of the effort and puerulus settlement variables in (3), consider the SARIMA models in (2) which are fitted as follows

$$\phi_i(B)\Phi_i\left(B^{s_i}\right)\nabla^d \nabla_{s_i}^D C_{ti} = \theta_i(B)\Theta_i\left(B^{s_i}\right)\varepsilon_{ti},$$

and then enter the puerulus settlement information and fishing effort into (3). The procedure we follow is to select and then fix the order of model (2) for each zone, and use the same respective model order to fit (3). The significance of the annual effort and puerulus settlement variables can be thus identified for each model by carrying out asymptotic *t* tests based on the information matrices. Orders of differencing, autoregression and moving average components for (2) are chosen by minimization of the AICc (Hurvich and Tsai 1989), subject to the model satisfying the stationarity and invertibility conditions. The AICc is a bias-corrected version of Akaike's (1974) AIC statistic for small samples. Stationarity and invertibility conditions are re-checked throughout the analyses of the models defined by (3). The AIC and AICc statistics depend on the actual size of the observations, so to ascertain approximately correct penalization factors for these statistics, we scale the catch data by dividing through by its mean. Selection of the dynamic characteristic polynomials is based on biological criteria. In this respect, it is assumed that only the effort in year *T* determines the catch in year *T* and, for biological reasons, the puerulus settlement information only in years $(T-3)$ and $(T-4)$ affect the catch in year *T* for all models analysed. These are the time lags which have been shown to affect the catch (Caputi et al. 1995b).

There are many model derivations for puerulus-catch relationships in fisheries science. Besides the log-log linear model (1) (Caputi et al. 1995a, 1995b), a traditional model that appears in fisheries literature (Phillips et al. 2001) is the power curve

(4) $$C_T = a\left(P_{T-3}^*\right)^b + \eta_T,$$

where *a* and *b* are constants to be estimated, $\eta_T \sim N\left(0, \sigma_\eta^2\right)$ and P_{T-3}^* is a linear combination of the lagged puerulus index data P_{T-3} and P_{T-4}, i.e.

(5) $$P_{T-3}^* = \pi P_{T-3} + (1-\pi)P_{T-4},$$

with $0 \le \pi \le 1$. Models (1) and (4) assume that the catch continues to increase as the pueruli rise in numbers. Such an assumption is often not justified because the food supply is limited for juveniles and possibly older lobsters. Neither of these models has a biological derivation, and the estimation of π for the power curve is heavily biased since the estimated π is often negative unless constrained by a trigonometric transformation (Phillips et al. 2001, chap. 1). One biologically derived model is the Ricker-related curve (Ricker 1975, Phillips et al. 2001), viz.

(6) $$C_T = \tilde{a}P_{T-3}^* \exp\left(-\tilde{b}P_{T-3}^*\right) + \tilde{\eta}_T,$$

where $\tilde{a}$ and $\tilde{b}$ are parameters to be estimated, P^*_{T-3} is defined in (5) and $\tilde{\eta}_T \sim N\left(0, \sigma^2_{\tilde{\eta}}\right)$. For $P^*_\bullet$ beyond a certain point, the expected catch decreases with increasing puerulus settlements. However, current levels of puerulus settlement and catches have shown no indication that this point has been reached.

We use the Beverton-Holt (1957) two-parameter density dependent mortality curve to define a catch-puerulus settlement curve

(7) $$C_T = \frac{lP^*_{T-3}}{P^*_{T-3} + \beta} + \varepsilon_{PT},$$

where l and β are parameters to be estimated and $\varepsilon_{PT} \sim N\left(0, \sigma^2_P\right)$. (7) is used in this paper on the empirical basis that the western rock lobster population exhibits compensatory mortality behaviour and that the biological derivation of (7) is straightforward. Other assumptions in (7) include: i) the expected puerulus settlement observations are proportional to the actual level of puerulus settlement for a given year and ii) the expected catch is proportional to the number of individuals present. While these assumptions are somewhat reasonable, a further assumption for the models in (2) and consequently (3) is that catches are linearly related to historical catches according to the specifications of the SARIMA models. This linearity assumption must be kept in mind throughout the analyses for respective zones.

An approximate catchability function that has been used (Phillips et al. 2001) to adjust (7) for fishing effort is given by

(8) $$\tilde{u}(T, k) = \rho\left(\frac{E_T}{\overline{E}}\right)^k,$$

where ρ and k are parameters to be estimated and $\overline{E}$ is the average annual effort. (8) is used because of the difficulty of very high correlations among parameters for the theoretical catchability function given by DeLury (1947, 1951; see Ricker 1975, pp. 153-154), viz.

$$u(T, q) = \zeta\left(1 - \exp\left(-q\frac{E_T}{\overline{E}}\right)\right),$$

where ζ is a proportionality constant to be estimated and q is a catchability parameter to be estimated. These problems provide further valid reasons for constructing linear interpolations of the fitted curves. The catch-effort-puerulus settlement model is thus constructed from (7) and (8) following the method of DeLury, viz.

(9) $$C_T = \frac{\alpha P^*_{T-3}}{P^*_{T-3} + \beta}\left(\frac{E_T}{\overline{E}}\right)^k + \varepsilon_{PE\,T},$$

where $\alpha = l\rho$, P^*_{T-3} is defined in (5) and $\varepsilon_{PE\,T} \sim N\left(0, \sigma^2_{PE}\right)$.

A nonlinear regression is performed to estimate the parameters α, β, π and *k*. We then construct a piecewise linear interpolation of the first term in (9) and rescale the puerulus settlement and fishing effort variables to achieve approximate linearity. Thus, the stationarity and invertibility conditions are easily checked so that a linear TFM software package can be used. The stationarity and invertibility conditions must be met to obtain reliable forecasts.

Our piecewise-linear interpolation method is as follows. Partition the in-sample domain of the puerulus settlement variable $P_{\bullet}^{*}$ into a finite number $\tilde{p}$ of subintervals. Then the set of endpoints of these subintervals can be written in the form $S_{\tilde{p}} = \{0, x_1, x_2, \ldots, x_{\tilde{p}}\}$, where $0 < x_1 < x_2 < \ldots < x_{\tilde{p}}$. Define piecewise-linear approximations of the projected puerulus-catch curve for each fixed effort value in the data set, where $S_{\tilde{p}}$ is the set of abscissae of points lying on each curve. For fixed $\tilde{p}$ and fixed effort level, minimize the total absolute area of the difference between each projected puerulus-catch curve and its corresponding piecewise-linear interpolation over all possible $S_{\tilde{p}}$. Let $S_{\tilde{p}t}^{*}$ be the set of abscissae of points that minimizes the absolute area for given effort level and $\tilde{p}$ as just described. Since the absolute area is minimized, it can be shown that the location of the points in $S_{\tilde{p}t}^{*}$ is independent of the effort level and thus independent of *t*. Thus, we can just write $S_{\tilde{p}}^{*}$ instead of $S_{\tilde{p}t}^{*}$. For the Beverton-Holt case (9) and $\tilde{p}$ fixed, we have a system of nonlinear equations

$$\text{(10)} \qquad \begin{aligned} \log(x_2 + \beta) &= \frac{x_1}{\beta} + \log(x_1 + \beta), \\ \log(x_j + \beta) &= \frac{x_{j-1} + \beta}{x_{j-2} + \beta} - 1 + \log(x_{j-1} + \beta), \quad \text{for } j = 3,4,\ldots,\tilde{p}, \end{aligned}$$

with $\beta > 0$. Remembering that $x_{\tilde{p}}$ is known, (10) reduces to a univariate equation in x_1. For the case of four interpolation points, for example, this equation is

$$\text{(11)} \qquad \log(x_3 + \beta) = \exp\left(\frac{x_1}{\beta}\right) - 1 + \frac{x_1}{\beta} + \log(x_1 + \beta).$$

This piecewise-linear interpolation defines the following rescaling of P_t^{*}:

$$\tilde{P}_t^{*} = \begin{cases} P_t^{*}, & 0 \le P_t^{*} \le x_1 \\ x_1 + m_{1t}\left(P_t^{*} - x_1\right), & x_1 < P_t^{*} \le x_2 \\ x_1 + m_{1t}\left(x_2 - x_1\right) + m_{2t}\left(P_t^{*} - x_2\right), & x_2 < P_t^{*} \le x_3, \end{cases}$$

where

$$\begin{aligned} m_{1t} &= \frac{x_1\left(C_{2t}^{*} - C_{1t}^{*}\right)}{\left(x_2 - x_1\right)C_{1t}^{*}} \\ m_{2t} &= \frac{x_1\left(C_{3t}^{*} - C_{2t}^{*}\right)}{\left(x_3 - x_2\right)C_{1t}^{*}}, \end{aligned}$$

and C_{jt}^{*} are the ordinates that correspond with $S_{\tilde{p}}^{*}$ on the projected puerulus-catch curve for each effort level. Figure 4.2 illustrates the fitted nonlinear regression and piecewise-linear interpolation procedure for the zone B puerulus-catch curves adjusted by effort. Finally, an adjustment is made for each approximate puerulus-catch line proportionately to its observed level of effort to form a new puerulus-effort index (Figure 4.3).

Selection of the number of points $\tilde{p}$ for the piecewise linear approximation can be obtained by minimization of the SICc criterion (McQuarrie 1999), which is a small-sample correction for Schwarz's (1978) BIC criterion.

Regarding the puerulus settlement information, there are six years of missing data for zone A (79/80 through 84/85). The procedure we follow is to substitute the corresponding mean-scaled puerulus settlement data from zone B, since zone A is wholly enclosed within zone B. A similar procedure is used for the zone C Alkimos puerulus settlement data by replacing the missing values from 69/70 to 81/82 and from 93/94 through 97/98 by the corresponding mean-scaled zone C Jurien puerulus settlement data. Alkimos data is chosen over Jurien data wherever possible. The Alkimos puerulus settlement data is more representative of the zone C catch as it is near the centre point of the fishery.

From the construction of TFMs, there is little analysis required to produce catch predictions and corresponding 95% confidence intervals for each zone. The data starting from the 1976/77 season through to the 1995/96 season is fitted, and four years of predictions are made from 1996/97 to 1999/2000 for the respective zones using the TFMs in (3).

4.4 Results

Using relevant years of data from each zone, the puerulus-effort-catch parameters were estimated as per (9) using nonlinear regression (Table 4.1). No selection of a subset of parameters is made at this stage since the estimates may be biased due to the correlation structure of the residuals in (9). The number of points for the linear interpolation method was 4, 4 and 3 for zones A, B and C, respectively (Table 4.2).

For each zone, we selected the SARIMA model in (2) with the lowest AICc statistic (Hurvich and Tsai 1989) that satisfied the stationarity and invertibility conditions and for which there is a biological interpretation. Values of the AIC (Akaike 1974) and BIC (Schwarz 1978) statistics are included for comparison with the AICc statistic.

Zone A

After a seasonal differencing of the catch data to achieve stationarity, the model that best describes that data on the basis of the AICc criterion is of the form $\text{SARIMA}(1,0,0)\times(0,1,2)_4\times(0,0,1)_{3\times 4}$. Table 4.3 summarises the method of order selection based on over- and under-fitted models of the selected one. The selected model describes autocorrelated monthly catch data up to first order with three moving average terms about a seasonal trend and residual white noise. The third order multiplicative seasonal moving average term is chosen to avoid unit root invertibility problems.

The parameters for SARIMA model (2) are, with standard errors in parentheses, $\phi_{\text{A1}} = 0.23\,(0.11)$, $\Theta_{\text{A1}} = -0.44\,(0.10)$, $\Theta_{\text{A2}} = -0.38\,(0.10)$, $\Theta_{\text{A3}\times 4} = -0.33\,(0.11)$.

Since $|\phi_{A1}| < 1$, the SARIMA model is stationary after a seasonal differencing. ϕ_{A1} decribes the month-to-month correlation structure, while the negative Θ_{A1} term indicates that a larger (smaller) than expected catch for one season results in a smaller (larger) than expected catch for the next season, and so on from one year to the next. The negative Θ_{A2} and $\Theta_{A3\times4}$ terms have similar effects from each year to two to three years henceforth.

The residual sums of squares from the 1978/79 season to the 1995/96 season were used to compare models (Table 4.6). R^2 percentages of variation compared to the total sum of squares of the null model $C_{tA} = \overline{C}_A + \varepsilon_{0tA}, \varepsilon_{0tA} \sim N(0, \sigma^2_{0A})$ are given in parentheses. The standard errors of the regression variables and the asymptotic analyses of variance based on SARIMAX (3) show that the annual puerulus variable has a significant effect on catch for zone A, but the annual effort data does not contribute significantly more information to the variation in catch data. Puerulus settlement is therefore included in (3) but not fishing effort. Figures 4.4 and 4.5 illustrate the seasonal predictions from 1977/78 to 1995/96 and seasonal forecasts from 1996/97 to 1999/2000 from zone A. SARIMAX model (3) gives reliable forecasts with 31 out of 32 actual catch points within the 95% confidence intervals.

Zone B

After a seasonal differencing of the catch data to achieve stationarity, the model that best described that data on the basis of the AICc criterion was of the form SARIMA$(3,0,0)\times(1,1,3)_8\times(0,0,1)_{7\times8}$. The method of order selection based on over- and under-fitted models of the selected one is summarised in Table 4.4. The selected model describes autocorrelated monthly catch data up to third order with a first order seasonal autocorrelation, third order seasonal moving averages and a seven year cycle about a seasonal trend with residual white noise.

The model parameters for the SARIMA model in (2) are

$\phi_{B1} = 0.12\ (0.08), \phi_{B2} = 0.045\ (0.084), \phi_{B3} = 0.15\ (0.08), \Phi_{B1} = -0.59\ (0.47),$

$\Theta_{B1} = 0.10\ (0.46), \Theta_{B2} = -0.49\ (0.28), \Theta_{B3} = -0.19\ (0.09), \Theta_{B7\times8} = 0.22\ (0.10).$

The nonseasonal parameters ϕ_{B1}, ϕ_{B2} and ϕ_{B3} describe the month-to-month correlations. The seasonal autoregressive term Φ_{B1} and seasonal moving average term Θ_{B1} describe a negative catch correlation for consecutive years, as expected. The two- and three-year moving average terms have the effect of smoothing fluctuations from year to year. We checked the stationarity and invertibility of the chosen model at each step of the TFM process after one seasonal differencing. For example, the roots of the monthly autoregressive characteristic polynomial for (2) were found to have magnitudes $|z| = 1.656, 2.001, 2.001$, which are all greater than one. Similarly, the magnitude of the roots of the seasonal moving average characteristic polynomial for (2) are $|z| = 1.241, 2.046, 2.046$, indicating the process is invertible.

One of the interesting results for this zone is the presence of a significant positive seven-year multiplicative moving average term. This correlation signifies that the average life cycle is approximately seven years. These biological properties of the life cycle can be illustrated by the following chronological diagram, where C_T, S_T and P_T represent catch, spawning activity and puerulus settlement levels, respectively, in year *T*.

$$C_{T-7} \rightarrow S_{T-4,T-5} \rightarrow P_{T-3,T-4} \rightarrow C_T$$

Western rock lobsters mature at about seven years, the larval stage exists for approximately one year, and lobsters are caught predominantly at the age of four or five years, including the larval stage. This interpretation is in approximate agreement with the accepted knowledge that "immature females are fished 1-2 years before they reach (sexual) maturity" (Chubb 2000).

The residual sums of squares are calculated from the 1979/80 season to 1995/96 (Table 4.6). It is clear from the standard errors and the *F* statistics that the puerulus variables for the white and red seasons on their own are only marginally significant for the catch model for zone B, but the combined puerulus settlement-effort variables are highly significant. Figures 4.4 and 4.5 illustrate the seasonal predictions from 1979/80 to 1995/96 and seasonal forecasts from 1996/97 to 1999/2000 for zone B using SARIMAX model (3). This model gives reliable forecasts with 1 actual catch point out of 32 outside the 95% confidence intervals.

Zone C

After a seasonal differencing of the catch data to achieve stationarity, the model that best described that data on the basis of the AICc criterion was of the form $\mathrm{SARIMA}(3,0,0)\times(4,1,2)_8$. Table 4.5 summarises the method of order selection based on over- and under-fitted models of the selected one. The selected model describes autocorrelated monthly catch data up to third order with four seasonal autocorrelation terms and second order seasonal moving averages about a seasonal trend with residual white noise.

The model parameters for SARIMA model (2) are $\phi_{C1} = 0.39\ (0.09)$, $\phi_{C2} = -0.12\ (0.09)$, $\phi_{C3} = 0.34\ (0.09)$, $\Phi_{C1} = -0.02\ (0.46)$, $\Phi_{C2} = -0.57\ (0.16)$, $\Phi_{C3} = -0.44\ (0.19)$, $\Phi_{C4} = -0.07\ (0.25)$, $\Theta_{C1} = -0.58\ (0.45)$, $\Theta_{C2} = 0.37\ (0.20)$.

The seasonal moving average terms are negative as expected. The observation that the fourth seasonal moving average term appears insignificant and yet contributes to the model implies that linear SARIMAX models may not be appropriate for zone C catches. There is no indication that normality assumptions have been broken. We checked the stationarity and invertibility of the model for zone C at each step of the TFM process after one seasonal differencing. For example, the roots of the monthly autoregressive characteristic polynomial for model (2) were found to have magnitudes $|z| = 1.275, 1.526, 1.526$, which are all greater than one. Similarly, the magnitudes of the roots of the seasonal autoregressive characteristic polynomial are $|z| = 1.102, 1.102, 2.668, 4.642$, indicating seasonal stationarity. Finally, the roots of the seasonal moving average characteristic polynomial have magnitudes $|z| = 1.652, 1.652$.

The residual sums of squares are calculated from the 1982/83 season to 1995/96 (Table 4.6). For zone C, the effort and puerulus settlement variables have a significant effect on catch. Figures 4.4 and 4.5 illustrate the seasonal predictions from 1982/83 to 1995/96 and seasonal forecasts from 1996/97 to 1999/2000 for zone C using SARIMAX model (3). This model gives guided forecasts for zone C with 7 actual catch points out of 32 outside the 95% confidence intervals. The reasons why this method has not produced very reliable forecasts will be discussed in the next section of this paper.

4.5 Discussion

Seasonal ARIMA catch models explain over 90% of the variation in monthly western rock lobster catches for each zone by taking into account the autocorrelation structure of the catch data and the correlation structure of the residuals. Our method separately incorporates the form of the exogenous puerulus settlement and fishing effort variables over the red and white seasons. An interesting outcome of the analysis was a confirmation of the approximate life cycle of lobsters caught in zone B from the order of the SARIMA model. Since the catch series satisified the stationarity and invertibility conditions for every zone, SARIMAX models are robust to the constant changes in management measures such as reductions in allowable fishing effort, changes to minimum and maximum legal sizes and release of mature females with visible setae. The main management implementations for the western rock lobster industry are summarised in Caputi et al. (1997) and Chubb (2000). However, a further enhancement to the SARIMAX modelling techniques used in this paper would be to conduct an intervention analysis to model the effects of the 1993/94 management changes. This study takes into account the enforced 18% pot reduction through the effort variable but the intervention analysis may be required to further model the increase in minimum size in white lobsters which has resulted in a transfer of catch to the red lobsters.

The required computing time for estimation of the proposed SARIMAX models is comparable with the log-log linear regression model (1) (Caputi 1995a, 1995b). Time series methods are more appropriate when the residuals in (1) or similar nonlinear regression models of catches are significantly serially correlated. The estimation procedures are faster than the delay-difference stock assessment model (Hall 1997, Walters et al. 1993, Sullivan 1992, Schnute 1985, Deriso 1980), which can take a day to estimate if a solution is found. The bias in parameter estimates is reduced significantly by using these time series methods. The information matrix is always positive definite and the seasonality is clearly detected.

The transfer function models we have used provide adequate descriptions of monthly western rock lobster catches for zones A and B but the linearity assumption for zone C may have been violated. A nonlinear model or volatility model such as one chosen from the generalized autoregressive conditional heteroscedastic (GARCH) family of models may therefore be more appropriate for modelling the zone C data. Examination of the autocorrelation function of the squared residuals for the best SARIMAX zone C model confirms that a GARCH model is more suitable. One would hardly question the use of the Beverton-Holt mortality model or other similar models, since puerulus settlement and fishing effort contribute significantly less to total monthly variation than the catch data does.

The 1999/2000 season was a difficult season for monthly catch forecasts. For example, there are 3 actual catch points out of 8 that lie outside the 95% confidence intervals for zone C over the 1999/2000 season, leaving 77% of points inside the confidence region between 1996/97 and 1998/99. The primary reason for these difficulties is that 1999/2000 provided a record catch for the western rock lobster fishing industry, and the bulk of that landed catch came from zone C. The extra market demand for western rock lobsters stemming from the Millenium celebrations could have contributed to this record catch, however our models did not include any econometric variables.

To carry out an analysis on the significance of puerulus settlement and fishing effort in the SARIMAX models, our procedure was to fix the order of the seasonal ARIMA noise component. The choice of model (3) may be a good fit, however this model may be globally suboptimal. Finding a global optimal order for (3) may therefore improve the predictions slightly further, but improving predictions was not the sole emphasis of this paper.

By applying a linear interpolation method and scaling the puerulus settlement and fishing effort data to form approximate linear relationships with the catch data, the model estimation process is possible in a linear SARIMAX framework. The main advantages of the linear interpolation method are that the stationarity/causality and invertibility conditions can be easily checked and a number of complications associated with the statistical analyses are significantly reduced. The stationarity and invertibility conditions are as important in time series analysis as the Gauss-Markov conditions for linear regression. The linear interpolation method can speed up the theoretical calculations while the time series problem remains nonlinear. An alternative approach is a nonlinear TFM analysis, but this would involve writing a nonlinear software package and deriving theoretical stationarity and invertibility conditions. The stationarity and invertibility conditions are unknown for many nonlinear formulations. Finding these conditions remains an open problem in time series analysis, requiring intense theoretical and computational work for specific cases.

The linear interpolation method is flexible since any continuous function can be interpolated and adapted to conform to the linear SARIMAX form. There are many ways of improving the approximation method. For example, splines or other smoothing functions could be used in a generalized additive modelling framework. Multivariate adaptive regression splines (MARS) (Friedman 1991) could be incorporated into the methodology to enhance the nonlinear parameter estimates.

The transfer function time series approach to modelling catches is generally useful in cases where there is an indicator of recruitment strength, as in the western rock lobster fishery. The methods also have considerable potential in fisheries where biological data is limited but a long time series of catch and fishing effort data is available.

4.6 Acknowledgements

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4.8 List of tables

4.9 List of figures

Table 4.1. Estimated catch-effort parameters for model (9). The standard error of each estimated parameter is given in parentheses.

	$\hat{a}$ $(\times 10^3)$	$\hat{\beta}$	$\hat{\pi}$	$\hat{k}$
Zone				
A	2083 (145)	13.26 (4.61)	0.684 (0.153)	-0.135 (0.221)
B (white)	2454 (197)	24.14 (8.57)	0.444 (0.154)	0.812 (0.207)
B (red)	1945 (153)	14.63 (7.47)	0.669 (0.216)	1.135 (0.171)
C (white)	3484 (353)	2.220 (1.351)	0.068 (0.155)	0.975 (0.388)
C (red)	3109 (235)	2.521 (0.939)	0.629 (0.127)	0.676 (0.303)

Table 4.2. Selection of the number of points in the partition (including the end-points) for the linear interpolation method based on minimization of the SICc criterion.

	2 points	3 points	4 points	5 points
Zone A	-2.423	-4.606	-4.787	-4.199
Zone B (white season)	-2.196	-3.094	-3.695	-3.441
Zone B (red season)	-1.881	-3.080	-3.799	-3.595
Zone C (white season)	-1.313	-3.311	-3.172	-2.929
Zone C (red season)	-1.724	-3.883	-3.682	-3.516

Table 4.3. Order selection process of the SARIMA model for zone A western rock lobster catch data. A SARIMA $(1,0,0)\times(0,1,2)_4\times(0,0,1)_{3\times4}$ model was chosen as it minimized both AICc and BIC statistics and satisfied the stationarity and invertibility conditions.

	AIC	AICc	BIC	Stationary?	Invertible?
$(0,1,0)_4$	-78.28	-78.28	-78.28	Y	Y
$(1,0,0)\times(0,1,0)_4$	-88.43	-88.37	-86.11	Y	Y
$(2,0,0)\times(0,1,0)_4$	-85.08	-84.91	-80.47	Y	Y
$(1,0,1)\times(0,1,0)_4$	-87.14	-86.97	-82.50	Y	Y
$(1,0,0)\times(1,1,0)_4$	-81.88	-81.70	-77.35	Y	Y
$(1,0,0)\times(0,1,1)_4$	-87.52	-87.35	-82.89	Y	Y
$(1,0,0)\times(0,1,2)_4$	-99.59	-99.25	-92.64	Y	N
$(1,0,0)\times(0,1,3)_4$	-101.38	-100.80	-92.11	Y	N
$(1,0,0)\times(3,1,1)_4$	-79.26	-78.21	-68.55	Y	Y
$(1,0,0)\times(0,1,0)_4\times(0,0,1)_{3\times4}$	-92.27	-92.10	-87.64	Y	Y
$(1,0,0)\times(0,1,1)_4\times(0,0,1)_{3\times4}$	-98.35	-98.01	-91.40	Y	Y
$(1,0,0)\times(0,1,2)_4\times(0,0,1)_{3\times4}$	-103.01	-102.44	-93.74	Y	Y
$(1,0,1)\times(0,1,2)_4\times(0,0,1)_{3\times4}$	-101.45	-100.58	-89.87	Y	Y

Table 4.4. Order selection process of the SARIMA model for zone B western rock lobster catch data. A SARIMA $(3,0,0)\times(1,1,3)_8\times(0,0,1)_{7\times8}$ model was chosen as it minimized the AICc statistic and satisfied the stationarity and invertibility conditions.

	AIC	AICc	BIC
$(2,0,0)\times(1,1,3)_8$	51.00	51.63	67.74
$(3,0,0)\times(1,1,3)_8$	50.18	51.02	70.82
$(4,0,0)\times(1,1,3)_8$	52.61	53.71	76.14
$(3,0,0)\times(0,1,3)_8$	57.12	57.71	75.14
$(3,0,0)\times(2,1,3)_8$	51.46	52.62	74.58
$(3,0,0)\times(1,1,1)_8$	60.57	61.01	75.31
$(3,0,0)\times(1,1,2)_8$	50.48	51.11	68.17
$(3,0,0)\times(1,1,4)_8$	50.79	51.88	74.38
$(3,0,0)\times(1,1,2)_8\times(0,0,1)_{7\times8}$	48.18	49.03	68.83
$(3,0,0)\times(1,1,3)_8\times(0,0,1)_{7\times8}$	47.47	48.57	71.06
$(3,0,0)\times(1,1,4)_8\times(0,0,1)_{7\times8}$	48.68	50.05	75.22

Table 4.5. Order selection process of the SARIMA model for zone C western rock lobster catch data. A SARIMA$(3,0,0)\times(4,1,2)_8$ model was chosen as it minimized the AICc statistic and satisfied the stationarity and invertibility conditions.

	AIC	AICc	BIC
$(2,0,0)\times(4,1,2)_8$	45.57	46.89	67.74
$(3,0,0)\times(4,1,2)_8$	27.08	28.76	51.94
$(4,0,0)\times(4,1,2)_8$	27.18	29.27	54.71
$(3,0,1)\times(4,1,2)_8$	27.97	30.04	55.59
$(3,0,0)\times(3,1,2)_8$	37.25	38.49	59.87
$(3,0,0)\times(5,1,2)_8$	31.51	33.75	58.42
$(3,0,0)\times(4,1,1)_8$	29.74	31.06	51.82
$(3,0,0)\times(4,1,0)_8$	29.49	30.52	48.82
$(3,0,0)\times(4,1,3)_8$	28.57	30.64	56.19

Table 4.6. Summary for the selected SARIMA and SARIMAX models for each zone. Details on regression parameter estimates with standard errors, residual sums of squares, R^2 percentages of variation and asymptotic F tests are given.

	Regression parameter estimates (st. err.)	RSS $(\times 10^9)$ (R^2)	$F_{\upsilon_1,\upsilon_2}^{(0.05)}$ $(F_{crit.})$ *p*-value
ZONE A			
Null model		4756.04	
SARIMA model		160.12 (96.6%)	
With puerulus	$\hat{\omega} = 0.0347\,(0.0136)$	148.37 (96.9%)	5.86 (> 3.97), 0.018
With effort and puerulus	$\hat{\omega} = 0.0358\,(0.0151)$	148.85 (96.9%)	5.60 (> 3.97), 0.021
ZONE B			
Null model		17588.19	
SARIMA model		1688.60 (90.4%)	
With puerulus	$\hat{\omega}_W = 0.0355\,(0.0154)$ $\hat{\omega}_R = 0.0411\,(0.0216)$	1620.91 (90.8%)	2.90 (≤ 3.06), 0.058
With effort and puerulus	$\hat{\omega}_W = 0.0479\,(0.0081)$ $\hat{\omega}_R = 0.0329\,(0.0083)$	1366.54 (92.2%)	16.38 (> 3.06), 0.000
ZONE C			
Null model		35831.91	
SARIMA model		2577.76 (92.8%)	
With puerulus	$\hat{\omega}_W = 0.1482\,(0.0380)$ $\hat{\omega}_R = 0.1701\,(0.0613)$	2319.83 (93.5%)	6.39 (> 3.07), 0.002
With effort and puerulus	$\hat{\omega}_W = 0.1361\,(0.0302)$ $\hat{\omega}_R = 0.1570\,(0.0483)$	2242.33 (93.7%)	8.60 (> 3.07), 0.000

Fig 4.1. Map of the fishing zones A, B and C off the Western Australian coast for the western rock lobster industry.

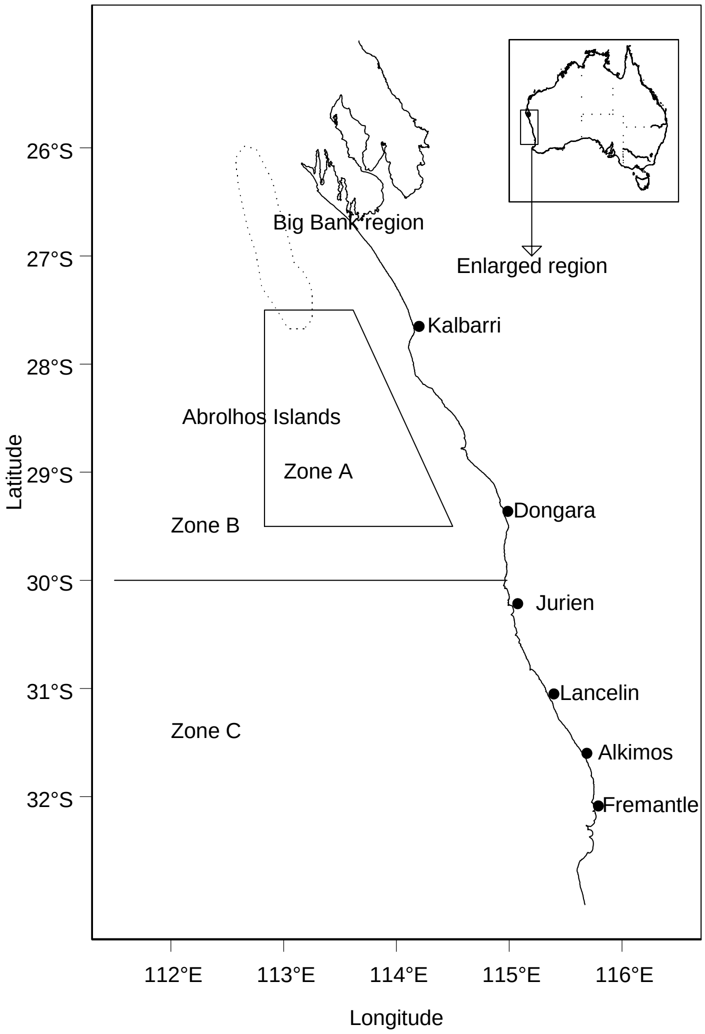


Fig. 4.2. The fitted puerulus-catch projection curves (solid lines) for different levels of effort for the zone B western rock lobster data measured annually over the white seasons from 1976/77 to 1995/96, and the linear interpolation (dotted line) for the $E = 1.8$ (million pot lifts) puerulus-catch projected curve connecting the points marked X.

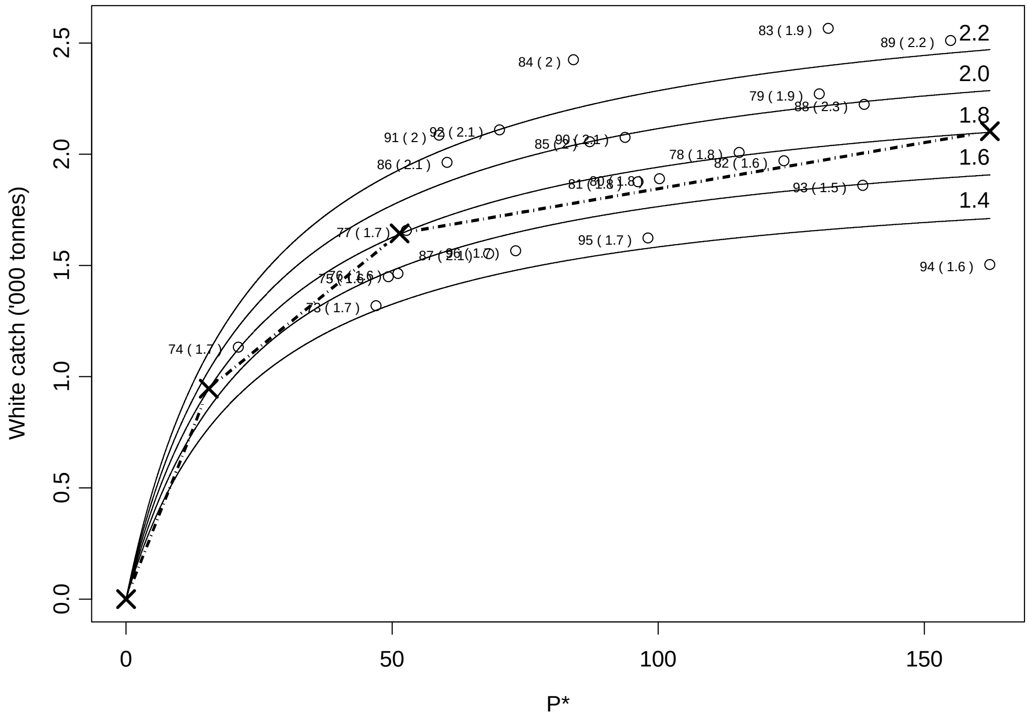


Fig 4.3. The adjustment of the fishing effort levels (millions of pot lifts) for each scaled puerulus-catch projected curve defines a new puerulus-effort index for the zone B white season.

