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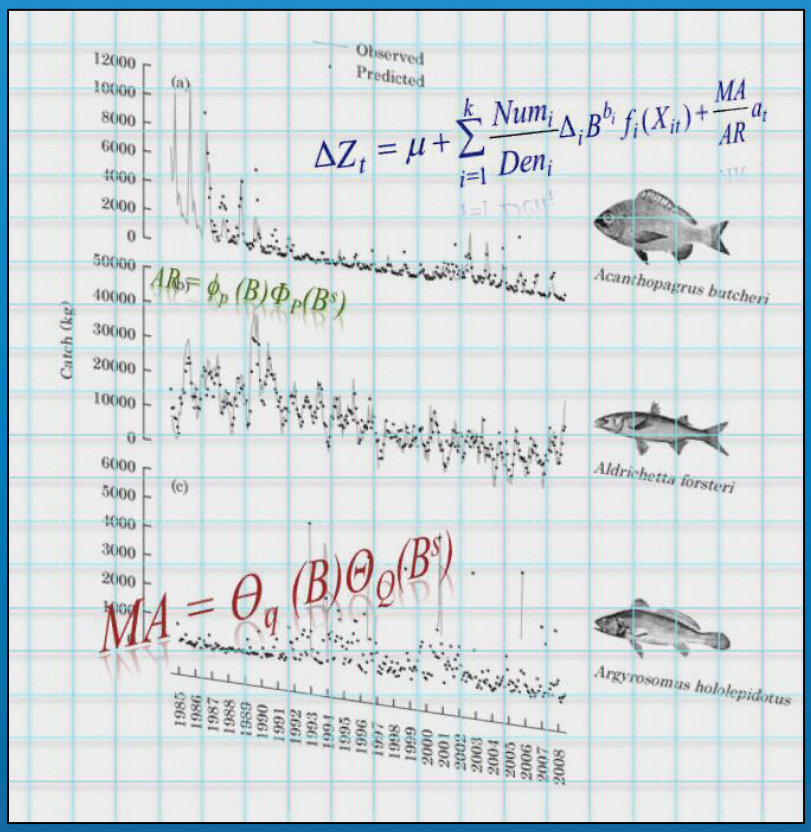
An investigation into the relationship between freshwater flow and production of key species in the South Australian Lakes and Coorong Fishery



C. J. Noell and Q. Ye

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Executive Summary

This report investigates the relationships between freshwater inflows and production of the key species in the South Australian Lakes and Coorong Fishery (hereafter referred to as Lakes and Coorong Fishery) using time series analysis. Specifically, the aim was to use univariate and multivariate autoregressive integrated moving average (ARIMA) time series modelling to identify relationships between freshwater flow and monthly commercial catches of key species in the Lakes and Coorong Fishery between July 1984 and June 2008. Catches of *Acanthopagrus butcheri* and *Argyrosomus hololepidotus* taken from outside the Murray Mouth were best-fitted by univariate ARIMA models, in which catch is predicted by previous catches alone. For *Aldrichetta forsteri* and *A. hololepidotus* inside the Murray Mouth, multivariate models (or transfer functions, TF) revealed that the inclusion of a predictor series slightly improved the fit compared to the univariate model. Two TF models were developed that explained catch of *A. forsteri*. The first indicated that increased flow leads to additional catch during the same month, whereas the other indicated a negative relationship with the catch of *A. hololepidotus* inside the Murray Mouth, which suggests a fisher behaviour influence. No model could be specified for *Rhombosolea tapirina*. Given that the TF models generally offered only slight improvements in predictive power to the univariate ARIMA model, four plausible sources were identified that may have interfered with the development of representative time series models: 1) catch is too delayed to detect the flow-recruitment signal; 2) catch does not accurately reflect production; 3) time series intervals conceal important information; and 4) errors in model-derived series. Although this study identified limitations of time series modelling when applied to commercial catch data of the Lakes and Coorong Fishery, some of these limitations may be overcome with careful planning of further research. However, it remains a potentially useful tool to describe the influence of flows on fishery production, as has been demonstrated in other fisheries.

1. Introduction

Freshwater flows interact directly and indirectly with fish species that inhabit estuaries for at least some part of their life cycle (direct influences include water quality variables, e.g. temperature, salinity, pH, dissolved oxygen, turbidity, nutrient status; indirect influences include primary and secondary productivity, fish recruitment, food availability) (Whitfield, 2005). Reductions of freshwater inflows to estuaries are generally recognised to have negative impacts on these species in regard to necessary biological processes such as spawning, nursery and protection, food availability, and recruitment (Drinkwater and Frank, 1994; Gillanders and Kingsford, 2002).

The Murray Mouth and Coorong lagoons are a good example for examining the effects of flows on these processes. The hydrodynamics inside the Murray Mouth and throughout the Coorong lagoons are mainly influenced by water exchange with the sea via the mouth (which is periodically dredged to keep the mouth open), regulated freshwater flows from the Lower Lakes of the Murray River that are discharged across a series of barrages, freshwater input from other tributaries and evaporation. As a result of these hydrodynamics and the geomorphological characteristics (e.g. variable opening/restriction of the mouth, and a very long and narrow lagoonal system) of the region, salinities can be quite variable, but generally range from brackish to marine inside the mouth, increasing to very hypersaline along the lagoons.

Over the past decade or so, the volume of freshwater discharged across the barrages has substantially reduced to a fraction of previous volumes, mainly due to upstream water extraction processes (predominantly for irrigation purposes) and drought conditions throughout the Murray-Darling Basin that have persisted since 2002. As a result of these anthropogenic and environmental stressors, there has been an increasing need by the South Australian Government to monitor the ecological health of the Murray Mouth and Coorong (Geddes, 2003, 2005*b*) and understand the response of the fish inhabitants to less frequent and small-scale releases of freshwater across the barrages (Geddes, 2005*a*, 2005*c*; Geddes and Wedderburn, 2007).

The Lakes and Coorong Fishery is a multi-species, multi-gear commercial fishery. The four most important species, in terms of landings and value, are black bream (*Acanthopagrus butcheri*), greenback flounder (*Rhombosolea tapirina*), mulloway (*Argyrosomus hololepidotus*), and yellow eye mullet (*Aldrichetta forsteri*). Since July 1984, licence holders of the Lakes and Coorong Fishery have been required to submit catch and effort returns to the South Australian Government at the end of each month for each species in the fishery. The availability of such a long uninterrupted time series, along with a corresponding series for flow volumes (also provided by the Government), provides the opportunity to

use time series modelling techniques to investigate the relationships between freshwater inflows and the production of these key species.

The autoregressive integrated moving average (ARIMA) methodology of time series modelling (Box and Jenkins, 1976) has been applied to many fisheries around the world to model and forecast catch or catch per unit effort (CPUE), analyse the dynamics of the fishery and related species, detect anomalies in the time series, and evaluate lagged-effects of environmental factors on catch or CPUE (Stergiou, 1990; Stergiou and Christou, 1996; Park, 1998; Lloret *et al.*, 2000, 2001, 2004; Georgakarakos *et al.*, 2002, 2006; Lloret, 2003; Tsitsika *et al.*, 2007). To the best of our knowledge, this is the first attempt to identify relationships between environmental variables and commercial catches in Australian fisheries using time series modelling techniques. In other Australian estuarine fisheries, correlation or regression analysis has generally been used to identify relationships between environmental variables and year-class strength (Staunton-Smith *et al.*, 2004; Robins *et al.*, 2005; Ferguson *et al.*, 2008; Halliday *et al.*, 2008).

The basic working objective of this study is to identify and characterise relationships between variations in freshwater inflows and production of the key species in the Lakes and Coorong Fishery using time series analysis. Specifically, it is expected that increased inflows have a positive influence on spawning aggregations of *A. hololepidotus* (Hall, 1984; Ferguson and Ward, 2003), a positive influence on recruitment of *A. forsteri* (Pellizari, 2001), *A. hololepidotus* (Ferguson *et al.*, 2008a) and *R. tapirina* (Hall, 1984), and a negative influence on recruitment of *A. butcheri* (Hobday and Moran, 1983; Morison *et al.*, 1998), and these influences are reflected in catches of these species.

2. Methods

Study region

The study region comprises the waters inside the Murray Mouth, the connecting Northern and Southern Lagoons of the Coorong, and the waters outside the Murray Mouth, which extend for ~180 km along the coastline (Figure 1). It encompasses the saltwater part of the Lakes and Coorong Fishery, which is separated by the barrages from the freshwater part of the fishery, Lakes Alexandrina and Albert.

The saltwater part of the fishery can be divided into four subregions, each of which are subdivided into two or three fishing areas (FA) for the reporting of catch and effort (i.e. the Murray Mouth comprises FA 6-8, the Northern Lagoon comprises FA 9-11, the Southern Lagoon comprises FA 12-14, and the coastal waters outside the Murray Mouth comprise FA 15 and 16) (Figure 1).

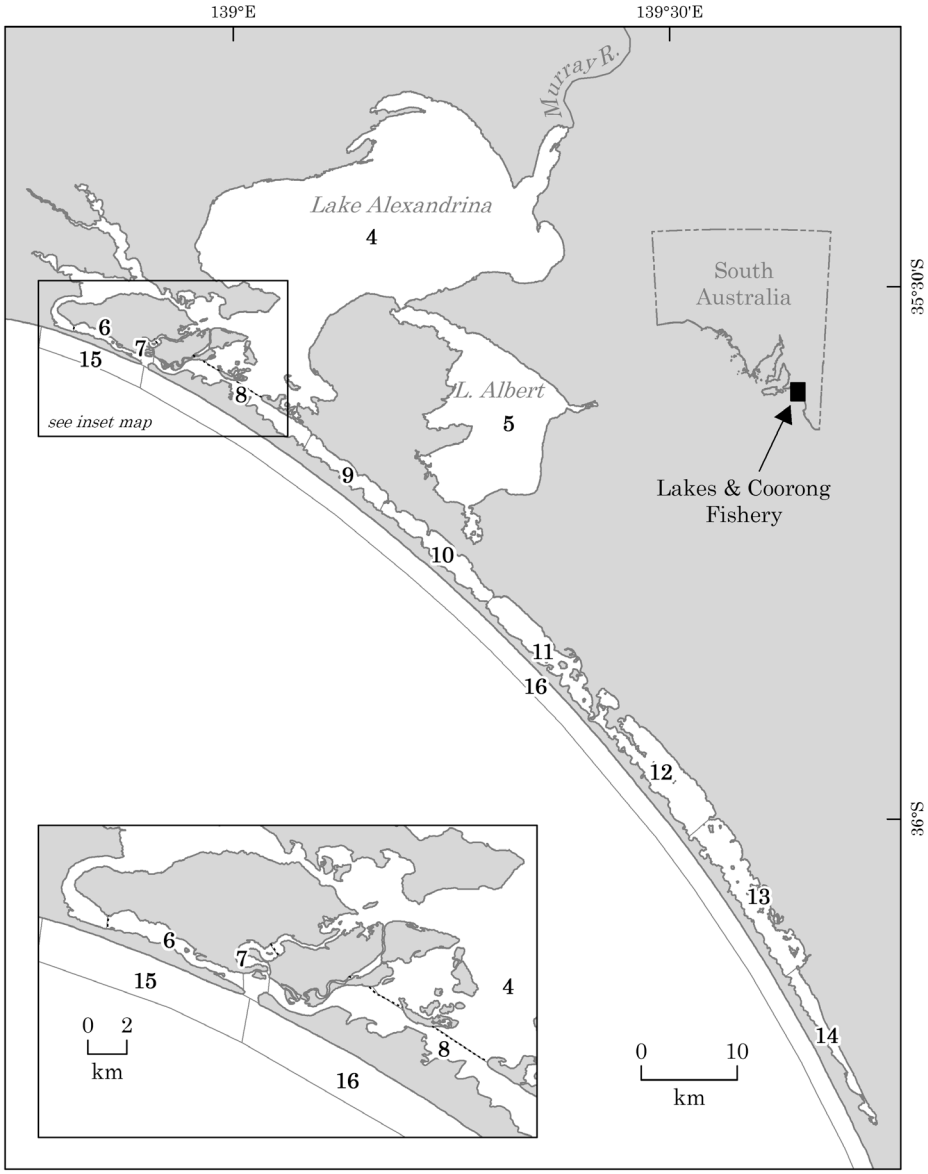

Figure 1. Map showing the location of the Murray Mouth (fishing areas 6-8), Northern Lagoon (9-11), Southern Lagoon (12-14), and coastal waters (outside the Murray Mouth) (15-16) subregions of the Lakes and Coorong Fishery.

Study species

A. butcheri and *R. tapirina* are both estuarine species that are generally taken from inside the Murray Mouth and Coorong lagoons, predominantly using large-mesh gill nets (89.1% and 95.0% of total catch, respectively) (Figure 2 and Figure 3). *R. tapirina* is referred to as 'flounder' in catch and effort returns. Although another pleuronectid species is also commonly found in the same region, i.e. the longsnout flounder (*Ammotretis rostratus*), very few of them reach the minimum legal length of 25 cm total length,

and so it is assumed that catches of this species group are almost entirely made up of the larger *R. tapirina*.