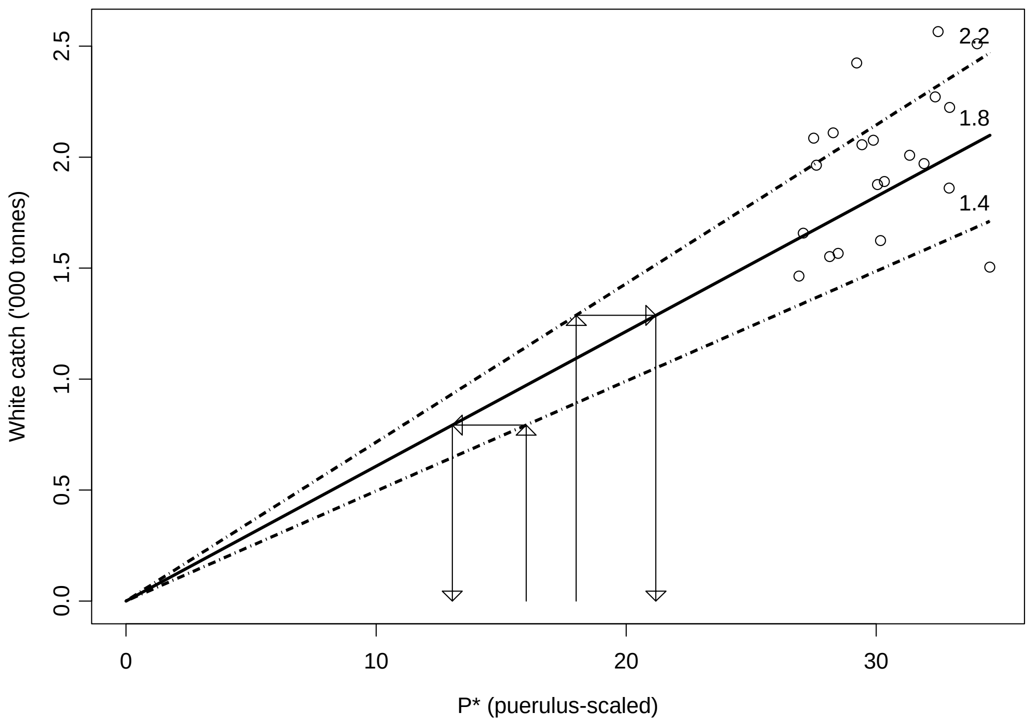


Fig. 4.4. SARIMAX seasonal predictions and forecasts of western rock lobster catch data for zones A, B and C, respectively.

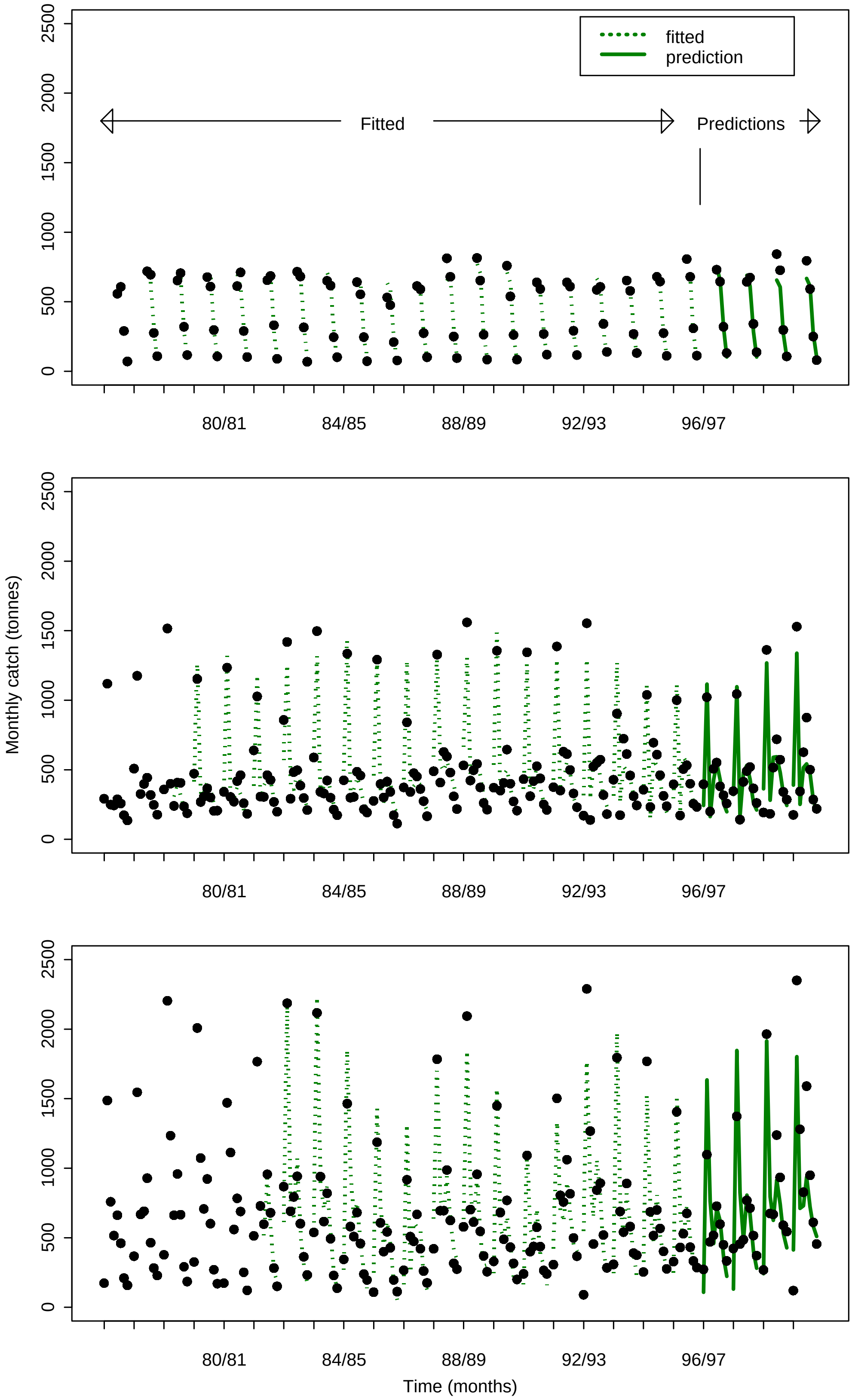
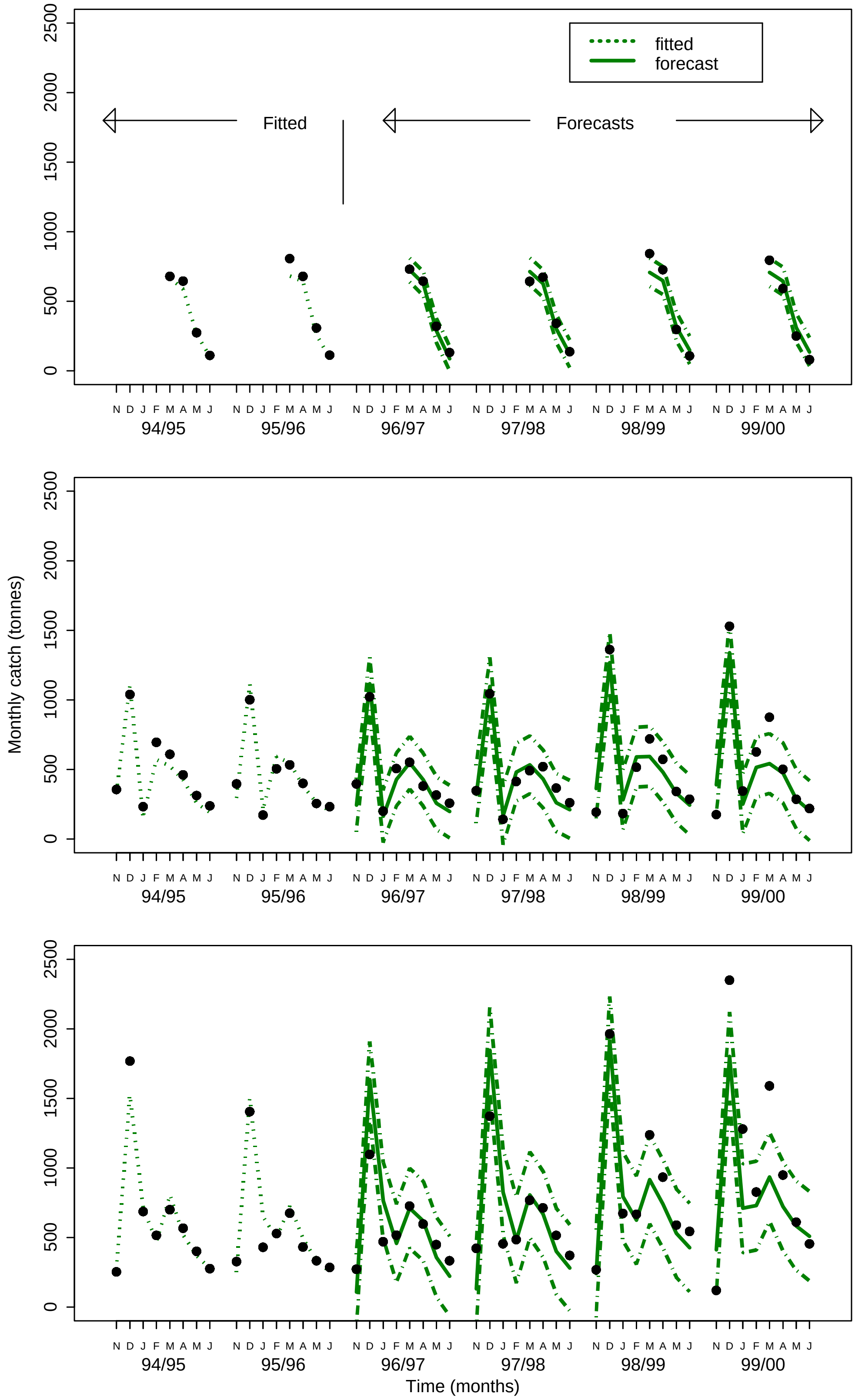


Fig. 4.5. Seasonal forecasts from 1996/97 to 1999/2000 with 95% confidence intervals of western rock lobster catch data for zones A, B and C, respectively.



5.0 Improving Catch Predictions for Management of the Western Rock Lobster (*Panulirus cygnus*) Fishery Using Time Series Analysis

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5.1 Abstract

The western rock lobster fishery is the most valuable single-species fishery in Australia, having posted a world record catch for rock lobster species for the 1999/00 season of 14 500 tonnes. Management is therefore interested in improving methods of catch prediction that are currently based on observed puerulus (one year-old post-larvae) settlement levels by designated collectors. The abundance of rock lobster three to four years into the future is reflected by the puerulus settlement indices for three zones, enabling accurate annual catch forecasts. However, catch forecasts for the migratory "whites" season (Nov-Jan) and the non-migratory "reds" season (Feb-Jun) are more challenging as these seasonal catches of different life history stages are significantly correlated. Thus, methods including nonlinear regression techniques and classical ARIMAX time series analysis are used to reduce the temporal bias in the seasonal catch predictions. In 1993/94, a management package was implemented to reduce the risk of exploitation in the western rock lobster fishery, to smooth the seasonal catches and to allow breeding stock levels to gradually increase. Some of the main effects of the management package on catches are analyzed in a time series intervention analysis framework. Forecasts of seasonal catches are made from 2000/01 to 2002/03 for all zones using ARIMAX time series models with puerulus settlement indices, fishing effort and management intervention terms.

Keywords: Western rock lobster; puerulus indices; nonlinear regression; time series analysis.

5.2 Introduction

The western rock lobster (*Panulirus cygnus*) is the most valuable single-species fishery in Australia comprising, on average, twenty percent of the total value of Australia's total fisheries production. The 1999/2000 western rock lobster catch was a world record, posting a landed catch of over 14,000 tonnes at an approximate value of A$390 million.

There are three major zones in the fishery off the Western Australian coast (Figure 1). Zone A operates between Dongara and Kalbarri, and comprises fishing grounds adjacent to the offshore Abrolhos Islands. Zone B is situated to the north of latitude 30°S, excluding that area of the fishery designated as zone A. Zone C extends south of latitude 30°S to Cape Leeuwin. The fishing season since 1977/78 consists of 7.5 months, with the migratory 'whites' fishing season operating from mid-November to January and the non-migratory 'reds' fishing season operating from February to June. These names relate to the colour of the exoskeleton of the lobsters. The lobsters moult in November and the whites moult again in February, changing colour to red. The fishing season for zone A only operates during the red season from mid-March to June. However, boats with a zone A licence are permitted to operate in zone B from November to mid-March.

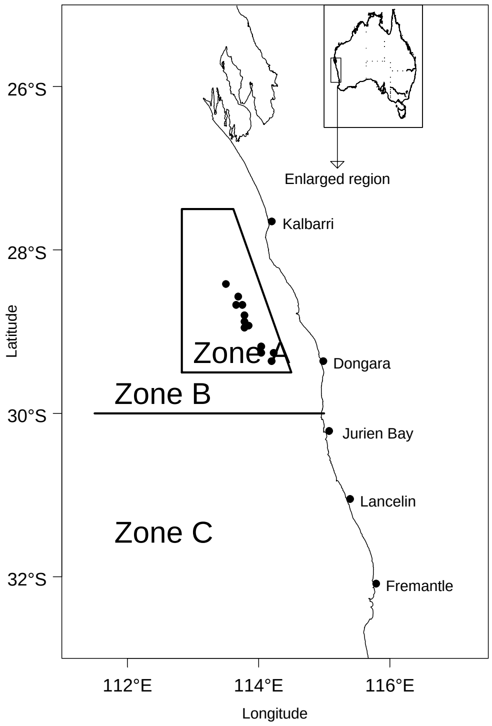

Figure 5.1. Map of the fishing zones off the West Australian coast for the western rock lobster industry.

To ensure that fishing pressure on this valuable fishery does not significantly reduce breeding stock levels, as occurred during the late 1980's, management can adjust fishing effort based on forecast catches if necessary [Chubb 2000]. The management objective is to keep breeding stocks at the levels of the late 1970's and early 1980's, above the biological reference point for this fishery of approximately 20-25% of the virgin biomass level [Hall and Brown 2000; Hall and Chubb 2001]. The approach to control annual catches has been possible for the western rock lobster fishery due to the relatively unique recruitment forecasting system for this stock [Caputi et al. 1995a and b].

During the early 1990's, it was contended that the western rock lobster breeding stock was becoming significantly reduced. Management therefore made a decision in the 1993/94 season to introduce a package aimed at a recovery in the breeding stock. The main elements of the management package that were implemented from 1993/94 to 1999/00 are as follows:

- 18% temporary reduction in pot usage;
- 1 mm increase in the legal minimum size from November 15 to January 31 ('whites' fishery);
- total protection for mature females (setose, tar-spotted and egg-bearing);
- maximum size limit for females of 115 mm for C zone and 105 mm for A and B zones).

The anticipated effects of this package included an overall reduction in exploitation rate leading to a greater survival of lobsters, a gradual boost in the number of large breeding females, a reduction of whites catches and a transfer of this reduction to the reds fishery with the objective that more lobsters are able to spawn. The 18% pot reduction is reflected through the fishing effort data. Also, a proportion of the transfer of whites catches to reds catches is due to fishing effort. However, accurate predictions of whites and reds catches and an analysis of the transfer of whites catches to reds catches requires a time series approach to account for the correlation structure of catches from one moult stage to the next and from year to year.

Seasonal catch and fishing effort data dates back to the 1964/65 season, while puerulus (post-larval) settlement information has been collected since the late 1960's at some locations. This information has been used to form a recruitment-catch relationship to predict annual catches [Caputi 1995a and b].

The focus of this paper is therefore to predict whites and reds catches for all zones of the western rock lobster fishery and to assess the effects of the 1993/94 management package on catches using time series intervention analysis and recruitment-catch relationships. Seasonal catches are forecasted from 2000/01 to 2002/03 using these classical time series models with puerulus settlement indices, fishing effort and management intervention variables.

5.3 Methods

Traditionally, log-log linear regression models have been used to model catch predictions based on levels of puerulus settlement 3 to 4 years prior to the season [Phillips 1986; Caputi et al. 1995b]. Catch predictions for western rock lobster can also be made using variations of an annual puerulus-effort-catch nonlinear regression model defined by

$$C_t = a\ f\left(P_{t-3}\sin^2\theta + P_{t-4}\cos^2\theta; b\right) E_t \left(\exp\left(-\frac{qE_t}{2} + \frac{q^2E_t^2}{24}\right)\right) + \varepsilon_{1t}, \quad (1)$$

where

$$f(x;b) = \frac{x}{bx+1} \quad (2)$$

is a Beverton-Holt [1957] mortality function, C_t is the annual catch data (kg) which can be disaggregated into whites and reds catches, E_t is the annual, whites or reds fishing effort in pot lifts, P_t is an annual accumulation of the Winsorized mean [Kendall and Stuart 1973, p.544] of puerulus settlement data obtained from up to six collectors, a, θ, b, q are parameters to be estimated and $\varepsilon_{1t} \sim N\left(0, \sigma_1^2\right)$. The effort function in (1) is a truncation of DeLury's [1947, 1951; see Ricker 1975] abundance-effort equation.

Regarding the puerulus settlement information, there are six years of missing Abrolhos Island collector data for zone A (79/80 through 84/85). The procedure we follow is to substitute the corresponding mean-scaled Dongara puerulus settlement data from zone B, since zone A is wholly enclosed within zone B. Dongara puerulus settlement data is complete and this data set is used to model zone B catches. A similar procedure to that of zone A is used for the zone C Alkimos puerulus settlement data by replacing the indices from 69/70 to 81/82 by the corresponding mean-scaled zone C Jurien Bay puerulus settlement data. The Alkimos puerulus settlement data is regarded as more representative of the zone C catches as it is near the centre of the fishery.

When the catch series is disaggregated into white/red seasonal catches, the errors are significantly correlated for all fishing zones. Thus, a time series analysis is required for reliable predictions of white and red seasonal catches. Linear autoregressive integrated moving average (ARIMA) models [Box and Jenkins 1976] are fitted to each chronological whites/reds catch series as follows:

$$\Phi_1(B)\nabla^d\left(\frac{C_{WR,t}}{\overline{C}_{WR}}-1\right)=\Theta_1(B)\,\varepsilon_{2t}\,, \qquad (3)$$

where $C_{WR,t}$ is the whites/reds catch series, $\overline{C}_{WR}$ is the mean of the whites/reds catches, Φ_1 and Θ_1 are finite autoregressive and moving average polynomials of orders *r* and *z* respectively, of the backward difference operator *B*, ∇ is a differencing operator, *d* is the number of differences required to achieve stationarity, and $\varepsilon_{2t} \sim N(0,\sigma_2^2)$.

The order component (r,d,z) of the ARIMA model for each zone is selected by minimization of Akaike's [1974] bias-corrected AICc statistic [Hurvich and Tsai 1989]. To validate the stationarity and invertibility conditions and to avoid nonlinear time series likelihood calculations, we estimate $\{\theta,b,q\}$ in (1) sub-optimally by performing a nonlinear regression and then enter the deterministic component of (1) as a transfer function component of an ARIMA transfer function (ARIMAX) model. White and red seasons are fitted separately for the nonlinear regression model (1) to estimate $\{\theta,b,q\}$ for each season. Two dummy intervention variables that measure a mean increase in catches or a further transfer from whites catches to reds catches that is not reflected through fishing effort as an effect of the 1993/94 management package are also analyzed as transfer function components. The whites (reds) seasonal intervention variable is defined as 1 for the whites (reds) season from 1993/94 onwards, and 0 otherwise.

The ARIMAX model is therefore defined as follows:

$$\Phi_2(B)\nabla^d\left(\frac{C_{WR,t}}{\overline{C}_{WR}}\right)=\Phi_2(B)\nabla^d\left(\sum_{i=1}^{N_T}\alpha_i\,\frac{T_{i,t}}{\overline{C}_{WR}}\right)+\Theta_2(B)\varepsilon_{3t}\,, \qquad (4)$$

where N_T is the number of transfer function variables, $T_{i,t}\ (i=1,\ldots,N_T)$ comprise the transfer function variables, $\alpha_i\ (i=1,\ldots,N_T)$ are the transfer function coefficients needed to be estimated, Φ_2 and Θ_2 are autoregressive and moving average polynomials of orders *r* and *z*, respectively, as in (3) and $\varepsilon_{3t} \sim N(0,\sigma_3^2)$ is assumed. Asymptotic *F* tests are conducted on the transfer function variables to attain their significance for each zone.

5.4 Results

Table 5.1 summarizes the parameter estimates and R^2 values for parsimonious models of the form (1) that describe whites and reds catches for respective zones. For all models, estimates for the nonlinear parameter $\hat{q}$ were insignificant. The inclusion of fishing effort enhances all zone B and C models, however fishing effort is not included in the zone A model. The puerulus settlement indices are significant for prediction of catches for zones B and C, but only significant for the zone A model when a dummy intervention variable (taking 0 values before 1993/94 and 1 values from 1993/94 onwards) is included.

Tables 5.2 and 5.3 describe the ARIMA and ARIMAX model fits and estimated parameters for the annual (reds) catches for zone A and the whites/reds chronological catch series for zones B and C. There are significant autocorrelations in catches taken from all zones from one moult season to the next and from year to year (Table 5.2). The puerulus settlement indices, combined with fishing effort in the case of zones B and C, obtained from nonlinear regression models (1) remain significant variables in these time series models.

The intervention variables represent percentage increases or decreases in whites and reds catches from 1993/94 onwards. These terms are significant for all zones, however the two intervention terms for zone C could be replaced by a single one, expressed as the sum of the two terms, since there is no significant difference between these. This means there is no significant transfer from whites to reds catches other than that which is reflected through fishing effort for zone C. Estimates from (1) and the intervention terms are therefore included as transfer functions in the ARIMAX models for all zones. Using these exogenous variables, seasonal ARIMAX catch predictions are shown for each zone in Figure 5.2, and forecasts for the three seasons 2000/01 to 2002/03 are calculated.

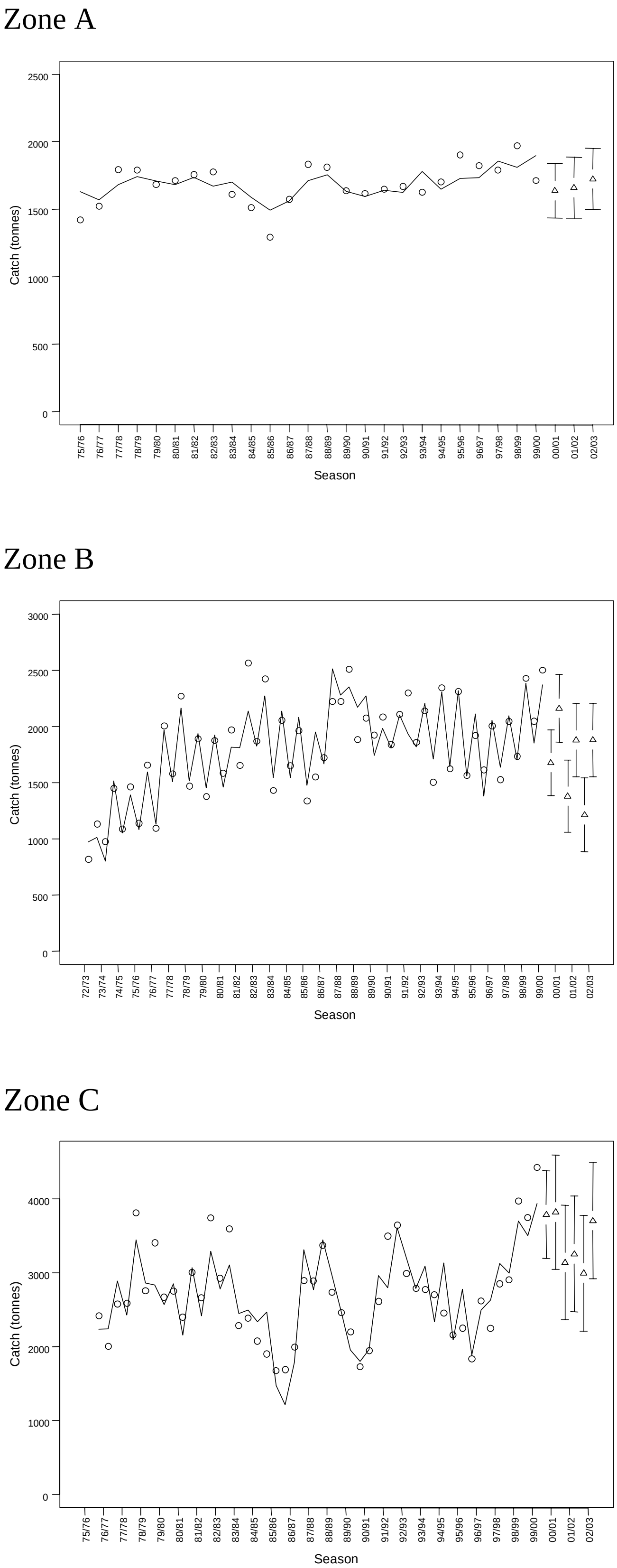

Figure 5.2. ARIMAX time series catch predictions and forecasts (2000/01 to 2002/03) with 95% confidence intervals for zones A, B and C, respectively.

The ARIMAX models are validated by fitting the catch data up to 1996/97 and comparing the forecast catches (with 95% confidence intervals) between 1997/98 and 1999/00 with the actual catches. For all zones, actual catches are within the forecasted confidence intervals for the three years.

Assessing the fishing effort effects of the 1993/94 management package, the changes in fishing effort in pot lifts are calculated by comparing 6-year means in effort immediately before and after the reduction in effort in 1993/94 for zone C and 1992/93 for zone B. The results are that fishing effort decreased by 18.6% in zone A, 24.2% and 18.4% for the white seasons in zones B and C, respectively, and 8.6% and 10.4% for the red seasons in zones B and C, respectively. The parsimonious ARIMAX model for zone A does not involve fishing effort and there is no whites season for zone A, so no changes would be expected from the pot reduction and minimum size change since 1993/94. However, setose females may affect the catches in zone A. In fact, the significant positive intervention term in the zone A ARIMAX model indicates overall catches have increased by 8.1% since 1993/94 despite the 18.6% decrease in fishing effort and the greater protection of females. There is evidence that some of the transfer from whites catches to reds catches for zones B and C is reflected by fishing effort since the percentage decreases in fishing effort for zone B during the white seasons exceeded 18% and the fishing effort for zones B and C during the red seasons decreased by significantly less than 18%. This reflects the latent fishing capacity which existed in the reds fishery. For zone B, the intervention analysis indicates significant decreases (-0.0583, Table 5.3) in whites catches transferring to increases in reds (0.2446, Table 3) catches beyond that which was reflected through fishing effort. For zone C, however, a further transfer (0.1464 and 0.2300, Table 5.3) from whites to reds catches since 1993/94 appears insignificant.

5.5 Discussion

The seasonal catch predictions and thus forecasts are significantly enhanced by the usage of ARIMAX time series models. These models account for significant correlations in the catch data while fitting the puerulus settlement indices and fishing effort information together with intervention variables associated with some of the outcomes of the 1993/94 management package. The time series models focus more accurately on the annual catches for zone A and the proportions of whites and reds catches for zones B and C. Seasonal catches were forecasted for the three years from 2000/01 to 2002/03 using the most parsimonious time series models encountered in this analysis.

The 1993/94 management intervention process has been effective in zones B and C. In particular, there have been significant transfers from whites to reds catches in zones B and C. For zone C, this was due to effort. For zone B, however, the intervention variables detected a further transfer from whites to reds. This reflects a higher proportion of smaller lobsters (76 mm) in zone B compared to zone C. Our methods used dummy variables that described instantaneous changes in catches and then constant effects of intervention for all years. These assumptions may not be valid. Mixture distribution time series methods may more accurately model the gradual and long-term effects of the management intervention process.

Further research is required to optimally estimate the nonlinear transfer function parameters for the ARIMAX equations presented in this paper. Our approach was hierarchical whereby nonlinear regression estimation was used and the estimated parameters were then put into the time series models. The effects are minimal for the modelling procedures in this paper, but errors would increase for a hierarchical monthly time series analysis.

5.6 Acknowledgements

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Table 5.1. Parameter estimates (and standard errors) and R^2 values for catch-puerulus-effort nonlinear regression models given by (1).

	$\hat{a}$ $(\times 10^5)$	$\hat{\theta}$	$\hat{b}$	R^2
Zone A	2.990 (1.829)	0.438 (0.570)	0.163 (0.108)	13.3%
Zone B : whites	1.014 (0.264)	0.912 (0.155)	0.042 (0.014)	67.3%
Zone B : reds	0.911 (0.267)	0.692 (0.178)	0.041 (0.015)	78.8%
Zone C : whites	9.342 (2.753)	1.122 (0.157)	0.254 (0.093)	62.0%
Zone C : reds	6.412 (1.325)	0.839 (0.121)	0.172 (0.047)	59.2%

Table 5.2. ARIMA and ARIMAX models and R^2 values for whites/reds chronological catch series for each zone.

	ARIMA		Puerulus index + Fishing effort ARIMAX	
	Model (r,d,z)	R^2	Model (r,d,z)	R^2
Zone A:				
without intervention	(0,0,1)	38.3%	(0,0,1)	48.7%
including intervention	(0,0,1)	43.1%	(0,0,1)	56.7%
Zone B:				
without intervention	(2,0,2)	72.7%	(1,0,2)	83.3%
including intervention	(2,0,1)	73.0%	(1,0,2)	88.7%
Zone C:				
without intervention	(3,0,0)	63.7%	(0,0,2)	70.5%
including intervention	(3,0,0)	66.6%	(2,0,1)	80.6%

Table 5.3. Estimated ARIMAX model (4) coefficients (with standard errors) for whites/reds catches.

	Puerulus index + effort on whites catches	Puerulus index + effort on reds catches	Whites intervention	Reds intervention
Zone A				
Puerulus index		0.9952 (0.0208)		
Puerulus index + intervention		0.9738 (0.0207)		0.0813 (0.0375)
Zone B				
Puerulus index	0.9901 (0.0325)	1.004 (0.0341)		
Puerulus index + intervention	1.0147 (0.0253)	0.9308 (0.0275)	-0.0583 (0.0489)	0.2446 (0.0508)
Zone C				
Puerulus index	0.9979 (0.0314)	0.9925 (0.0330)		
Puerulus index + intervention	0.9491 (0.0318)	0.9121 (0.0348)	0.1464 (0.0611)	0.2300 (0.0671)

6.0 A catch rate-environment time series approach to the prediction of catches taken from the Esperance southern rock lobster fishery

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6.1 Abstract

Catches for the southern rock lobster fishery in the Esperance area (120°E to 125°E) of Western Australia are a challenge to predict. Southern rock lobsters at the puerulus stage are difficult to find, and a stock assessment is economically infeasible. The CPUE series for the fishery has varied widely between 0.50 and 1.17 kg/pot lift in the past. The fishery has experienced catch rates of below 0.91 kg/pot lift for the past eight seasons. This paper explores the possibility of catch prediction using existing monthly catch and fishing effort data from relevant fishing regions in South Australia and Western Australia, and an environmental variable. We show that annual catches are highly correlated with lagged interactions involving catch rate data in May from the central area of the northern zone of the South Australian southern rock lobster fishery and a yearly moving average of the Fremantle Sea Level indicator. The formulation emulates the biological possibility that larvae may be transported from South Australian waters to the Esperance area during a one to two year timeframe. This assessment highlights some interesting relationships that need to be confirmed with further analyses and an understanding of the source of recruitment for WA populations. Monthly catches are predicted using a seasonal ARIMAX model, where the transfer function is defined by the annual nonlinear regression specification. The model is validated by forecasting the latest three fishing seasons (1999/2000 to 2001/2002) of catches. The transfer function component is highly significant for the seasonal ARIMAX model. Further techniques to enhance the error forecasts are discussed.

Keywords: Time series; ARIMAX; Nonlinear regression; Fishery.

6.2 Introduction

One of the main issues concerning the southern rock lobster (*Jasus edwardsii*) fishery off the Western Australian coast is the absence of puerulus index data as a biological predictor of annual catches. Catches of the WA southern rock lobster fishery are taken from November to June along the south coast of WA, with peak fishing occurring from December through February. Reliable data dates from 1975/76 to 2001/02; less reliable data dates back to 1968/69. Catches are greatest in the Esperance area, defined from 120°E to 125°E . A plot of historical annual southern rock lobster catch data from the Esperance area of the Western Australian fishery reveals significant time trends (Fig. 6.1). Annual catch-per-unit-effort (CPUE) data for the Esperance fishery exhibit a widely fluctuating distribution with a decreasing trend over the last eight years (Fig. 6.1). Time-lagged monthly catch rates measured from the Esperance fishery cannot explain the variation in annual CPUE data in Esperance. We therefore seek to explain annual catches adjusted for fishing effort by dynamically constructed catch rate-environment indices from South Australia. Lagged monthly catch rates may indicate annual variations in spawning activity from relevant regions in South Australia. Environmental data provide information on currents, wind speed and other effects on larval recruitment.

It is hypothesized that a proportion of the recruitment of Jasus edwardsii in the Western Australian fishery is likely to be independent of the WA brood stock (Melville-Smith, 1999). Upon inspection of the South Australian fishery data, which is available for as many seasons as the Western Australian data, we found that the central northern zone of South Australia (Fig. 6.2) is a good candidate for recruitment. The bulk of the southern rock lobster catches in the northern zone of the South Australian fishery is also taken from the central region. The duration of larval development for southern rock lobsters near New Zealand is said to be at least 12-22 months (Lesser 1978, Booth 1994). Research by Pashkin (1968) and Natarov and Pashkin (1968) indicated that winter currents could direct larvae from the northern zone of South Australia across the Great Australian Bight to the Esperance area during certain years.

The focus of this paper is the modelling of annual and monthly catches of the southern rock lobster in the Esperance area using nonlinear regression and ARIMA transfer function time series analysis, respectively. The annual models are derived on the basis of fisheries science theory, combining fishing effort data with lagged monthly catch rates and environmental data.

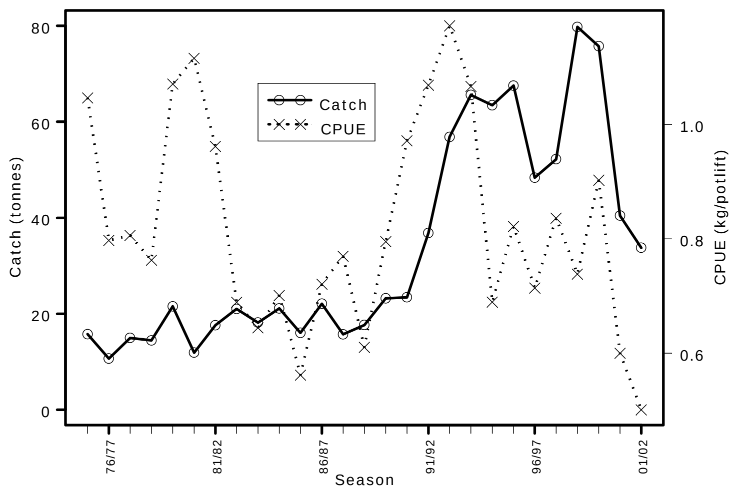

Figure 6.1. The annual southern rock lobster catch and CPUE series from 1975/76 to 2001/02 for the Esperance area.

6.3 Methods

Following the methodology of DeLury (1947, 1951), a theoretical annual catch-abundance-effort equation is

$$C_t = N_t[1-\exp(-qE_t)] + \varepsilon_{1t}, \qquad (1)$$

where C_t is the catch subject to abundance N_t and fishing effort E_t in season t (available from 1975/76 to 1998/99), $q \in R$ is a catchability estimate and $\varepsilon_{1t} \sim N(0,\sigma_1^2)$. Finding initial points generally makes q difficult to estimate, so a fourth order Taylor series approximation in (qE_t) of (1) is used, viz.

$$C_t = N_t qE_t \exp\left(-\frac{q}{2}E_t + \frac{q^2}{24}E_t^2\right) + \varepsilon_{2t}, \qquad (2)$$

where $\varepsilon_{2t} \sim N(0,\sigma_2^2)$. Another advantage of (2) is that the nonlinear component can be dropped if q is not significantly different from zero. For q small in magnitude, the estimation becomes linear in (qE_t), viz.

$$C_t = N_t qE_t + \varepsilon_{3t}, \qquad (3)$$

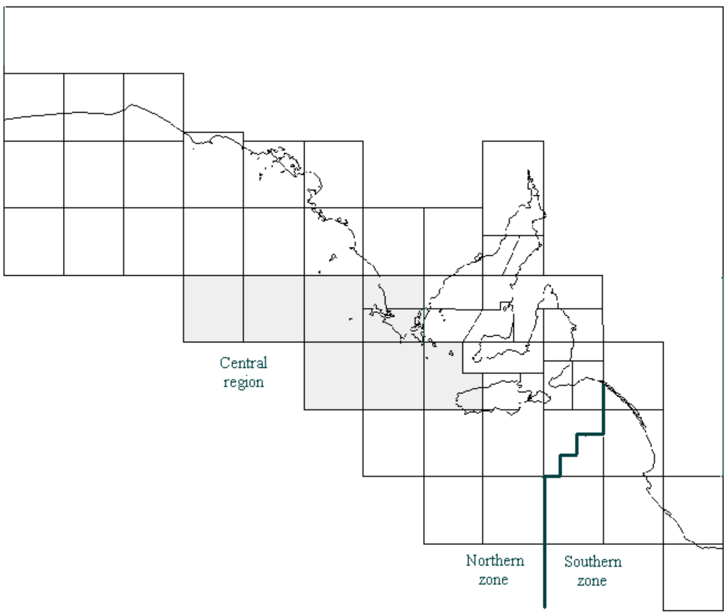

Figure 6.2. Map of the northern fishing zone of South Australia.

where $\varepsilon_{3t} \sim N(0, \sigma_3^2)$. Since N_t is unknown, (3) is more parsimonious than (2). (3) is a first order Taylor approximation of (1).

Estimation of N_t is the next consideration of the model formulation. We assume a Beverton-Holt mortality function over an l to $(l + j)$ year time lag $(j > 0)$, where data availability restricts us to only consider $j = 1$ for the analysis in this paper, viz.

$$E[N_t] = \frac{\alpha N_{t-l}^*}{b N_{t-l}^* + 1}. \qquad (4)$$

Here, $E[N_t]$ is the expectation of N_t, α and b are parameters to be estimated, and N_{t-l}^* is a population abundance estimate lagged l and $(l+1)$ years. Much of the relevant environmental information is contained in the Fremantle Sea Level (Pearce and Phillips, 1988), denoted S_t, which is calculated as a yearly aggregate of the monthly data. It is thus proposed that the Fremantle Sea Level is an indicator of environmental factors on the first year of larval life of a southern rock lobster caught in Esperance. A model for N_{t-l}^* is therefore

$$E[N_{t-l}^*] = \frac{\cos^2 \varphi \cdot C_{t-l,SA} \exp(\omega_{SA} S_{t-l})}{\left\{E_{t-l,SA} \exp\left(-\frac{q_{SA}}{2} E_{t-l,SA} + \frac{q_{SA}^2}{24} E_{t-l,SA}^2\right)\right\}} + \frac{\sin^2 \varphi \cdot C_{t-(l+1),SA} \exp(\omega_{SA} S_{t-(l+1)})}{\left\{E_{t-(l+1),SA} \exp\left(-\frac{q_{SA}}{2} E_{t-(l+1),SA} + \frac{q_{SA}^2}{24} E_{t-(l+1),SA}^2\right)\right\}}. \qquad (5)$$

$C_{t,SA}$ and $E_{t,SA}$ are monthly catches and fishing efforts, in season *t*, respectively, taken from one or a combination of the western, central or southern areas of the northern zonal fishery of South Australia. The selection of region and month, or combinations of months, is based on the best correlation between those catch rates and the total catches in l to $(l+1)$ years henceforth. φ describes the year-class proportion for lobsters originating from the chosen area of the northern zone of South Australia. ω_{SA} describes the strength of the effect of the Fremantle Sea Level average on the catches. The denominators in (5) are expressed in parsimonious form in the same way that (2) approximates (1). q_{SA} is therefore a nonlinearity parameter to be estimated.

The model that is used to describe catches of southern rock lobster in the Esperance area is thus

$$C_t = aE_t \exp\left(-\frac{q}{2}E_t + \frac{q^2}{24}E_t^2\right)\times$$
$$f\left[\begin{array}{l}\cos^2\varphi\cdot C_{t-l,SA}\exp(\omega_{SA}S_{t-l})/ \\ E_{t-l,SA}\exp\left(-\frac{q_{SA}}{2}E_{t-l,SA}+\frac{q_{SA}^2}{24}E_{t-l,SA}^2\right)+ \\ \sin^2\varphi\cdot C_{t-(l+1),SA}\exp(\omega_{SA}S_{t-(l+1)})/ \\ E_{t-(l+1),SA}\exp\left(-\frac{q_{SA}}{2}E_{t-(l+1),SA}+\frac{q_{SA}^2}{24}E_{t-(l+1),SA}^2\right) \\ ;b\end{array}\right]+\eta_t, \qquad (6)$$

where

$$f(x;b) = \frac{x}{bx+1} \qquad (7)$$

is the Beverton-Holt mortality formulation and $\eta_t \sim N(0,\sigma^2)$. Following the methodology of Box and Jenkins (1976), a seasonal autoregressive integrated moving average transfer function (SARIMAX) model is used to fit the monthly catches for the southern rock lobster fishery in the Esperance area, viz.

$$c_{tm} = g(E_t, S_t; a, b, \varphi, q, \omega_{SA}, q_{SA}) + \zeta_{tm}. \qquad (8)$$

Here, c_{tm} is the monthly catch in fishing season *t* (available from 1975/76 to 1998/99) and month *m* (from November to June). *g* is the (annual) expectation of (6) replicated over the eight fishing months of season *t*. The parameter *a* becomes the transfer function coefficient. The other parameters defining *g* are estimated using (6). ζ_{tm} are seasonal ARIMA (SARIMA) errors defined as

$$\zeta_{tm} = \frac{\Theta(B^8)\theta(B)}{\nabla_8^D\nabla^d\Phi(B^8)\phi(B)}\xi_{tm}. \qquad (9)$$

where ϕ, θ, Φ and Θ are polynomials of finite order p, r, P and R, respectively, of the backward difference operator *B*, defined by $B(\cdot_t) = \cdot_{(t-1)}$. $\nabla_8 = 1 - B^8$ and $\nabla = 1 - B$ are seasonal and nonseasonal backward difference operators, respectively. *D* and *d* are seasonal and nonseasonal orders of differencing, respectively, selected as the minimum non-negative integers required for the data to be seasonally and nonseasonally stationary. ξ_{tm} is assumed to be a zero mean white noise process. The notation for (9) is thus SARIMA$(p,d,r)\times(P,D,R)_8$. Order selection of the model for (8) is calculated by minimization of the AICc statistic (Hurvich and Tsai, 1989), which is a bias-corrected version of the AIC (Akaike, 1974). 95% confidence intervals are calculated based on the assumption that the SARIMA errors ζ_{tm} are normally distributed. The significance of the transfer function component *g* in (8) is tested by comparing residual sums of squares for (8) and for the corresponding SARIMA model (without the transfer function).

6.4 Results

Catch rates taken from one of three northern zones in South Australia or additive combinations of those zones were tested in model (6) by individual fishing months or consecutive combinations of fishing months. Our best measure for a settlement index as specified in (6) is obtained by calculating central northern South Australian catch rates in May. Since May occurs near the end of the fishing season, these catch rates may be approximating unfished biomass available for spawning throughout winter and spring. In addition, it was found that the sex ratio for the May catches from 1993/94 to 1996/97 in the central northern zone of South Australia was heavily biased towards females (Prescott et al. 1998).

Lags of six and seven years were found to be the best combination for explaining annual catch variation. This result approximately agrees with Booth's (2000) New Zealand estimates which state that "most female *J. edwardsii* take 7-11 years to reach legal size, and males 5-7 years." Von Bertalanffy (1938) growth estimates were calculated for *Jasus edwardsii* near Stewart Island, New Zealand using tagged samples (McKoy 1985). According to those estimates, the minimum legal sizes of 96 mm for males and 92 mm for males would be attained at about 6 years after settlement. The minimum legal size for *Jasus edwardsii* in the Esperance area is 98.5 mm for males and females. Given that southern rock lobsters may mature approximately one year earlier in the warmer waters of the southern coast of Western Australia or the northern zone of South Australia, the six and seven year lags are in approximate agreement with these results.

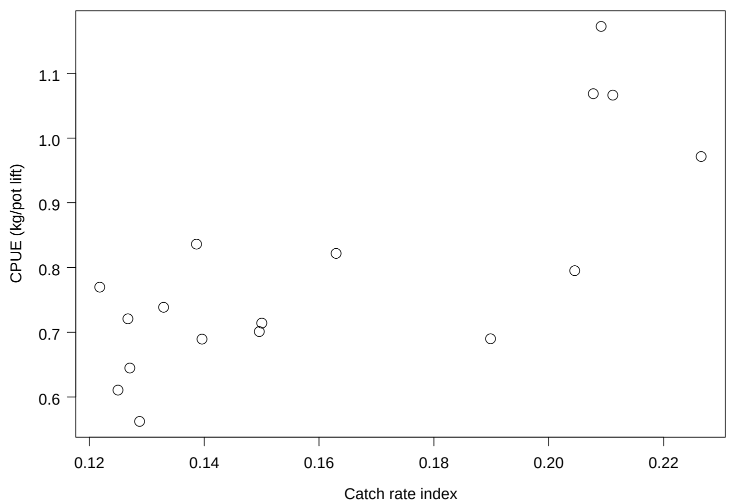

Figure 6.3. CPUE for the Esperance fishery from 1982/83 to 2001/02 versus catch rates from South Australia lagged six to seven years.

q in (2) was found to be insignificantly ($p = 0.22$) different from zero. Table 6.1 summarises the parameter estimates for a, b, φ, q_{SA} and ω_{SA}. ω_{SA} is negative, which indicates that a stronger west-to-east current may restrict larvae from flowing against the current. The nonlinear function on the right-hand side of (6) is highly significant ($p < 0.0001$). Figure 3 depicts the relationship between annual Esperance CPUE and May catch rates lagged six and seven years from the centre of the northern zone of South Australia. (6) is fitted using the data from 1982/83 to 1998/99 (17 fishing seasons) and forecasts are made from 1999/00 to

2001/02 (Fig. 4). The forecasts reveal a large decrease in catches from a near-peak in 1999/00 to pre-1992 levels in 2001/02. Table 6.2 summarizes the improvement in the annual catch models.

The SARIMAX model (8) is used to predict and forecast monthly southern rock lobster catches in the Esperance area (Fig. 6.5). The SARIMA component that best fits the monthly catch data in (8) is SARIMA$(1,0,0)\times(1,1,1)_8$. The estimated parameters (with standard errors in parentheses) are $\hat{\phi}_1 = 0.479\,(0.080)$ for the nonseasonal autoregressive term, and $\hat{\Phi}_1 = -0.276\,(0.140)$ and $\hat{\Theta}_1 = -0.429\,(0.131)$ for the seasonal autoregressive and moving average terms, respectively. The transfer function component of this seasonal time series model is highly significant ($p < 0.0001$) with (linear) coefficient of 0.604 and asymptotic standard error 0.097. The R^2 value for SARIMAX model (8) is 85.4%, compared with 76.3% for the equivalent SARIMA model. GARCH effects appear to be marginal in the monthly time series. For example, the McLeod and Li (1983) test with $L = 24$ gives a *p*-value of 0.050. The 1999/00 to 2001/02 forecasts for monthly catches are reliable (Fig. 6.6) with 5 out of 24 actual data points outside the 95% confidence intervals. Model (8) has forecast a decreasing trend in annual catches from 1999/00 to 2001/02, in line with the actual fishing realizations during these three years. Catches for fishing season 2000/01 were lower than expected, similar to the annual forecasts in Fig. 6.4.

6.5 Discussion

Our analysis shows that catches are correlated with relevant lagged South Australian catch rates and environmental data. Thus if South Australian catch rates for the southern rock lobster fishery in the northern zone continue to drop, it would not be surprising for the Esperance fishery to face similar difficulties. Both annual and seasonal models predicted the significant reduction in catches from 1999/00 to 2001/02. Although our models imitate a hypothesized recruitment process, there is very little biological evidence of the larval transportation phenomenon. Further investigations may be needed to show that the Jasus edwardsii fishery in Western Australia is not self-contained.

The Fremantle Sea Level was used to indicate the environmental factors governing the current flow. However, the effects of water currents, water temperatures and upwelling are probably more complicated in reality than the modelling of the single data stream measured at Fremantle.

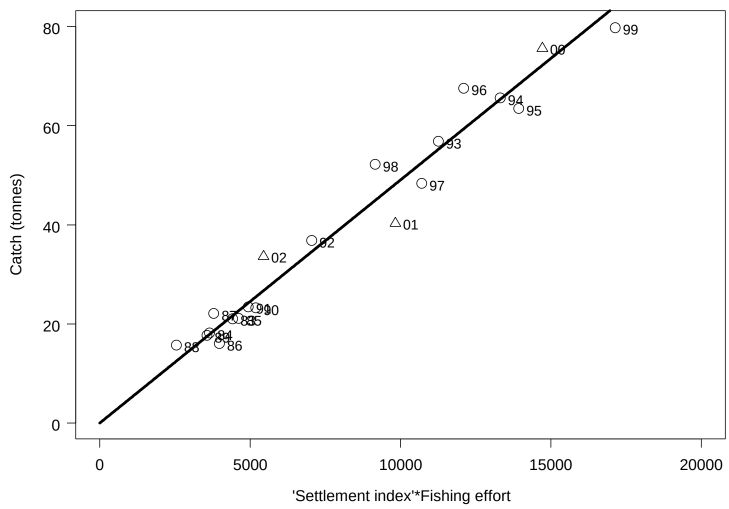

Figure 6.4. Annual catch-settlement index relationship for the Esperance area with forecasts from 1999/00 to 2001/02.

The diagnostic residual time series for SARIMAX model (8) shows the presence of conditional heteroscedasticity. If the residuals are split into two subsets of equal length, namely (i) from November 1982 to February 1990 and (ii) from March 1990 to June 1997, then the ratio of the variance of series (ii) to the variance of series (i) is 4.1. Using an *F*-test, this difference is highly significant ($p < 0.0001$). The residuals plot shows that the variance undergoes a change in regime from about 1990 onwards. This timeframe coincides with the simultaneous introduction of GPS technology and live tanks to stock the lobster product. Before 1990, the lobsters were placed in freezers and stocking space was limited. From 1990 onwards, live tanks have availed more product storage space and expanded the international export market. Thus, a further model of the Esperance southern rock lobster monthly catches may include a SARIMAX model with two levels of variance. If the time series components of the model were found to involve seasonal or nonseasonal moving averages, however, the computational estimation process for this type of model would potentially be difficult.

Another problem observed during the analysis was that the assumption of normally distributed SARIMA errors resulting in the 95% confidence intervals falling in the negative catch region. A block bootstrap of the stationary, stochastic seasonal ARMA component was carried out, but there was very little improvement. A multiplicative error modelling approach is also possible as follows. Replace the additive stochastic SARIMA component on the right-hand side of (8) by a non-negative multiplicative error term from a distribution such as the lognormal density function. Then the 95% confidence intervals are theoretically and practically more valid. However, taking transformations (e.g. logarithmic) of the catch and fishing effort data may not preserve the behaviour of the autoregressive and moving average processes. Transformations may also lead to difficult estimation problems not least because there are zero catches in the southern rock lobster data.

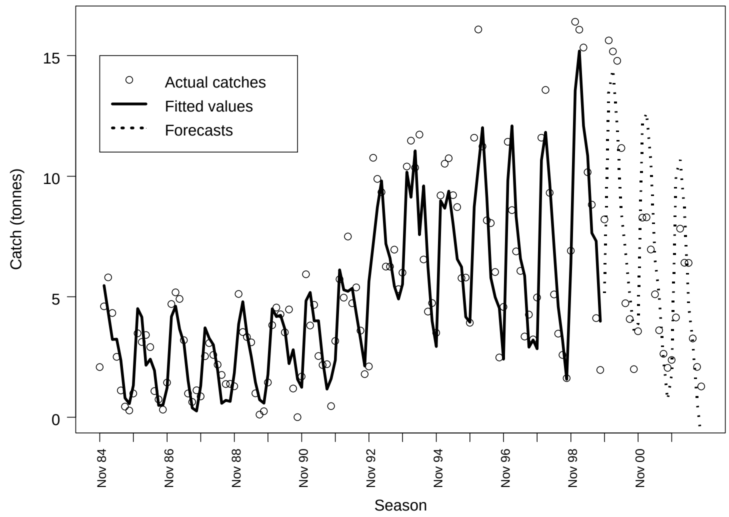

Figure 6.5. Predictions from 1984/85 to 1998/99 and forecasts from 1999/00 to 2001/02 by (8) of Esperance southern rock lobster monthly catches.

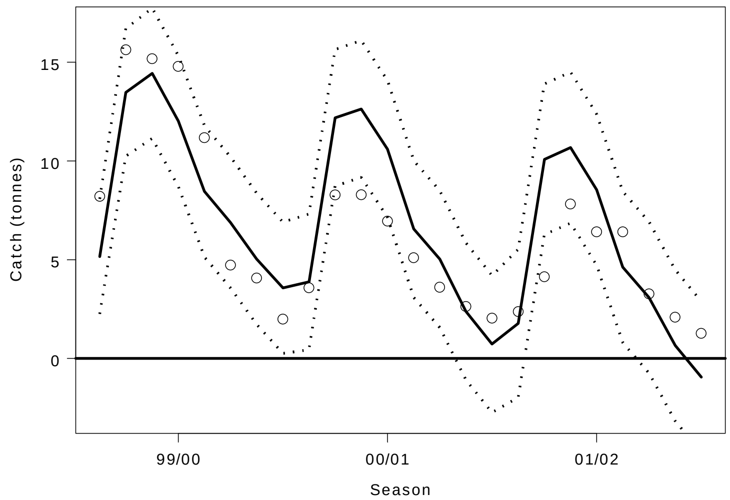

Figure 6.6. Forecast monthly catches (solid line) from 1999/00 to 2001/02 and 95% confidence intervals (dotted lines) assuming normal errors.

6.6 Acknowledgements

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Table 6.1. Parameter estimates with standard errors for the nonlinear regression model specified by (6).

	$\hat{a}$	$\hat{b}$	$\hat{\varphi}$	$\hat{q}_{SA}$	$\hat{\omega}_{SA}$
Estimates	4.91 (1.17)	2.94 (1.13)	0.73 (0.11)	-1.40 (0.13)	-0.070 (0.016)

Table 6.2. R^2 values for model subsets of (6).

	R^2	Number of parameters in model	Problems with model
Effort	87.0%	1	Time trends in residuals
Effort-recruitment	91.9%	4	1994/95 catch unexplained (< -2 std. err.)
Effort-recruitment-environment	97.0%	5	

7.0 Modelling the spatial distribution of the prawn fisheries in Shark Bay, Western Australia, by seasonal autoregressive moving average models

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7.1 Abstract

The Shark Bay Prawn (SBP) Managed Fishery is bounded by the Ningaloo Marine Park in the north and a point just below Zuytdorp Point in the south, including waters within Shark Bay below this latitude. It is the largest prawn fishery in Western Australia. The SBP fishery targets two major species - king and tiger prawns. The catch in 2000 was 2250 tonnes, which was comprised of 1555 tonnes of king prawns and 689 tonnes of tiger prawns and valued at around $40 million. Seasonal autoregressive moving average (SARIMA) time series models are used to model the spatial distribution of king and tiger prawns in the seven regions extended from West Peron to Quobba. Thirty years of monthly catch and effort logbook data are fitted to investigate the spatial autocorrelations over the seven regions. The SARIMA model order is consistently $(1,0,1)\times(1,1,1)_{12}$ over all areas for king catches, tiger catches and total catches, and $(2,0,1)\times(1,1,1)_{12}$ for total monthly catch rates. The monthly autoregressive coefficients for the SARIMA models are high over the main spawning regions, and low elsewhere. A SARIMA transfer function model was used to study the effect of fishing effort on the total monthly catches. The variability in fishing efficiency among the areas is explained. Multivariate contemporaneous SARIMA (CSARIMA) models are tested and validated for the total monthly catch rate data to investigate correlations among the seven fishing areas. The main result is that the two Denham Sound areas form a separate sub-fishery from the sub-fishery containing the five zones northward of Peron Point.

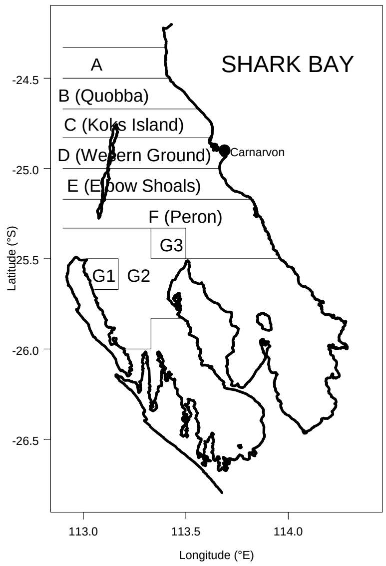
Keywords: prawn; fishery; time series; SARIMA.

7.2 Introduction

Prawning is Western Australia's third most valuable commercial fishing industry, (after rock lobster and pearling) and is worth around $62 million annually. Prawns are trawled in several managed fisheries off the Western Australian coast (Figure 7.1). There have been small subsistence prawn fisheries around Perth and the Peel Inlet since settlement in 1829, but serious commercial prawning did not begin in WA until the early 1960s. The commercial prawning industry in Shark Bay (Figure 7.2), WA takes primarily the western king prawn *(Penaeus latisulcatus)* and brown tiger prawn *(P. esculentus)*, along with by-catch such as the blue endeavour prawn *(Metapenaeus endeavouri)*, squid, scallops and crabs.

Figure 7.1. Main commercial prawn fishing areas in Western Australia.

Figure 7.2. Location of management zones in Shark Bay.



Careful management of the fishing effort has ensured that breeding stocks are maintained, which assists in maintaining stable prawn stocks and catches. Management of the prawning industry in Western Australia is complex and arrangements can vary annually to maintain breeding stocks and to optimise the value of the catch from each fishery. Management aims include sustaining prawn stocks and maintaining economic viability. Management measures have produced an increased proportion of large (and more valuable) prawns. Currently, management priority is on the tiger prawn stocks which are vulnerable to overfishing in multi-species fisheries. However, the mainstay of the Exmouth Gulf and Shark Bay prawn fisheries is the king prawn, which is caught in greatest quantity.

Catches of prawns can be highly variable in Shark Bay and other areas, due to environmental factors such as water temperatures, cyclones, and broad-scale oceanographic features. King prawns dominate the catch (69%), ranging between 1110 tonnes and 1656t and averaging 1404t, during the period 1995-2001. Tiger prawns make up the rest of the catch (31%), ranging 371t-784t and averaging 617t during the same period. Tiger prawn annual catches have varied from an average of 600t in the 1970s to 300t in the 1980s (Figure 7.3). Research assessments suggested that fishing pressure on the tiger prawn stock contributed to the lower catches. In 1989, management measures were introduced to reduce fishing effort on the juvenile tiger prawns and enhance the spawning stock. These, combined with favourable environmental conditions, resulted in the annual catches returning to the 600t average from 1995 to 2000.

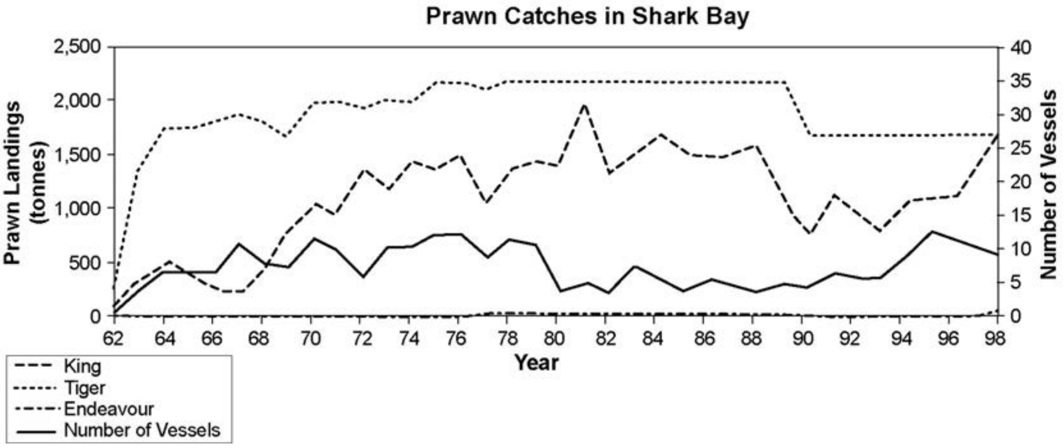


Figure 7.3. The annual catch of prawns in Shark Bay from 1962 to 1998.

Fishing Management

Because the Western Australian prawning industry did not really develop until the late 1960’s, the Department of Fisheries researchers and managers were able to develop and implement a variety of fishing controls and modern management measures to ensure prawn stocks were not over-fished. These controls aimed at safeguarding the long-term sustainability of prawn stocks, improving quality, and working with industry members to maintain high economic returns from these fisheries.

Fishing controls employed in managing the prawn fisheries include:

- seasonal closures (prawns are normally fished between March and November, with fishing closed during Summer).
- temporary closures of some areas within each fishery to protect spawning stocks and increase the proportion of larger export grade prawns in the catch,
- nursery areas in which trawling is banned to protect habitat,
- limiting vessel numbers and licences, and
- trawl gear and vessel restrictions (covering vessel size, net head-rope lengths and mesh size specifications).

A number of buy-back schemes have operated in Exmouth, Shark Bay and Onslow. These schemes have removed boats from these fisheries, with part of the licence fees for boats which remain going towards the purchase and cancellation of licences.

‘Moon closures’ in Shark Bay and Exmouth Gulf involve closing the fishery for three to five nights around the full moon. The closures reduce the proportion of soft, newly-moulted prawns in the catch and improves the efficiency of the fleet. Other benefits are improved vessel maintenance and a better social or family life for crews.

Seasonal autoregressive integrated moving average (SARIMA) time series models have proven more accurate than many other modelling methods for the prediction of monthly fisheries catch or catch per unit effort (CPUE) data (Lloret et al. [7], Stergiou [11], Noakes et al. [8], Stocker and Noakes [12], Saila et al. [9]). These methods are very time conserving and need not use any biological data. It is shown that monthly catches and catch rates of king and tiger prawns in Shark Bay can be reliably predicted by SARIMA models. Estimates of fishing efficiency are calculated for each area using a SARIMA transfer function model (SARIMAX). The correlation structure of catch rates over the eight fishing areas is examined and estimated. Thus, the spatial structure of the fishery can be better understood.

The approach in this paper is contemporaneous by assuming that catches or catch rates by area are correlated at the same time. Furthermore, the model order is kept the same over all areas to allow for comparison of relevant parameter estimates over the different regions.

7.3 Methods

SARIMA models are fitted to 31 years of monthly king prawn catches, tiger prawn catches and combined species catch rates over the eight fishing regions of Shark Bay. Area A contains very little to no catch each year, so it is included in the analysis only for completeness, thus leaving seven main fishing regions. The behaviour of these time series may be predicted by estimating the parameters of the $\mathrm{SARIMA}(p,d,q)\times(P,D,Q)_{12}$ models, where p and P are the order of nonseasonal and seasonal autoregressive parameters, d and D are the order of nonseasonal and seasonal differencing, and q and Q are the order of nonseasonal and seasonal moving average parameters. d and D are chosen to be the minimum non-negative integers required to achieve stationarity for all areas. p, P, q and Q are chosen by the ACF and PACF of the appropriately differenced series as the minimum non-negative integers required for the residual series to be white noise processes over all areas. This differs to the AIC selection method of Akaike [1], however the suggested method is more parsimonious across all areas. Thus, the model selection parameters are fixed over all fishing areas.

The variance-covariance matrix of the residual series of the catch rate models for the seven areas is contemporaneously calculated to understand how the catches are spatially correlated. This multivariate approach is contemporaneous because the correlations between are significant primarily at the same time, but at a much lesser extent at lagged monthly intervals. Contemporaneous multivariate models have been used in water resources by Salas et al. [10] and Hipel [6], and some contemporaneous ARMA applications were researched in Camacho [2] and Camacho et al. [3], [4].

SARIMAX models are fitted to the monthly combined species catches, where the exogenous variable is monthly fishing effort. The fishing efficiency may thus be calculated for each area. Total monthly catch and fishing effort data are linearly related for all areas. Therefore, the fishing effort is entered into the SARIMAX model as a linear, additive variable. The significance of the fishing effort variables over each area is calculated using a likelihood ratio test.

7.4 Results

In most cases, the time series required seasonal differencing to achieve stationarity. The SARIMA model order for the king prawn catches, tiger prawn catches and combined species catches with fishing effort were of the form $(1,0,1)\times(1,1,1)_{12}$, while the order for the combined species catch rates was $(2,0,1)\times(1,1,1)_{12}$. The coefficients for the SARIMA king and tiger prawn catch models, SARIMAX combined species catch model with fishing effort, and SARIMA catch rate model are tabulated in Tables 7.1 through 7.4, respectively. The king prawn, tiger prawn and catch rate model predictions are illustrated in Figures 7.4 through 7.6. The fishing effort coefficients for the SARIMAX combined species catch model suggest that fishing is the most efficient throughout the season in area F (Figure 7.2), but the least efficient in the Denham Sound areas G1, G2 and G3 (Figure 7.2).

We observe that the seasonal autoregressive coefficients are insignificant or small in magnitude. This means that catches or catch rates are affected by catches and catch rates up to 12 months previously, but no longer. This agrees with the known biological properties of the species, since prawns mature at about 10-12 months of age. The spawning occurs in offshore waters, larvae drift shoreward to shallow, hypersaline waters, and the juveniles develop until physiological changes demand they move back to oceanic waters to spawn, completing their life cycle. At the end of this migration of juvenile prawns, the prawns enter the trawl grounds where they can first be caught commercially. The seasonal moving average coefficients were significantly negative in all cases, which is a sign of fishing pressure on the prawn fishery in Shark Bay.

The contemporaneous correlation matrix of the residuals (Table 7.5) given by the combined species catch rate model suggests that fishing through areas B to F are significantly correlated, as are G3 with G1+G2. However, there is a distinct lack of correlation between areas B to F and G1+G2+G3. Furthermore, there was a significant lag 3 correlation for the catch rate series in fishing areas G3 and G1+G2. Thus, we conclude that the dynamics of the fishing in Denham Sound (G1 to G3) is separate from the remainder of the fishery (B to F).

7.5 Discussion

The seasonal ARIMA modelling methods produce reliable predictions for the seven main fishing areas of Shark Bay. Time series models also enable the prediction of the 1981 season catches and catch rates, of which the data is missing in entirety. Another advantage of SARIMA time series models is that they do not require biological information. However, the predictions remain at least as accurate using time series models when compared to the predictions made by age-length structured models (Hall [5], ch. 3).

An unbiased correlation matrix of the catch rates across all areas was estimated using a SARIMA time series model. Without a time series analysis, it would not have been possible to quantitatively verify that the Denham Sound sub-fishery is uncorrelated with the remainder of the Shark Bay fishery. This information is helpful for fishery management purposes, as it is known that king and tiger prawns spawn in the Denham regions. The Denham Sound area may therefore be considered a self-confined fishing region to be monitored from year to year.

To enable future planning, research is needed into the relationship between marketing changes and fleet dynamics as the patterns of fishing effort may change according to the product demanded by the market. A recent shift in marketing requirements has meant fishers are targeting larger sizes of prawns. This has had the effect of reducing overall annual tonnage caught from the fishery but may increase its value. A study of the market prices over time may generalize and improve the SARIMA or SARIMAX models.

Further studies of environmentally driven changes in recruitment, such as the effects of the Leeuwin Current and tide cycles may prove useful in making future catch predictions. These environmental variables may be incorporated as exogenous variables in the seasonal ARIMA models.

7.6 Acknowledgements

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Table 7.1. SARIMA model coefficients for king prawn catches in Shark Bay.

Species	Area	SARIMA model	ar1	ma1	sar1	sma1
Kings	A	$(1,0,1)\times(1,1,1)_{12}$	0.00	0.02	-0.04	-1.00
Kings	B	$(1,0,1)\times(1,1,1)_{12}$	0.13	0.12	-0.12	-0.82
Kings	C	$(1,0,1)\times(1,1,1)_{12}$	0.76	-0.71	0.24	-0.91
Kings	D	$(1,0,1)\times(1,1,1)_{12}$	0.53	0.03	0.18	-0.80
Kings	E	$(1,0,1)\times(1,1,1)_{12}$	0.56	-0.20	0.29	-0.85
Kings	F	$(1,0,1)\times(1,1,1)_{12}$	-0.02	0.30	0.33	-0.82
Kings	G3	$(1,0,1)\times(1,1,1)_{12}$	0.41	-0.02	0.00	-0.79
Kings	G1+G2	$(1,0,1)\times(1,1,1)_{12}$	0.35	0.00	0.06	-0.63

Table 7.2. SARIMA model coefficients for tiger prawn catches in Shark Bay.

Species	Area	SARIMA model	ar1	ma1	sar1	sma1
Tigers	A	$(1,0,1)\times(1,1,1)_{12}$	0.00	0.35	0.17	-0.71
Tigers	B	$(1,0,1)\times(1,1,1)_{12}$	0.48	-0.21	-0.22	-0.54
Tigers	C	$(1,0,1)\times(1,1,1)_{12}$	0.78	-0.71	0.17	-0.86
Tigers	D	$(1,0,1)\times(1,1,1)_{12}$	0.30	-0.10	-0.06	-0.79
Tigers	E	$(1,0,1)\times(1,1,1)_{12}$	0.42	-0.10	-0.14	-0.64
Tigers	F	$(1,0,1)\times(1,1,1)_{12}$	0.31	0.21	0.18	-0.91
Tigers	G3	$(1,0,1)\times(1,1,1)_{12}$	0.49	-0.22	0.13	-0.88
Tigers	G1+G2	$(1,0,1)\times(1,1,1)_{12}$	0.52	-0.20	0.20	-0.61

Table 7.3. SARIMAX model coefficients for combined species catches in Shark Bay with exogenous fishing effort variable.

Species	Area	SARIMA model	ar1	ma1	sar1	sma1	Transfer function
Total	A	$(1,0,1)\times(1,1,1)_{12}$	0.11	−0.22	0.06	−0.89	7.14 (0.07)
Total	B	$(1,0,1)\times(1,1,1)_{12}$	0.32	0.11	−0.12	−0.58	9.77 (0.21)
Total	C	$(1,0,1)\times(1,1,1)_{12}$	0.42	0.07	0.13	−0.91	7.63 (0.21)
Total	D	$(1,0,1)\times(1,1,1)_{12}$	0.55	−0.07	0.14	−0.79	8.41 (0.35)
Total	E	$(1,0,1)\times(1,1,1)_{12}$	0.57	−0.10	0.03	−0.66	9.34 (0.41)
Total	F	$(1,0,1)\times(1,1,1)_{12}$	0.40	0.05	0.13	−0.82	13.25 (0.63)
Total	G3	$(1,0,1)\times(1,1,1)_{12}$	0.34	0.10	0.09	−0.79	6.46 (0.22)
Total	G1+G2	$(1,0,1)\times(1,1,1)_{12}$	0.38	0.04	0.10	−0.82	6.11 (0.22)

Table 7.4. SARIMA model coefficients for combined species catch rates in Shark Bay.