A. hololepidotus is a marine estuarine-opportunist that has a spatially-segregated life cycle, in which adults (>6 years of age) aggregate and spawn in coastal waters outside the Murray Mouth, while juveniles (3-6 years of age) are found inside the Murray Mouth and Coorong lagoons (Hall, 1984, 1986; Ferguson *et al.*, 2008a). Accordingly, catches of *A. hololepidotus* are regulated by different minimum legal lengths depending on where they are caught. For this reason, *A. hololepidotus* is divided into two 'species groups' for analysis of time series, i.e. those inside the Murray Mouth and Coorong lagoons (minimum legal size, MLS 46 cm), which are taken predominantly using a large-mesh gill net (94.7% of total catch), are separated from those outside the Murray Mouth (MLS 75 cm), which are taken predominantly using a swinger net (96.4% of total catch) (Figure 3).

A. forsteri is another marine estuarine-opportunist that is taken from inside and outside the Murray Mouth, but this species is taken predominantly using small-mesh gill nets (93.1% of total catch) (Figure 2 and Figure 3).

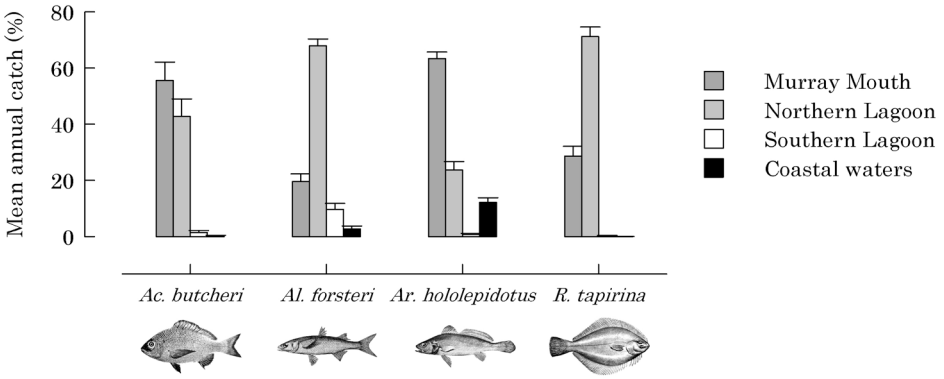

Figure 2. Distribution of annual catch by subregion (mean % ± 1 S.E.) of *A. butcheri*, *A. forsteri*, *A. hololepidotus* and *R. tapirina* from the Lakes and Coorong Fishery between July 1984 and June 2008. Annual catch refers to fiscal years.

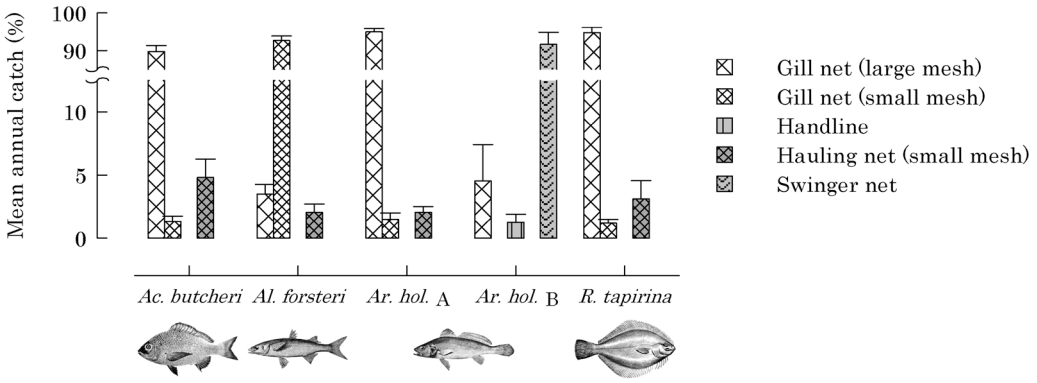

Figure 3. Distribution of annual catch by gear type (mean % ± 1 S.E.) of *A. butcheri*, *A. forsteri*, *A. hololepidotus* A (inside the Murray Mouth), *A. hololepidotus* B (outside the Murray Mouth) and *R. tapirina* from the Lakes and Coorong Fishery between July 1984 and June 2008. For each species group, catch is shown for the three predominant gear types used. Annual catch refers to fiscal years.

Data sources

Fishery Production

Total catch was chosen as the measure of production for each of the species' groups. At the time of analysing the data for this report, catch statistics were entered and verified up to the end of June 2008. Thus the available time series for monthly total catch is July 1984 to June 2008 (Figure 4). As a result, each time series used for model development spans a total of 288 months (July 1984−June 2008), which easily meets the minimum 50 observations required for the development of an acceptable time series model (Pankratz, 1991).

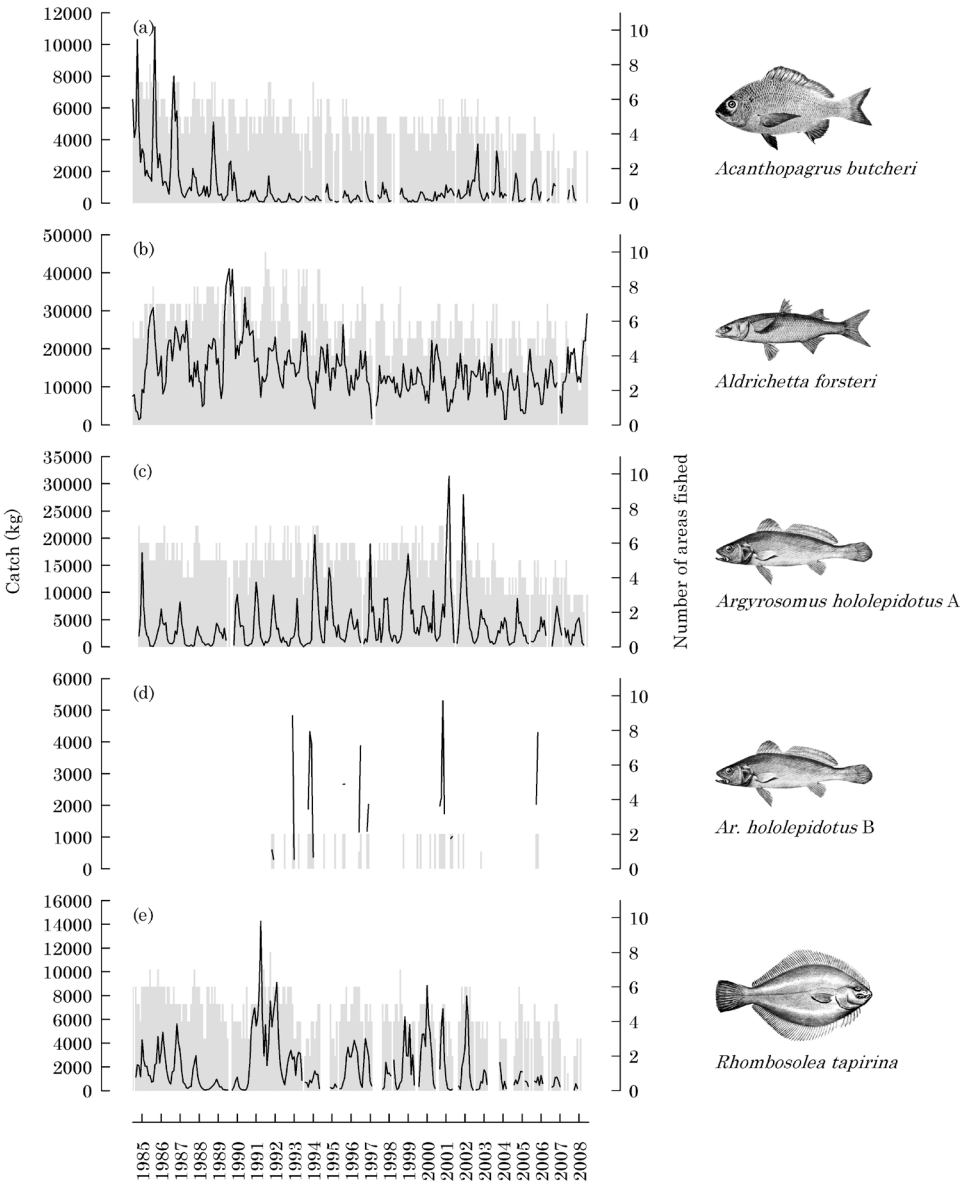

Figure 4. Monthly time series of catch (kg) of (a) *A. butcheri*, (b) *A. forsteri*, (c) *A. hololepidotus* A (inside the Murray Mouth), (d) *A. hololepidotus* B (outside the Murray Mouth) and (e) *R. tapirina* from the Lakes and Coorong Fishery between July 1984 and June 2008. Also shown is the number of areas fished (out of a total of 11, except for *A. hololepidotus* A and *A. hololepidotus* B, which are taken from a total of 9 and 2 areas, respectively). Note: where catch represents <5 licence holders, these data are confidential and are therefore omitted from the graph.

Freshwater flow

Freshwater input from Lake Alexandrina (via discharge across barrages, hereafter referred to as 'flow') was identified as a potential predictor for fishery production of each of the species' groups. Flow volume was calculated using the regression-based hydrological model (MSM-BIGMOD, Murray-Darling Basin Commission). To investigate relationships between flow and fisheries production, flow volumes across the barrages were determined at a monthly frequency for the same 24-year period (July 1984−June 2008) as the species' catch time series (Figure 5).

The flow time series is characterised by several drought periods, which we define in this study as periods of at least six consecutive months with zero flows. These drought periods have become more frequent and protracted since January 2002 (Figure 5); therefore, for the purpose of comparison, the time series was divided into general 'pre-drought' (prior to 2002) and 'drought' phases. Non-parametric statistics were used to detect significant differences in catch variables associated with these two phases. To determine whether differences existed between pre-drought and drought phases with respect to mean monthly catch, number of areas fished and number of active licences (contributing to catch) for each species group, a Mann-Whitney U test was used because these variables were not normally distributed (Shapiro Wilk W).

To help understand the effect that flow volume and frequency has on the salinity gradient along the Coorong, salinities were interpolated for every 0.5 km of the 102 km distance from the Murray Mouth based on model-derived mean monthly salinities at 14 stations along the length of the Coorong (Webster, 2007; I. Webster, pers. comm.). Interpolative calculations were performed using the cubic spline function in the Microsoft Excel add-in program Data Curve Fit Creator 2.2 (SRS1 Software, http://www.srs1software.com/).

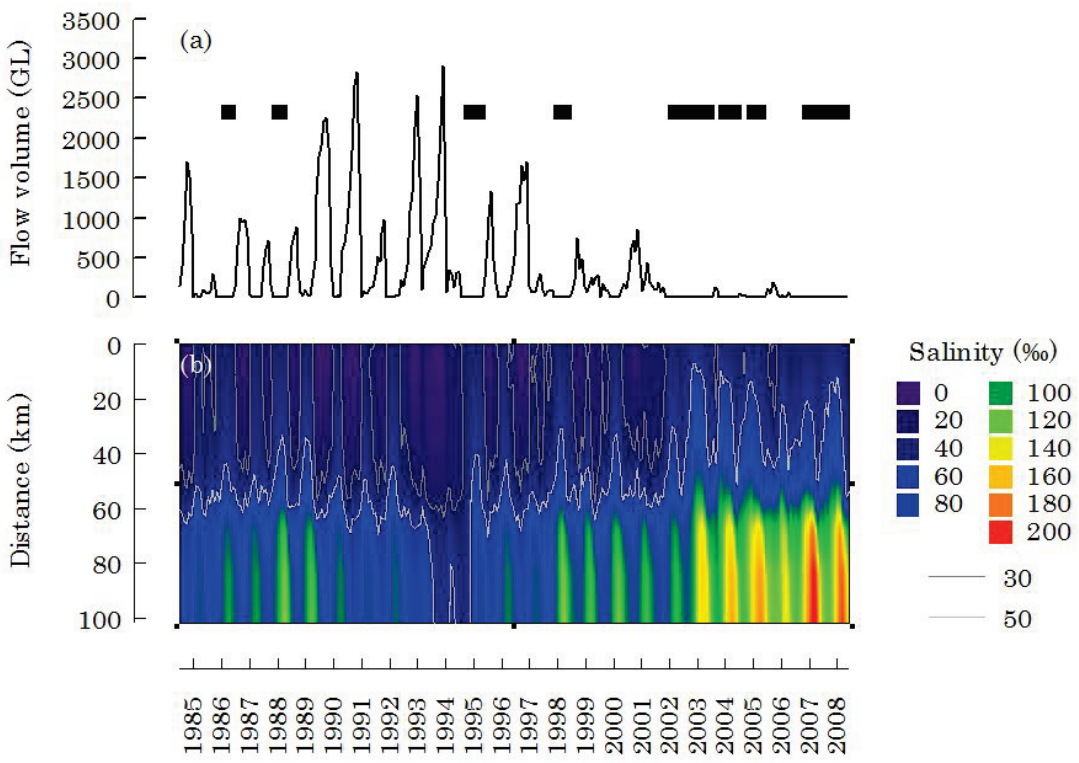

Figure 5. Monthly time series of (a) flow volume (GL) across the barrages, with corresponding drought periods ≥6 months, and (b) model-interpolated salinities (‰) throughout the Murray Mouth, Northern and Southern Lagoons between July 1984 and June 2008. Distance (km) refers to the south-easterly distance along the Coorong from the Murray Mouth. Salinity contours for 30‰ and 50‰ are shown to identify brackish (0.5-29.9‰), saline (30-49.9‰) and hypersaline (≥50‰) boundaries along the Coorong. Note: The Northern and Southern Lagoons are divided by significant reductions in channel width and depth near Parnka Point at ~55 km from the Murray Mouth.