Species	Area	SARIMA model	ar1	ar2	ma1	sar1	sma1
Total	A	$(2,0,1)\times(1,1,1)_{12}$	−0.06	0.01	0.18	0.30	−0.75
Total	B	$(2,0,1)\times(1,1,1)_{12}$	0.19	0.20	0.07	−0.09	−0.66
Total	C	$(2,0,1)\times(1,1,1)_{12}$	0.20	0.28	0.07	−0.06	−0.65
Total	D	$(2,0,1)\times(1,1,1)_{12}$	−0.08	0.43	0.60	−0.09	−0.62
Total	E	$(2,0,1)\times(1,1,1)_{12}$	0.28	0.18	0.06	−0.09	−0.49
Total	F	$(2,0,1)\times(1,1,1)_{12}$	0.17	0.18	0.28	0.07	−0.70
Total	G3	$(2,0,1)\times(1,1,1)_{12}$	1.04	−0.15	−0.80	−0.19	−0.36
Total	G1+G2	$(2,0,1)\times(1,1,1)_{12}$	0.00	0.13	0.35	0.05	−0.80

Table 7.5. Contemporaneous correlation matrix of residuals from the combined species catch rate model.

	A	B	C	D	E	F	G3	G1+G2
A	1.00	0.07	0.03	−0.02	−0.05	−0.03	−0.02	0.05
B		1.00	0.42	0.34	0.37	0.28	0.05	0.12
C			1.00	0.33	0.32	0.27	0.00	0.14
D				1.00	0.66	0.47	0.17	0.16
E					1.00	0.74	0.07	0.10
F						1.00	0.17	0.07
G3							1.00	0.32
G1+G2								1.00

Figure 7.4. Catch predictions for the king prawn fishery in Shark Bay using the SARIMA$(1,0,1)\times(1,1,1)_{12}$ model.

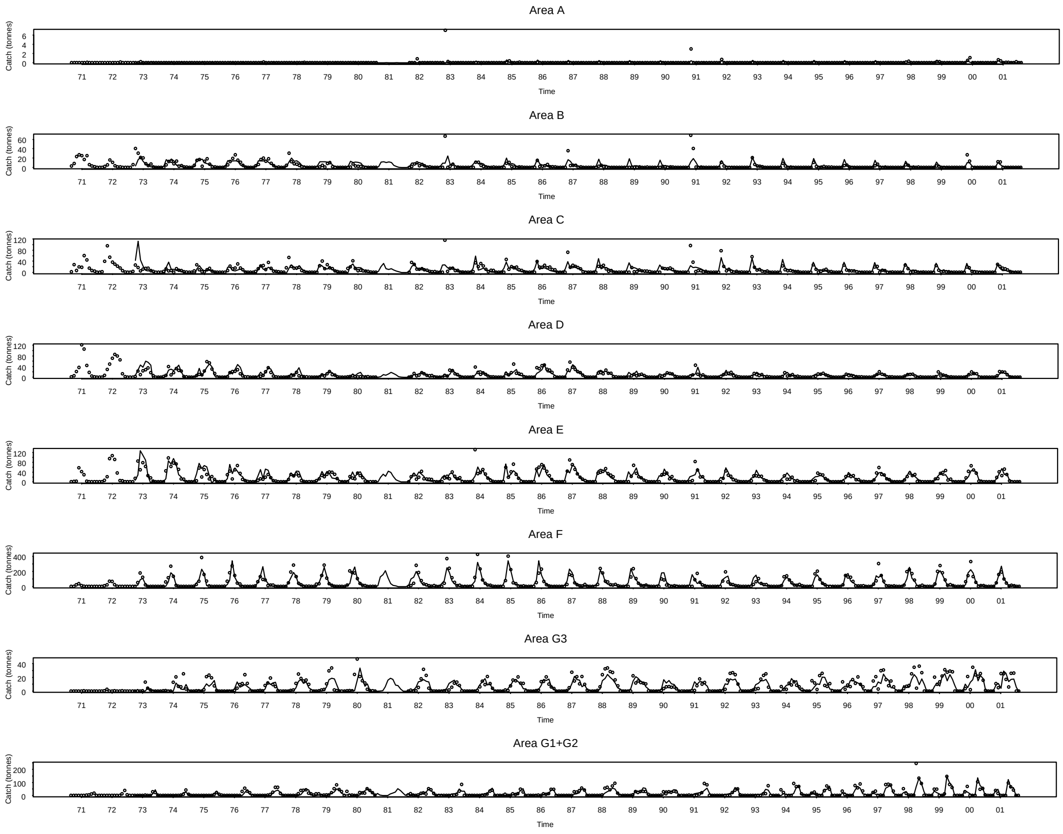


Figure 7.5. Catch predictions for the tiger prawn fishery in Shark Bay using the SARIMA$(1,0,1)\times(1,1,1)_{12}$ model.

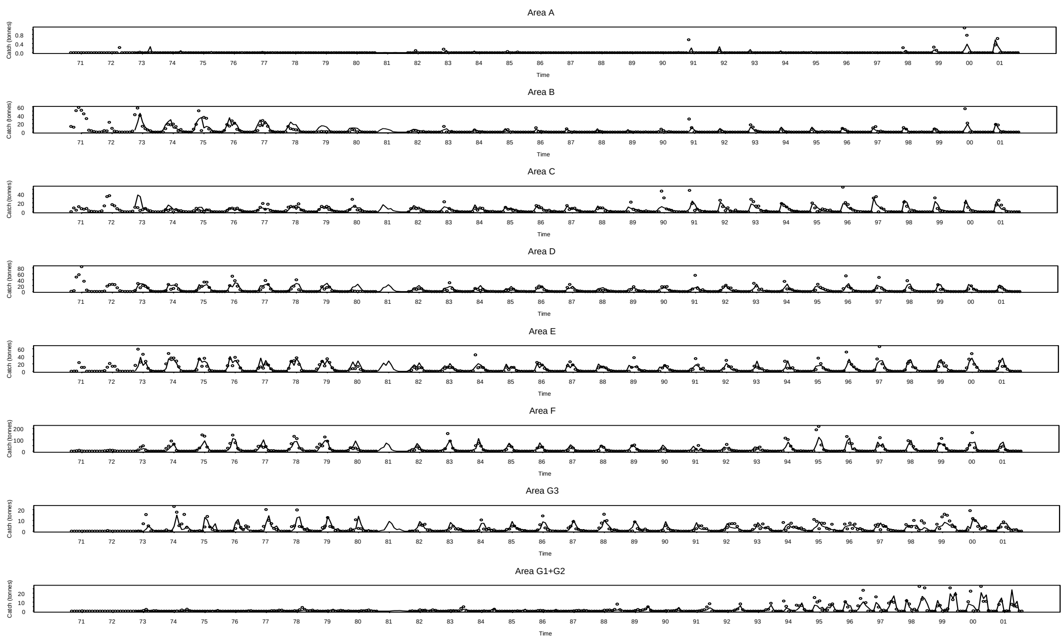
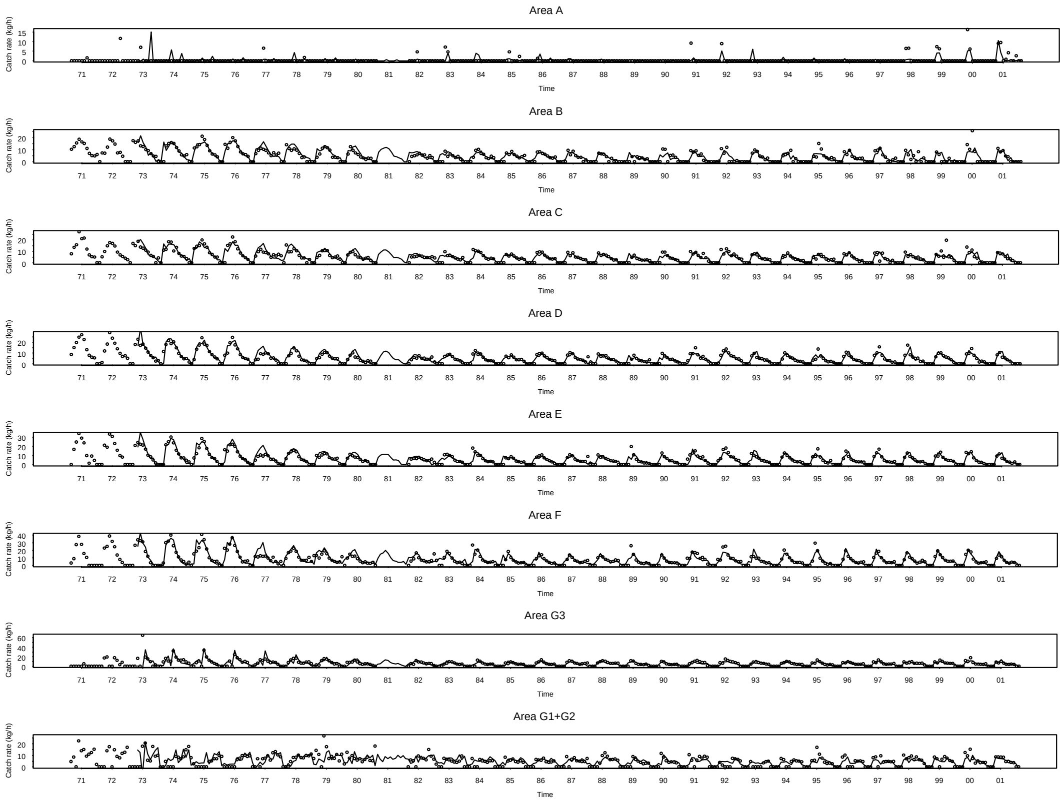


Figure 7.6. Catch rate predictions for the combined species prawn fishery in Shark Bay using the SARIMA $(2,0,1)\times(1,1,1)_{12}$ model.



8.0 Time series modelling for south and west coastal finfish fisheries of Western Australia and implications for management

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8.1 Abstract

In recent years, the allocation of fish resources between the commercial and recreational fishing sectors and within the commercial sector has become a high priority issue for fisheries management in Western Australia. Recovery of total management costs (stock monitoring research, compliance, etc.) from small-scale commercial fisheries is unlikely to be viable due to their lower revenue levels and profit margins compared with the larger, more productive commercial fisheries. The lack of biological, environmental and economic information for some finfish species make them favourable targets for the use of time series modelling in fish stock assessment. Time series techniques were applied to monthly commercial catch data for twelve important finfish species in the west coast and the south coast regions of Western Australia from 1976 to the present. Seasonal trends in the catch for these species were observed. Seasonal autoregressive integrated moving average (SARIMA) models were identified by analysing the autocorrelation function (ACF) and partial autocorrelation function (PACF). These finfish fisheries follow an ARIMA(1,1,1) process in the seasonal component. The Akaike information criterion (AIC) has been used for non-seasonal model component selection. Eleven out of 12 finfish fisheries on the west coast follow a $\text{SARIMA}(1,0,0)\times(1,1,1)_{12}$ process. Based on fitting the data from 1976 to 1998, forecasts of monthly catches for 1999 and 2000 are compared with the actual figures. From the result of the transfer function model estimation, the effect of fishing effort is significant for most of the west coast finfish fisheries, but not for the south coast. In the long term, the west coast region is likely to experience the greater risk of fishing pressure, and should be given preferential management priority compared with the south coast fisheries. Fishing effort can be used as an effective input control for most of the finfish fisheries in this region. On the south coast, the total allowable catch can be used as an effective output control for the majority of the finfish fisheries.

Keywords: input control; output control; SARIMA; ACF; AIC.

8.2 Introduction

Over the last ten years, the coastal finfish production in Western Australia (WA) has on average been worth about $40 million dollars each year. Consumption of this resource has mainly been domestic ([15]). The fish resources also provide fish stock for fishing bait and recreational angling. With the increasing pressure from a growing population, coastal development and demands of competing user groups such as the commercial, recreational and conservation sectors, the majority of fish stocks are now fully exploited. To maintain both sustainability and community values around the use of WA's fisheries resources, effective fishery management is required.

In fisheries management, allocation of fish resources can be made using the four common management tools (Charles, [1]):

- Input controls – regulating what fishers bring into the fishing process, such as regulating the fishing gear types and the amount of gear to be used, restricting the number of fishers, restricting the time when access to the fishing ground is allowed.
- Output controls – regulating what comes out of the fishing process such as restricting the catch in form of a total allowable catch, setting up fish size limits and bag limits for recreational catch.
- Ecologically based management – establishing marine protected areas, setting up legislation to protect endangered species.
- Indirect economic instruments – putting taxes on catches and licences.

To make use of such management tools, a variety of information is needed for effective decision-making. A knowledge of the fishery, historical levels of catch taken by each user group, the species biology, yield status, locality of the catch, information relating to important regional employment, economic and social lifestyle issues are all relevant. Furthermore, future trend information on the catch and fishing effort levels, population, coastal development, and data on social and economic issues affecting future resource use patterns are also necessary.

For small multi-species, multi-gear finfish fisheries, it is very difficult and expensive to collect the above data due to the lack of financial support and the diversity of the finfish species. However, the data are essential, in particular, for reporting under the Ecologically Sustainability Development (ESD) framework which has recently been adopted by the WA fisheries management (Fisher, [4]; Fletcher, [13]). All commercial, recreational and aquaculture fisheries need to be assessed against the ESD objectives with the report made available for public comment. Furthermore, all export fisheries are now (or in the near future) required through legislation to have an assessment on their environmental sustainability before being granted an export licence. Therefore, not only the maintenance of the target fish stocks is important, but protection of the by-catch or the non-target stocks is also needed.

When there is lack of biological, environmental and economic information to assess the stock of a fish species with the traditional quantitative methods, such as the surplus production model, and the age and size-structured models, time series modelling is an alternative low cost method for estimation. Various studies indicate that time series modelling is appropriate for determining the catch level for those fisheries where biological data are limited (Stergiou and Christou, [8]; Stergiou *et al.*,[9]; Lai *et al.*, [5]). Furthermore, He and Boggs found that transfer function models (TFMs) could be useful for estimating the fisheries impacts on fish abundance when only limited commercial data were available (He and Boggs, [14]). They used TFMs to investigate the impact of different fishing mortality in the Hawaii's yellowfin tuna fisheries. The basic requirements for using TFMs are that the time series of catch and catch-per-unit-effort (CPUE) have to be long term and the variation in catchability and in measurement of CPUE are minimal.

In this paper, the usefulness of time series modelling is tested for forecasting the catch levels for twelve finfish species in the west and south coasts of WA. This method is cost effective and can make use of the already available commercial catch and fishing effort data alone. The *S-plus* software has all the required functions to fit the series of monthly catch and fishing effort data (over 20 years), with seasonal autoregressive integrated moving average (SARIMA) models and SARIMA transfer function models (SARIMAX). The effect of fishing effort on the catch has been tested for its significance using the likelihood ratio test. Implementation for fisheries management is discussed based on the results of the analysis.

8.3 Methods and materials

Autoregressive integrated moving average (ARIMA) modelling was developed by Box and Jenkins in 1976 (Box and Jenkins, [6]). It assumes that a time series is a linear combination of its own past values and current and past values of a random error term, and the models can capture the historic autocorrelation of the data to extrapolate them into the future. The technique applies to stationary time series. Hence, for a time series which exhibits trends and seasonality, first or second-order differencing (non-seasonal and/or seasonal) is required to ensure that it is stationary before fitting the model. A seasonal component is added into the ARIMA model when there is a seasonal pattern apparent in the data. The definition of such a model is as follows:-

Definition 1. Seasonal Autoregressive Integrated Moving Average (SARIMA) model

Let $\{Y_t\}$ be a set of observations, each one being related to a specific time t. Then a time series $\{Y_t\}$ is a SARIMA$(p,d,q)\times(P,D,Q)_s$ process with period s if it satisfies a difference equation of the form

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)Z_t \;, \quad \{Z_t\} \sim \mathrm{N}(0,\sigma^2) \qquad [1]$$

where p, d, q, P, D and Q are non-negative integers; $\phi(z) = 1 - \left(\sum_{i=1}^{p} \phi_i z^i\right)$, $\Phi(z) = 1 - \left(\sum_{i=1}^{P} \Phi_i z^i\right)$, $\theta(z) = 1 + \left(\sum_{j=1}^{q} \theta_j z^j\right)$ and $\Theta(z) = 1 + \left(\sum_{j=1}^{Q} \Theta_j z^j\right)$; B is the backward shift operator $\left(B^j Y_t = Y_{t-j}, B^j Z_t = Z_{t-j}, j = 0,1,\cdots\right)$ and Z_t is the error term. The parameters $\phi_1,\ldots,\phi_p$ are the autoregressive coefficients, $\Phi_1,\ldots,\Phi_P$ are the seasonal autoregressive coefficients, $\theta_1,\ldots,\theta_q$ are the moving-average coefficients and $\Theta_1,\ldots,\Theta_Q$ are the seasonal moving average coefficients. d and D are the degrees of non-seasonal and seasonal differencing required to achieve stationarity respectively.

When there is other relevant data available, the data can be incorporated into the SARIMA model as a *transfer function* (Brockwell and David, [10]), i.e.

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D(Y_t-\tau X_t)=\theta(B)\Theta(B^s)Z_t\ ,\quad \{Z_t\}\sim \mathrm{N}(0,\sigma^2) \qquad [2]$$

where X_t can be another time series, a constant term, a deterministic function of time, or dummy variables to model outliers. This model is often referred to as SARIMAX model.

The appropriate seasonal component of the model is identified by examining the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the time series. In addition, the Akaike information criteria (AIC) is used to choose the best non-seasonal component of the model. Verification of the model is performed through diagnostic checks of residuals. These procedures are performed with the existing functions, such as the functions *arima.mle* and *arima.filt*, provided by the statistical software *S-plus* ([16]). The *S-plus* function *arima.mle* fits ARIMA models to univariate time series data through Gaussian maximum likelihood. With no missing data, an algorithm similar to that of Ansley (Ansley, [2]), which is based on the Choleski decomposition of the covariance of the process Y_t, is used to compute the likelihood. With missing values present, the likelihood is computed using the Kalman filter (Kohn and Ansley, [11]). The computational time for estimating the parameters in the model usually takes a couple of seconds.

Commercial fisheries data of twelve finfish species caught in the west coast of Western Australia, south of latitude 27°S and west of longitude 116°E, and in the south coast, east of longitude 116°E, are used in this paper (Figure 8.1). All of these species can be caught throughout the year. Some of them are the major species for the finfish fisheries in the west coast such as sea mullet (*Mugil cephalus*) and black bream (*Acanthopagrus butcheri*) for the estuarine fishery; while others are the targeted species in the south coast, like the Western Australian salmon (*Arripis truttaceus*) and Australian herring (*Arripis georgianus*). Series of monthly catch and fishing effort (days fished) data from 1976 to 2000 of the selected species are provided by the Department of Fisheries, Government of Western Australia. Seasonal pattern and trends can be observed from the data. Monthly catch for the last two years 1999 and 2000 is predicted using the previous years data with the SARIMA and SARIMAX models and compared with the actual data.

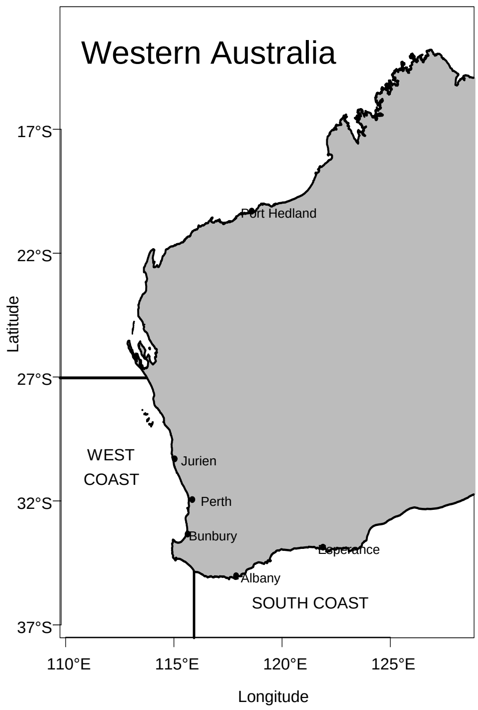

Figure 8.1.

8.4 Results

The selected SARIMA models fitted to the monthly catches of the twelve finfish species are presented in Table 8.1 and Table 8.2. All of the series were seasonally non-stationary and had negative correlation at lag 12. Hence, the seasonal component of the SARIMA model for all of the species was $(1,1,1)_{12,}$ which indicated that the catch at month t was weighted with the catch of the same month a year ago. The seasonal cycle of the catch was yearly based. Winter was the low season for the major targeted species such as the sea mullet, Western Australian salmon and Australian herring, while it was the high season for many of the other less valuable species.

The non-seasonal component of the model was (1,0,0) for most of the species in the west coast (Table 8.1). This showed that the catch for a month was dependent on the catch for the previous month. The model $(1,0,1)\mathrm{x}(1,1,1)_{12}$ for the herrings and sea mullet showed that the catch for a month was not only dependent on the catch for the previous month, but also depended on the moving average of the series ended at the previous month.

There were more variations in the model for the south coast (Table 8.2). The non-seasonal component of the model for many of the species was different to that in the west coast. This was due to the trends in the catch levels being quite different in the two regions for the same species. For example, the trend of the monthly catch data for cobbler (*Cnidoglanis macrocephalus*) was gradually decreasing in the west coast, while the trend was fluctuating seasonally in the south coast. The resulting model indicated that the catch for one month was dependent on the previous three months.

Table 8.1. Parameter estimates for the SARIMA model (p,d,q) x $(P,D,Q)_s$ for each finfish species in the west coast. Standard errors for each estimate are included in brackets.

Finfish species	SARIMA	$\hat{\sigma}$	$\hat{\phi}_1$	$\hat{\theta}_1$	$\hat{\Phi}_1$	$\hat{\Theta}_1$
Black bream (*Acanthopagrus butcheri*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	1.176	0.436 (0.058)	-	0.036 (0.068)	0.958 (0.019)
Cobbler (*Cnidoglanis macrocephalus*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	0.851	0.723 (0.045)	-	-0.008 (0.082)	0.789 (0.050)
Sea garfish (*Hyporhamphus melanochir*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	1.000	0.316 (0.061)	-	-0.073 (0.093)	0.653 (0.071)
Australian herring (*Arripis georgianus*)	$(1,0,1)\mathrm{x}(1,1,1)_{12}$	0.662	0.757 (0.151)	0.605 (0.184)	0.193 (0.064)	1.000 (0.000)
Perth herring (*Nematalosa vlaminghi*)	$(1,0,1)\mathrm{x}(1,1,1)_{12}$	0.725	0.703 (0.093)	0.321 (0.124)	-0.013 (0.164)	0.383 (0.151)
Leather jacket (*Monacanthidae*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	1.911	0.322 (0.061)	-	-0.019 (0.072)	0.893 (0.032)
Sea mullet (*Mugil cephalus*)	$(1,0,1)\mathrm{x}(1,1,1)_{12}$	0.418	0.375 (0.106)	-0.239 (0.111)	0.161 (0.076)	0.883 (0.0361)
Yellow-eye mullet (*Aldrichetta forsteri*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	0.373	0.739 (0.044)	-	-0.083 (0.085)	0.723 (0.059)
Western Australian salmon (*Arripis truttaceus*)	$(0,0,1)\mathrm{x}(1,1,1)_{12}$	2.203	-	-0.232 (0.063)	0.177 (0.068)	0.954 (0.021)
Tailor (*Pomatomus saltatrix*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	0.819	0.428 (0.058)	-	0.017 (0.065)	1.000 (0.000)
King george whiting (*Sillaginodes punctata*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	0.635	0.567 (0.053)	-	0.289 (0.062)	1.000 (0.000)
Western sand whiting (*Sillago schomburgkii*)	$(1,0,0)\mathrm{x}(1,1,1)_{12}$	0.392	0.680 (0.047)	-	0.015 (0.074)	0.881 (0.035)

Table 8.2. Parameter estimates for the SARIMA model (p,d,q) x (P,D,Q) $_s$ for each finfish species in the south coast. Standard errors for each estimate are included in brackets.

Finfish species	SARIMA	$\hat{\sigma}$	$\hat{\phi}_1$	$\hat{\phi}_2$	$\hat{\phi}_3$	$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\Phi}_1$	$\hat{\Theta}_1$
Black bream	$(1,0,2)x(1,1,1)_{12}$	0.911	0.943 (0.040)	-	-	0.448 (0.078)	0.280 (0.072)	0.102 (0.068)	1.000 (0.001)
Cobbler	$(3,0,0)x(1,1,1)_{12}$	0.305	0.560 (0.065)	0.127 (0.074)	0.032 (0.065)	-	-	0.169 (0.064)	1.000 (0.000)
Sea garfish	$(1,0,0)x(1,1,1)_{12}$	1.082	0.250 (0.062)	-	-	-	-	0.075 (0.064)	1.000 (0.000)
Australian herring	$(0,0,1)x(1,1,1)_{12}$	0.857	-	-	-	-0.005 (0.065)	-	0.185 (0.097)	0.748 (0.066)
Leather jacket	$(2,0,0)x(1,1,1)_{12}$	0.815	0.430 (0.059)	0.394 (0.059)	-	-	-	0.114 (0.065)	1.000 (0.000)
Sea mullet	$(1,0,1)x(1,1,1)_{12}$	0.73	0.816 (0.073)	-	-	0.514 (0.108)	-	0.064 (0.084)	0.792 (0.052)
Yellow-eye mullet	$(1,0,2)x(1,1,1)_{12}$	0.654	0.869 (0.133)	-	-	0.471 (0.154)	0.221 (0.100)	0.007 (0.075)	0.871 (0.041)
Western Australian salmon	$(0,0,1)x(1,1,1)_{12}$	1.220	-	-	-	-0.008 (0.065)	-	-0.353 (0.109)	0.251 (0.113)
Tailor	$(1,0,1)x(1,1,1)_{12}$	2.648	0.318 (0.121)	-	-	-0.226 (0.124)	-	-0.089 (0.076)	0.821 (0.043)
King george whiting	$(1,0,2)x(1,1,1)_{12}$	0.517	0.928 (0.039)	-	-	0.382 (0.077)	0.107 (0.073)	-0.076 (0.079)	0.793 (0.055)
Western sand whiting	$(0,0,1)x(1,1,1)_{12}$	5.193	-	-	-	-0.006 (0.065)	-	0.224 (0.668)	0.312 (0.651)

Table 8.3. Parameter estimates for the SARIMA model (p,d,q) x (P,D,Q) $_s$ with transfer function (τ) for the finfish species in the west coast, of which the effect of fishing effort is significant at the 5% level. Standard errors for each estimate are included in brackets.

Finfish species	SARIMA	$\hat{\sigma}$	$\hat{\phi}_1$	$\hat{\theta}_1$	$\hat{\Phi}_1$	$\hat{\Theta}_1$	$\hat{\tau}$
Cobbler	$(1,0,0)x(1,1,1)_{12}$	0.8260	0.6115 (0.0511)	-	-0.0130 (0.0777)	0.8268 (0.0437)	3.4015 (0.7973)
Australian herring	$(1,0,1)x(1,1,1)_{12}$	0.6504	0.4406 (0.3282)	0.2861 (0.3502)	0.1980 (0.0638)	1.000 (0.0066)	4.6439 (1.3032)
Perth herring	$(1,0,1)x(1,1,1)_{12}$	0.7055	0.5859 (0.1368)	0.2622 (0.1629)	0.0119 (0.1545)	0.4274 (0.1397)	7.4435 (1.9218)
Leather jacket	$(1,0,0)x(1,1,1)_{12}$	1.7955	0.2450 (0.0626)	-	-0.0312 (0.0645)	0.9997 (0.0017)	0.6122 (0.1332)
Sea mullet	$(1,0,1)x(1,1,1)_{12}$	0.4025	0.2428 (0.1193)	-0.3236 (0.1163)	0.1573 (0.0699)	0.9350 (0.0251)	3.7784 (0.9730)
Yellow-eye mullet	$(1,0,0)x(1,1,1)_{12}$	0.3557	0.6196 (0.0507)	-	-0.0445 (0.0767)	0.8272 (0.0431)	6.0231 (1.0448)
Western Australian salmon	$(0,0,1)x(1,1,1)_{12}$	2.1637	-	-0.2136 (0.0631)	0.1796 (0.0667)	0.9671 (0172)	74.2739 (27.0170)
Tailor	$(1,0,0)x(1,1,1)_{12}$	0.7922	0.3632 (0.0601)	-	0.0217 (0.0645)	1.000 (0.0004)	0.7537 (0.1494)
King george whiting	$(1,0,0)x(1,1,1)_{12}$	0.6182	0.4581 (0.0574)	-	0.2683 (0.0622)	1.000 (0.0004)	0.8701 (0.1985)
Western sand whiting	$(1,0,0)x(1,1,1)_{12}$	0.3747	0.5438 (0.0542)	-	0.0269 (0.0706)	0.9181 (0.0280)	1.4219 (0.2440)

The predicted and actual monthly catch data were compared. Figure 8.2 shows three examples of these comparisons for the west coast and Figure 8.3 shows three examples for the south coast. In general, about 83-100 % of the actual monthly catches for 1999 and 2000 were within the 95 % confidence intervals.

The fishing effort is measured as the total number of days fished per year. It was added into the SARIMA model as a transfer function in order to test the significance of the effect of fishing effort on the catch. Likelihood ratio tests were performed. It was found that the effect was not significant for all the species in the south coast, but was significant for most of the species in the west coast such as the sea mullet, Australian herring and western sand whiting (Table 8.3). Figure 8.4 shows these three examples comparing the fitted values without fishing effort and the fitted values with fishing effort incorporated in the SARIMA model.

8.5 Discussion

The SARIMA models fitted to the monthly catch data were found to be reliable for the major targeted species such as the sea mullet, cobbler, Australian herring and western sand whiting, in the west coast and in the south coast of WA. The effect of fishing effort on the catch was tested and found to be significant for most of the species in the west coast. The models fitted to the data were similar to those results obtained by Lloret for the species in the Northwest Mediterranean Sea in terms of the simplicity of the model (Lloret *et al.*, [7]). Univariate SARIMA models were used to forecast monthly catches of fifty-three commercial species. It was found that models fitted to most of the targeted demersal and benthic species. One defect in the study was that only 27 models were identified. However, models were identified for all species in this paper. This may be related to the estimation methods used to obtain the model.

Under the assumption that the fishing effort is calculated in a reasonable manner, it can be a significant factor for forecasting the catch level of a species. The results in this paper showed that the effect of fishing effort on the catch level was significant for 10 out of 12 finfish species found in the west coast. Some of them are commercially targeted species and some of them have become popular for recreational fishing. Many of them are currently caught without restrictions on fishing gears or limitations on quantity. In fact, these species are only a small selection of a large diversity of finfish species in the west coast caught by commercial and recreational fishers. Management plans are in strong demand to protect biodiversity and maintain essential ecological processes in this region. Based on the results, the use of input controls may be more effective in managing the west coast finfish species.

The effect of fishing effort on forecasting the catch level was not significant for any of the twelve species in the south coast. Most of the finfish fisheries in this region are relatively small and are multi-species and/or multi-gear fisheries. Attributing the level of fishing effort targeted to a particular species is not possible. Thus, using the total number of days fished may not be an appropriate effort measure. Despite all the difficulties, unmanaged fishing activities still need to be controlled to sustain the fish resources for the future. Based on the results from the analysis, the use of output controls may be a more effective management tool for the south coast finfish species.

The method used in this paper can be applied to all species with existing long-term commercial fisheries data to understand the historical catch levels and forecast future trends of species in Western Australia. Unfortunately, in a biological aspect, time series modelling cannot estimate the population parameters such as natural mortality and catchability that is used in traditional stock assessment methods. Nevertheless, time series modelling can be useful for developing management plans which involve detecting certainty and predictability. Time series modelling can be a cost effective method to provide rapid feedback to fisheries managers that a major perturbation has occurred, or that the system is changing, so that appropriate management action may be implemented (Fisher, [4]). With simple mathematical formulations and a few assumptions, time series modelling can be a low cost method for providing fisheries managers with immediate prediction using limited data.

8.6 Further research

It is often desirable to study the effects of environmental factors such as water temperature and tides on the catch and biomass of fish species. If the biological and environmental data are available, they can be incorporated into the SARIMA model as a transfer function to estimate the catch and enhance the knowledge of the species life history from the trend behaviour. If the errors from the fitted model are not independently normal distributed, SARIMA models with generalised autoregressive conditional heteroscedasticity (GARCH) errors can be used to improve the outcomes (Bollerslev, [12]; Wong and Li, [3]). It can be observed from the data that when the catch of one major species is high, it will be low for another major species within the same fishing ground such as the Western Australian salmon and herring in the west coast. For this phenomenon, multivariate time series modelling may be useful to study the relationship among different species in the same region.

8.7 Acknowledgements

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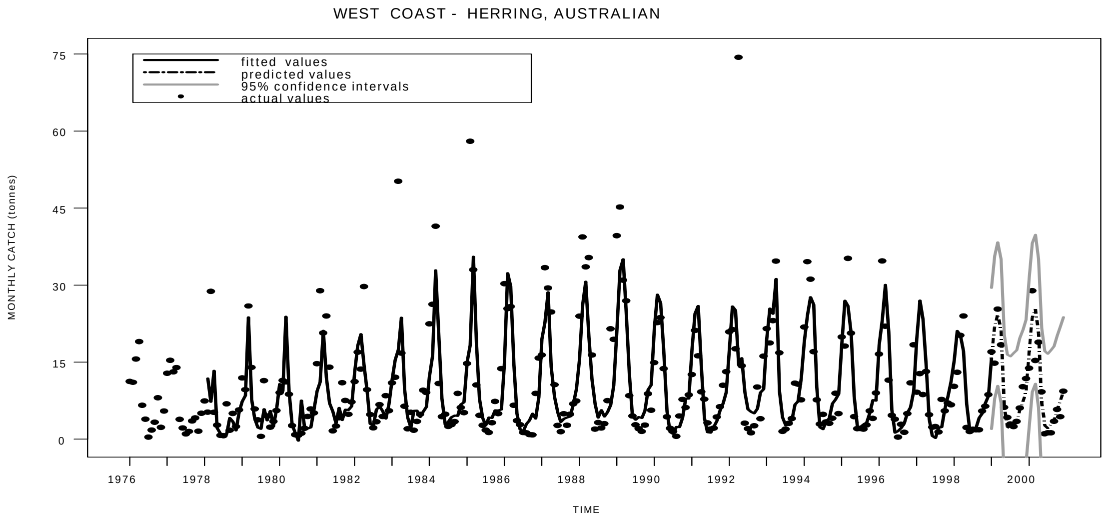
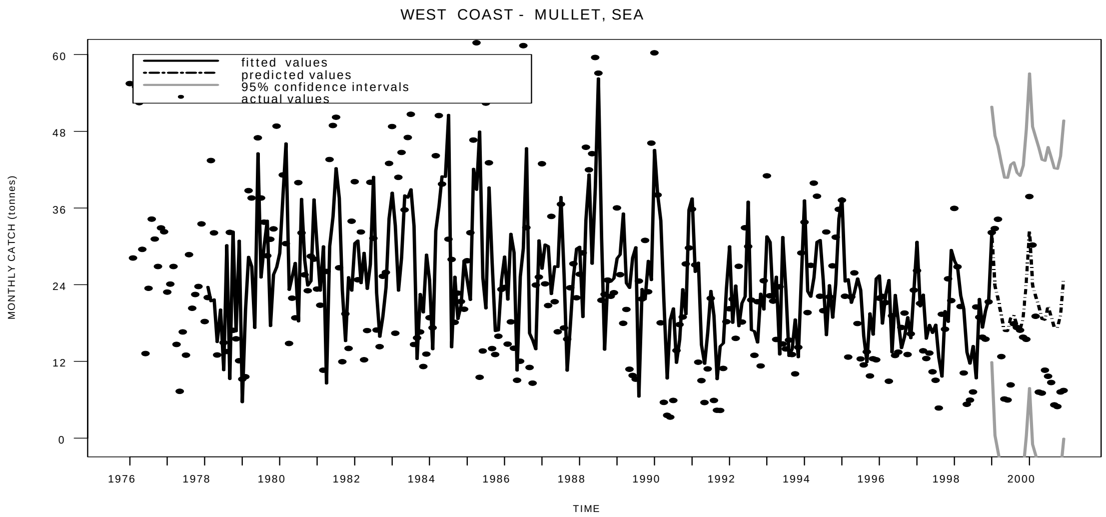
Figure 8.2. Comparison between actual monthly catches of fish species together with fits and forecasts predicted from the SARIMA models for the west coast of WA.