Time series analysis

All time series analyses were performed using PASW Statistics 18 with the Forecasting add-on module (SPSS Inc., n.d.*a*).

Exploratory data analysis

Monthly time series for total catch (kg) and flow volume (gigalitres, GL) from July 1984 to June 2008 were firstly examined from an exploratory perspective. Spectral analysis was used to identify periodic behaviour by analysis of the variation of time series as a whole into periodic components of different frequencies. An additive seasonal decomposition procedure was then used to decompose the original time series (catch or flow), such that:

Catch (or flow) = SAF + SAS

= SAF + STC + ERR, where:

- SAF is the seasonal adjustment factor;
- SAS is the seasonally adjusted series;
- STC is the smoothed trend-cycle component; and
- ERR is the residual or 'error' values.

The SAF, in particular, was used to describe the relative distribution or seasonality of total catch or flow on a monthly basis.

Univariate ARIMA models

The development of ARIMA (AutoRegressive Integrated Moving Average) models was based on the methodology described in the classical work of Box and Jenkins (1976). Univariate ARIMA models are constructed using only information contained in the series itself. Thus, models are constructed as linear functions of its own past values and current and/or past values of an error term.

A non-seasonal ARIMA model has the general form (p,d,q), where p is the order of the non-seasonal autoregressive (AR) term and specifies which past value(s) of a series are used to predict the current value, d is the order of differencing required to achieve stationarity in the series, and q is the order of the

non-seasonal moving average (MA) term and specifies how deviations from the series mean for past values are used to predict the current value.

Fisheries catch and environmental time series often exhibit seasonal behaviour, and so require another set of terms (i.e. *P*, *D* and *Q*) analogous to the simple non-seasonal model, which also accounts for current values being affected by past values separated by one or more seasons. Therefore, the seasonal ARIMA model has the general form $(p,d,q)*(P,D,Q)_s$, where *s* is the seasonal span (e.g. *s* = 12 for an annual periodicity in monthly time series).

Model notation

This study adopted the same notation used by SPSS Inc. (n.d.*b*) to describe ARIMA models:

$a_t(t = 1, 2, \ldots, n)$	White series normally distributed with mean zero and variance σ^2
p	Order of the non-seasonal autoregressive part of the model
q	Order of the non-seasonal moving-average part of the model
d	Order of the non-seasonal differencing
P	Order of the seasonal autoregressive part of the model
Q	Order of the seasonal moving-average part of the model
D	Order of the seasonal differencing
s	Seasonality or period of the model
$\phi_p(B)$	AR polynomial of *B* of order *p*, $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p Bp$
$\theta_q(B)$	MA polynomial of *B* of order *q*, $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$
$\Phi_P(B^s)$	Seasonal AR polynomial of B^s of order *P*, $\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{s2} - \ldots - \Phi_P B^{sP}$
$\Theta_Q(B^s)$	Seasonal MA polynomial of B^s of order *Q*, $\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{s2} - \ldots - \Theta_Q B^{sQ}$
Δ	Differencing operator $\Delta = (1 - B)^d (1 - B^s)^D$
B	Backward shift operator with $BY_t = Y_{t-1}$ and $Ba_t = a_{t-1}$

$Z\sigma_t^2$ Prediction variance of Z_t

$N\sigma_t^2$ Prediction variance of the noise forecasts

A univariate/seasonal ARIMA model describing the relationship between the transformed time series Z_t and the dependent series Y_t has the following form:

$$Z_t = f(Y_t),$$

$$\Delta Z_t = \mu + \frac{MA}{AR} a_t \qquad \text{\{Eq. 1\}}$$

The main features of this model are:

- Initial transformation of the dependent series *f* where it is necessary to stabilise variance.
- A constant term μ.
- The unobserved i.i.d., zero mean, Gaussian error process a_t with variance σ^2.
- The moving-average lag polynomial $MA = \theta_q(B)\Theta_Q(B^s)$ and the autoregressive lag polynomial $AR = \phi_p(B)\Phi_P(B^s)$.
- The difference/lag operator Δ.
- A delay term, B^{b_i}, where b_i is the order of the delay.

Multivariate ARIMA models (transfer function models)

To investigate the use of flow volume as a predictor series that systematically influences the total catch of any of the species' groups, there is a need to go beyond the univariate model. A model must be developed that incorporates more than one time series and introduces explicitly the dynamic characteristics of the system (Vandaele, 1983), and these are referred to as multivariate ARIMA models or transfer function (TF) models. The developed TF models in this study are unidirectional, and do not allow for the possible feedback of catch predicting flow.

In addition to the autoregressive and moving average properties of the dependent series, another set of terms with similar properties is introduced for the predictor series. The numerator order of the TF specifies which past values of the predictor series are used to predict current values of the dependent series, differencing is applied where necessary to achieve stationarity in the predictor series, and the denominator order specifies how deviations from the series mean, for past values of the predictor series, are used to predict current values of the dependent series (SPSS Inc., n.d.*a*).

As with univariate models, there may also be a seasonal effect, in which the seasonal numerator, differencing and denominator components play the same roles as their non-seasonal counterparts. For seasonal orders, however, current values are affected by past values separated by one or more seasons.

Introducing a predictor series X_{1t}, X_{2t}, …, X_{kt} to the univariate ARIMA model {Eq. 1} yields the TF model, and this has the following form:

$$\Delta Z_t = \mu + \sum_{i=1}^{k} \frac{Num_i}{Den_i} \Delta_i B^{b_i} f_i(X_{it}) + \frac{MA}{AR} a_t \qquad \text{\{Eq. 2\}}$$

In addition to the features of univariate ARIMA models described above, the main features of a TF model are:

- Initial transformation of the dependent and predictor series, f and f_i where it is necessary to stabilise variance.
- Predictors are assumed given. Their numerator and denominator lag polynomials are of the form: $Num_i = (\omega_{i0} - \omega_{i1}B - \ldots - \omega_{iu}B^u)(1 - \Omega_{i1}B^s - \ldots - \Omega_{iv}B^{vs})B^b$ and $Den_i = (1 - \delta_{i1}B - \ldots - \delta_{ir}B^r)(1 - \Delta_{i1}B^s - \ldots)$.
- The 'noise' series $N_t = \Delta Z_t - \mu - \sum_{i=1}^{k} \frac{Num_i}{Den_i} \Delta_i B^{b_i} X_{it}$ is assumed to be a zero mean, stationary ARIMA process.

An extension of all ARIMA/TF models is that forecasts can be generated under the assumption that current and/or past values can be used to predict future values. However, forecasting was not undertaken as it was beyond the scope of this study. Besides, validation of forecast accuracy is likely to be confounded in this study due to protracted drought periods or relatively small flows resulting in atypical conditions of the Coorong since 2002.

'Expert Modeler'

All models were developed using the 'Expert Modeler' subroutine in the Forecasting add-on module. We chose this option as it eliminates the need to identify an appropriate model through the trial-and-error process of the traditional Box-Jenkins modelling framework (1976) (i.e. tentative identification of a model, estimation of the coefficients, and verification of the model), thus avoiding much of the subjectivity in the decision-making process, and thereby greatly reducing the chance of user-error.

The Expert Modeler automatically determines the best-fit model for each dependent (catch) series using a maximum-likelihood method for estimating its parameters and their coefficients. If a predictor series (e.g. flow) is specified (i.e. in TF models), the Expert Modeler only selects that series for inclusion in the model if it has a significant statistical relationship with the dependent series (SPSS Inc., n.d.*a*). In addition, variables of the model are appropriately transformed where necessary to stabilise variance.

The final output of each model includes details of the model parameters (estimate of coefficient, standard error, and *t*-statistic) and goodness-of-fit measures for model comparison (r^2 or stationary-r^2; normalised Bayesian information criterion, BIC; and Ljung-Box *Q*-statistic).

Normalised BIC is a measure that attempts to account for model complexity by including a penalty for the number of parameters in the model and the length of the series (i.e. the penalty removes the advantage of models with more parameters, making the measure easy to compare different models for the same series), while Ljung-Box *Q*-statistic tests for 'whiteness' or randomness of the model error values. The Ljung-Box *Q*-statistic is used to test whether a model is correctly specified. A *P*-value <0.05 indicates that the model is not correctly specified, i.e. there is still structure in the dependent series that is not accounted for, whereas a *P*-value ≥ 0.05 indicates the model is adequate for describing the time series.

Given the evidence of seasonality in the total catch and flow time series during the exploratory phase, the Expert Modeler was used to consider all seasonal models. (The full procedure used to develop all models is provided in the Appendix)

Model development strategy

Before the investigation of any relationship between flows and fisheries production, univariate ARIMA models were developed to describe the monthly catch for each species group (Type A models). These univariate models provided a baseline with which TF models can be compared to determine whether the inclusion of a predictor series improves the model fit.

The first type of TF model developed included flow as the predictor series (Type B models). The identification of Type B models would suggest that flow has an influence on the catchability of a species group through their aggregation or disaggregation, and that this is expected to occur at the same time or soon after flow.

In an attempt to further specify the flow-production relationship, particularly from flows that occur at a critical phase of a species' life history, a second type of TF model was developed in which only flow data corresponding to the spawning season of each species were included as the predictor series (Type C models), because this is the time interval when larvae are in the water column, and their survival is ultimately the key determinant of interannual recruitment variability (Cushing, 1982; Houde, 1987). Using the same approach as Lloret *et al.* (2004), flow data for the remaining months were replaced by zeros that meant, as can be seen from deduction of Eq. 1, they had 'no influence on total catch.' Thus, identification of Type C models would suggest that flow during the spawning season for a species has an influence on subsequent catches once that species has recruited to the fishery. The influence on catch is expected to occur sometime after flow, where time period approximates the age-of-recruitment for that species group.

For the purpose of Type C models, the spawning season for each species was determined from trends in species' gonadosomatic indices (Cheshire *et al.*, 2013) and/or reproductive biology in the literature. These were defined as August−December for *A. butcheri* (Harbison, 1973), January−May for *A. forsteri* (Harris, 1968), November−March for *A. hololepidotus* (Hall, 1984, 1986; Ferguson and Ward, 2003), and June−October for *R. tapirina* (Crawford, 1984).

Since the Lakes and Coorong Fishery is a multi-species fishery, and that the study species groups are all predominantly caught by a small number of licensed net fishers, it is reasonable to expect that the catch of a particular species group may be influenced by the catches of other species groups. Therefore, the third and final type of TF model is the same as Type C models, but with the inclusion of catches of other species groups (Type D models), and their influence on the catch of the species group for which the model is being developed is expected to occur at the same time.

3. Results

Description of time series

The time series for monthly catch of the species groups between July 1984 and June 2008 and the corresponding number of areas fished are shown in Figure 4. Confidentiality provisions prohibited monthly catches to be shown where less than five licence holders are represented. This restriction resulted in minor or moderate concealment of data (1.0-17.7%) for the species groups, except for *A. hololepidotus* B, where most of the data were confidential (85.0%).

Of the time series shown, the monthly catches of the species groups appear to fluctuate greatly in any given year. Regularly spaced peak catches suggest seasonality in catches of *A. butcheri*, *A. hololepidotus* A, *R. tapirina* and, to a lesser extent, *A. forsteri*. Relatively large catches were taken in October 1984, September 1985 and September 1986 for *A. butcheri* (>8,000 kg), March and December 2001 for *A. hololepidotus* A (≥28,000 kg), and April 1991 for *R. tapirina* (>14,000 kg). Also apparent in Figure 4, corresponding to monthly catch, is a general reduction in the number of areas that were fished.

Similarly, the flow time series exhibits large intra-annual variation, and the peak monthly volumes occur on a seasonal basis (Figure 5(a)). Monthly flow volumes were particularly high (>2,500 GL) in November 1990, and January and December 1993. The study region has been subjected to several droughts (defined here as periods of at least six months with zero flows) over the 24-year time series; however, these have become more frequent and protracted since January 2002. Furthermore, the few flows that intersperse these recent drought periods are relatively low compared to the pre-drought period (i.e. prior to 2002).