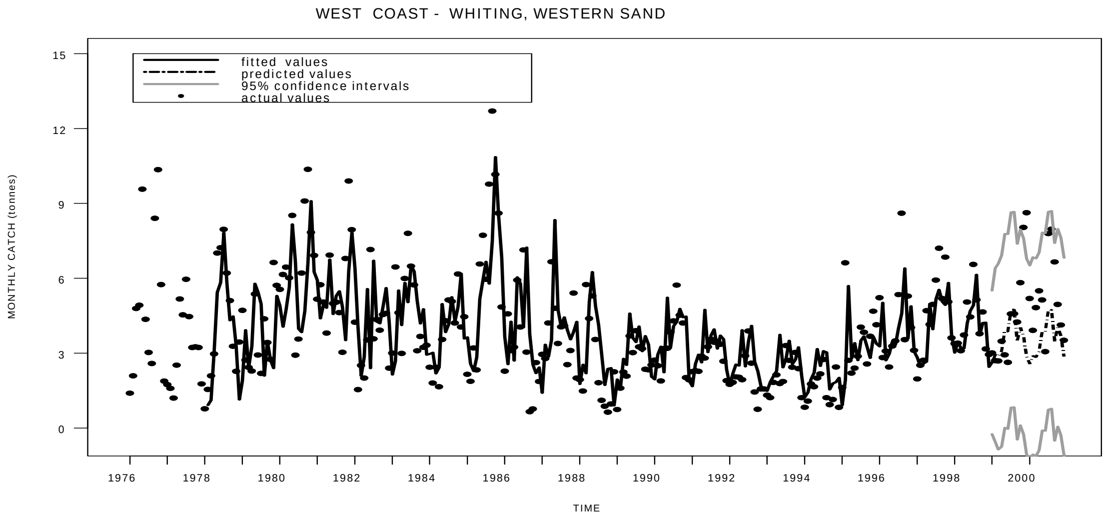
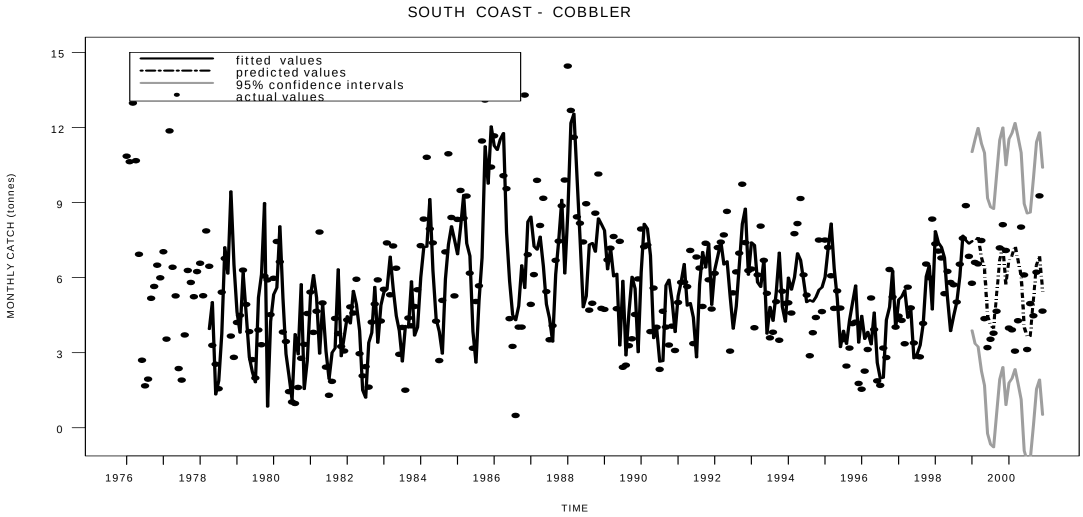
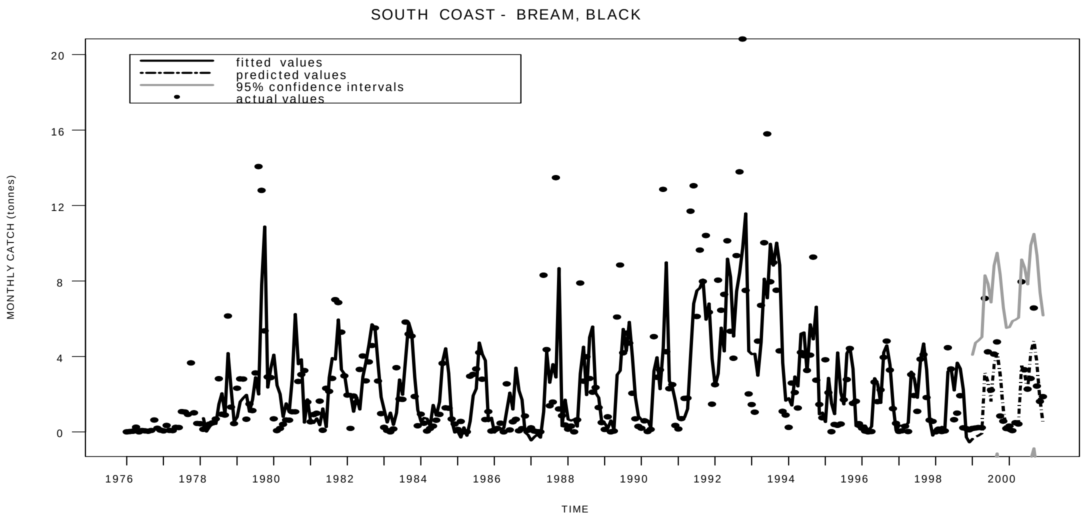


Figure 8.3. Comparison between actual monthly catches of fish species together with fits and forecasts predicted from the SARIMA models for the south coast of WA.





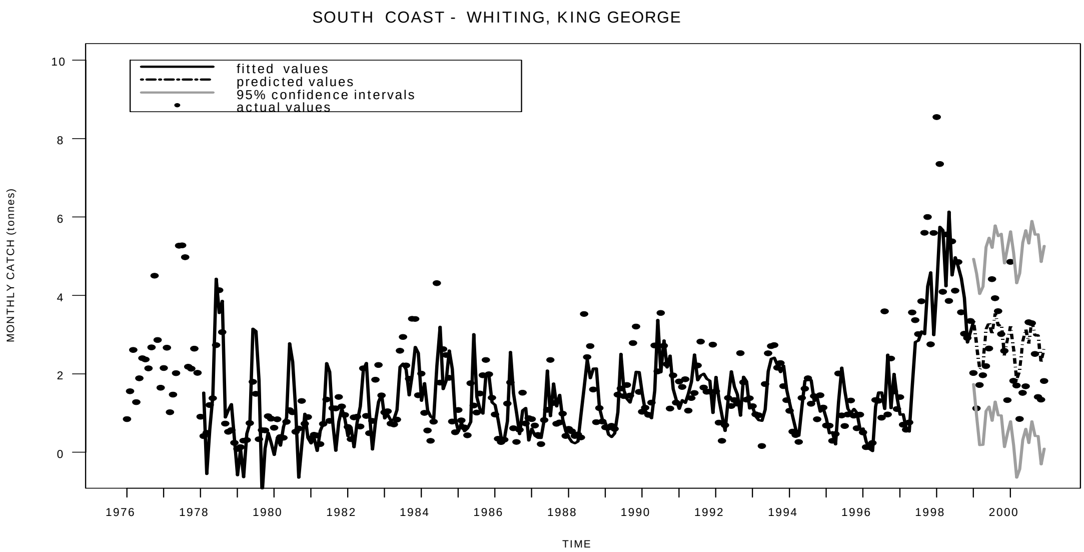
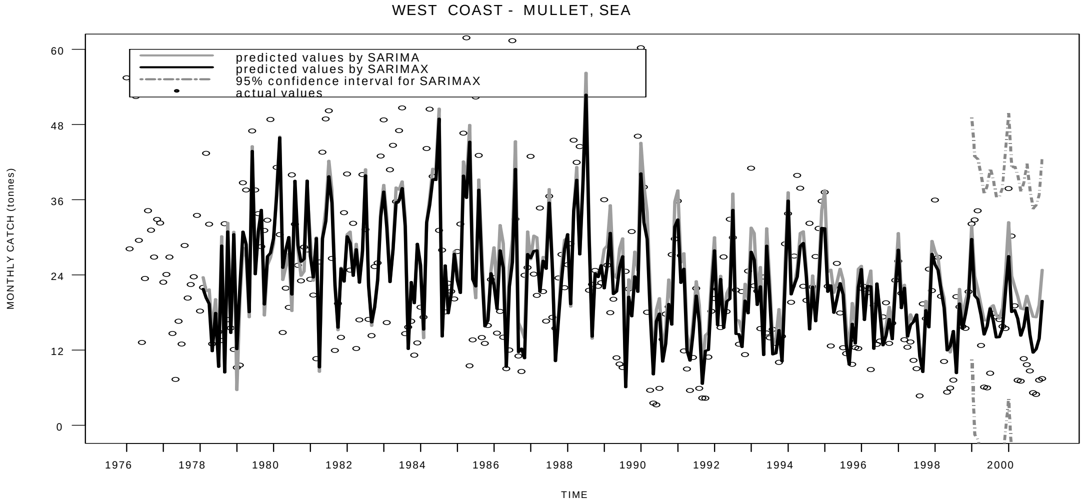
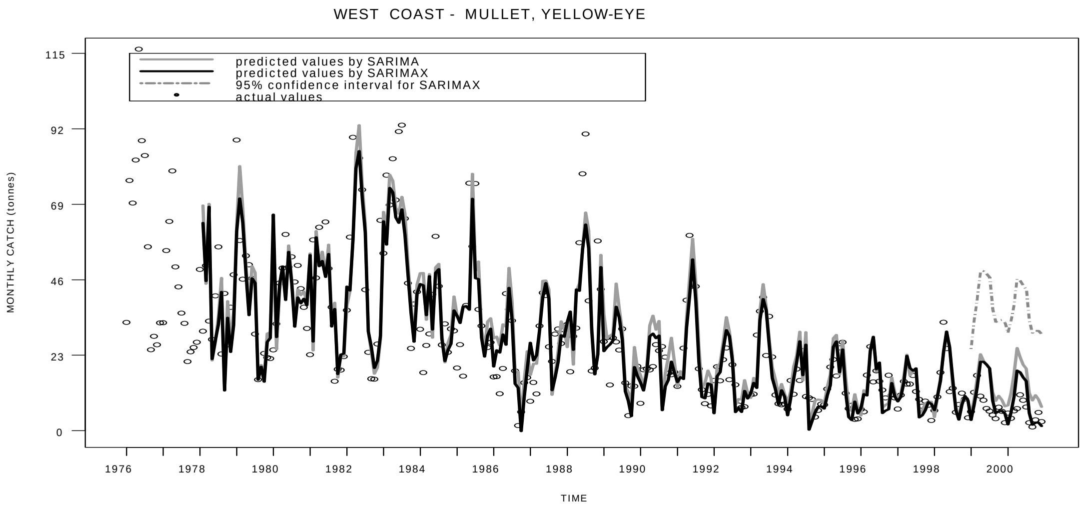
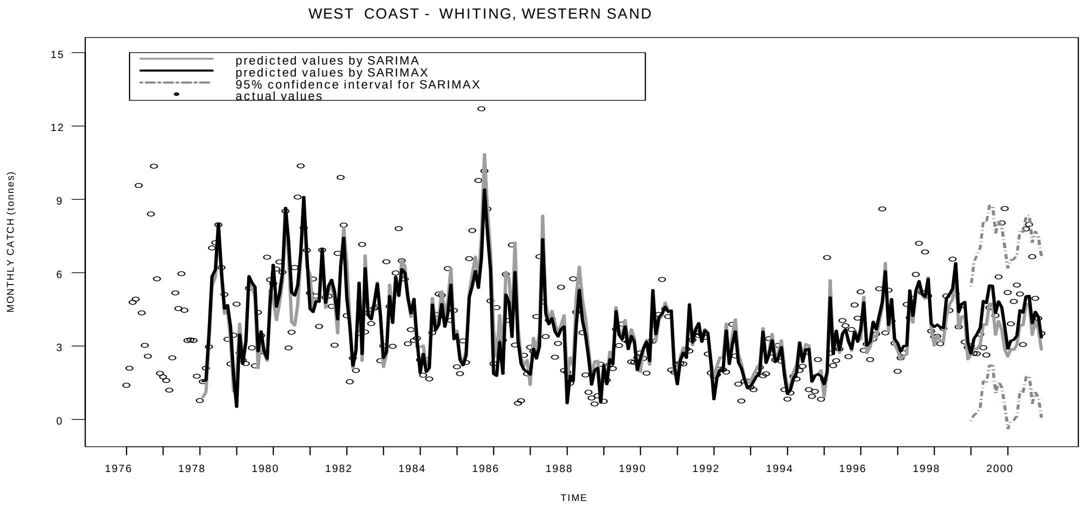


Figure 8.4. Comparison between the predicted monthly catches of fish species from a SARIMA model and the predicted values from a SARIMAX model for the west.







9.0 Predicting Monthly Catch for Some Western Australia Coastal Finfish Species with Seasonal ARIMA – GARCH models

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9.1 Abstract

In recent years, the conflict in sharing fish stocks between the commercial and recreational sectors has become a high priority issue for fisheries management in Western Australia. The recreational anglers are concerned about the effect of commercial fishing activities on the stocks of some key recreational finfish species of the estuaries and the nearshore areas of WA. The lack of biological and economic information for some of these species makes them favourable targets for the use of time series modelling in fish stock assessment. Monthly commercial catch data for four finfish species was available, back to 1976. The species are King George whiting (*Sillaginodes punctata*), red emperor (*Lutjanus sebae*), sea mullet (*Mugil cephalus*) and yellow eye mullet (*Aldrichetta forsteri*). Seasonal variations and trends in the catches for these species were observed. The data was usually found to be stationary after one seasonal differencing. Seasonal autoregressive integrated moving average (ARIMA) models were identified by analysing the autocorrelation function (ACF) and partial autocorrelation function (PACF). Criteria for model selection such as Akaike information criterion (AIC) and bias-corrected version of the Akaike information criterion (AICc) were used. After fitting the seasonal ARIMA models to the data, trends could be observed in the time series of the noise. The conditional variance for the time series of the noise might not be constant over time. A generalized autoregressive conditional heteroscedasticity (GARCH) model was then used to model the noise. A Ljung-Box test and a McLeod Li test were used to test the randomness of the noise. It was found that the GARCH effect exists in the catch data of most of these species. Based on fitting to data from 1976 to 1998, predictions of monthly catches for 1999 and 2000 were calculated and compared with the actual figures. The results showed that the ARIMA-GARCH models applied in this study can describe the catch data and give better predictions in some cases.

Keywords: Seasonal ARIMA; GARCH; ACF; AIC.

9.2 Introduction

The principal objectives for commercial fisheries management are to ensure the sustainability of fish stocks, establish a firm basis for a sustainable and profitable commercial fishing industry, and to fairly allocate fish stocks among the commercial fishing and recreational fishing and other sectors. Prediction of commercial catches of fish in terms of whole weight is important for management decision making. For fisheries in Western Australia, the traditional methods for prediction are based on biological and environmental factors, such as spawning stock, recruitment and lunar cycle (Mendelssohn, 1988; Hall, 1997). Unfortunately, collecting the biological and environmental data is very expensive and difficult. These methods are especially difficult to apply to smaller and less valuable finfish fisheries in which the main species stocks are fully exploited. Various studies indicate that time series modeling is appropriate for predicting catches for those fisheries where biological data are lacking (e.g. Mendelssohn, 1981; Freeman and Kirkwood, 1995; Stergiou et al., 1997). In this paper, we study the application of the seasonal autoregressive integrated moving average (ARIMA) model with generalized autoregressive conditional heteroscedasticity (GARCH) errors for four finfish species with voer twenty years of commercial catch data.

Autoregressive integrated moving average (ARIMA) models assume that a time series is a linear combination of its own past values and current and past values of an error term (Box & Jenkins, 1976). They capture the historic autocorrelation of the data and extrapolate them into the future. In classical ARIMA time series models, the conditional variance is assumed to be a constant, however, this may not be a sensible assumption in practice. Among the models which take this into consideration, the generalized autoregressive conditional heteroscedasticity (GARCH) models are both popular and useful (Bollerslev, 1986). Definitions for these models will be given in the next section.

Commercial fishermen are required by the Western Australian Department of Fisheries to report their monthly catch under the Fish Resources Management Act (1994) regulations. The data are entered into the Catch and Effort Statistics (CAES) System held in the research division of the department. Monthly catch data for four finfish species since 1976 were obtained from the CAES system for this study. They are King George whiting (*Sillaginodes punctata*), red emperor (*Lutjanus sebae*), sea mullet (*Mugil cephalus*) and yellow-eye mullet (*Aldrichetta forsteri*).

King George whiting (*Sillaginodes punctata*) are popular recreational fish as well as targeted fish for some small fisheries located around Albany and Bunbury (Figure 9.1). They inhabit shallow inner continental shelf waters, including bays and inlets (Jones et al., 1990). In 1998, the total commercial catch in Western Australia was the highest for last 25 years. Since then, the commercial catch has gradually decreased.

Red emperor (*Lutjanus sebae*) are demersal fish inhabiting tropical and subtropical waters. They can be found in waters from Shark Bay to the W.A./Northern Territory border (Figure 9.1). They are the dominant sea perch taken in the commercial trap fishery around this area (Moran et al., 1988). The catch of red emperor increased rapidly in the early 90's and has gradually decreased from 1996 onwards. This decrease was due to the introduction of a management plan which aims to reduce the commercial fishing effort, however, recreational fishing pressure has continued to increase.

Sea mullet (*Mugil cephalus*) are pelagic fish found in coastal bays and estuaries. They occasionally venture into freshwater and are common from Port Hedland to Esperance in Western Australia (Figure 1). They are caught throughout the year in estuaries, but the highest catches occur in late summer and autumn when movement of mature fish through the estuaries is greatest (Thomson, 1950). There was a trend of slow depletion in the commercial catch for recent years which may relate to the decrease in fishing effort and market demands.

Yellow-eye mullet (*Aldrichetta forsteri*) are schooling fish inhabiting bays, estuaries and open coastlines, from Shark Bay to the southern coast in Western Australia (Figure 9.1). They have been sold traditionally as rock lobster bait. As there are now other bait sources being used, the demand for yellow-eye mullet has gradually decreased (Lenanton et al., 1984). Therefore the commercial fishery has decreased. On the other hand, the species has become more popular for recreational fishing.

9.3 Methods

A hierarchical approach will be used to fit a seasonal ARIMA model with GARCH errors to the time series of the mentioned finfish species. Firstly, the data will be fitted with a seasonal ARIMA model. Then the resulting residuals will be modeled by a GARCH model if necessary. The estimated values using GARCH model will be compared with the predictions from the seasonal ARIMA model.

The appropriate model is identified by examining the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the time series. Model selection can also based on the minimization of the Akaike information criterion (AIC) (Akaike, 1974) and bias-corrected version of the Akaike information criterion (AICc) (Hurvich & Tsai, 1989). If the resulting residuals are found to be volatile with time then a GARCH model can be applied to smoothen the conditional variance and provide better predictions. We often regard this phenomenon as "GARCH effect".

Definition 9.1. Autoregressive integrated moving average (ARIMA) model

Let $\{X_t\}$ be a set of observations X_t, each one being related to a specific time t. The set $\{X_t\}$ is referred as a time series. If d is a nonnegative integer, then the time series $\{X_t\}$ is an ARIMA (p,d,q) process if $\{X_t\}$ satisfies a difference equation of the form

$$\phi(B)(1-B)^d X_t = \theta(B)Z_t, \qquad \{Z_t\} \sim \mathrm{N}(0,\sigma^2),$$

where p, q are positive integers, $\phi(\cdot)$ and $\theta(\cdot)$ are the p^{th} and q^{th} degree polynomials, $\phi(z) = 1 - \phi_1 z - \cdots - \phi_p z^p$ and $\theta(z) = 1 + \theta_1 z + \cdots + \theta_q z^q$ and B is the backward shift operator $(B^j X_t = X_{t-j}, B^j Z_t = Z_{t-j}, j = 0, \pm 1, \cdots)$. Z_t is the error term. The parameters $\phi_1, \ldots, \phi_p$ are the autoregressive coefficients, and the parameters $\theta_1, \ldots, \theta_q$ are the moving-average coefficients. d is the degree of differencing required to achieve stationarity.

Definition 9.2. Seasonal ARIMA model

If d and D are nonnegative integers, then the time series $\{X_t\}$ is a seasonal ARIMA$(p,d,q)\times(P,D,Q)_s$ process with period s if the (differenced) series $Y_t = (1-B)^d (1-B^s)^D X_t$ satisfies a difference equation of the form

$$\phi(B)\Phi(B^s)Y_t = \theta(B)\Theta(B^s)Z_t, \qquad \{Z_t\} \sim \mathrm{N}(0,\sigma^2),$$

where $\phi(z) = 1 - \phi_1 z - \cdots - \phi_p z^p$, $\Phi(z) = 1 - \Phi_1 z - \cdots - \Phi_P z^P$, $\theta(z) = 1 + \theta_1 z + \cdots + \theta_q z^q$ and $\Theta(z) = 1 + \Theta_1 z + \cdots + \Theta_Q z^Q$. The parameters $\Phi_1, \ldots, \Phi_P$ are the seasonal autoregressive coefficients, and the parameters $\Theta_1, \ldots, \Theta_Q$ are the seasonal moving average coefficients.

Definition 9.3. GARCH model - Modeling volatility

The generalized autoregressive conditional heteroscedasticity GARCH (m,n) process $\{X_t\}$ is a solution of the equations

$$X_t = \sigma_t Z_t, \quad \{Z_t\} \sim \mathrm{NID}(0,1)$$

where σ_t is the function of $\{X_s, s < t\}$, defined by

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i X^2{}_{t-i} + \sum_{j=1}^{m} \beta_j \sigma^2{}_{t-j},$$

with $\alpha_0 > 0$ and $\alpha_j, \beta_j \geq 0,\ j = 1,2,\ldots$.

Checking model accuracy

There are several methods to validate an ARIMA model, such as examining the autocorrelation function of the estimated residuals, calculating the Ljung-Box portmanteau statistic Q (Ljung and Box, 1978) for the estimated residuals which is defined by

$$Q = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\gamma}^2(k),$$

where K is the number of lags, n is the number of observations used to compute the likelihood and $\hat{\gamma}(k)$ is the autocorrelation of the data at lag *k*. If the correct ARIMA model is fit, and the data are Gaussian, then Q is approximately distributed as a chi-squared χ^2 random variable with K degrees of freedom.

The existence of "GARCH effect' can be checked with the McLeod-Li test statistic for the squared estimated residuals (McLeod and Li, 1983). The McLeod-Li test statistic $\tilde{Q}$ is defined by

$$\tilde{Q} = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\rho}^2(k),$$

where K is the number of lags, n is the number of observations used to compute the likelihood and $\hat{\rho}(k)$ is the autocorrelation of the squared data at lag *k*. The hypothesis of IID normal data is then rejected at level $\alpha = 0.05$ if $\tilde{Q}$ is larger than the 0.95 quantile of the chi-squared distribution with K degrees of freedom. In other words, the "GARCH effect" exists if the *p*-value of $\tilde{Q}$ is significant at level $\alpha = 0.05$.

9.4 Results

King George Whiting

There was a seasonal pattern in the catch time series with the peak at April in each year. The data was first fitted with a seasonal ARIMA $(1,1,1)\times(1,1,1)_{12}$ model which was identified by the AIC and AICc criteria. The estimated parameters were $\phi_1 = 5.05\times10^{-1}$, $\theta_1 = 8.95\times10^{-1}$, $\Phi_1 = 6.70\times10^{-2}$ and $\Theta_1 = 8.94\times10^{-1}$. The Ljung-Box portmanteau statistic $Q = 19.04$ $(p = 0.52)$ indicated that the selected model was appropriate for the data. The McLeod-Li statistic $\tilde{Q} = 19.65$ $(p = 0.47)$ indicated that the "GARCH effect" did not exist. The plot of the estimated residuals showed a random pattern. Hence, the conditional variance could be assumed as a constant and further modeling on the noise was not necessary. The fitted and predicted catch values are shown in Figure 9.2. About 96% of the real monthly catches for 1999 & 2000 lay within the 95% confidence interval (Figure 9.3).

Red emperor

There was a seasonal pattern in the catch time series with the peak around August in each year. The commercial catch increased rapidly from an average of 10 tonnes in 1988 to 50 tonnes in 1996, but was gradually decreasing after 1996. This was due to the reduction of commercial fishing effort for the purpose of fish stock control. A seasonal ARIMA $(2,1,1)\times(2,1,1)_{12}$ model was selected to fit the data. The estimated parameters were $\phi_1 = 4.02\times10^{-1}$, $\phi_2 = -7.10\times10^{-2}$, $\theta_1 = 8.27\times10^{-1}$, $\Phi_1 = -1.94\times10^{-1}$, $\Phi_2 = -2.30\times10^{-1}$ and $\Theta_1 = 5.20\times10^{-1}$. The Ljung-Box portmanteau statistic $Q = 15.75$ $(p = 0.73)$ indicated that the selected model was appropriate for the data. The fitted and predicted catch values are shown in Figure 9.2. The McLeod-Li statistic $\tilde{Q} = 1.08\times10^{2}$ $(p = 4.24\times10^{-14})$ indicated that there exist the "GARCH effect". The estimated residuals were found to be gradually increasing with time. Hence, a GARCH $(1,1)$ model was selected by AIC to fit the estimated residuals. The resulting parameter values were $\alpha_0 = 1.85\times10^{6}$ $(p = 0.004)$, $\alpha_1 = 1.20\times10^{-1}$ $(p = 0.001)$ and $\beta_1 = 8.32\times10^{-1}$ $(p = 0.00)$. Predictions for 1999 & 2000 are shown in Figure 9.3. These predictions obtained by using the GARCH model were similar to those using only the seasonal ARIMA model. The Q statistic for the estimated standard residuals and the $\tilde{Q}$ statistic for the squared standardized residuals were 5.98 $(p = 0.92)$ and 8.31 $(p = 0.76)$. These results showed that the selected GARCH model was appropriate for the data. About 98% of the real monthly catches for 1999 & 2000 lay within the 95% confidence interval (Figure 9.3).

Sea mullet

There was a seasonal pattern in the catch time series where most of the catch was taken in winter. There was also a trend of slow depletion which might be related to the decrease in commercial fishing effort, or to the number of fishermen. The data was first fitted with a seasonal ARIMA $(1,1,1)\times(0,1,1)_{12}$ model. The estimated parameters were $\phi_1 = 5.01\times10^{-1}$, $\theta_1 = 9.85\times10^{-1}$ and $\Theta_1 = 8.14\times10^{-1}$. The Ljung-Box portmanteau statistic $Q = 24.14$ $(p = 0.06)$ indicated that the selected model was appropriate. The fitted and predicted catch values are shown in Figure 9.2. The McLeod-Li statistic $\tilde{Q} = 43.92$ $(p = 1.12\times10^{-4})$ indicated that there exist the "GARCH effect". The estimated residuals were found to be gradually decreasing with time. Hence, a GARCH $(1,1)$ model was selected by AIC to fit the estimated residuals. The resulting parameter values were $\alpha_0 = 2.30 \times 10^6$ $(p = 0.22)$, $\alpha_1 = 7.01 \times 10^{-2}$ $(p = 0.03)$ and $\beta_1 = 9.10 \times 10^{-1}$ $(p = 0.00)$. Predictions for 1999 & 2000 are shown in Figure 9.3. Better predictions for months with low catch in a year were obtained by applying the GARCH model. The Q statistic for the estimated standard residuals and the $\tilde{Q}$ statistic for the squared standardized residuals were 9.07 $(p = 0.69)$ and 16.81 $(p = 0.16)$. This showed the selected GARCH model was appropriate. About 88% of the actual monthly catches for 1999 & 2000 lay within the 95% confidence interval (Figure 9.3).

Yellow-eye mullet

In general, there was a seasonal pattern in the catch time series. Most of the catch was taken in winter. The catch has been following a decreasing trend since 1976, along with the number of commercial fishermen. The data was first fitted with a seasonal ARIMA $(3,0,0)\times(1,1,1)_{12}$ model. The estimated parameters were $\phi_1 = 6.77 \times 10^{-1}$, $\phi_2 = 1.81 \times 10^{-1}$, $\phi_3 = -1.68 \times 10^{-1}$, $\Phi_1 = -9.70 \times 10^{-2}$ and $\Theta_1 = 7.10 \times 10^{-1}$. The Ljung-Box portmanteau statistic $Q = 10.95$ $(p = 0.95)$ indicated that the selected model was appropriate. The fitted and predicted catch values are shown in Figure 9.2. The McLeod-Li statistic $\tilde{Q} = 6.66 \times 10^1$ $(p = 6.42 \times 10^{-7})$ indicated that there exist the "GARCH effect". The estimated residuals were found to be gradually decreasing with time. Hence, a GARCH $(1,1)$ model was fitted to the estimated residuals. The resulting parameters' values were $\alpha_0 = 1.27 \times 10^6$ $(p = 0.19)$, $\alpha_1 = 5.03 \times 10^{-2}$ $(p = 0.06)$ and $\beta_1 = 9.34 \times 10^{-1}$ $(p = 0.00)$. Predictions for 1999 & 2000 are shown in Figure 9.3. The GARCH model had improved the predictions for most of the months with low catch. The Q statistic for the estimated standard residuals and the $\tilde{Q}$ statistic for the squared standardized residuals were 8.88 $(p = 0.71)$ and 9.57 $(p = 0.65)$. The selected GARCH model was appropriate. About 92% of the actual monthly catches for 1999 & 2000 lay within the 95% confidence interval (Figure 3).

9.5 Discussion

In this study, the commercial catch history of the four species over twenty years was used to predict the catch of two consecutive years. The method of modeling time series of catch data in a hierarchical approach was found to be the most satisfactory for sea mullet and yellow-eye mullet. As the conditional variance of the model is found to be volatile with time for these two species, the GARCH model has well addressed this phenomenon. It is reasonable to use the past history as basis for prediction because of the steady decreasing trend in the time series and the slowly diminishing noise.

The time series for red emperor has reflected a common scenario in commercial fisheries. The species was targeted by some commercial fisheries in recent years and its stocks were found to be fully exploited. This led to the introduction of management controls on fishing effort and the number of commercial fishers. The effect is clearly shown in the time series. Fishing effort was down in 1998 in response to the introduction of management controls for red emperor. The models have addressed this change and give good predictions. The GARCH model made no great impact on the predictions in this case due to this unexpected change.

Similar situation in reverse occurred for King George whiting in 1998. The catches were steadily decreasing prior to 1997. A sudden jump happened in 1998 and the catch fell down again from 1999. This very high 1998 catches resulted from high juvenile recruitment into

Wilson Inlet several years earlier (Penn et al. 2000; pp87-89). The seasonal ARIMA model has addressed this change and gives good predictions. The volatility of the time series was found to be not significant.

There are several other factors which many fishermen and biologists think have of strong impact on the catch rates, for example, fishing effort, fishing power and weather. However, these relevant biological and environmental data are very difficult to record properly and precisely. They are also expensive to collect evaluate, however, when they are available, these factors can be added to the ARIMA model as a transfer function. Moreover, it can be observed that some of the time series of finfish species exhibit long memory time series properties. Long memory time series modeling could be used to examine finfish data. Also, the optimization for forecasting the catch is to model both the seasonal ARIMA part and the GARCH part together as one step instead of in a hierarchical approach as in this study. Further study using different types of GARCH models could be done. Multivariate time series modeling could be explored to study the relationship among different species in the same region.