It appears that the frequency and magnitude of flows have a direct impact on the spatial extent of the study region that comprises brackish water (0.5-29.9‰ salinity). Therefore, as a consequence of the extensive drought periods since 2002, brackish areas diminished to the point that the study region almost exclusively comprised saline (30-49.9‰) and hypersaline (≥50‰) waters during this 'drought' phase, with salinities reaching unprecedented levels (up to 200‰ on one occasion) in the Southern Lagoon (Figure 5 (b)).

Mann-Whitney U test results revealed significant differences in underlying distributions of mean monthly catch (using median values as the measure of central tendency) between pre-drought and drought phases for *A. forsteri*, *A. hololepidotus* B and *R. tapirina*, whereby catches for *A. forsteri* and *R. tapirina* were significantly reduced during the drought phase, whilst *A. hololepidotus* B catch significantly increased (Table 1). Significant differences were also found for each of the species groups (except *A. hololepidotus*

B) with respect to the number of areas fished and number of active licences contributing to catch, all of which were reduced during the drought phase (by 1-2 areas fished and 3-5 active licences).

Table 1. Results of two-sample Mann-Whitney U test for difference in mean monthly catch, number of areas fished and number of active licenses between pre-drought (before 2002) and drought (2002 onward) phases from July 1984 to June 2008. Median values are presented.

Species group	Median values		*Z*
	Pre-drought (n = 210)	Drought (n = 78)	
Total catch (kg)			
A. butcheri	397	325	-0.957
A. forsteri	14,191	11,682	-3.355***
A. hololepidotus A	2,246	2,247	-0.345
A. hololepidotus B	117	333	-2.830**
R. tapirina	1,107	343	-5.041***
No. areas fished			
A. butcheri	5	3	-8.858***
A. forsteri	6	5	-8.005***
A. hololepidotus A	5	4	-9.139***
A. hololepidotus B	1	1	-1.257
R. tapirina	5	3	-7.190***
No. licences			
A. butcheri	10	6	-6.553***
A. forsteri	14	10	-6.427***
A. hololepidotus A	12	9	-5.784***
A. hololepidotus B	2	2	-1.760
R. tapirina	10	5	-6.068***

**$P < 0.01$; ***$P < 0.001$.

Abbreviations: n, number of months; Z, Z-statistic.
Note: the absolute value of the Z-statistic is used since U is approximately normally distributed for large samples (Zar, 2009).

The spectral density plot of monthly catch for each of the species groups reveals a peak at a frequency of 0.083, which corresponds to 12 months (i.e. 1/0.083) (Figure 6). We conclude from this that the monthly catch series exhibit periodic behaviour, and that the development of time series models for all species groups should consider seasonal models with a periodicity of 12 months.

Seasonality of monthly catch for the species groups were suspected from visual examination of the time series plots, and then confirmed through spectral analysis techniques. Details of this seasonality, in terms

of distinctiveness and timing, were determined by isolating the seasonal adjustment factor (SAF) of each time series, along with other components, through a seasonal decomposition procedure (**Error! Reference source not found.**).

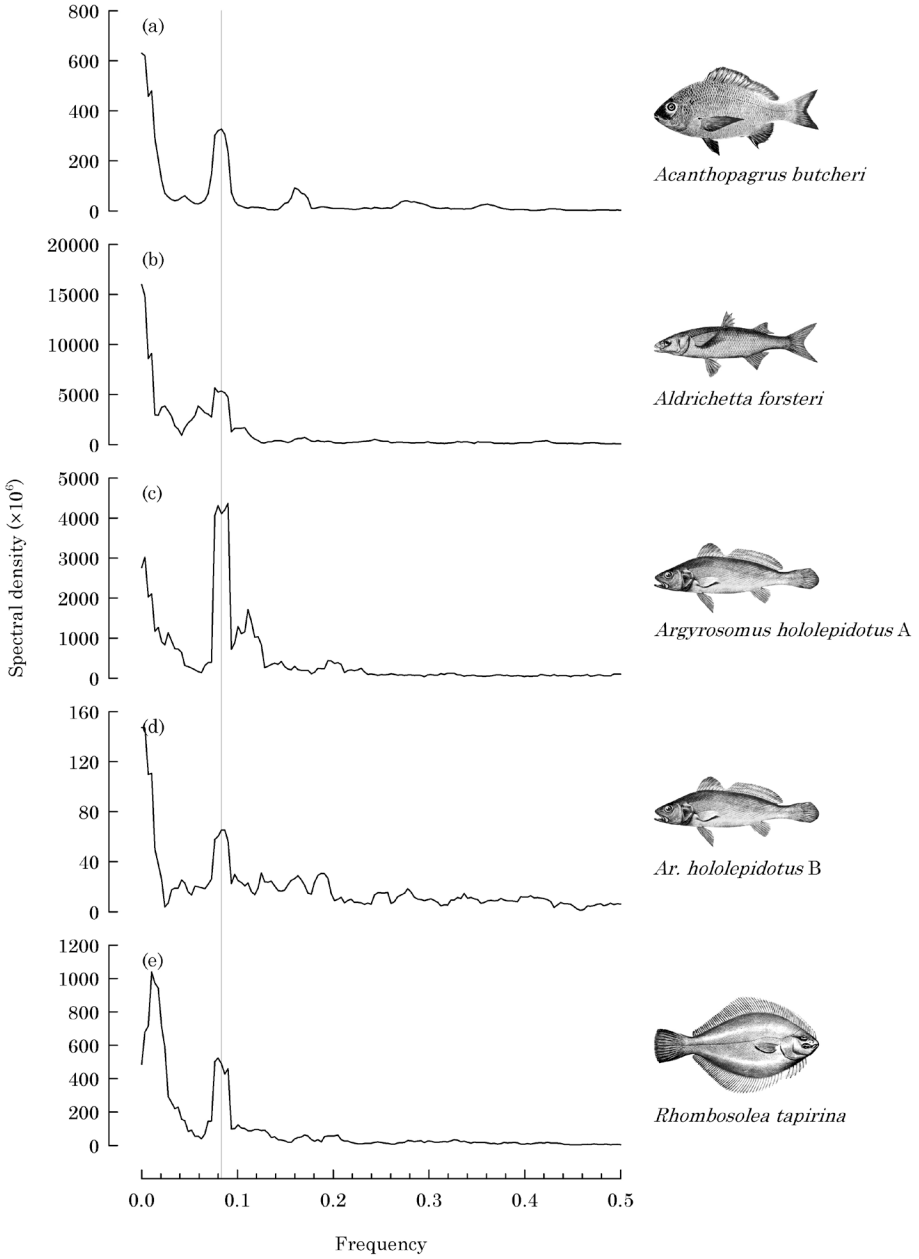

Figure 6. Spectral density of monthly catch of (a) *A. butcheri*, (b) *A. forsteri*, (c) *A. hololepidotus* A (inside the Murray Mouth), (d) *A. hololepidotus* B (outside the Murray Mouth) and (e) *R. tapirina* from the Lakes and Coorong Fishery between July 1984 and June 2008. The reference line (grey) indicates a frequency of 0.083, which corresponds to a periodicity of 12 months (i.e. 1/0.083).

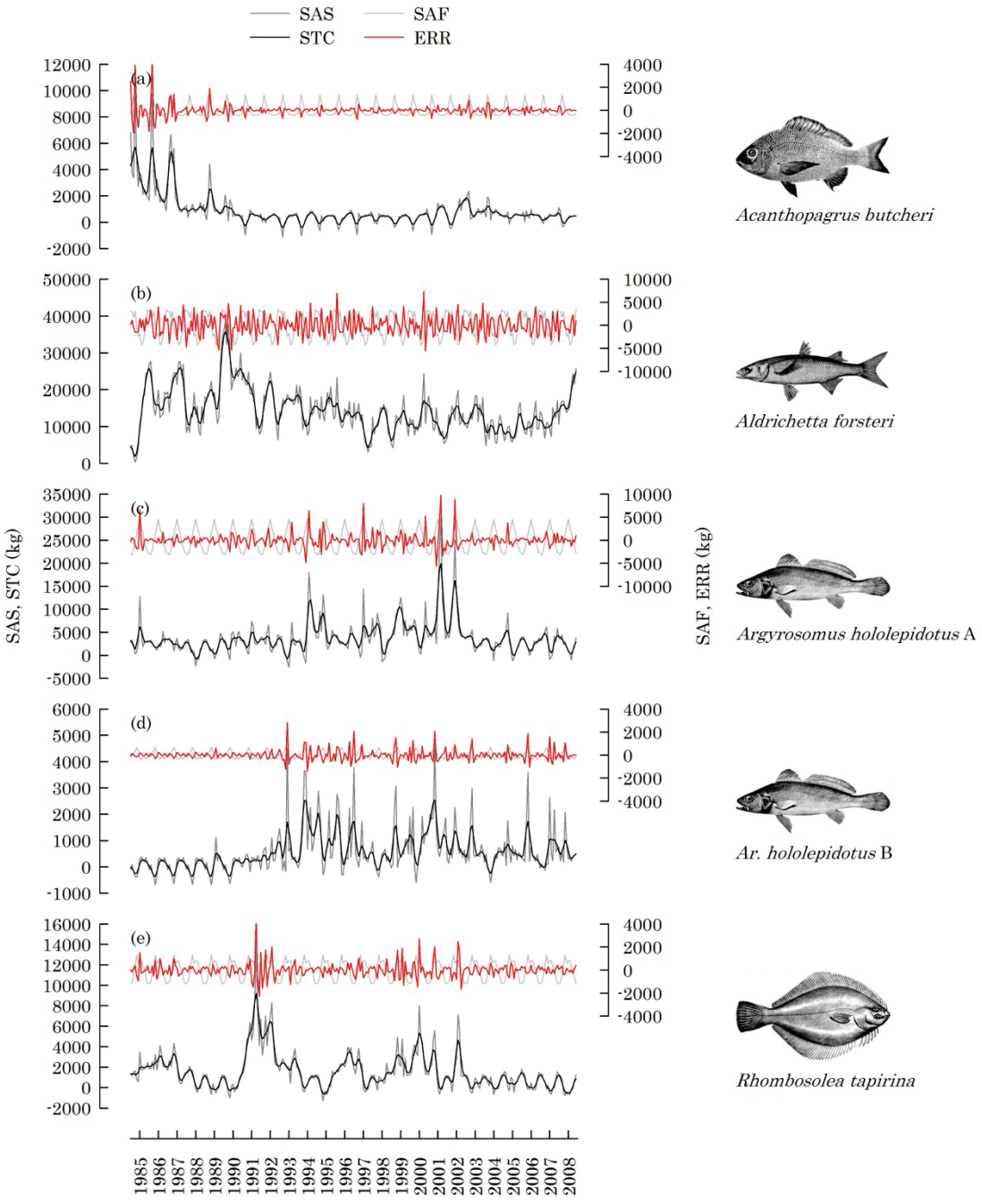

Figure 7. Seasonal decomposition of monthly catch of (a) *A. butcheri*, (b) *A. forsteri*, (c) *A. hololepidotus* A (inside the Murray Mouth), (d) *A. hololepidotus* B (outside the Murray Mouth) and (e) *R. tapirina* from the Lakes and Coorong Fishery between July 1984 and June 2008. Abbreviations: SAS, seasonally adjusted series; STC, smoothed trend-cycle component; SAF, seasonal adjustment factors; ERR, residuals or 'error' values.

Mean monthly catches were largest in early spring (September) for *A. butcheri*, summer (January) for *A. hololepidotus* A, and late spring (November) for *A. hololepidotus* B and *R. tapirina* (Figure 8). Seasonality was pronounced in these species groups, as their maxima were at least 100% greater than the mean monthly catch for the respective species group obtained over the 24-year time series (except for *R. tapirina*, where the November catch was 83% greater than the overall mean). Seasonality was relatively weak for *A. forsteri*, where mean monthly catch only deviated <30% from the overall mean. In comparison, mean monthly flow volumes across the barrages were highest during spring (September to November), and 99% greater than the overall mean.

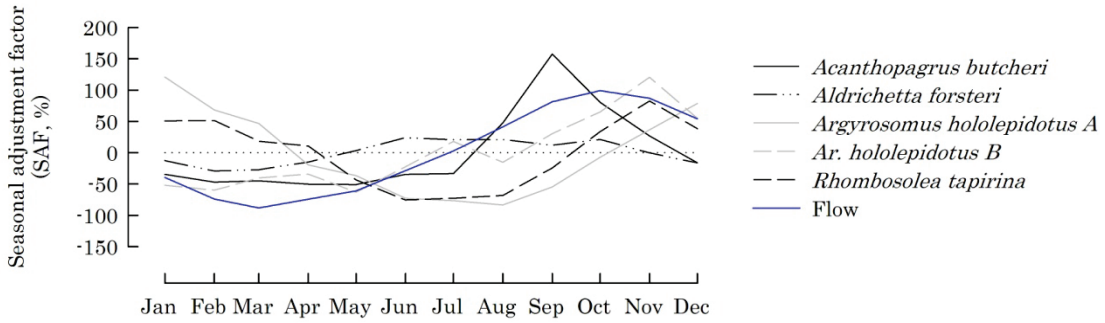

Figure 8. Seasonal adjustment factor (SAF, %) of flow and monthly catch of *A. butcheri*, *A. forsteri*, *A. hololepidotus* A (inside the Murray Mouth), *A. hololepidotus* B (outside the Murray Mouth) and *R. tapirina* from the Lakes and Coorong Fishery. The SAF for each calendar month represents the percentage above/below the mean monthly catch obtained between July 1984 and June 2008.

Univariate ARIMA (Type A model) and transfer function models (Type B, C, D models)

For the development of a model for any dependent time series, Expert Modeler only identifies those models whose parameters and coefficients are statistically significant. The best model for that series is then selected based on goodness-of-fit (SPSS Inc., n.d.*b*).

Once a univariate ARIMA model (Type A model) was established for catch of a species group, flow volume and catches of other species groups were systematically selected as candidate predictor series for the development of TF models (Type B, C, D models). In doing so, the univariate model was considered as a baseline to assess whether the inclusion of predictor series in TF models offer greater predictive power than previous catches of the dependent series alone.

To facilitate the interpretation of models, including the differences between model types, model output summary tables are arranged for each species group (Table 2 - Table 5). On the other hand, all graphical comparisons between observed and model-predicted catches of the different species groups are arranged by model type (Figure 9 - Figure 12).

Rhombosolea tapirina

The monthly catch of *R. tapirina* was not modelled successfully using any of the ARIMA time series modelling techniques presented in this study. Either the Type A or D model was not correctly specified by virtue of its significant *Q*-value or a Type B or C model could not be identified.

Acanthopagrus butcheri (Table 2)

Mean monthly catch for *A. butcheri* was successfully modelled based on previous catches alone (Type A model). The catch time series for *A. butcheri* was natural log-transformed to stabilise variance, and seasonal differencing applied in order to achieve stationarity (i.e. to account for the decreasing trend resulting from relatively large periodic catches in the 1980s). Catch at time t is influenced by catch at time t-1 as indicated by a non-seasonal AR parameter with an order of 1, and is also affected by the deviation of the series mean at time t-12 as indicated by a seasonal MA term with order 1 (= 12 months).

For the development of Type B models, monthly flow was selected as the input series to (partly) predict the catch of a species group (along with previous catches). The model output for *A. butcheri* identified no predictors, which indicates that no model could be identified that improved on the univariate model for this species.

For Type C models, only monthly flow volumes during the spawning season of the respective species group were selected as the input series to (partly) predict the catch of that species group (along with previous catches) – flow data for the remaining months were replaced by zeros. Again, no TF model could be identified for the *A. butcheri* catch series.

Type D models build upon Type C models with the inclusion of catches of other species groups as potential predictors, particularly given that the Lakes and Coorong Fishery is a multi-species fishery. As for the univariate model, the *A. butcheri* catch series was natural log-transformed and seasonal differencing was applied. Whilst the Type D model identified season-specific flows (August−December), and catches of *A. hololepidotus B* and *R. tapirina* as predictors of catch of *A. butcheri*, the coefficients of the model parameters all approached zero, which means that they virtually cancel themselves out in Eq. 1, and therefore have a negligible effect. Non-seasonal MA orders of 1 and 2 indicate that catch of *A.*

butcheri at time *t* is affected by the deviation of the series mean at times *t*-1 and *t*-2, and a seasonal AR order of 1 (= 12 months) indicates that catch is also influenced by catch at time *t*-12. The Type D model for *A. butcheri* has a smaller stationary-r^2 value but an improved (lower) BIC measure compared to the Type A model.

Aldrichetta forsteri (Table 3)

A Type A model for the *A. forsteri* catch series could not be correctly specified, by virtue of a significant *Q*-statistic.

The Type B model for *A. forsteri* revealed that catch is partly predicted by flows during the same month, as indicated by the Numerator (*Num*) lag order of 0. It can be deduced from Eq. 1 that, since there is no confounding Denominator (*Den*) coefficient or delay (the delay before the predictor series has an influence), the *Num* coefficient (2.423, $P < 0.001$) indicates that, at time *t*, every 1 GL of freshwater discharged across the barrages leads to an additional catch of *A. forsteri* of 2.4 kg. The catch of *A. forsteri* is also influenced by non-seasonal MA orders of 1-4 and a seasonal AR order of 1. An estimated 63% of the total variation in the series is explained by this model.

No Type C model could be identified for *A. forsteri*.

The Type D model identified that catch of *A. forsteri* is partly predicted by *A. hololepidotus* A catch during the same month, as indicated by the *Num* order of 0. As for the Type B model for *A. forsteri*, the relationship can be quantified. The *Num* coefficient (-0.268, $P < 0.001$) indicates that, at time *t*, every 1 kg of *A. hololepidotus* A that is caught corresponds with a reduction in catch of *A. forsteri* by 0.3 kg. The Type D model for *A. forsteri* has only a slightly higher r^2 and improved BIC measure compared to the Type B model.

Table 2. Univariate ARIMA (Type A model) and transfer function models (Type B, C, D models) for monthly catch of *A. butcheri* from the Lakes and Coorong Fishery between July 1984 and June 2008.

Model Type	Model form	Predictor series	Parameter	Order	Estimate	S.E.	*t*	Sig.	Model-fit statistics				
									r^2	Normalised BIC	Ljung-Box $Q(18)$	d.f.	Sig.
A†	$(1,0,0)*(0,1,1)_{12}$		Constant		-0.091	0.030	-3.010	0.003	0.497*	14.734	21.049	16	0.177
			AR	Lag 1	0.519	0.052	9.898	0.000					
			Seasonal Difference	1									
			MA, Seasonal	Lag 1	0.885	0.052	16.898	0.000					
B					*Transfer function model not identified*								
C					*Transfer function model not identified*								
D†	$(0,0,2)*(1,1,0)_{12}$		Constant		-0.193	0.054	-3.596	0.000	0.458*	13.461	24.562	15	0.056
			MA	Lag 1	-0.448	0.063	-7.106	0.000					
				Lag 2	-0.154	0.063	-2.462	0.015					
			AR, Seasonal	Lag 1	-0.436	0.060	-7.270	0.000					
			Seasonal Difference	1									
		$Flow_{Aug\text{-}Dec}$	Delay	12									
			Numerator	Lag 0	0.000	0.000	-3.374	0.001					
				Lag 1	0.000	0.000	-2.216	0.028					
			Seasonal Difference	1									
		$Catch_{A.ho/B}$	Delay	6									
			Numerator	Lag 0	0.000	0.000	3.535	0.000					
			Seasonal Difference	1									
		$Catch_{R.tap}$	Delay	5									
			Numerator	Lag 0	0.000	0.000	2.913	0.004					
				Lag 5	0.000	0.000	2.824	0.005					
			Seasonal Difference	1									

Abbreviations: S.E., standard error; *t*, *t*-statistic; Sig., significance; r^2, coefficient of determination; BIC, Bayesian information criterion; *Q*, *Q*-statistic; d.f., degrees of freedom. Dagger (†) denotes natural-log transformation of dependent time series; asterisk (*) denotes stationary-r^2 value is used, i.e. where model required differencing.

Table 3. Univariate ARIMA (Type A model) and transfer function models (Type B, C, D models) for monthly catch of *A. forsteri* from the Lakes and Coorong Fishery between July 1984 and June 2008.

Model Type	Model form	Predictor series	Parameter	Order	Estimate	S.E.	*t*	Sig.	Model-fit statistics				
									r^2	Normalised BIC	Ljung-Box $Q(18)$	d.f.	Sig.
A					*Model not correctly specified*								
B	$(0,0,4)*(1,0,0)_{12}$		Constant		13661.230	936.168	14.593	0.000	0.626	16.848	18.853	13	0.128
			MA	Lag 1	-0.694	0.059	-11.698	0.000					
				Lag 2	-0.514	0.068	-7.560	0.000					
				Lag 3	-0.411	0.069	-6.002	0.000					
				Lag 4	-0.187	0.059	-3.138	0.002					
			AR, Seasonal	Lag 1	0.237	0.060	3.942	0.000					
		Flow	Numerator	Lag 0	2.423	0.803	3.018	0.003					
C					*Transfer function model not identified*								
D	$(0,0,4)*(0,0,1)_{12}$		Constant		15410.917	910.790	16.920	0.000	0.629	16.841	21.978	13	0.056
			MA	Lag 1	-0.702	0.059	-11.830	0.000					
				Lag 2	-0.509	0.068	-7.457	0.000					
				Lag 3	-0.415	0.069	-6.017	0.000					
				Lag 4	-0.184	0.059	-3.104	0.002					
			MA, Seasonal	Lag 1	-0.256	0.060	-4.264	0.000					
		$Catch_{A.holA}$	Numerator	Lag 0	-0.268	0.076	-3.508	0.001					

Abbreviations are the same as those defined for Table 2.

Argyrosomus hololepidotus A (Table 4)

The Type A model for catch of *A. hololepidotus* A has non-seasonal AR orders of 1 and 2, a seasonal AR order of 1 and a seasonal MA order of 1. This model explains an estimated 86% of the total variation in the *A. hololepidotus* A catch series.

The Type B model for catch of *A. hololepidotus* A includes *Num* orders of 0-2 and *Den* orders of 1 and 2, which indicate that catch is partly predicted by concurrent flows and flows of the 1st and 2nd lagged months (coefficients reveal that the flow-catch relationship is negative at *t* and *t*-1), and by deviations in the 1st and 2nd lagged months from the series mean. The catch of *A. hololepidotus* A is also influenced by non-seasonal AR orders of 1 and 2 and non-seasonal MA orders of 9 and 10. The Type B model for *A. hololepidotus* A is a poorer fit to the catch series (in terms of r^2 and BIC measure) compared to the Type A model.

Type C models were successfully developed only for *A. hololepidotus* species groups A and B, therefore the season-specific flow data for this species refers to the spawning season of November−March. The catch model for *A. hololepidotus* A has *Num* orders of 0 and 1, and *Den* orders of 1 and 2, which indicate that catch is partly predicted by season-specific flow at times *t* and *t*-1, and by deviations at times *t*-1 and *t*-2 from the series mean. As for the Type B model, the coefficients for *Num* orders 0 and 1 for *A. hololepidotus* A are both negative. The catch of *A. hololepidotus* A is also influenced by a non-seasonal AR order of 1, a non-seasonal MA order of 9, a seasonal AR order of 1 and a seasonal MA order of 1. The Type C model for *A. hololepidotus* A has only a slightly improved BIC measure compared to the Type A model.

A Type D model for the *A. hololepidotus* A catch series could not be correctly specified.

Table 4. Univariate ARIMA (Type A model) and transfer function models (Type B, C, D models) for monthly catch of *A. hololepidotus* A (inside the Murray Mouth) from the Lakes and Coorong Fishery between July 1984 and June 2008.

Model Type	Model form	Predictor series	Parameter	Order	Estimate	S.E.	*t*	Sig.	Model-fit statistics				
									r^2	Normalised BIC	Ljung-Box $Q(18)$	d.f.	Sig.
A	$(2,0,0)*(1,0,1)_{12}$		Constant		3356.051	934.111	3.593	0.000	0.858	15.314	19.350	14	0.152
			AR	Lag 1	1.143	0.058	19.845	0.000					
				Lag 2	-0.406	0.057	-7.068	0.000					
			AR, Seasonal	Lag 1	0.967	0.034	28.686	0.000					
			MA, Seasonal	Lag 1	0.869	0.074	11.750	0.000					
B	(2,0,10)		Constant		4482.431	520.076	8.619	0.000	0.823	15.491	15.780	14	0.327
			AR	Lag 1	0.949	0.060	15.698	0.000					
				Lag 2	-0.251	0.060	-4.166	0.000					
			MA	Lag 9	-0.171	0.061	-2.801	0.005					
				Lag 10	-0.161	0.062	-2.591	0.010					
		Flow	Numerator	Lag 0	-3.060	0.400	-7.653	0.000					
				Lag 1	-5.394	0.704	-7.668	0.000					
				Lag 2	3.031	0.409	7.419	0.000					
			Denominator	Lag 1	1.714	0.008	219.209	0.000					
				Lag 2	-0.980	0.008	-126.582	0.000					
C	$(1,0,9)*(1,0,1)_{12}$		AR	Lag 1	0.785	0.039	20.324	0.000	0.856	15.284	19.797	14	0.137
			MA	Lag 9	-0.178	0.063	-2.812	0.005					
			AR, Seasonal	Lag 1	0.981	0.018	53.362	0.000					
			MA, Seasonal	Lag 1	0.846	0.062	13.542	0.000					
		$Flow_{Nov\text{-}Mar}$	Numerator	Lag 0	-1.859	0.324	-5.738	0.000					
				Lag 1	-3.200	0.332	-9.645	0.000					
			Denominator	Lag 1	0.850	0.084	10.095	0.000					
				Lag 2	-0.327	0.081	-4.010	0.000					
D			*Model not correctly specified*										

Abbreviations are the same as those defined for Table 2.