9.6 Acknowledgements

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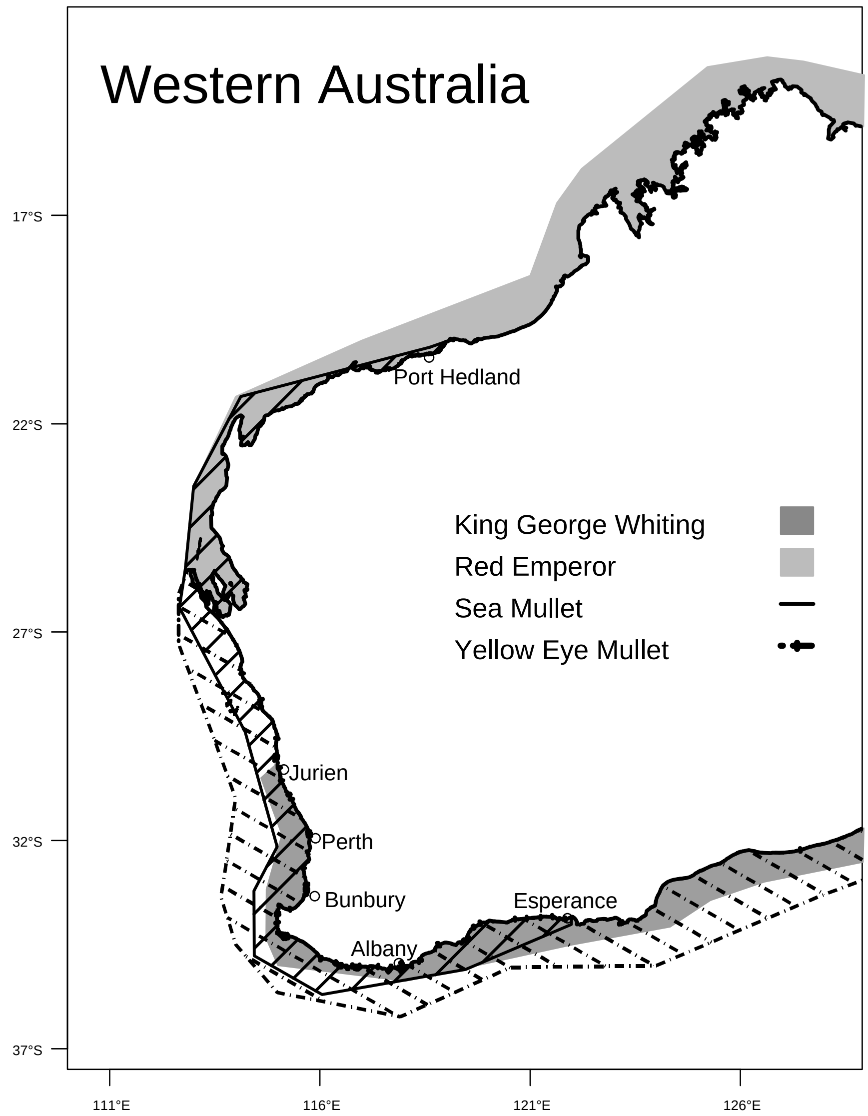

Figure 9.1. Geographic distribution of the four species in Western Australia

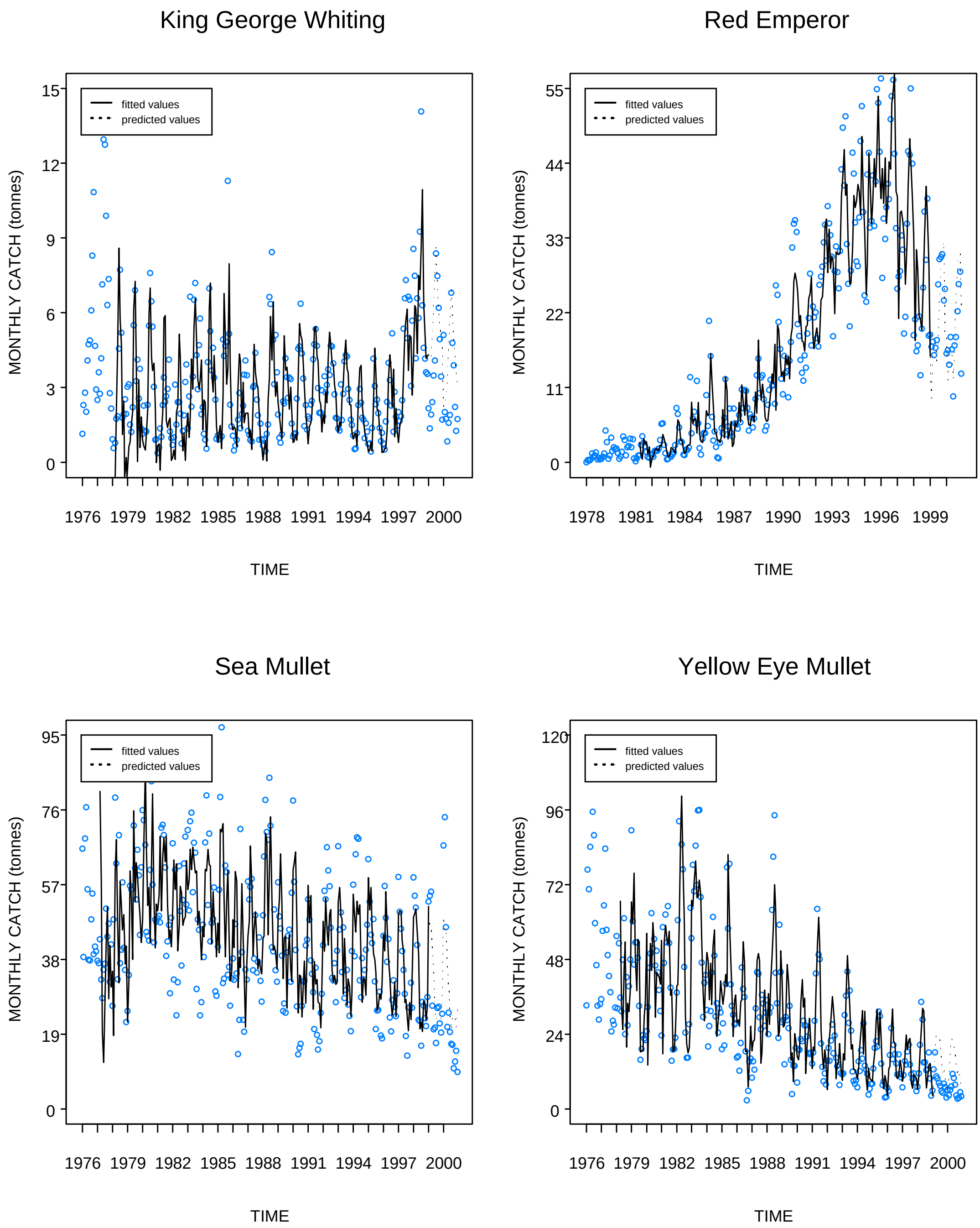

Figure 9.2. Graphical presentation of the fitted and predicted monthly catch values from a seasonal ARIMA model for the four finfish species time series over the last 25 years.

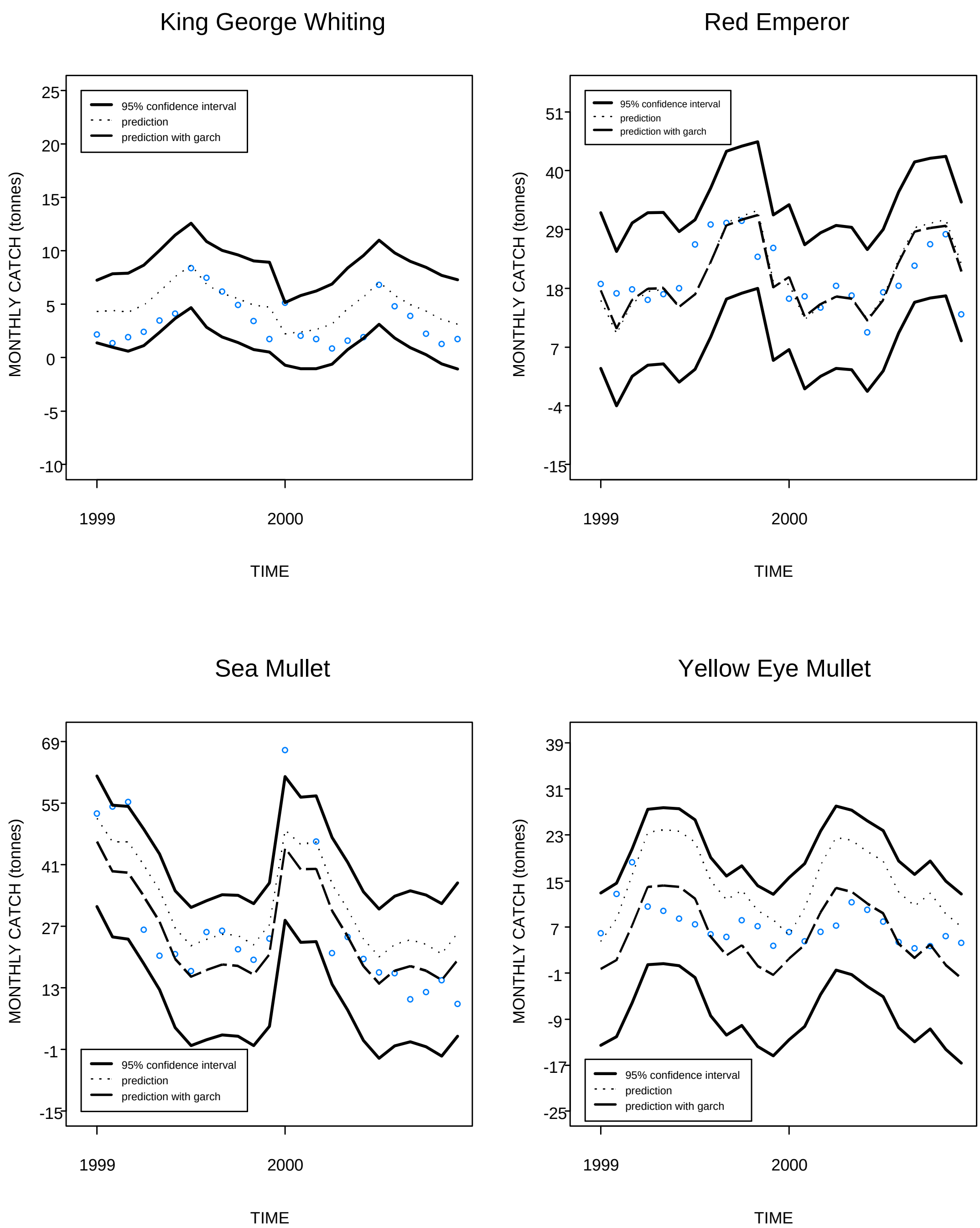

Figure 9.3. Graphical presentation of the predicted monthly catch values for 1999 & 2000 from a seasonal ARIMA model with or without GARCH errors for the four finfish species time series.

10.0 A dynamical reconstruction of monthly and annual catch prediction indices for five key Western Australian finfish fisheries

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10.1 Abstract

Much of the biological information that affects catches for many Western Australian fisheries is difficult and expensive to collect. Alternative methodologies are required to explain variations in catches from year to year and to make reliable forecasts. In this paper, dynamical spawning indices are statistically developed by nonlinear regression techniques using catch rates, environmental data and fishing effort to predict annual catches for five finfish fisheries of Western Australia. The results indicate that multiplicative interactions involving some or all of these factors significantly contribute to annual catch variations. The statistically significant factors closely resemble the biological characteristics of each of the five fisheries. Seasonal ARIMA transfer function models using the annual spawning indices are developed to predict monthly catches. To validate the respective annual regression and monthly catch models, the last three available years of catches (1998-2000) are forecasted and compared with the actual catches for each species.

10.2 Introduction

One of the main concerns surrounding the modelling of fish populations is the absence of useful spawning or recruitment index data. It is a very difficult and expensive exercise to obtain and maintain reliable, real-time spawning or juvenile recruitment data for one or many species. The emphasis in this paper is the development of biology-based catch prediction indices using the existing monthly catch and fishing effort time series data of selected fisheries. The advantage of these techniques is that at least 25 years of data is available for most commercial fisheries off the Western Australian coast. Reliable catch prediction indices are necessary for stock assessment purposes since they provide much of the information on the status of the population at a given time. Information on global environmental effects is known to improve the indices for Western Australian fisheries (Lenanton et al. 1991, Caputi et al. 1996). This paper makes use of the Fremantle Sea Level indicator of the Leeuwin Current following the aforementioned papers, but also reveals the significance of the Southern Oscillation Index. Use of these historical indices allows the forecasting of catches into the future with a measurable degree of accuracy.

We present an alternative to biological collector problems in the form of a dynamical reconstruction of spawning data for five major finfish populations. These species are Australian herring (*Arripis georgiana*), western Australian salmon (*Arripis truttacea*), pilchards (*Sardinops sagax*), Spanish mackerel (*Scomberomorus commerson*) and Westralian dhufish (*Glaucosoma hebraicum*). Our findings are that catch rate estimates during specific months can signify a pattern of spawning activity and indicate trends in juvenile stocks over the long term. The variation in catch rates in a given month for different years coupled with information on global environmental effects during the first year of development of the species may indicate a similar variation in abundance and therefore catches *n* years later, where n is approximately the age at catch of the fish species. There are many factors influencing the biological processes between spawning and catch. However, we demonstrate that monthly catch rate estimates combined with a single global environmental variable are sufficient to capture a large amount of time series predictor information on the annual catch for the selected fisheries.

The data used in this analysis consist of Western Australian commercial catches by weight and fishing effort in boat days per boat. The commercial data from June 1975 to December 2000 have been extracted from the Catch and Effort System (CAES) of the Department of Fisheries, Western Australia. A brief description of the five commercial fisheries is given below.

Australian herring
Australian herring catches in Western Australia for 1999 totalled 765 tonnes, with 642 tonnes being caught on the south coast. The estimated annual value for this season for only the south coast fisheries was $260 000. Approximately 86% of the total Australian herring catch from WA is taken off the south coast. The main fishing methods include the use of trap ('G') nets and beach seines. Catches are highly seasonal and peak when the south coast trap net fishery catches fish during their spawning migration to the lower west coast of Western Australia between March and April. The fishery is open all year except from February to late March.

Western Australian salmon
For 1999, Western Australian salmon catches totalled 1725 tonnes for an estimated value of $827 000. Approximately 77% of the total WA salmon catch is taken off the south coast. Beach seining is the main fishing method. Catches peak between February and April each year as the salmon make a pre-spawning migration from eastern to western Australia. There are two managed salmon fisheries. The south coast managed fishery permits authorised licence holders to fish from specific beaches between Shoal Cape and Cape Beaufort. The south west coast managed fishery operates north of Cape Beaufort along specific beaches through a sharing arrangement of netting.

Spanish mackerel
The total catch of Spanish mackerel in Western Australia for 1999 was 336 tonnes to the value of $1.75 million. The main method of fishing is trolling. Spanish mackerel can be found mostly in the northern waters of Western Australia. Annual catches rose slowly between 1978 and 1990, but the entry of two main present-day operators increased catches in the Kimberley region by over 110 tonnes from 1991 onwards. The Western Australian Spanish mackerel fishery is controlled by allowing access to the fishery by licensed fishers only.

Pilchards
The largest pilchard fisheries in Australia are located off Fremantle, in King George Sound and surrounding Albany and Bremer Bay. The bulk of catches occurs in winter. However, the impact of mass mortality events in 1998/99, probably due to herpesvirus (Gaughan et al. 2000), has led to large-scale reductions in stock size and catches in Western Australia. Catches for the calendar year 2000 totalled only 932 tonnes to the value of approximately $900 000, compared with a mean of 8750 million tonnes during 1988-1997. Purse seine nets are the main fishing gear used to target pilchards. The distribution of schools of pilchards extends from Red Bluff on the west coast southward across the Great Australian Bight. The management controlling processes are complicated, including limited entry schemes,

additional controls on boat and net sizes, limited licences, and individually transferable quotas. Total allowable catches are imposed on developing fishery regions.

Westralian dhufish

The main methods of commercial fishing are bottom set gillnets, droplines, bottom set longlines and handlines. Peak catches generally occur between December and February, coinciding with the main spawning period. The catches are taken off the Western Australian coast from Bremer Bay northward to Shark Bay with the bulk coming from the mid-west region of Geraldton. The commercial catch for the 1999/2000 season totalled 207 tonnes with an estimated value of $1.6 million. The only commercial restriction is a legal minimum total length of 500mm.

Predictions of annual fish catches for the five species listed above involve nonlinear regression models developed from fisheries science theory. Seasonal autoregressive integrated moving average transfer function models are used to model monthly catches. The transfer function component incorporates the annual expression. Three years of forecasts are then made for each fishery and compared with the actual catch data for validation purposes.

10.3 Methods

Following the methodology of DeLury (1947, 1951; see Ricker 1975), a theoretical catch-abundance-effort equation for a single species is

$$\frac{dC_T}{dE_T} = qN_T \exp(-qE_T), \tag{1}$$

where T is time in years, N_T is the abundance subject to fishing and $\exp(-q)$ is the probability of survival of a fish for one boat day of fishing effort. Solving (1) gives

$$C_T = N_T(1-\exp(-qE_T)). \tag{2}$$

The estimation of q in (2) is usually difficult because numerical schemes such as the Gauss-Newton method may not converge. A very good initial condition is required, however this is usually difficult to find. We therefore approximate the catchability function

$$u(E_T;q) = (1-\exp(-qE_T)) \tag{3}$$

by a second order analytic approximation of the form

$$\tilde{u}(E_T;q) = qE_t \exp\left(-\frac{1}{2}qE_T + \frac{1}{24}(qE_T)^2\right). \tag{4}$$

It turns out that (4) is also a third order approximation, and we assume that qE_T is small. The estimation of q in (4) is significantly easier. At the same time, (3) and (4) differ only by fourth order in qE_T. The annual model used in this paper is therefore a stochastic form of the following deterministic equation.

$$C_T = N_T\ \tilde{u}(E_T;q). \tag{5}$$

In general, N_T is unknown. In the simplest case, $N_T q$ may be replaced by a time-independent parameter to be estimated. Then for some fisheries, the estimate of q in (5) may not be significantly different from zero. In these cases, (5) becomes a linear regression of catch against effort. Thus, annual catch per unit effort (CPUE) may be a reliable indication of abundance within the ranges of the data series. Catch and effort are related in a nonlinear way if q is nonzero.

There are two components in (5), namely abundance N_T and catchability $\tilde{u}(E_T;q)$. Catchability was expressed in (4). Abundance is estimated by calculating monthly catch rates for the specific months that significantly contribute to variation in (5). There may be more than one month that contributes to variation in catch. Combining two or more months may be a difficult modelling procedure. Such methods are not included in this paper, so only one month is included in the model. Catch also comprises a distribution of age classes of the species, so there may be several significant time lags, say $l_1, l_2, \ldots, l_s$. The catch rates are weighted over significant age classes in the form of linear combinations. An appropriate mortality function f is multiplied into the model to account for mortality from the juvenile recruitment stage until catch. A multiplicative function g of a suitable environmental index may be a significant factor in determining abundance. A deterministic model of catch incorporating these variables is thus

$$C_T = \exp(a)\ f\left[\sum_{i=1}^{s} \alpha_i\ g\left(V_{T-l_i};\omega\right)\frac{C_{M,T-l_i}}{\tilde{u}\left(E_{M,T-l_i};q_M\right)};b\right]\tilde{u}\left(E_T;q\right), \qquad (6)$$

where l is the time lag between spawning and catch, C_M, E_M and q_M are monthly catches, monthly fishing effort and a monthly catchability coefficient, respectively. Parameters to be estimated are $a, \alpha_1, \alpha_2, \ldots, \alpha_s, b, q_M, \omega$ and q, where the α_i's sum to one and are estimated by reparameterisation into hyper-spherical coordinates $\{\varphi_1, \varphi_2, \ldots, \varphi_{s-1}\}$. The parameters are estimated by nonlinear regression of the natural logarithms of each side of (6) and by assuming additive normally distributed error terms, viz.

$$\log C_T = a + \log f\left[\sum_{i=1}^{s} \alpha_i\ g\left(V_{T-l_i};\omega\right)\frac{C_{M,T-l_i}}{\tilde{u}\left(E_{M,T-l_i};q_M\right)};b\right] + \log\tilde{u}\left(E_T;q\right) + \varepsilon_T\,. \qquad (7)$$

The logarithmic transformation assumes that the deviation of the catch data is proportional to its expected value. This transformation is used to reduce bias that may be caused by outliers in the regression process. Selection of feasible parameters is based on partial likelihood ratio tests, where $\varepsilon_T \sim N\left(0,\sigma^2\right)$. The month M is selected by maximizing the likelihood function.

V_T defines a suitable environmental variable which we choose from either the Southern Oscillation Index (SOI) or the Fremantle Sea Level (FSL). For the given fisheries, our assumption is that fish in their egg/larval or early juvenile stage are more vulnerable, and thus more sensitive, to environmental factors than for the later stage of their lives. We therefore assume that a large proportion of the mortality effects due to environmental influences occur over the first year of life, on average, so the SOI and FSL data are calculated as one-year moving averages of the raw monthly series.

The function *f* is defined as follows:

$$f(x;b)=\frac{x}{bx+1}. \qquad (8)$$

Thus, f is chosen to be the more parsimonious function between the Beverton-Holt specification if there is significant density dependent mortality, or the identity (if $b=0$) if there is insufficient evidence of density dependent effects. For purposes of simplicity, we restrict the function *g* in (7) to the exponential function, viz.

$$g(x;\omega)=\exp(\omega x), \qquad (9)$$

or the identity if the parameter ω does not significantly differ from zero. The parameter ω indicates the strength of the environmental effect on survival of the species.

The linear combination of the catch rate-environmental terms in (7) is similar to an age-class description of the fishery. However, (7) assumes that the mortality function *f* is statistically the same for all l_i's. In most cases, $s \leq 2$ so this assumption is adequate. In summary, the data used to predict annual catches in (7) include annual fishing effort, catch rates for a specific month and an environmental variable.

For each fishery, the monthly catches c_t are predicted using SARIMAX models.

$$\Phi_1\left(B^{12}\right)\phi_1(B)\nabla_{12}^{D_1}\nabla^{d_1}\left(\frac{c_t}{\bar{c}}-1\right)=\Theta_1\left(B^{12}\right)\theta_1(B)\varepsilon_{1t}, \qquad (10)$$

In (10), B is the backward difference operator defined by $B(\cdot_t)=\cdot_{t-1}$, and $\nabla = I - B$ and $\nabla_{12} = I - B^{12}$ are nonseasonal and seasonal differencing operators. Φ_1 and ϕ_1 are seasonal and nonseasonal autoregressive polynomials, respectively, Θ_1 and θ_1 are seasonal and nonseasonal moving average polynomials, D_1 and d_1 are nonnegative integers, and $\varepsilon_{1t} \sim N\left(0,\sigma_1^2\right)$. The seasonal ARIMA (SARIMA) component is optimized by minimization of the AICc statistic (Hurvich and Tsai 1989), which is a small-sample bias correction of the AIC statistic (Akaike 1974). Stationarity and invertibility conditions are verified for each optimal model.

The transfer function for the SARIMAX model is the annual index defined by (7) with the same estimated parameter values repeated for each month of the designated fishing season. For the fisheries where the transfer function component significantly improves the monthly catch model, the SARIMAX model that is estimated is of the following form:

$$\Phi_2\left(B^{12}\right)\phi_2(B)\nabla_{12}^{D_2}\nabla^{d_2}\left[c_t-\delta\, h\left(E_T,V_T,C_{M,T},E_{M,T};\hat{\vartheta}\right)\right]=\Theta_2\left(B^{12}\right)\theta_2(B)\varepsilon_{2t}, \qquad (11)$$

where *h* is the annual index formulation repeated for every month of the given season, viz.

$$h\left(E_T, V_T, C_{M,T}, E_{M,T}; \vartheta\right) = f\left[\sum_{i=1}^{s} \alpha_i g\left(V_{T-l_i}; \omega\right) \frac{C_{M,T-l_i}}{\tilde{u}\left(E_{M,T-l_i}; q_M\right)}; b\right] \tilde{u}\left(E_T; q\right). \qquad (12)$$

$\hat{\vartheta} = \left\{\hat{\varphi}_1, \hat{\varphi}_2, \ldots, \hat{\varphi}_{s-1}, \hat{b}, \hat{q}_M, \hat{\omega}, \hat{q}\right\}$ is the vector of estimated parameters from (7), δ is a parameter to be estimated, Φ_2, ϕ_2, Θ_2 and θ_2 are polynomials, D_2 and d_2 are nonnegative integers, and $\varepsilon_{2t} \sim N\left(0, \sigma_2^2\right)$. Monthly forecasts are made for the next three years using the most parsimonious model chosen from (10) or (11).

10.4 Results

The mackerel and pilchard fisheries are modelled by calendar year (January 1 to December 31), whereas the other three fisheries are modelled by financial year (July 1 to June 30). For each fishery, the choice between calendar or financial year was made by separating the fishing seasons according to where the annual troughs in catchability occurred, on average. The results for each fishery governed by models (7), (10) and (11) are summarized in Tables 10.1, 10.2 and 10.3. These results are explained below for each fishery.

Australian herring

The analysis of the annual catch rate estimates suggests that 5 to 6 year old Australian herring females produce more offspring than any other pair of consecutive age classes, on average. The lags associated with the Southern Oscillation Index are 2 or 3, indicating that A. herring are predominantly 2 to 3 years of age at catch. The SOI parameter is positive, meaning that warmer water temperatures off the coast of Western Australia are more favourable for survival of A. herring than colder water temperatures. This is one species of the five studied where catches do not appear to depend on fishing effort. October catch rates correlate the highest with annual catches. The data for the month of October is describing the spatial movements of spawning fish better than the data from other months, since herring can be found in many south coast estuaries only in October. February catch rates also correlated significantly with annual catches but not to the degree that October catch rates did. This is probably because the south coast A. herring fishery comprises over 80% of the total catch, on average.

Seasonal ARIMA models did not fit the monthly data well. This is because there are a couple of months of high catches (usually March and April) with relatively little caught between. Instead, we aggregated the monthly catch and effort data into four seasonal groups, namely i) July to February, ii) March, iii) April and iv) May and June. The time series models were then fitted in the usual way to this data. A $\text{SARIMA}(0,1,1)_4$ model was optimal by AICc (see Table 10.3). The seasonal moving average parameter is given in Table 4. The seasonal ARIMAX model proved very reliable, with the actual catches from 1997/98 to 1999/2000 falling within the 95% confidence intervals.

Western Australian salmon

For the annual model, estimates for age of maturity and age at catch are one year older for western Australian salmon than for A. herring. The parameter indicating the strength of the FSL oscillator on catches was negative. It is stated in State of the Fisheries 1999/2000 that "with respect to the south west salmon managed fishery, warmer waters are believed to deter a significant quantity of salmon from migrating around to the west coast". Our statistical observation is that there is a stronger effect of the FSL indicator than the SOI oscillator on catches. Thus, for years when the Leeuwin current is strong, there may be a restriction of northward migration of WA salmon from the south coast to the west coast of Western Australia. April is posited as the primary spawning month for WA salmon.

Similar to the herring data, problems were encountered when attempting to fit a SARIMA model to the monthly catch data. The monthly catch and fishing effort data were aggregated in the same way as for the herring fishery. The seasonal ARIMA model that best fit the salmon catch data was $\text{SARIMA}\,(1,0,0)\times(1,1,0)_4$. The transfer function was marginally significant (see Table 10.3), so the exogenous component was included for forecasting purposes. The catch forecasts from 1997/98 to 1999/2000 were not as reliable as for the herring fishery. While the forecasts showed a decrease in catches for the 1998/99 and 1999/2000 seasons, the 1998/99 catch was over-predicted. This is mainly due to the irregular catching patterns from year to year in the salmon industry. For example, the month of high catches occurred later in 2000 than in 1998 and 1999. Warmer waters and/or a southward flowing current in 1998/99 and 1999/2000 most likely deterred the salmon from migrating around to the west coast.

Spanish mackerel

Our estimates of age at catch and age at maturity are 2 to 3 years. This coincides with the primary age classes of Spanish mackerel. The estimated SOI recruitment parameter is positive and the stock is known to prefer warmer waters. Catches are taken north of $28°$S latitude. Little is known about the spawning behaviour of Spanish mackerel. October catch rate estimates correlate best with annual catch.

Based on the AICc criterion, the optimal model was $\text{SARIMA}\,(1,0,0)\times(1,1,2)_{12}$. The transfer function component of the SARIMAX model proved insignificant, so it was not used in the forecasting procedure. The SARIMA model was reliable, producing 33 out of 36 monthly catch forecasts from 1998 to 2000 inside the 95% confidence intervals.

Pilchards

Fishing effort did not improve the model of pilchard catches. Our age at catch estimates include the 2 to 3 year range. Catches are known to usually range between 2 and 5 years of age. Our model suggests that maturity is achieved mostly at 3 years of age. Pilchards are known to be mature when caught. The estimated SOI environmental parameter was negative, suggesting the pilchard fishery performs better in colder temperatures. Pilchards prefer mean annual water temperatures of between $9°$ and $21°\text{C}$ and spawning has been recorded only when surface temperatures are between $14°$ and $21°\text{C}$. It is also known that a strong Leeuwin current can push the larvae and juveniles up to 140km per week to the east of Albany (Caputi et al. 1996) to the detriment of the WA fishery.

A $\text{SARIMA}\,(1,1,1)\times(0,1,1)_{12}$ model was optimal for pilchards. Because the mass mortality event for pilchards approximately occurred at the commencement of the forecasting period, the forecasts given by the SARIMAX model gave over-predictions. An intervention term is required and can be calculated using the available data to 2000, but could not be calculated based on the data to 1997.

Westralian dhufish

The fishing effort data used to describe the catch model was given by

$$\tilde{u}(E_T;q)\cdot\exp\left[\omega_2\left(FSL_{T-5}-\overline{FSL}\right)\right],$$

where q and ω_2 were estimated parameters. The correlation between FSL_{T-5} and the residuals of the model fitted with just the $\tilde{u}(E_T;q)$ fishing effort term was found to be -0.91 (see Fig 10.2). The fishing effort is dependent on the western rock lobster industry, since Westralian dhufish fishing licences are predominantly shared with western rock lobster fishing licences. We postulate that FSL_{T-5} is an approximate measure of western rock lobster abundance. If lobsters are highly (lowly) abundant at catch, then there will be less (more) fishing effort applied to dhufish catches. We estimated age at catch is dominated by 6 to 7 year olds. This agrees with the von Bertalanffy growth estimates for ages at legal size. Age at maturity was estimated between 4 and 5 years. The estimated SOI parameter is positive, indicating that dhufish prefer warmer waters. We found that November catch rates when combined with the SOI indicator form reliable predictions. The spawning season is postulated to occur between October and March.

A $\text{SARIMA}(2,0,1)\times(3,0,0)_{12}$ model was optimal. The forecasts show a decrease from 1997/98 to 1999/2000, but the actual catches remained stable. 7 out of 36 points occurred above the upper 95% confidence interval, showing an overall under-prediction of catches during the 1997/98 and 1999/2000 fishing seasons. The reasons for this may include loose management regulations on the fishery and a recent increase in economic demand in dhufish licences.

10.5 Discussion

Monthly catch rates describe temporal and spatial distributional information of fish responsible for spawning. Typically, the month that gives the best estimate of abundance consists of low catch rates following shortly after the peak months of catches. Therefore, monthly catch rates may also reflect remaining biomass information from year to year, which is often represented by the DeLury (1947) depletion experiments for the estimation of fish populations. The methods in this paper are thus applicable if catch at age is not too variable from year to year and there is evidence of seasonal variability in the catches.

The index information is highly significant for the annual specifications described by (7). However, the significance of the annual transfer function is highly variable when applied to the seasonal model (11), depending on the seasonal composition of the fishery. The transfer functions enhance the SARIMA model for Australian herring, pilchards and dhufish, but not for Western Australian salmon nor Spanish mackerel.

The three-year forecasts proved to be helpful for ascertaining the status of the five selected fisheries. The exogenous variables were significant for the monthly catch models for herring, pilchards and dhufish. However they were only marginally significant for salmon and insignificant for Spanish mackerel. It is possible that carefully selected temperature data may be more reliable than the Fremantle Sea Level or Southern Oscillation Index data for these fisheries, thus enhancing the significance of the exogenous components for these and other fisheries.

Other methods such as generalized additive modelling techniques or isotonic regression could be used to semi-parametrically define the functions *f* and *g* in (8) and (9), respectively. These techniques are more appropriate since the theoretical relationships between environmental variables or mortality and catch are not usually known. The model specifications in (7) and (11) would thereby be enhanced.

Further research methods that may improve the monthly prediction and forecasting methods of finfish fisheries include multivariate nonlinear regression and multivariate time series analysis. These techniques may further assist the annual predictions for fisheries with shared licences. For example, the negative correlation between western rock lobster and westralian dhufish catches may be further qualified. Fishing effort for herring and fishing effort for salmon may be analyzed for a negative correlation, although this relationship has never been found to be significant.

10.6 Further Developments

A linear annual relationship between an independently sampled lagged recruitment index for herring interacted with the lagged Southern Oscillation Index (SOI) versus the Melville Angling and Aquatic Club (MAAC) recreational herring catch series from the Swan River affirms the validity of the significant positive correlation effect of the SOI on herring catches in WA. The sampled recruitment index has been constructed from two FRDC projects, calculated as mean catch rates of recruits taken from Warnbro on the west coast and Emu Pt on the south coast from September of each year to August of the subsequent year. The recruitment index is lagged 1-3 years, while the SOI index is lagged 0-1 year. While there is no direct effect of the lagged recruitment index on the MAAC catches for herring (Fig. 10.5), the introduction of the lagged SOI interaction effect provides a significant relationship (Fig. 10.6, $p = 0.039$). Furthermore, the strength of the SOI effect (0.0426) and the corresponding standard error of the ω parameter (0.0167) for the Swan River model are similar to those found in Table 10.1 for commercial herring catches.

10.7 References

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10.8 List of tables

10.9 List of figures

Table 10.1. Annual model specification and estimated parameters for (7) for each fishery.

	Fishing Year	Fishing Effort Function	f	Lag time s	Environmental Variable	Catch rate month M	$\hat{a}$	$\hat{q}$	$\hat{\theta}$	$\hat{b}$	$\hat{q}_M$	$\hat{\omega}$
Herring	Financial	None	Beverton -Holt	5,6	$SOI_{t-2,t-3}$	Oct	16.572 (0.293)		1.190 (0.176)	7.730 (3.885)		0.0382 (0.0187)
Salmon	Financial	$\log E_t$	Beverton -Holt	6,7	$FSL_{t-3,t-4} - \overline{FSL}$	Apr	9.513 (1.836)		0.756 (0.499)	14.09 (27.10)	3.954 (0.577)	-0.300 (0.164)
Spanish mackerel	Calendar	$\log E_t - \frac{q}{2} E_t + \frac{q^2}{24} E_t^2$	Identity	2,3	$SOI_{t-2,t-3}$	Oct	5.957 (0.067)	0.00144 (0.00016)	2.346 (0.078)			0.0346 (0.0090)
Pilchards	Calendar	None	Beverton -Holt	3,4	$SOI_{t-2,t-3}$	Jun	15.889 (0.107)		0.614 (0.112)	0.278 (0.108)		-0.0332 (0.0131)
Dhufish	Financial	$\log E_t - \frac{q}{2} E_t + \frac{q^2}{24} E_t^2$	Beverton -Holt	5	SOI_{t-7} $FSL_{t-5} - \overline{FSL}$	Nov	9.858 (1.165)	0.000467 (0.000005)		248.3 (291.0)		0.2502 (0.0903) -0.00731 (0.00105)

Table 10.2. Annual model calibration.

Species	R^2 for model with fishing effort	R^2 for model with fishing effort, mortality and catch rates	R^2 for full model
Herring	N/A	47.0%	62.5%
Salmon	18.0%	50.2%	73.0%
Spanish mackerel	N/A	47.8%	73.5%
Pilchards	38.6%	92.5%	94.8%
Dhufish	86.1%	93.5%	95.2%

Table 10.3. SARIMA model specification for monthly transfer function time series model for each fishery. The standard error of each transfer function is an asymptotic calculation. The *p*-value of each transfer function is calculated by an *F*-test on the change in variation between the SARIMA model and the SARIMAX model. The change of degrees of freedom for each model equals the number of parameters estimated in (7).

Species	SARIMA Model	Transfer function (s.e.)	Transfer function *p*-value
Herring	$(0,1,1)_4$	0.226 (0.062)	0.020
Salmon	$(1,0,0)\times(1,1,0)_4$	0.451 (0.115)	0.12
Spanish mackerel	$(1,0,0)\times(1,1,2)_{12}$	0.035 (0.014)	0.32
Pilchards	$(1,1,1)\times(0,1,1)_{12}$	0.058 (0.016)	0.016
Dhufish	$(2,0,1)\times(3,0,0)_{12}$	0.082 (0.0004)	$< 1\times10^{-4}$

Table 10.4. SARIMA model (10) parameters for each finfish fishery.