Argyrosomus hololepidotus B (Table 5)

The Type A model for catch of *A. hololepidotus* B has a non-seasonal order of 1 and a seasonal AR order of 1. This model explains an estimated 82% of the total variation in the *A. hololepidotus* B catch series.

The Type B model identified that catch of *A. hololepidotus* B has no *Den* coefficients or delay; therefore, the *Num* coefficients of orders of 0 and 15 (0.268 and -0.259, respectively, $P < 0.01$) indicate that every 1 GL of flow at time t and t–15 leads to an increase and reduction in catch by 0.3 kg, respectively. The catch of *A. hololepidotus* B is also influenced by a non-seasonal AR order of 1, a non-seasonal MA order of 10 and a seasonal AR order of 1. The Type B model for *A. hololepidotus* B is a poorer fit to the catch series compared to the Type A model.

The Type C model for catch of *A. hololepidotus* B is similar to the Type B model, but its *Num* coefficient of order 0 (0.405, $P < 0.001$) further specifies that every 1 GL of flow during the spawning season (November−March) at time t leads to an additional catch of 0.4 kg. The catch of *A. hololepidotus* B is also influenced by a non-seasonal AR order of 1 and a seasonal AR order of 1. The Type C model for *A. hololepidotus* B is a better fit to the catch series than the Type B model but is still a poorer fit compared to the Type A model.

The Type D model identified that, in addition to season-specific flows, catch of *R. tapirina* partly predicts catch of *A. hololepidotus* B. Flow has a *Num* order of 1, whereas *R. tapirina* catch has *Num* orders of 0 and 1 and a delay of 4. The combined influence of these predictors, in the absence of *Den* coefficients, is that every 1 GL of flow during the spawning season (November−March) at time t leads to an additional catch of 0.4 kg and every 1 kg of *R. tapirina* that is caught at time t and t-1 leads to small reductions in catch of *A. hololepidotus* B by 0.1 and 0.1 kg, respectively. The Type D model was the poorest fitting of all four model types for predicting catch of *A. hololepidotus* B.

Table 5. Univariate ARIMA (Type A model) and transfer function models (Type B, C, D models) for monthly catch of *A. hololepidotus* B (outside the Murray Mouth) from the Lakes and Coorong Fishery between July 1984 and June 2008. Abbreviations are the same as those defined for Table 2.

Model Type	Model form	Predictor series	Parameter	Order	Estimate	S.E.	*t*	Sig.	Model-fit statistics				
									r^2	Normalised BIC	Ljung-Box $Q(18)$	d.f.	Sig.
A	$(1,0,0)*(1,0,0)_{12}$		Constant		389.036	98.231	3.960	0.000	0.824	12.399	18.365	16	0.303
			AR	Lag 1	0.664	0.047	14.158	0.000					
			AR, Seasonal	Lag 1	0.316	0.061	5.212	0.000					
B	$(1,0,10)*(1,0,0)_{12}$		Constant		291.865	116.977	2.495	0.013	0.744	12.735	18.705	15	0.227
			AR	Lag 1	0.581	0.053	11.038	0.000					
			MA	Lag 10	-0.183	0.063	-2.887	0.004					
			AR, Seasonal	Lag 1	0.280	0.063	4.424	0.000					
		Flow	Numerator	Lag 0	0.268	0.097	2.765	0.006					
				Lag 15	-0.259	0.087	-2.980	0.003					
C	$(1,0,0)*(1,0,0)_{12}$		Constant		376.953	112.569	3.349	0.001	0.795	12.526	21.507	16	0.160
			AR	Lag 1	0.700	0.044	15.757	0.000					
			AR, Seasonal	Lag 1	0.277	0.063	4.387	0.000					
		$Flow_{Nov\text{-}Mar}$	Numerator	Lag 0	0.405	0.077	5.272	0.000					
D	$(1,0,0)*(1,0,0)_{12}$		Constant		404.724	109.535	3.695	0.000	0.711	12.796	25.834	16	0.056
			AR	Lag 1	0.585	0.052	11.219	0.000					
			AR, Seasonal	Lag 1	0.290	0.061	4.759	0.000					
		$Flow_{Nov\text{-}Mar}$	Numerator	Lag 0	0.425	0.096	4.444	0.000					
		$Catch_{R.tap}$	Delay	4									
			Numerator	Lag 0	-0.061	0.023	-2.622	0.009					
				Lag 1	-0.071	0.023	-3.058	0.002					

Abbreviations are the same as those defined for Table 2.

Model fit

Only minor improvements to model fit were obtained through the inclusion of predictor series (a poorer fit actually resulted in some cases). Nevertheless, the overall fit of model-predicted values compared to actual catch time series for each of the species groups is satisfactory. This is evident in the comparison plots (Figure 9 - Figure 12) and the r^2-values, which generally ranged between 0.63 and 0.86 (the exception being the models for *A. butcheri*, which had r^2-values of almost 0.5).

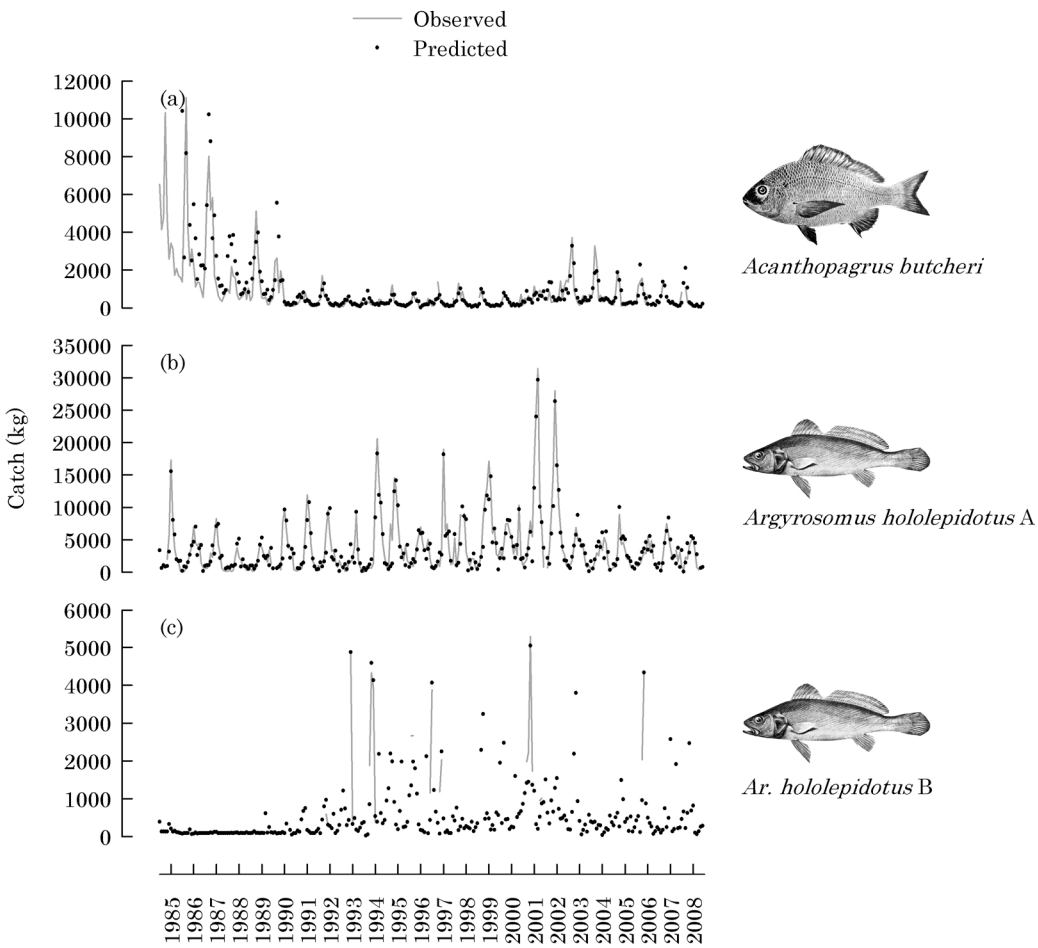

Figure 9. A comparison between observed and predicted (determined from univariate ARIMA models in Table 2) monthly catch of (a) *A. butcheri*, (b) *A. hololepidotus* A (inside the Murray Mouth) and (c) *A. hololepidotus* B (outside the Murray Mouth) from the Lakes and Coorong Fishery between July 1984 and June 2008. Note: where catch represents <5 licence holders, these data are confidential and are therefore omitted from the graph.

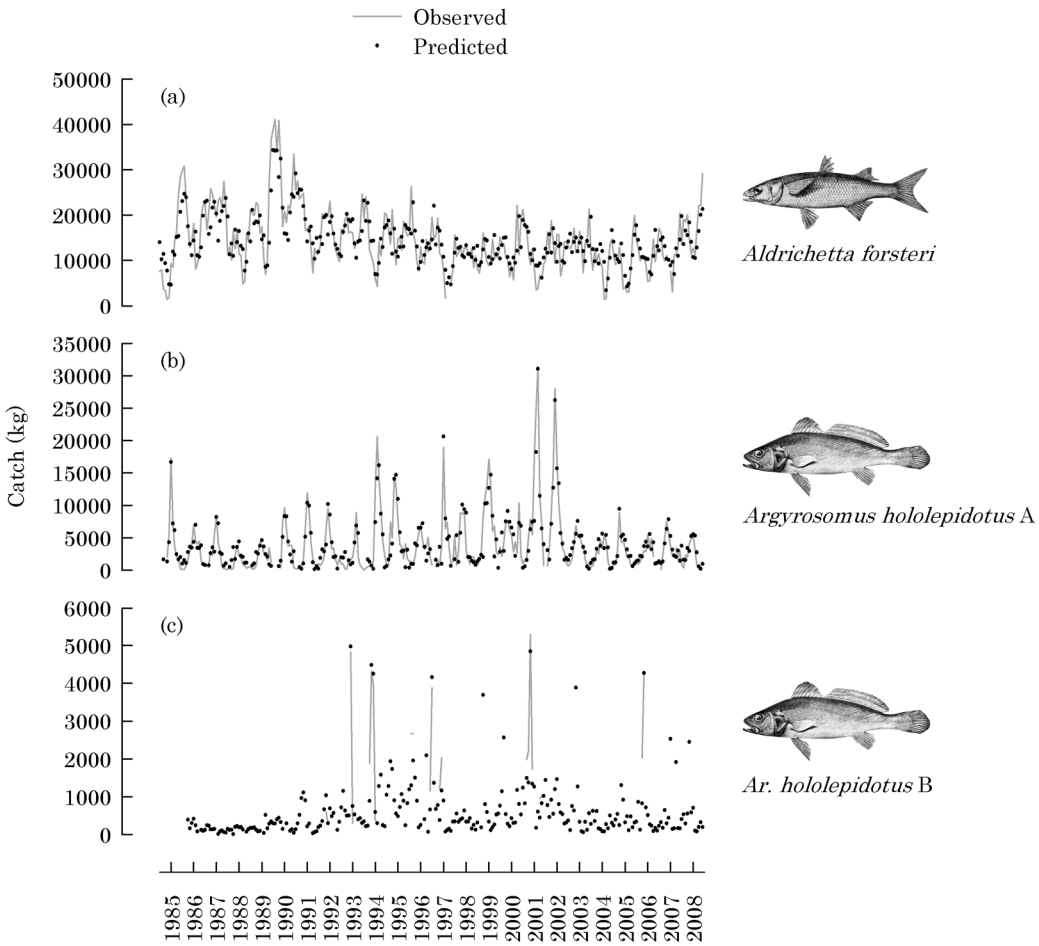

Figure 10. A comparison between observed and predicted (determined from transfer function models in Table 3) monthly catch of (a) *A. forsteri*, (b) *A. hololepidotus* A (inside the Murray Mouth) and (c) *A. hololepidotus* B (outside the Murray Mouth) from the Lakes and Coorong Fishery between July 1984 and June 2008, using flow volume as the predictor series. Note: where catch represents <5 licence holders, these data are confidential and are therefore omitted from the graph.

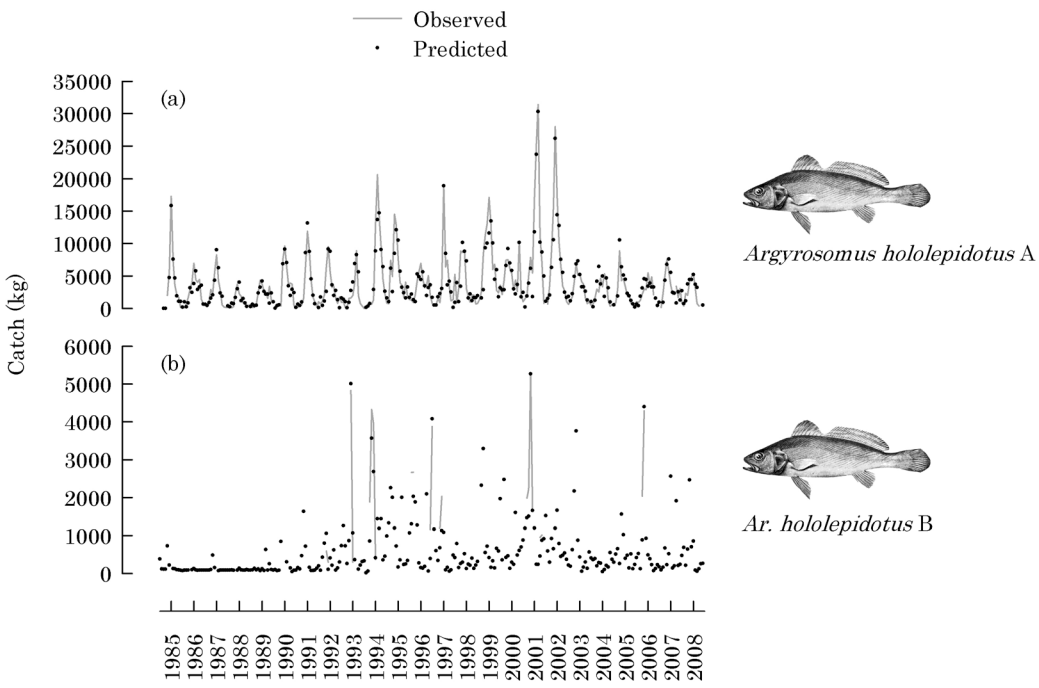

Figure 11. A comparison between observed and predicted (determined from transfer function models in Table 4) monthly catch of (a) *A. hololepidotus* A (inside the Murray Mouth) and (b) *A. hololepidotus* B (outside the Murray Mouth) from the Lakes and Coorong Fishery between July 1984 and June 2008, using spawning season-specific flow volume as the predictor series. Note: where catch represents <5 licence holders, these data are confidential and are therefore omitted from the graph.

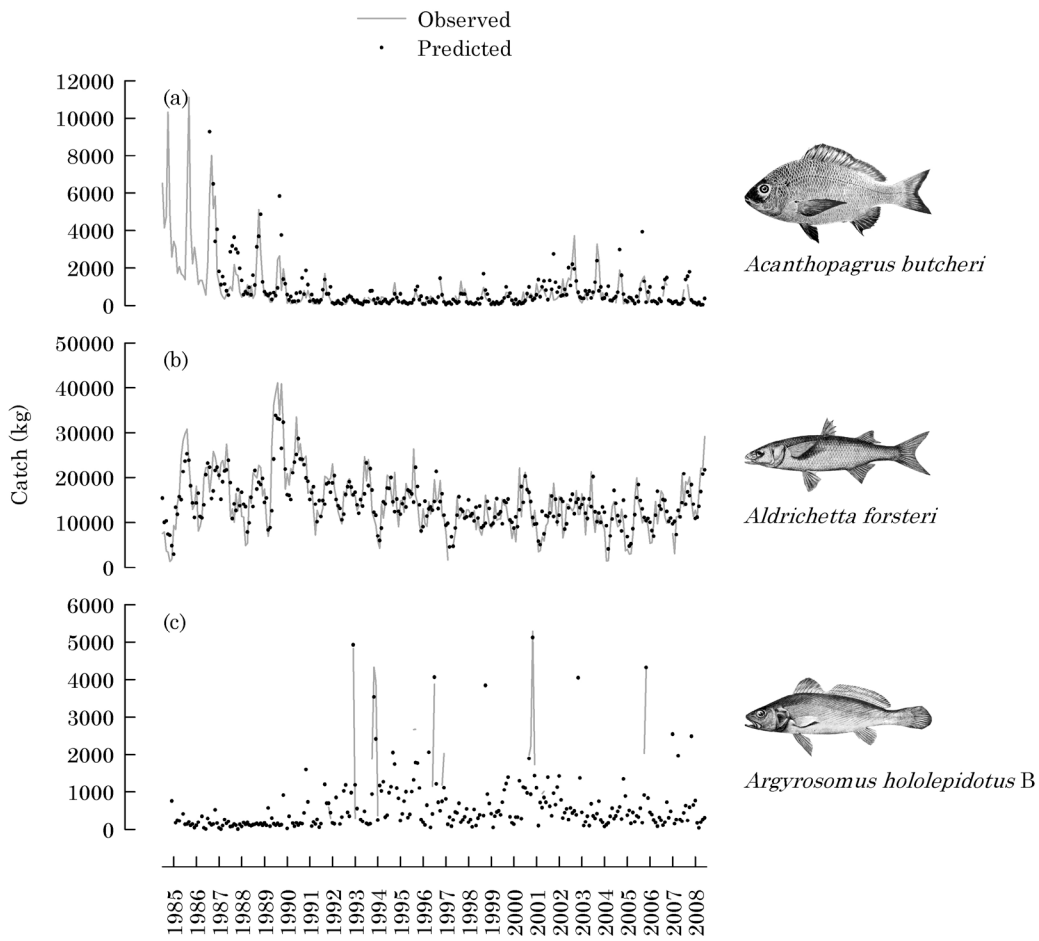

Figure 12. A comparison between observed and predicted (determined from transfer function models in Table 5) monthly catch of (a) *A. butcheri*, (b) *A. forsteri* and (c) *A. hololepidotus* B (outside the Murray Mouth) from the Lakes and Coorong Fishery between July 1984 and June 2008, using spawning season-specific flow volume and/or catch of other species as predictor series. Note: where catch represents <5 licence holders, these data are confidential and are therefore omitted from the graph.

4. Discussion

Time series analysis was identified as a potentially useful tool to investigate the influence of freshwater discharge (flow volume) across barrages as a predictor of catch of key species groups in the Lakes and Coorong Fishery. Specifically, it is hypothesised that flow has an influence on the spawning and recruitment (sp. *A. butcheri*, *A. hololepidotus*, *R. tapirina*) or spawning aggregation (*A. hololepidotus*) of most of these species, although it is unclear what effect flow has, if any, on *A. forsteri*.

The basic premise of this study is that these biological processes have a causal effect on fish production, which is reflected (concurrently or some time later) in the catches of the species concerned. Catches in another multi-species fishery in the northwest Mediterranean Sea were typically found to correspond to either the time of spawning or recruitment to the fishery (Lloret *et al.*, 2000).

Importantly, the development of time series models to investigate these relationships accounts for any inherent seasonality and underlying trends and cyclicity in the time series before the final model is developed. The specific nature of the relationships can then be inferred from the model parameters and their coefficients.

As the Lakes and Coorong Fishery is a multi-species fishery, the licensed net fishers are able to target different species under different circumstances (season, time of day, weather, etc.). Therefore, the catch of any species is usually not independent of the catch of another species. To allow for any confounding influence of catches of other species, further models were developed to include these catches as potential predictors (in addition to flow).

The univariate ARIMA model (Type A) described the catch series for *A. butcheri* and *A. hololepidotus* B better than any TF model (Types B, C, D). Both models exhibited a positive autoregressive component, which indicates that catch is predominantly influenced by catch in the previous month. No valid model was produced for *R. tapirina*. The catches of *A. forsteri* and *A. hololepidotus* A, on the other hand, were best described using TF models, some of which can be explained by biological processes or fisher behaviour.

The TF model identified for catch of *A. forsteri* indicated that increases in flow lead to additional catch taken during the same month (Type B model). If we assume that catch of *A. forsteri*, in this case, is a proxy for abundance, then this model could be explained by their: 1) aggregation to take advantage of an increased food supply from the nutrient-enriched freshwater discharge; 2) immigration from the sea into the Murray Mouth and Coorong to shelter from predation in more

turbulent water; or 3) immigration from the sea to occupy the increasing area available that comprises preferred lower salinities or other optimal conditions (Geddes, 1987). The latter of these explanations is supported by Hall's (1984) observation of a general southward expansion of the range of fish species when salinities fall.

The latter explanation is supported by the observation that larger catches of *A. forsteri* generally corresponded to more fishing areas being fished, and *vice versa* (Figure 4). Potter and Hyndes (1994) found that *A. forsteri* in estuaries of the southern coast of Western Australia has an apparent preference for reduced salinities and/or features associated with riverine environments.

With the inclusion of catches of other species groups as potential predictors (Type D model), an alternative TF model that describes catch of *A. forsteri* was developed. This model indicated that *A. forsteri* catch was inversely related to catch of *A. hololepidotus* A (taken from inside the Murray Mouth). This model may be explained by licensed net fishers targeting one species at a time, particularly since *A. forsteri* are predominantly caught using small-mesh gill nets, whereas *A. hololepidotus* A are caught using large-mesh gill nets.

The TF model identified for catch of *A. hololepidotus* A indicated that catch was inversely influenced by flows that occurred 1 and 2 months earlier (during the spawning season of this species), i.e. catches of *A. hololepidotus* A during December−May are reduced with increasing flows 1 or 2 months earlier during its spawning season (November−March). However, this model is difficult to interpret as there is no conceivable explanation for this relationship.

Despite the hypothesised relationship between flow and catch of species groups, it was difficult to establish these relationships in this study. Transfer function models, which included flow as a predictor series, offered only slight improvements in predictive power to the univariate ARIMA models, in which catch is modelled on previous catches alone.

The lack of predictive models does not preclude that these relationships exist. However, without knowing the level of impact, it is worth considering that there are a number of possible reasons that have interfered with the model development:

Catch is too delayed to detect flow-recruitment signal. The species groups in this study are estimated to generally recruit to the fishery at 2-3 years of age (Hall, 1984; Ferguson and Ward, 2003; Ferguson and Ye, 2008). In regard to detecting a relationship between flow and successful recruitment to the fishery, these time delays between the spawning of a species and its recruitment and subsequent capture are probably too long such that they allow other unaccounted sources of variation to occur and thereby diminish the flow-catch signal that may otherwise be realised.

In comparison, Lloret *et al.* (2001, and references therein) successfully developed models relationships that were able to detect between environmental variables (e.g. river run-off, wind mixing index) and yields of short-lived pelagic species that enter the fishery at 12 months of age or less.

Catch does not accurately reflect production. The assumption that greater production of a species or its abundance is expected to lead to larger catches may be violated. Catch per unit of effort (CPUE), which is often used as a measure of abundance, is the alternative measure that could have been used in this study. However, catch was considered as the more reliable measure in a data series where catches fluctuate greatly, as there was a requirement to avoid situations of some small catches misleadingly inferring spuriously high abundances relative to large catches, which can occur when CPUE is used.

Time series intervals conceal important information. The chosen time series intervals may not correspond well with the temporal scale of the biological process of influence (e.g. recruitment, spawning aggregation). Catch was aggregated into monthly totals for this study. The problem with aggregating data, however, is that information can be 'lost'. There are specific characteristics of flow that may not be detected using time series modelling techniques. For example, frequent small flows may be preferred to infrequent large flows (Geddes, 2005*a*; Geddes and Wedderburn, 2007), however if there is no difference in the monthly total, then this signal will be hidden in the monthly time series.

With careful planning of further research, some of these limitations may be overcome. Fishery-independent sampling, for instance, may be employed to sample and estimate abundance of earlier life stages of the species concerned. This would reduce the opportunity for external factors (other than flow) to interfere with the relationship as well as provide an improved measure of fish production. Since there must be at least 50 observations required to develop a reliable time series model, the research sampling may be undertaken monthly over at least four years or more frequently with intensive sampling, but this depends on the timescale that the relationship under investigation is likely to exist.

Although this study identified limitations of time series modelling when applied to commercial catch data of the Lakes and Coorong Fishery, it remains a potentially useful tool to describe the influence of flows on fishery production, as has been demonstrated in other fisheries.