Species	ar1	ar2	ma1	sar1	sar2	sar3	sma1	sma2
Herring							−0.58 (0.11)	
Salmon	0.14 (0.14)			−0.58 (0.11)				
Spanish mackerel	0.44 (0.07)			−0.73 (0.24)			0.14 (0.26)	−0.27 (0.17)
Pilchards	0.42 (0.07)		−0.97 (0.02)				−0.63 (0.06)	
Dhufish	1.11 (0.80)	−0.24 (0.40)	−0.72 (0.78)	0.24 (0.10)	0.12 (0.10)	0.24 (0.11)		

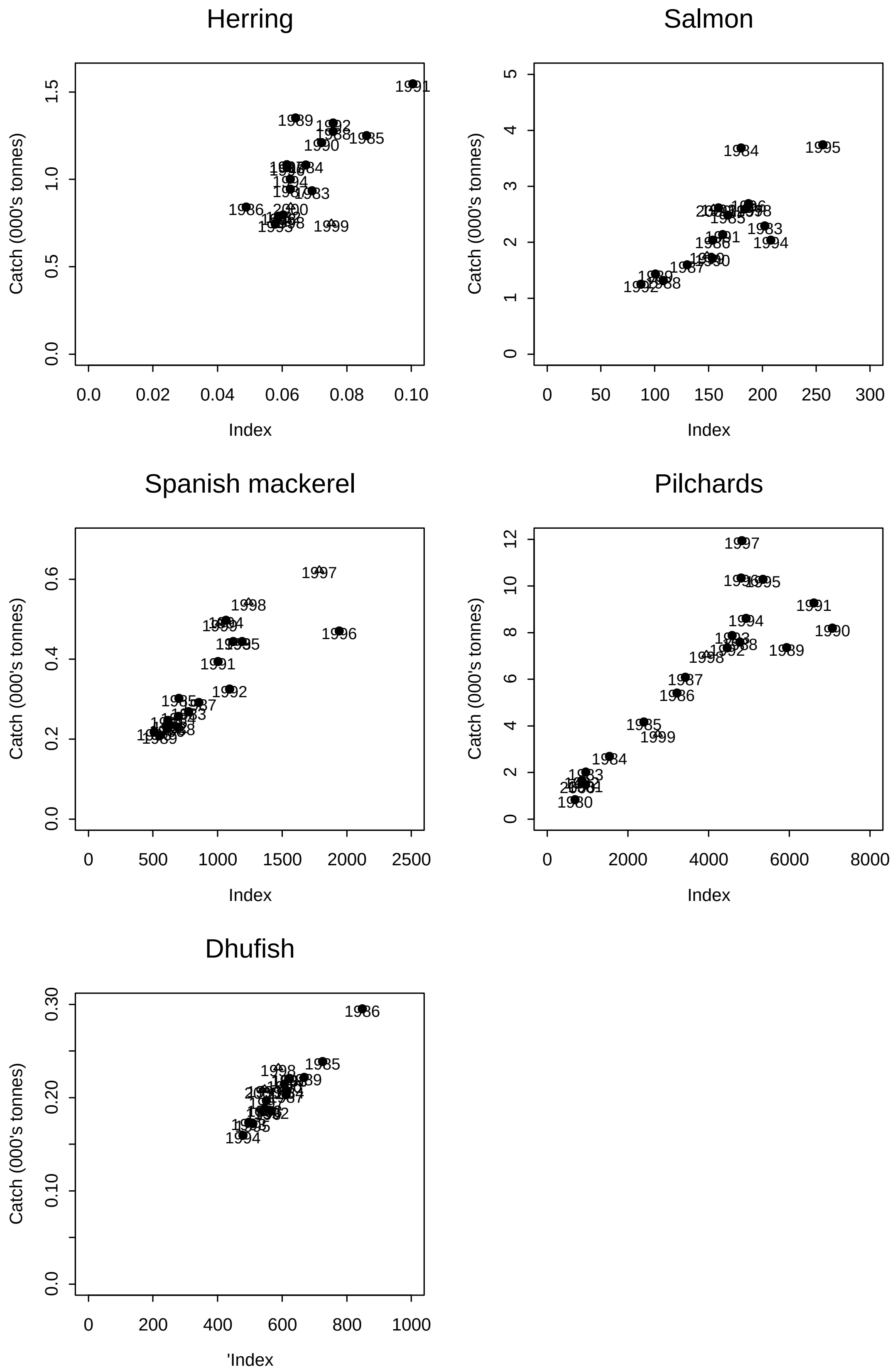

Fig 10.1. Annual catch-index relationship for each fishery with three years of forecasts.

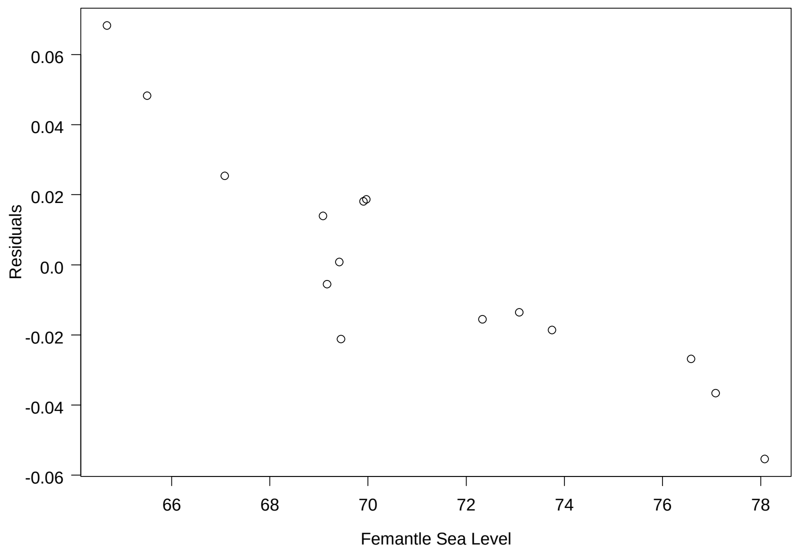

Fig 10.2. Relationship between residuals for dhufish model (7) and Fremantle Sea Level lagged 5 years.

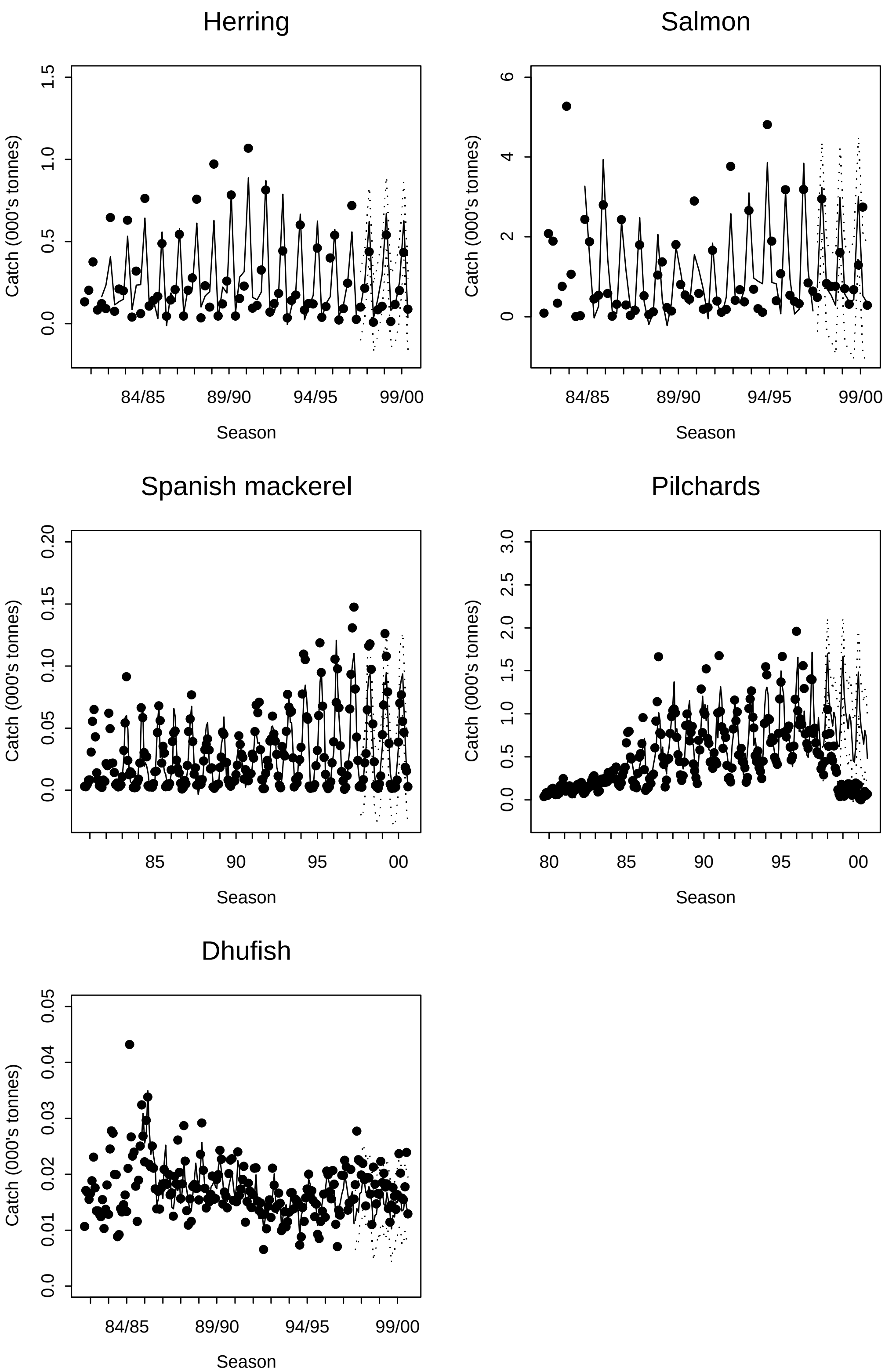

Fig 10.3. Seasonal ARIMA transfer function (SARIMAX) model predictions for each fishery.

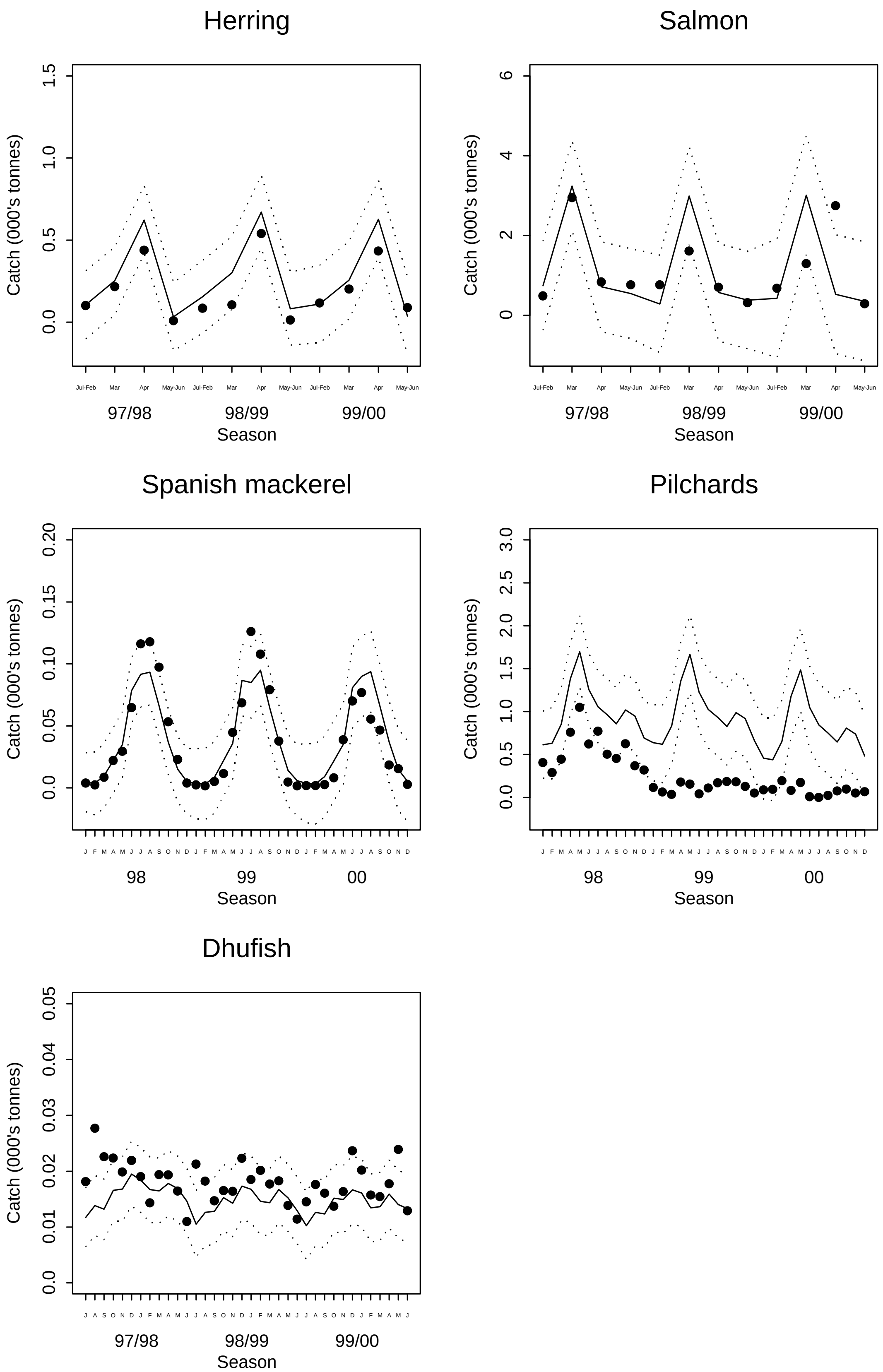

Fig 10.4. Seasonal ARIMA transfer function forecasts for each fishery.

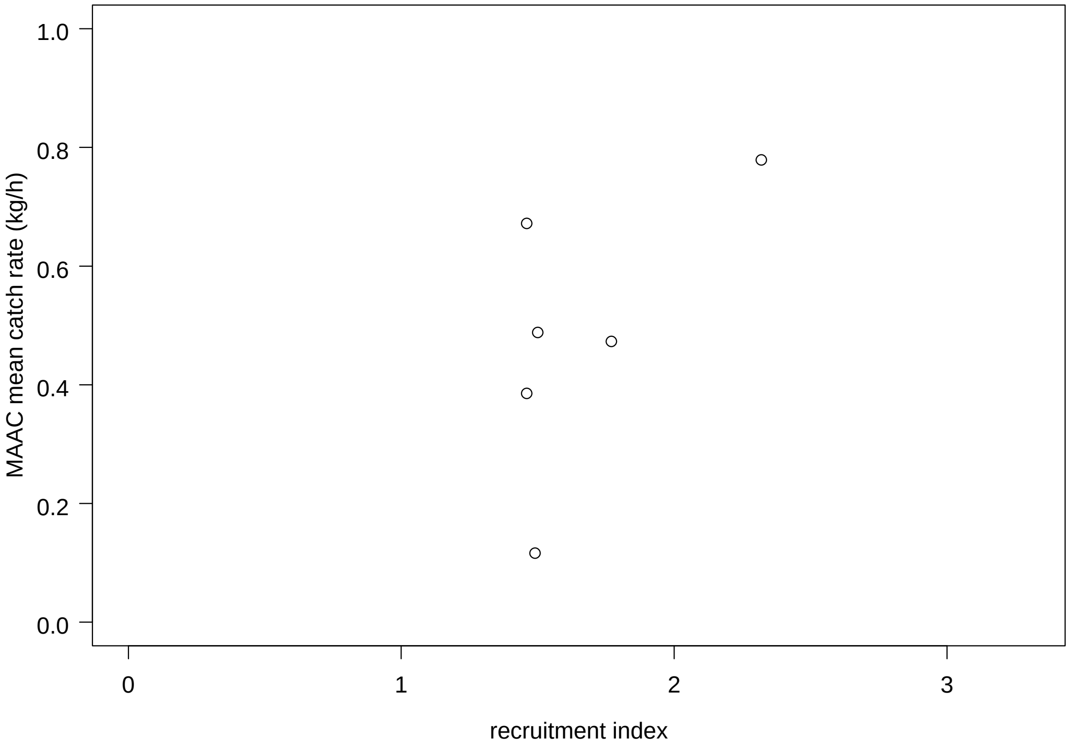

Fig 10.5. Recruitment index from Warnbro and Emu Pt (lagged 1-3 years) versus Melville Angling and Aquaculture Club mean monthly recreational catch rates.

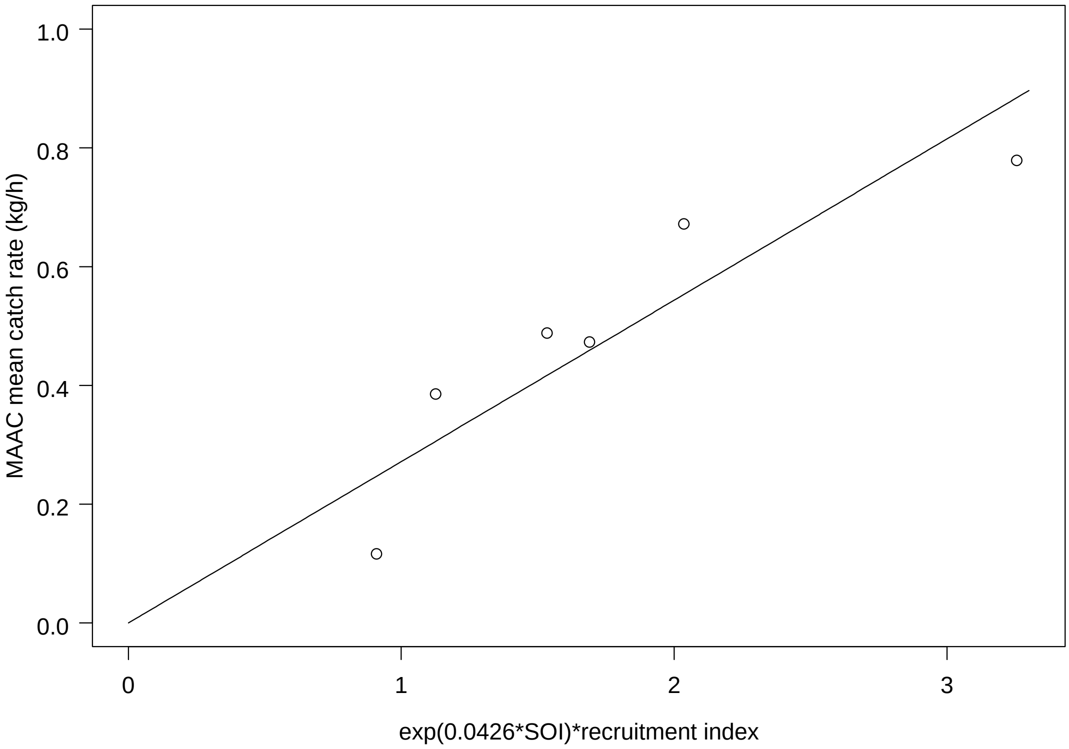

Fig 10.6. Interaction of recruitment index from Warnbro and Emu Pt (lagged 1-3 years) and the Southern Oscillation Index (lagged 0-1 year) versus Melville Angling and Aquaculture Club mean monthly recreational catch rates.

11.0 A juvenile-recruitment relationship for the commercial tailor fishery in the Swan River, Western Australia

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11.1 Abstract

A unique estuarine juvenile-recruitment relationship for tailor is discovered in the Swan River, Western Australia. Annual and juvenile tailor catch rate surveys from 1994/95 to 1999/2000 at Point Walter are shown to significantly correlate with commercial catches of tailor in the Swan River approximately two years later. The Point Walter index may therefore be used as a forecasting tool for commercial tailor catches in the Swan River. These monthly catches are predicted by a seasonal ARIMA transfer function model using the annual juvenile index from Point Walter. Forecasts for 2003 and 2004 using this model reveal a decreasing pattern in commercial Swan River catches. This information combined with a decreasing proportion of 0^+ juvenile tailor in the Swan River indicate stock levels are most likely at their lowest levels over the seven-year measurement period. The presence of a significant nonlinear relationship between annual commercial catches in the Swan River and commercial tailor catches taken between the previous November and April of the current season in the Perth metropolitan area indicates that stock levels are probably in a similar state in the Perth metropolitan ocean. Oceanic indices of tailor juveniles to the south (Koombana Bay) and to the north (Pinnaroo Point) are compared with the Point Walter juvenile tailor index as alternative predictors. Correlations between the juvenile tailor index at Point Walter and environmental effects, such as the Southern Oscillation Index and Fremantle Sea Level, are investigated to determine possible effects on settlement.

11.2 Introduction

Tailor (*Pomatomus saltatrix*) is a cosmopolitan pelagic species occurring in warm temperate and cool tropical continental-shelf waters around the world (van der Elst 1981), and in particular the Atlantic Ocean (Juanes et al. 1996). Around Australia, tailor occurs chiefly between the midwest coast of Western Australia, along the south coast and midway up the eastern coast to Queensland (Hutchins and Swainston 1991; Lenanton et al. 1996).

Tailor is one of the most important recreational finfish resources in Western Australia (Lenanton et al. 1996, Malseed and Sumner 2001). While the total recreational catch in WA is not known the current recreational catch estimate is between 500t and 1,000t per year based on preliminary assessments from an early census (Anon. 1987) and mark and recapture information (Young et al. 1999). The commercial catch of tailor in Australia is relatively small with an estimated annual total catch of <1,000 tonnes (Pollack 1980, Morton et al. 1993, Anon. 1994, Cribb 1994) compared with those off the Atlantic coast of Brazil where annual catches of 7,000-12,000 tonnes (Krug and Haimovici 1991) and along the eastern coast of the USA annual commercial catches have averaged about 5,000 tonnes and recreational catches in the order of 20,000 metric tons annually over the past two decades (Lazar and Gibson, unpublished report). The annual commercial catch of tailor in nearshore and estuarine waters in Western Australia is in the order of 50 tonnes with a total of up to two tonnes reported from the Swan River since 1995. There are presently only four active commercial fishing units in the Swan River compared to 25 fishers actively fishing in the mid 1970’s. If interest in commercial tailor fishing in the Swan River grows again in the future, the management of the fishery would be well advised to verify that stocks are maintained.

Currently, new recommended legal minimum length regulations propose that the tail length for tailor be increased from 250 mm to 280 mm. This will mean the proportion of tailor in the Swan River that is legally available for capture will decrease from the current 15% to 1.8%. The data in this study suggests that the Swan population and the nearshore oceanic population exchange freely. Therefore, the proposed regulations would also affect availability of commercial and recreational tailor in the ocean. Thus, if the increase in legal minimum length is implemented and the compliance levels are high, the summer beach and estuarine fishery will effectively be closed down.

Stock assessment methods for estuarine fisheries face considerable challenges, since fishing practices target multiple species, biological data are often scarce (data poor) and the cost of obtaining relevant biological and fisheries data may be expensive. One method advocated to assess future catches is the development of a juvenile abundance index which links to future adult catches through time series analysis (Magnusson and Johannesson 1997, Shepard 1997, Helle et al. 2000). Determining the life history stage which will provide a reliable forecast of the year class strength is paramount as environmental and climatic conditions (Conover et al. 1995, Koslow et al. 1987, Lenanton et al. 1991) and predator and prey availability (Cushing 1995) may impact recruitment strength (Ulltang 1996).

A dynamic regression model was used to associate recruitment indices of relative year class strength for black bream (*Acanthopagrus butcheri*) in the Gippsland Lakes, Victoria with environmental conditions such as river flow and water temperatures (Hobday and Moran 1983, Walker et al. 2000). Recruitment variability has been assessed for several finfish species in estuaries by examining the size, sex and age compositions of commercial catches of found in New South Wales (Virgona et al. 1998, Gray et al. 2000). Helle et al. (2000) conducted a thorough investigation of five life history stages of the Arcto-Norwegian cod to develop a reliable prediction of future stock abundance. Regression analysis indicated that the early juvenile stage (approximately 3 months old) represented the best indication of future abundance in the fishery.

In Western Australia, research on the age structure, growth rates, movements and commercial catches of sea mullet and yellow-eye mullet was undertaken in the Swan-Avon river system (Chubb et al. 1981). Sea and yellow-eye mullets were collected from February 1977 to June 1980 over several sites in the estuary using beach seines and gill nets. The abundance and spawning behaviour of the two species of mullets were highly seasonal. The paper advocates that the Swan-Avon “provides a system which is particularly conducive to the study of fish populations in estuaries.” The tailor species in the Swan is shown to be another example.

Annual reported commercial catches of tailor in the Swan River have recently declined, with low catches occurring in 2000 and 2002. Although the number of fishers has declined, annual commercial catches are independent of fishing effort measured in boat days. Several novel approaches to assess tailor stocks in the Swan River are introduced in this paper. Tailor recruitment surveys have focused on the young of the year age class. A recreational angling survey has been undertaken weekly at Point Walter from the Swan River from November through to April, May or June since 1994/95. More recently, the surveys have commenced in February. These surveys rely on the capture of 0^+ and 1^+ fish (the age at first capture). Fishery independent monthly juvenile tailor recruitment surveys have also been conducted at coastal sites north and south of the Swan River. The catch rate indices calculated for both of these techniques will be used to monitor tailor stocks in the Swan River. A seasonal autoregressive integrated moving average transfer function (SARIMAX) model of the monthly Swan River commercial catches from 1995 to 2002 serves as a forecasting tool for future catches.

The aims of this paper are to present the results from these assessment techniques, and to determine the linkages among the recruitment indices and the commercial landings of tailor in the Swan River estuary and nearby oceanic waters.

11.3 Methods

Juvenile angling survey

Tailor were caught by anglers from Point Walter jetty on the Swan River. Approximately 10 to 18 research staff from the Department of Fisheries and Volunteer Fisheries Liaison Officers were supplied with a small gang of three hooks (size 2). Ganged hooks are constructed as a series of hooks arranged by threading the barbed tip of the proximal hook through the eye of the distal hook. The hook design accommodates small whole fish or strips of fish as bait for tailor fishing. The small gangs were baited with whole sandy sprat (*Hyperlophus vittatus*) (Ayvazian et al. 2002). All tailor were caught, measured (total length to the nearest mm) and released during a nominated time period in the early evening when fish are potentially most catchable. The abundance of tailor was expressed as a catch rate of number per angler hour.

Fishery independent juvenile recruitment survey

Monthly sampling for juvenile tailor was conducted between February 1994 and July 2001, inclusive. Samples were collected during the day from five locations along the lower west coast, Pinnaroo Point, Warnbro Sound, Mangles Bay, Koombana Bay, Quindalup Bay. The foreshore of each beach was divided into two blocks. Within each block one fixed site (F1 and F2) and three random sites (R1, 2, 3, and R4, 5, 6, for blocks 1 and 2 respectively) were established. At each sampling occasion the fixed site and one of the random sites was sampled for a total of four samples at each beach for each month.

Sampling for juvenile tailor was undertaken using a 61 m long beach seine net with 29.1 m wings (22 mm mesh) and a 2.4 m bunt (8 mm mesh), which sampled to a depth of 2 metres. The seine net was deployed from a small dinghy and, when set in this fashion, swept an area of 592.2 m^2. All tailor were removed from the net and returned to the laboratory. Tailor were counted and each fish measured (total length to the nearest mm) and weighed (to the nearest 0.01 g). The abundance of tailor from each seine haul was expressed as the number per standard haul.

Links between juvenile indices and the commercial landings

The Point Walter juvenile index is calculated by taking the mean of the catch rates of the 0^+ and 1^+ tailor fish taken from November to April. The tailor juveniles are aged using a nonlinear von Bertalanffy age-length relationship based on juvenile data in several locations on the west coast of Australia. A linear relationship is assumed between the mean Point

Walter juvenile index I_{T-2} and the mean Swan River commercial tailor catch rates C_T, where T is time in years.

To investigate the possibility of other useful catch rate indices, the mean catch rate at Pinnaroo Point between November and April and the Koombana Bay juvenile catch rate in February are correlated against the mean catch rate at Point Walter between November and April. The juvenile index for Pinnaroo Point was calculated using the period from November through April to closely match the Point Walter juvenile index calculation. The Koombana Bay juvenile catches are sparce, with only February showing long-term variation. The indices from Pinnaroo Point and Koombana Bay are also correlated against mean commercial catch rates from the Swan River two years later.

A Beverton-Holt (1957) specification is assumed for the nonlinear contemporaneous relationship between the Swan River commercial CPUE U_T for each calendar year and the Perth metropolitan commercial sea CPUE P_T lagged from November of the previous year to April of the same year, viz.

$$U_T = \frac{aP_T}{bP_T + 1} + \varepsilon_T, \qquad (1)$$

where *a* and *b* are parameters to be estimated and $\varepsilon_T \sim N(0, \sigma^2)$. The relationship is nonlinear if *b* significantly differs from zero, representing density dependent mortality effects. (1) reverts to a linear regression if *b* does not significantly differ from zero.

A SARIMA transfer function time series model is used to predict monthly Swan River commercial tailor catches. Firstly, a SARIMA model is fitted to the monthly commercial catches from the Swan River, viz.

$$\phi(B)\Phi(B^{12})\nabla^d(B)\nabla_{12}^D(B^{12})\left(\frac{C_t}{\overline{C}} - 1\right) = \theta(B)\Theta(B^{12})\varepsilon_t, \qquad (2)$$

where C_t is the monthly catch data, ϕ and Φ are nonseasonal and seasonal autoregressive polynomials of order *p* and *P*, θ and Θ are nonseasonal and seasonal moving average polynomials of order *q* and *Q*, ∇ and ∇_{12} are nonseasonal and seasonal differencing polynomials of order *d* and *D*, respectively, of the backward difference operator *B*. The SARIMA model is denoted $\mathrm{SARIMA}(\mathrm{p,d,q}) \times (P, D, Q)_{12}$. *d* and *D* are chosen to be the minimum non-negative integers to obtain stationarity. We chose *p* and *q* by Hurvich and Tsai's (1989) bias-corrected version (AICc) of Akaike's (1978) AIC criterion. The catch series is divided and subtracted by its mean to facilitate the use of the AICc, since the AICc depends on the magnitude of the data. To make comparisons with AICc upon selecting the optimal model, care must be taken to ensure the point used after conditioning on the autoregressive parameters is the same for each model. *P* and *Q* are chosen by viewing the ACF and PACF. Once the optimal model is found, that is, *p*, *d*, *q*, *P*, *D* and *Q* are determined, the same model order is used to fit the transfer function model, viz.

$$\phi(B)\Phi(B^{12})\nabla^d(B)\nabla_{12}^D(B^{12})\left(\frac{C_t - \delta\, PW_{T-2}}{\overline{C}}\right) = \theta(B)\Theta(B^{12})\varepsilon_t, \qquad (3)$$

where PW_{T-2} is the annual Point Walter mean catch rate between November and April lagged two years, and replicated for each month of the fishing season. δ is the transfer function coefficient to be estimated.

11.4 Results

The juvenile tailor indices are shown in Figure 11.1. While the indices representing juveniles caught from Point Walter and Koombana are similar, the juvenile index at Pinnaroo Point differs to the other two indices. There is a significant correlation $(r = 0.86,\ p = 0.006)$ between the Koombana catch rates of tailor juveniles in February and the mean Point Walter catch rates of tailor between November and April (Figure 11.2). However, only a marginally significant relationship exists between the Koombana catch rates in February and the mean commercial catch rates in the Swan River $(r = 0.76,\ p = 0.081)$. The Koombana juvenile tailor catch rate in February could potentially be used as an early indicator of the Point Walter juvenile index and hence the recruitment of tailor two years later.

A bar plot of commercial Swan River tailor catches for each calendar year and the commercial Perth metropolitan region sea catches from November of the preceding year to April of the current year showed similar trends, with the exception of a large catch in the ocean in 1998/99 (Figure 11.3). The variation explained by the nonlinear regression model (1) describing the relationship between the Swan River CPUE for each calendar year and the Perth sea CPUE from the previous November to April of the same year is 92% (Figure 11.4). The fitted parameters are $\hat{a} = 4.25\,(0.76),\ \hat{b} = 1.84\,(0.45)$, both of which are significant. Since $\hat{b}$ significantly differs from zero, the relationship is nonlinear.

The linear correlation between the mean Point Walter juvenile index lagged two years and the mean Swan River commercial tailor catch rates is 0.65 $(p = 0.16)$ (Figure 11.5). An outlier exists for the Point Walter data in 1998/99 and the mean Swan River catch rates for 2001. Occurrences of juvenile tailor at Point Walter were well below average during the 1998/99 survey season. The correlation when the outlier is removed is 0.98 $(p = 0.003)$. Thus, the relationship is considered highly significant. The two-year lag between juvenile sightings and commercial catches is consistent with age-length estimates that claim age at minimum size (250 mm TL) is 18-22 months (Young et al. 1999). A linear regression was fitted to the data after the outlier was removed. The forecasts for annual commercial tailor catches in the Swan River for calendar years 2003 and 2004 based on this linear regression and provided fishing practices do not change (i.e. the mean of the last three years' fishing effort is assumed for the next two years' fishing effort) are 275 kg and 263 kg, respectively.

A SARIMA $(1,0,0)\times(1,0,0)_{12}$ model was used for (2) and thus (3). The parameters ϕ_1 and Φ_1 were estimated to be $0.61\,(0.10)$ and $0.41\,(0.12)$, respectively, for (2), and $0.53\,(0.11)$ and $0.36\,(0.12)$ for (3). Since these coefficients are less than 1 in magnitude, the fitted models are stationary. The transfer function component $\delta = 0.35\,(0.18)$ was significant $(p = 0.030)$, suggesting that the Point Walter juvenile index contributes information to the monthly catch model. Using the Point Walter juvenile indices for 2000/01 and 2001/02, the catch forecasts for 2003 and 2004 are tending to be lower than any other year (Figure 11.6), although the 95% confidence intervals are very wide based on the fitted model.

11.5 Discussion

There is a significant correlation between the mean of the Point Walter monthly catch rates and an annually calculated mean of monthly commercial catch rates of tailor taken from the Swan River two years later. Therefore, Point Walter juvenile tailor stock levels can provide an indication of fishery recruitment levels in the future. There is a significant annual nonlinear relationship for commercial tailor between the Perth metropolitan sea CPUE and the Swan River CPUE lagged approximately six months. This relationship shows that tailor stocks vary in the Perth metropolitan sea region in a similar way to the stock levels in the Swan River.

A time series analysis of the monthly Swan River commercial catches from 1995 to 2002 serves as a forecasting tool for tailor catches in the future. A seasonal autoregressive integrated moving average transfer function (SARIMAX) model was used. This model produced forecasts based on the annual Point Walter juvenile index together with lags of the monthly catches and lags of the previous errors. Time series methods are very useful when there is limited available biological information. Time series analysis is a very efficient way to produce reliable forecasts. Even when there is much biological information, simpler models seem to have equal predictive power compared to more complex models (Stillman et al. 2000). It has also been shown that time series models such as SARIMAX models tend to provide better catch or CPUE forecasts than other methods in the fisheries literature (Roff 1983, Stocker and Noakes 1988, Noakes et al. 1990).

Both annual and seasonal models suggest the catch forecasts for 2003 and 2004 will be lower than current levels. This analysis is largely based on the fishery-independent recruitment survey located at Point Walter. Juvenile catch rates from Point Walter have been decreasing for a number of years. Furthermore, the age proportions of 0^+ to 1^+ fish caught from Point Walter have decreased over time (Figure 11.7). Has there been a behavioural change in the Swan estuarine entry pattern of tailor juveniles in the last two years? Or has there been a poor overall recruitment along the metropolitan coast? Is the recreational sector having a strong bearing on commercial catches in the Swan River in recent times? This drop in juvenile numbers may serve as a warning to management of the commercial and recreational tailor fishery that stocks of tailor are under pressure.

Environmental-recruitment relationship could not be found. The Southern Oscillation Index (SOI) and Fremantle Sea Level (FSL) are used to test environmental effects on the Point Walter juvenile tailor index. There seemed a marginally significant negative correlation between the SOI $(r = -0.80,\ p = 0.055)$ or FSL $(r = -0.73,\ p = 0.10)$ and the first six years of Point Walter juvenile tailor catch rate data, but not once the data from 2001 and 2002 were included (Figure 11.8). The theory is that a strong Leeuwin Current (as measured by the FSL or as correlates with the SOI) prevents settlement of available juvenile tailor in nearshore waters. However, the statistics suggest that the factors influencing tailor recruitment into the Swan River from the nearby ocean appear to be more complicated than this hypothesis.

11.6 Further Developments

Fishing data from the Melville Angling and Aquatic Club (MAAC) indicates that there was a recruitment failure in the Swan River for tailor during the 1999 season. While the numbers of tailor caught decreased in 2001 and 2002, the average weights of the fish were significantly above the historical average during these two years (Figure 11.9). This indicates that the age distributions of fish caught in 2001 and 2002 were similar, but significantly older, on average, than for any other year between 1987 and 2003. This result would explain the absence of recruits at Point Walter yet normal catches that led to the outlier in Figure 11.5. An improved model was proposed for prediction of Swan River commercial catches, namely the addition of the Perth metropolitan sea catch rates of tailor from November to April lagged two and a half years. This variable is thought to be a representation of mature population size in the metropolitan area. As shown in Figure 11.3, the Perth metropolitan sea catch rate (Nov-Apr) was above average during the 1998/99 season. The result of the linear regression with this added variable is shown in Figure 11.10 (cf. Figure 11.5). The relationship when the two-and-a-half year lagged Perth metropolitan sea catch index is added to the model is significant $\left(r = 0.91,\ p = 0.029\right)$.

Inclusion of the MAAC data provides one more piece of evidence towards pressure on tailor stocks in the Swan River and neighbouring oceanic areas. Excluding the data from 2001 and 2002, the average weight of fish caught by the Melville angling club has trended upwards $\left(p = 0.01\right)$ since 1987 to the present day. This observation indicates an older distribution of tailor currently residing in the Swan River compared with the past, pointing towards a growing change in breeding behaviour or decreasing numbers of recruits in the Swan River.

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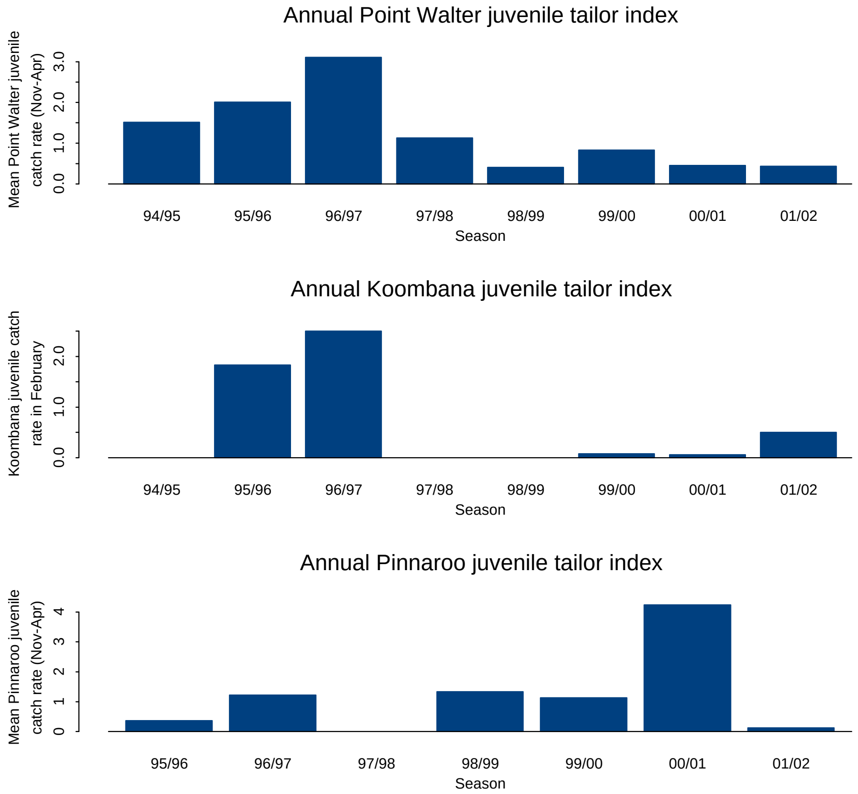

Figure 11.1. Juvenile tailor indices measured at Point Walter, Koombana and Pinnaroo.

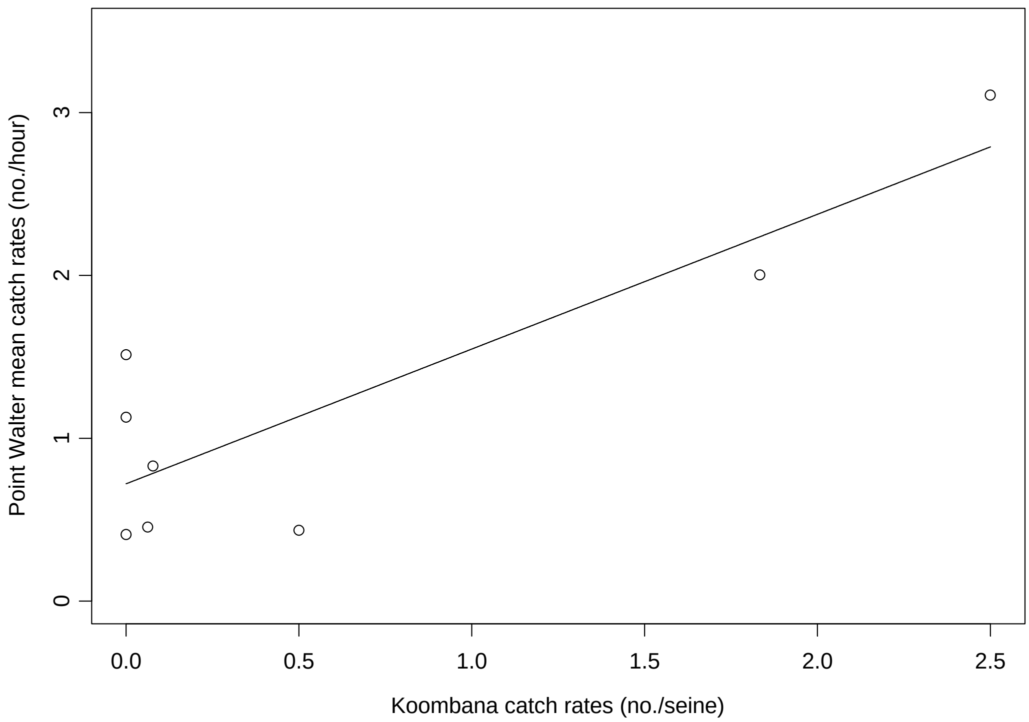

Figure 11.2. Relationship between Point Walter juvenile index and Koombana juvenile index.

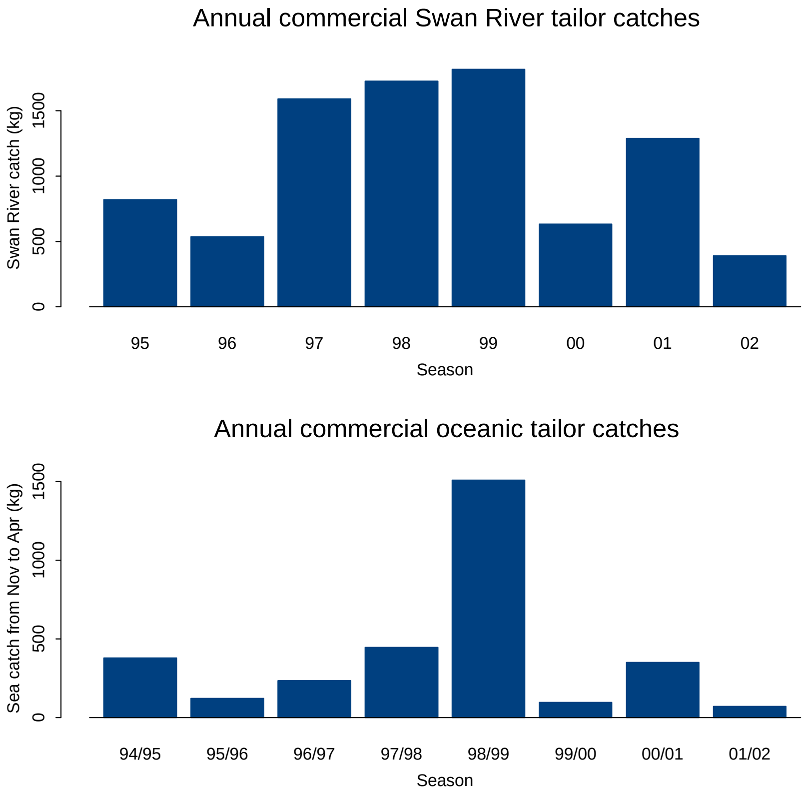

Figure 11.3. Commercial catches of tailor taken from the Swan River for each calendar year and the Perth ocean from November of the previous year to April of the same year.

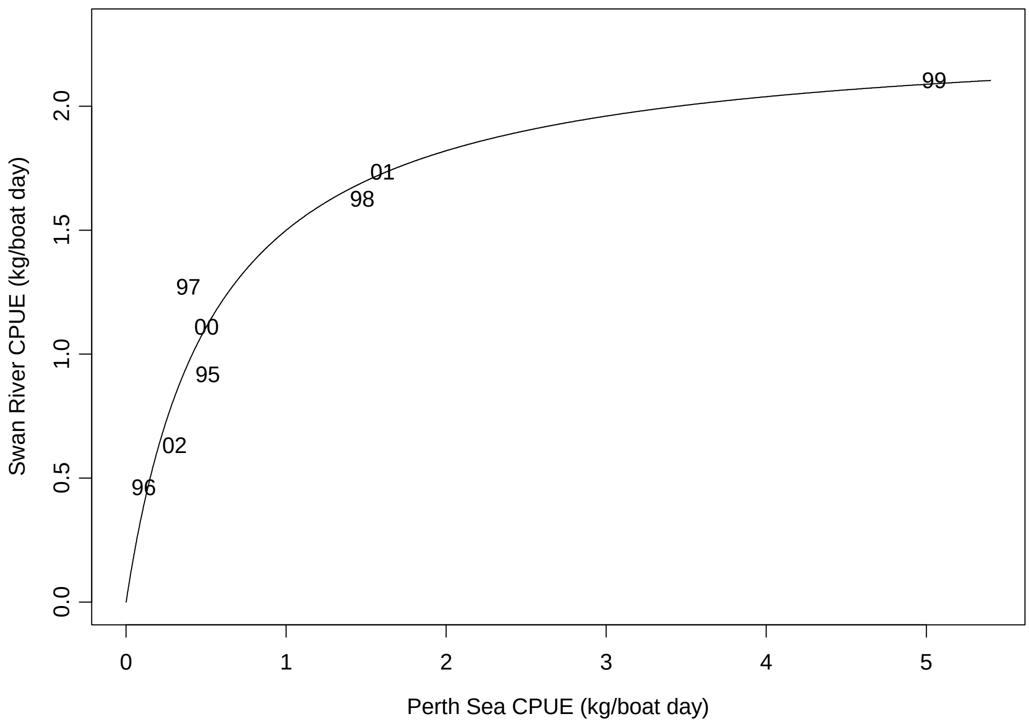

Figure 11.4. Beverton-Holt mortality annual relationship between Swan River CPUE and Perth metropolitan sea CPUE lagged approximately six months.

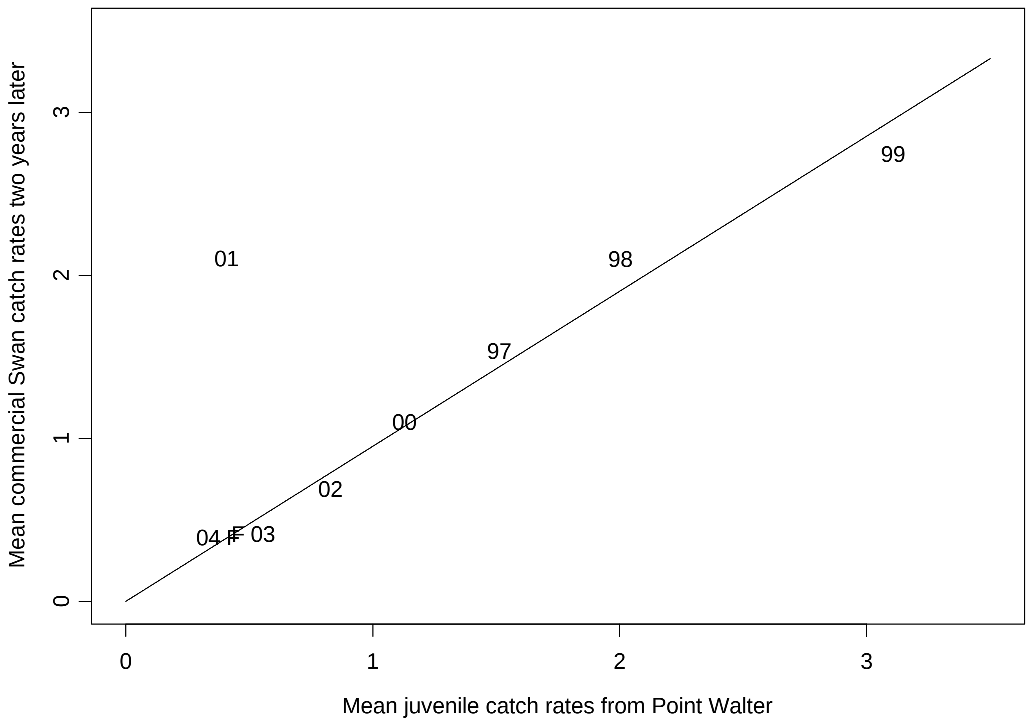

Figure 11.5. Point Walter juvenile catch rate index versus Swan River commercial catch rates. Fishing years given are for the actual commercial catches (1997-2002) and the forecasted commercial catches (denoted “F”; 2003-2004).

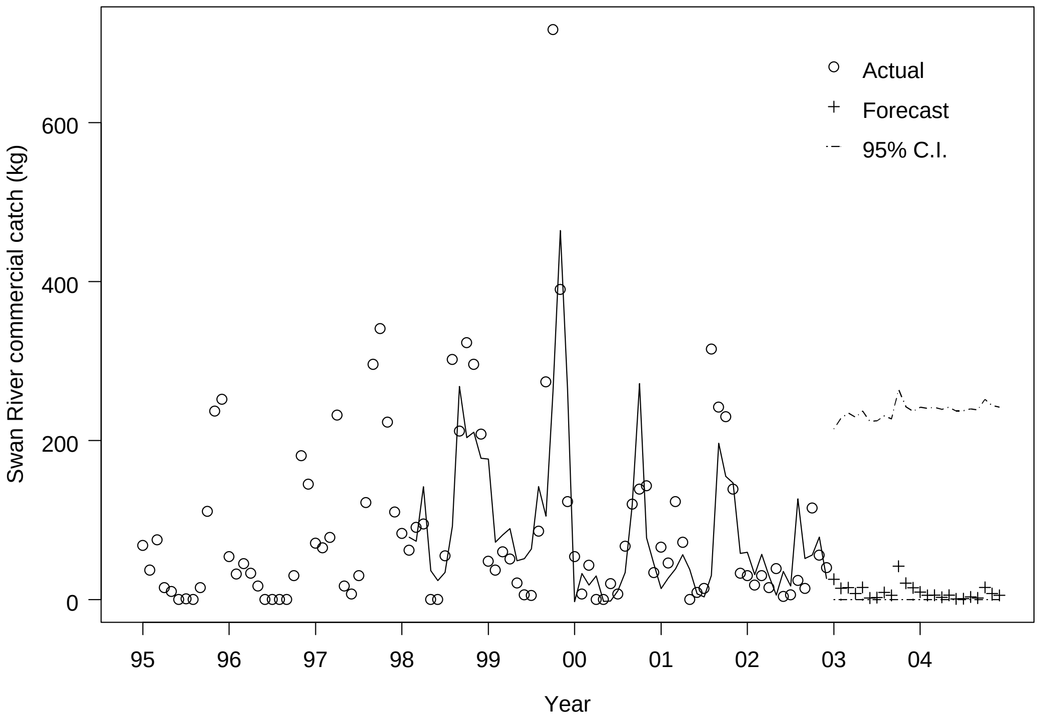

Figure 11.6. Transfer function time series model of Swan River commercial tailor catches using the Point Walter juvenile tailor index.

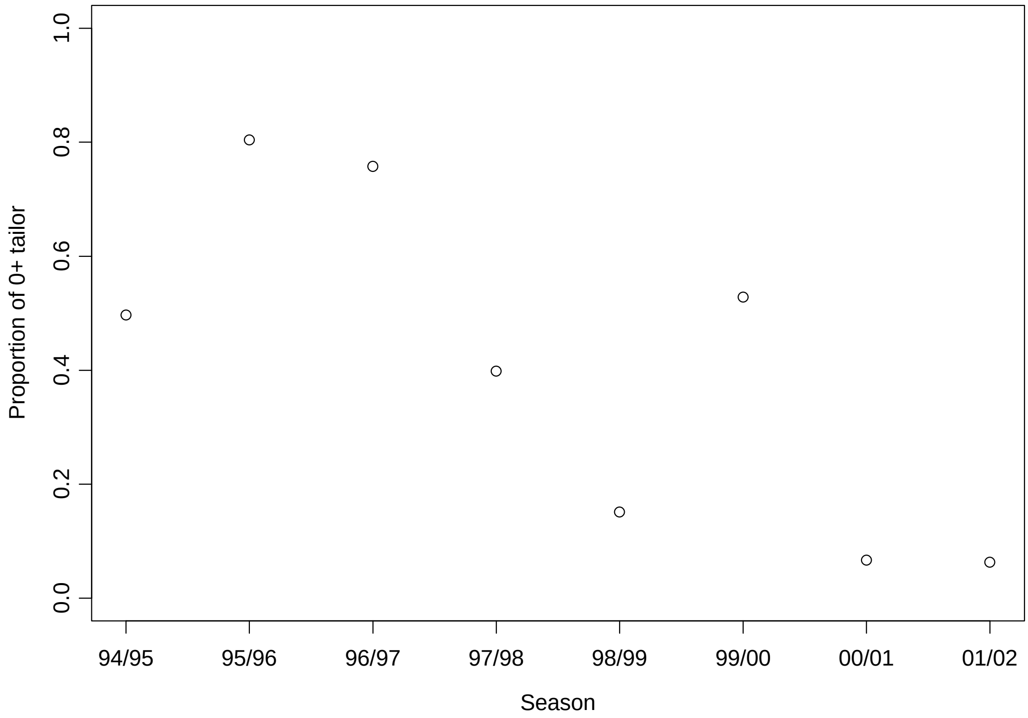

Figure 11.7. Downward trending proportion of 0+ juveniles comprising the Point Walter juvenile tailor index.

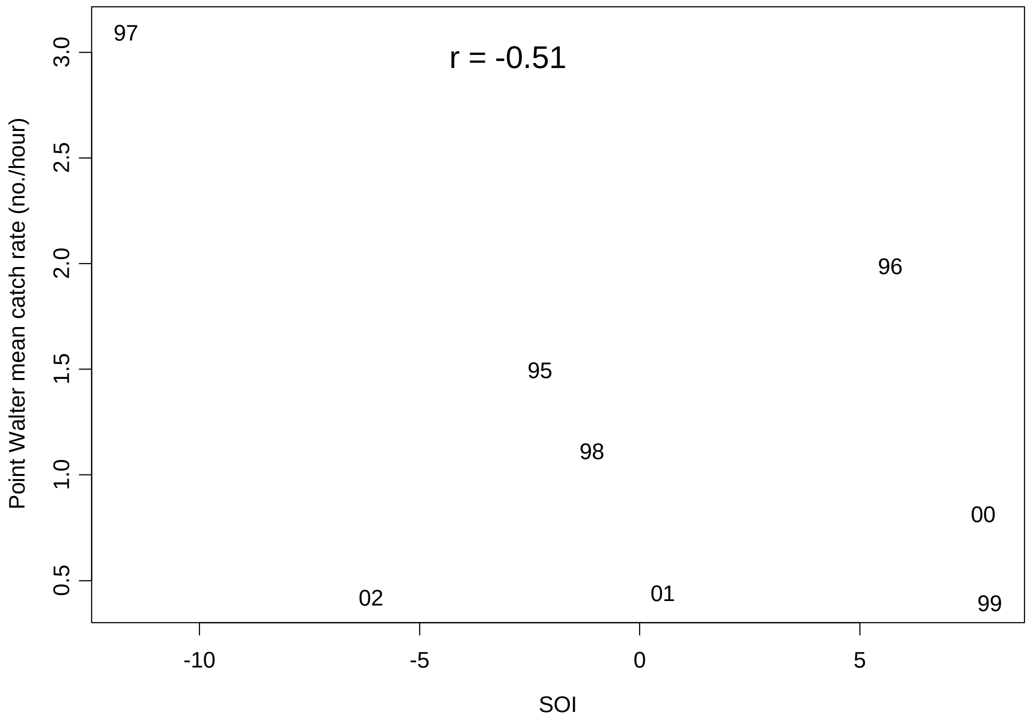

Figure 11.8. Plot of SOI against Point Walter juvenile tailor catch rates.

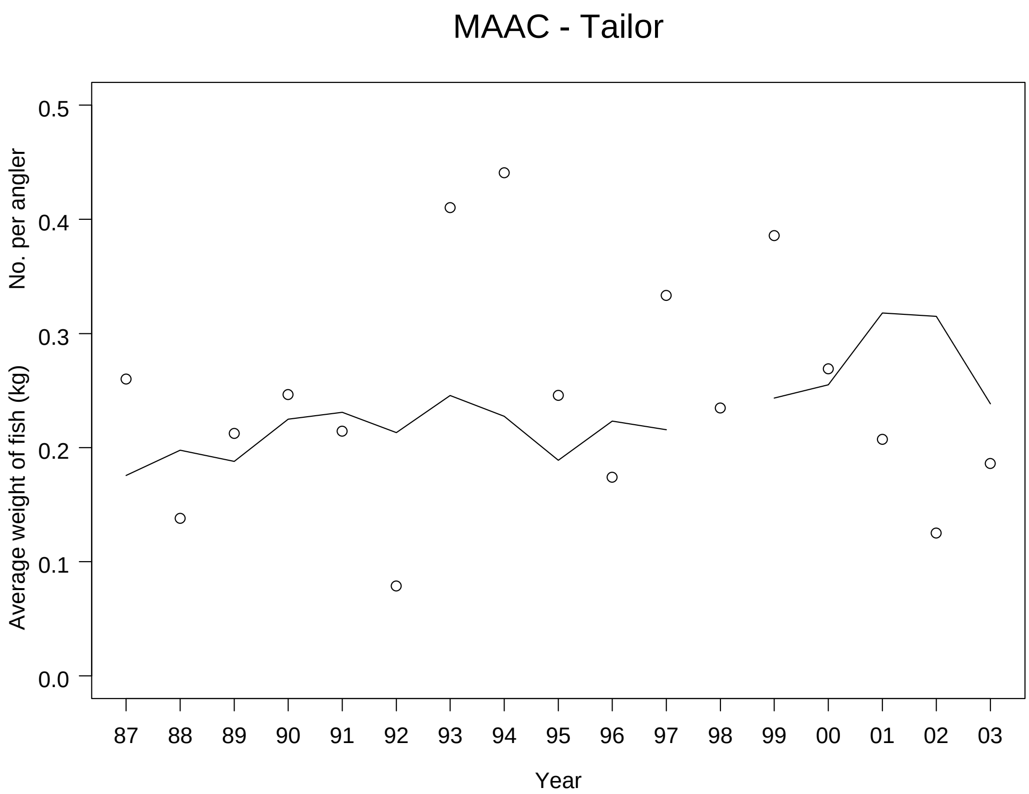

Figure 11.9. Average numbers of tailor per angler (points) and average weight of tailor (lines) caught by the Melville recreational angling club from 1987 to 2003.

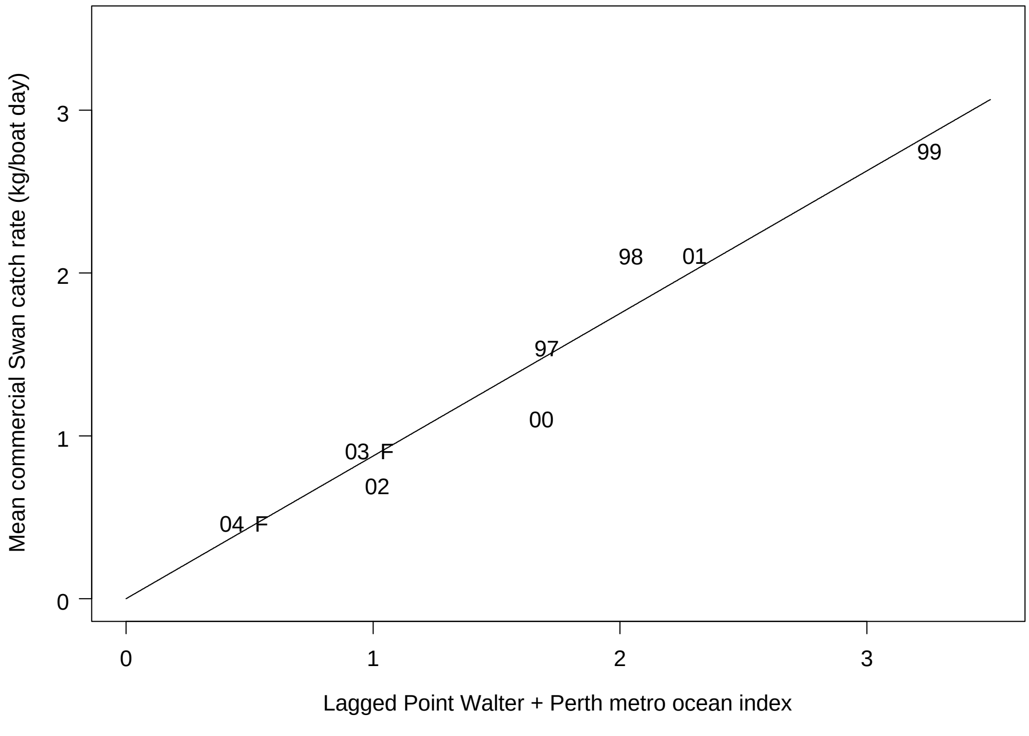

Figure 11.10. Swan River commercial catch rate versus tailor index using a combination of the Point Walter juvenile catch rate lagged two years and the Perth metropolitan sea catch rate (Nov-Apr) lagged two and a half years. Fishing years given are for the actual commercial catches (1997-2002) and the forecasted commercial catches (denoted "F"; 2003-2004).

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13.0 Project Summary

Table 13.1. Table of available data (A=annual, S=seasonal, M=monthly) and appropriate models.

	ARIMA, SARIMA	ARIMAX, SARIMAX	SARIMA-GARCH	Statistical control charting	Data tested	Scientists/managers involved
Western RL (Zone A)	✓	✓		✓	A,S, M	Caputi, Chubb
Western RL (Zone B)	✓	✓		✓	A,S, M	Caputi, Chubb
Western RL (Zone C)	✓	✓	✓	✓	A,S, M	Caputi, Chubb
Southern RL	✓	✓		✓	A,M	Melville-Smith, Caputi
Prawns	✓			✓	A,M	Kangas, Sporer
Sp. Mackerel	✓	✓		✓	A,M	Lenanton, Mackie
Pilchards	✓	✓			A,M	Lenanton, Gaughan
A. Herring	✓	✓		✓	A,M	Lenanton, Ayvazian
Salmon	✓	✓		✓	A,M	Lenanton, Ayvazian
Dhufish	✓	✓		✓	A,M	Lenanton, St. John
Red Emperor	✓		✓	✓	A,M	Lenanton
Sea Mullet	✓		✓	✓	A,M	Lenanton
Y.-eye Mullet	✓		✓	✓	A,M	Lenanton
K.G. Whiting	✓			✓	A,M	Lenanton
Tailor	✓	✓		✓	A,M	Lenanton, Ayvazian
Baldchin Groper				✓	A	Lenanton
Pink snapper				✓	A	Lenanton, Jackson

13.1 Further Developments

- Derive enhanced statistical quality control methods to improve estimates of the acceptable catch ranges for fisheries in the annual *State of the Fisheries* reports. Exponential smoothing and double exponential smoothing methods lead to biased confidence intervals for many fisheries in Western Australia. Techniques that account for autocorrelation in the data will be examined.
- Effects and recovery time estimates for the pilchard fishery can be quantified using transfer function models. Impulse-response transfer function variables may be added to the monthly catch model. The variable would emulate population recovery based on biological reproduction properties such as age at maturity.
- Fit southern rock lobster monthly time series catch model with two levels of variance, estimating the increase since 1990.
- Nonlinear volatility analysis and interpretation required on western rock lobster zone C monthly catch series and whites/reds seasonal catch series. There is evidence that predictions and 95% confidence intervals may be improved using nonlinear methods such as GARCH.
- Use multivariate adaptive regression splines (MARS) (Friedman 1991) to more accurately estimate the parameters of the nonlinear transfer function components for western rock lobster (see chapter 4) and other fisheries.
- Multivariate control charting as an enhanced stock assessment tool may be a viable possibility.
- A closer study of the spatial recruitment effects on the prawn fishery in Exmouth Gulf is required. Recruitment survey indices from certain fishing areas prior to the commencement of the fishing season significantly correlate with commercial catches, while other areas show no significant relationship. A time series model may be constructed using the three recruitment survey periods to forecast commercial catches for the season.
- A time series analysis is required on regional subfisheries of those studied in this report, particularly for some finfish fisheries. The seasonal dynamics of some subfisheries behave differently over several regions for many fisheries, and thus an analysis of aggregated catches and fishing effort over the whole of Western Australia may be sub-optimal. Some catch rate or environmental relationships may therefore more distinct over the spatial regions. A correlation analysis could be considered among the different regions of the subfisheries to compare regional behaviours.
- Time series models with alternative error structure, such as poisson or binomial count data may be more appropriate for fisheries with more sparse data. An example of this may be an analysis of seasonal effects on monthly tag-recapture data in a commercial fishery such as the Shark Bay pink snapper fishery.
- More analysis on catch rate data for management purposes is needed, including the WA red emperor fishery where a catch rate analysis is used as a stock assessment tool.
- More relevant environmental information may enhance the catch-catch rate-environmental relationships for the fisheries studied, especially the finfish fisheries. Global environmental data such as the Southern Oscillation Index and Fremantle Sea Level were

used since they were readily accessible. However, more localized current, temperature, swell, etc. data may be more useful.

- Economic effects on fisheries need to be studied when sufficiently reliable data becomes available. For example, what effects do a downturn in the export industry (e.g. SARS) have on the whites and/or reds catches of western rock lobster presently and for future seasons?

13.2 Benefits, Adoption and Planned Outcomes

The results of the project include the development of a set of time series models for better prediction of future fisheries dynamics including catch, effort, catch-per-unit-effort (CPUE), etc. for several key Western Australian fisheries (e.g. western rock lobster, prawns, herring, salmon, tailor). The study has also developed a set of time series models for better understanding of some important relationships, for example, catch-effort, catch-recruitment and catch-environment for WA fisheries. The Western Australian rock lobster, prawn and many finfish fisheries receive the benefits that flow from this project, through improved prediction of future catches and/or CPUE. Recreational fishers also benefit as a consequence of the improved predictions and improved stock assessment advice to fisheries managers.

Immediate benefits of the time series project are to the management of those Western Australian fisheries possessing relatively little biological information. The modelling techniques provide rigorous quantifiable ways to predict acceptable catch or CPUE ranges through statistical control charting, and forecast future catches or CPUEs using time series methods to assist with the management of the fisheries. The project showed that easily obtainable data over a sufficiently long timeframe could provide insight into the fishery dynamics. For most fisheries, there is sufficient amount of catch and fishing effort data, usually at least 10 years. Even when there is less data, for example, the commercial Swan River tailor data, the use of seasonal time series methods has allowed a useful analysis to be applied to the data.

There are several highly managed commercial fisheries in Western Australia, including the western rock lobster industry and the prawn fisheries in Shark Bay and Exmouth Gulf. The time series techniques proved to be very useful and tractable for analyzing changes in the dynamics of several WA fisheries. For the western rock lobster fishery, the quantitative seasonal and in-season outcomes of the 1993/94 management changes to the fishery were calculated by using an intervention analysis in the models. Seasonal proportions of “whites” to “reds” catches could then be modelled accounting for the management intervention. In Shark Bay, the management of the fishery did not have a large impact on the catch dynamics. A management strategy was suggested based on the outcome of the time series analyses. This was to treat the southwestern areas differently to the remainder of the fishery. Time series models did not prove to be particularly helpful for the management of the Exmouth Gulf prawn fishery, however, where there have been many management changes each year. For the Shark Bay snapper fishery, highly variable age classes prevent the use of time series methods. Age-structured models are more reliable in this context.

A further benefit to fisheries such as zone C western rock lobster, yellow-eye mullet, sea mullet and red emperor is the recognition of seasonal volatility in the catch data. This knowledge may impact on the management of these fisheries in the future. Volatility usually implies risk, possibly to the breeding stock levels, for example. So management may need to be more stringent on these types of fisheries if required.

Effects of environmental factors such as the Southern Oscillation Index and Fremantle Sea Level on some Western Australian fisheries have been identified or more fully quantified in this report. The effects typically appear as lagged interactions between environmental conditions and relevant fisheries data such as monthly catch rates. Examples where these methods have been successful include the southern rock lobster fishery, herring, salmon, Spanish mackerel, pilchards and dhufish.

Statistical control charting presents an alternative method of stock assessment for Western Australian fisheries. Improved acceptable catch range estimates and catch forecasts are planned to be implemented in the *State of the Fisheries report* series in the future using statistical control charting and time series analysis.

Time series modelling comprises alternative techniques to aid in the assessment of fisheries stocks in Western Australia and beyond. The methods of stock assessment contained in this report are widely applicable and would benefit fisheries in other states of Australia. The time series methodology is especially suited to fisheries with low historical management intervention, although it can be adapted to cater for more moderately managed fisheries. Also, time series methods provide a tool for those fisheries with a high recreational component (e.g. tailor, herring), where difficulties assessing the stock may emerge. Using these methods in conjunction with the more traditional methods (aging, tag/recapture experiments, etc.) provides management with more confidence of the current and future status of fisheries. Therefore, there are clear advantages for time series research to be adopted into the stock assessment of Western Australian fisheries.

13.3 Conclusions

- Phenomenological time series models were very useful as a prediction and forecasting tool for annual and seasonal catch and catch-per-unit-effort time series in Western Australian fisheries. The results of the project showed that time series models could be used as stock assessment tools without intricate knowledge of the fishery. The models could be used to reliably forecast catches up to three years in advance for most fisheries. Data departing from model predictions are either used as indications to management of unforeseen changes in the fishery, or the models are adjusted by interventions variables if the causes to the discrepancies are known.
- Statistical quality control methods assisted with the understanding of the sustainability of many of the Western Australian fisheries, and proved an aid to the management of those fisheries. Methods taken from mainstream quality control charting literature could easily be applied to a variety of WA fisheries.
- Catch-environment and stock-recruitment-catch relationships were discovered during the analyses. These were used as indicators of catch fluctuations. Environmental factors were quantified more accurately than in the existing literature for some species. New research showed the significance of interactions between environmental variables and relevant data such as recruitment indices or catch rate data. A number of years' forecasts are available for fisheries using these models since these variables are generally lagged in time. Exogenous variables and management intervention terms were fitted, analyzed and successfully interpreted.

- Improvements were made in the quantification of spatial effects within the fisheries. Examples included the study of the relevance of fishing effort for many finfish species off the west coast and south coast of Western Australia, and the effect on the spatial management of the Shark Bay prawn fishery.
- There was insufficient reliability of economic data at this stage to carry out a product value effect on fisheries and to analyze product value time series. Economical fisheries data analysis is also a sensitive issue.

14.0 Appendices

Appendix 1: Intellectual property and valuable information

No saleable items were developed during this project.

Appendix 2: Staff

Staff who were employed on the project were:
Dr Monty Craine, Dr (Henry) Yuk Wing Cheng, Dr L Y Cao, Dr Norm Hall, Dr Nic Caputi, Dr Chris Chubb, Dr Mike Moran, Dr Suzy Ayvazian.