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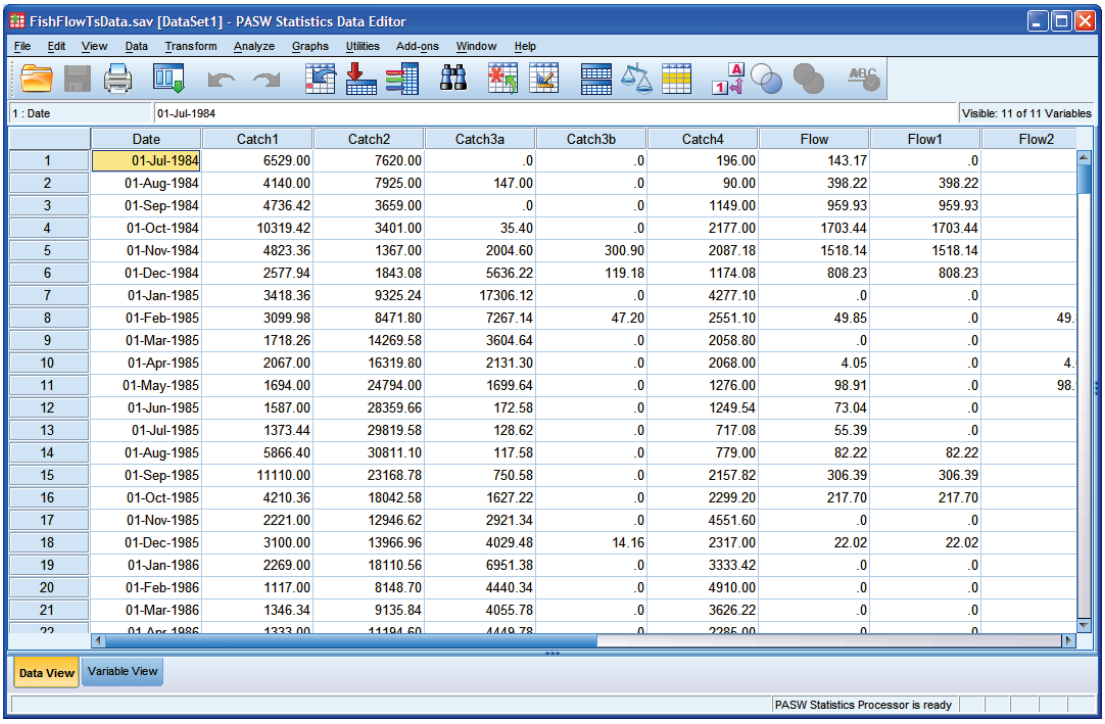
6. Appendix

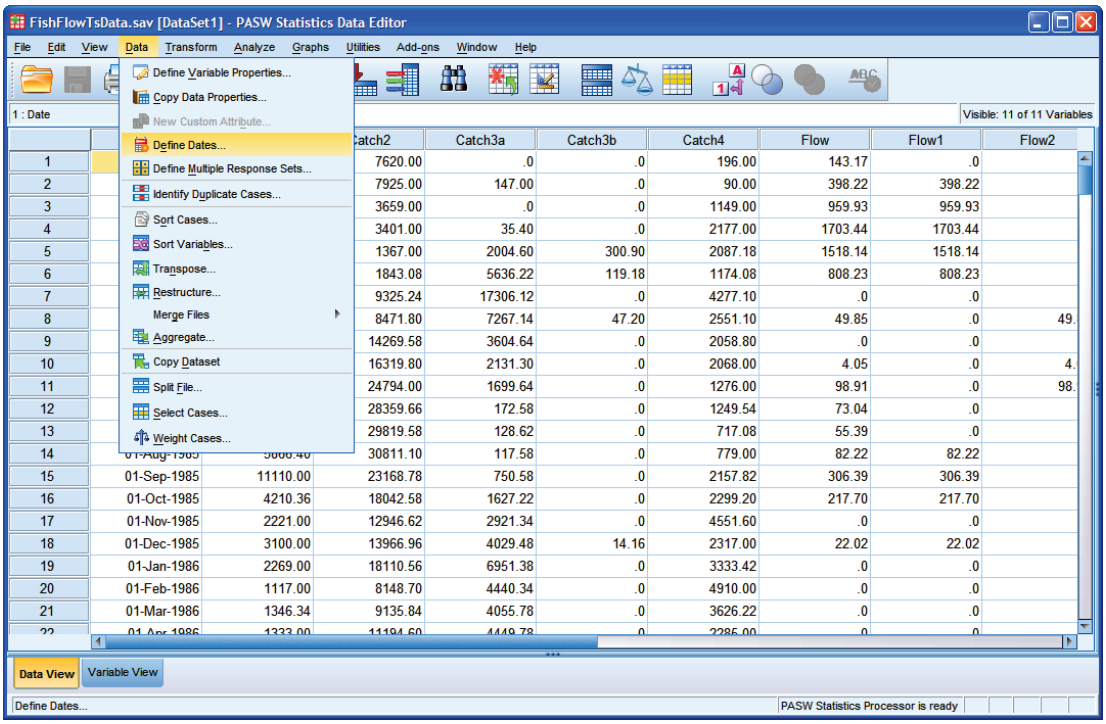
Appendix 1. Details of the Expert Modeler subroutine in PASW® Forecasting 18 (SPSS Inc., n.d.*a*) that was used to develop time series models.

Step 1. Open the data source (import from Microsoft Excel into PASW) and save as *.sav file.

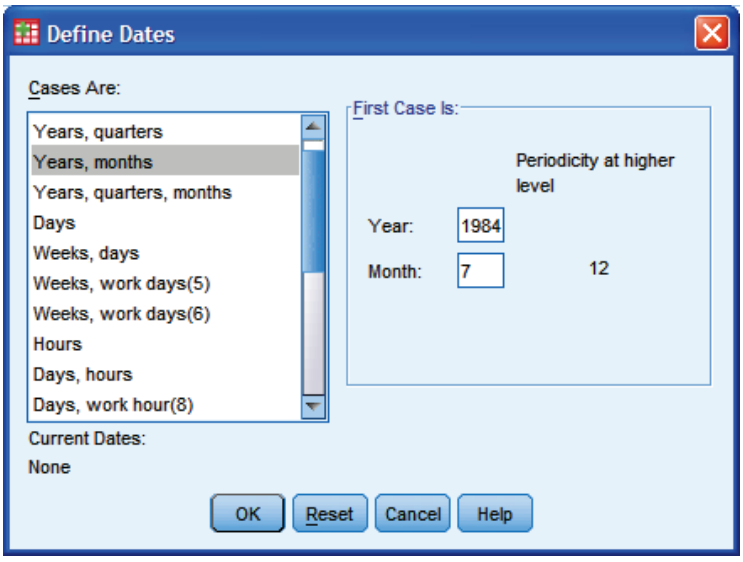


	Date	Catch1	Catch2	Catch3a	Catch3b	Catch4	Flow	Flow1	Flow2
1	01-Jul-1984	6529.00	7620.00	.0	.0	196.00	143.17	.0	
2	01-Aug-1984	4140.00	7925.00	147.00	.0	90.00	398.22	398.22	
3	01-Sep-1984	4736.42	3659.00	.0	.0	1149.00	959.93	959.93	
4	01-Oct-1984	10319.42	3401.00	35.40	.0	2177.00	1703.44	1703.44	
5	01-Nov-1984	4823.36	1367.00	2004.60	300.90	2087.18	1518.14	1518.14	
6	01-Dec-1984	2577.94	1843.08	5636.22	119.18	1174.08	808.23	808.23	
7	01-Jan-1985	3418.36	9325.24	17306.12	.0	4277.10	.0	.0	
8	01-Feb-1985	3099.98	8471.80	7267.14	47.20	2551.10	49.85	.0	49.
9	01-Mar-1985	1718.26	14269.58	3604.64	.0	2058.80	.0	.0	
10	01-Apr-1985	2067.00	16319.80	2131.30	.0	2068.00	4.05	.0	4.
11	01-May-1985	1694.00	24794.00	1699.64	.0	1276.00	98.91	.0	98.
12	01-Jun-1985	1587.00	28359.66	172.58	.0	1249.54	73.04	.0	
13	01-Jul-1985	1373.44	29819.58	128.62	.0	717.08	55.39	.0	
14	01-Aug-1985	5866.40	30811.10	117.58	.0	779.00	82.22	82.22	
15	01-Sep-1985	11110.00	23168.78	750.58	.0	2157.82	306.39	306.39	
16	01-Oct-1985	4210.36	18042.58	1627.22	.0	2299.20	217.70	217.70	
17	01-Nov-1985	2221.00	12946.62	2921.34	.0	4551.60	.0	.0	
18	01-Dec-1985	3100.00	13966.96	4029.48	14.16	2317.00	22.02	22.02	
19	01-Jan-1986	2269.00	18110.56	6951.38	.0	3333.42	.0	.0	
20	01-Feb-1986	1117.00	8148.70	4440.34	.0	4910.00	.0	.0	
21	01-Mar-1986	1346.34	9135.84	4055.78	.0	3626.22	.0	.0	

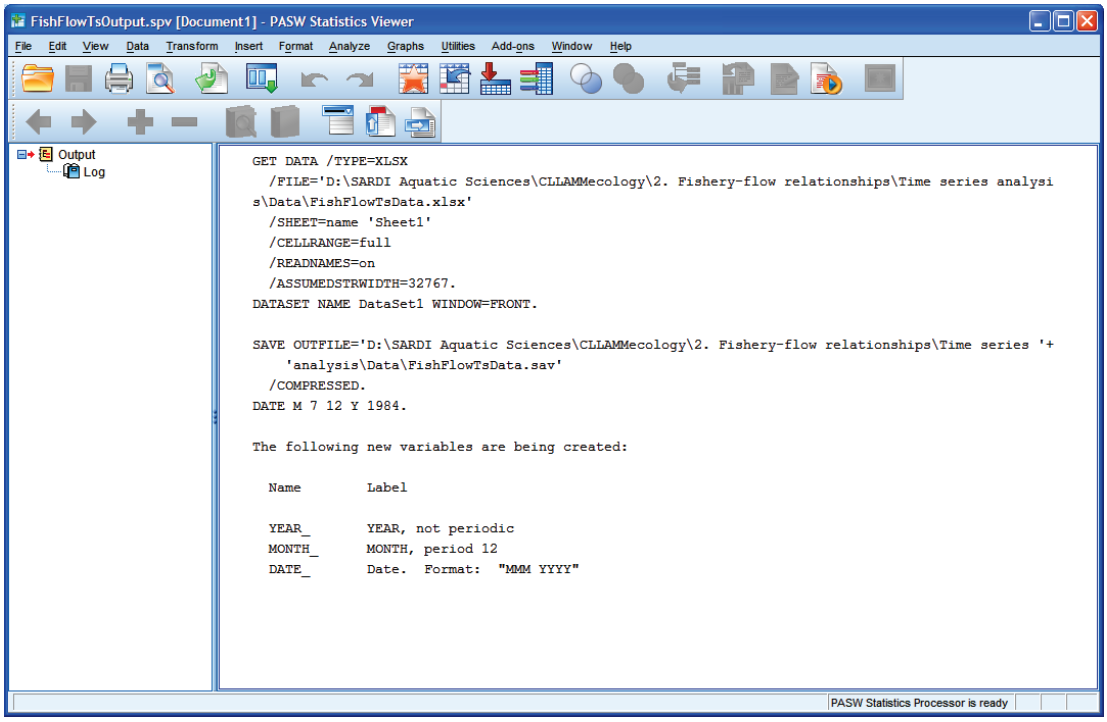
Step 2. Define dates.



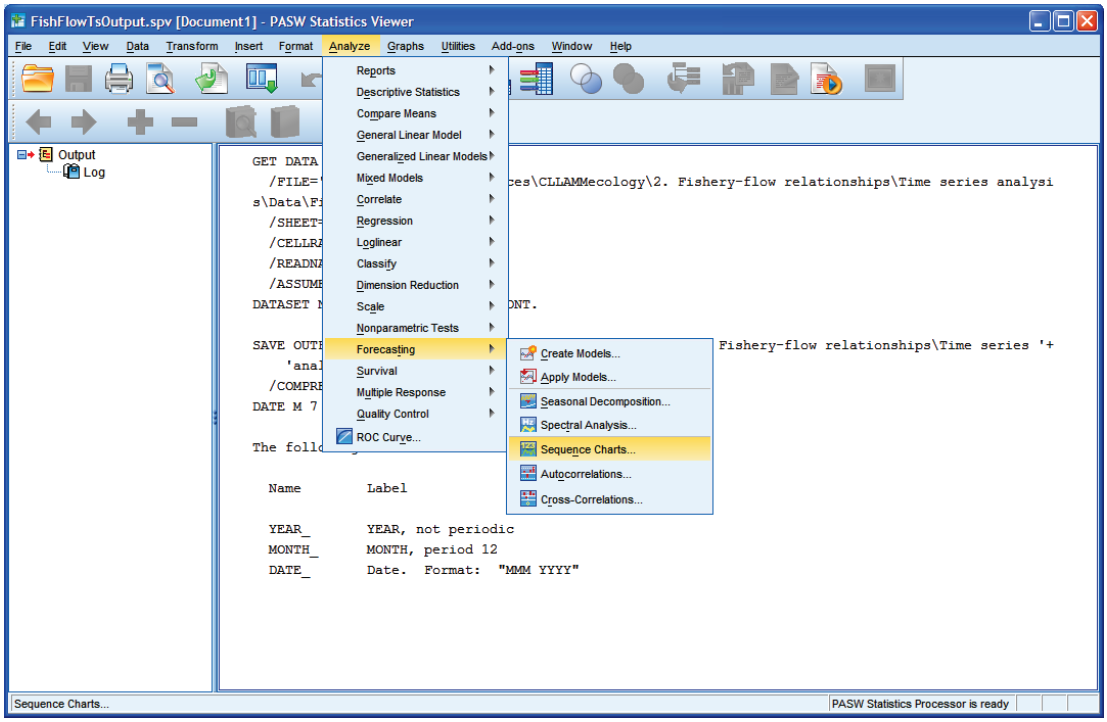
Step 3. Cases are years, months (first case is year 1984 and month 7).



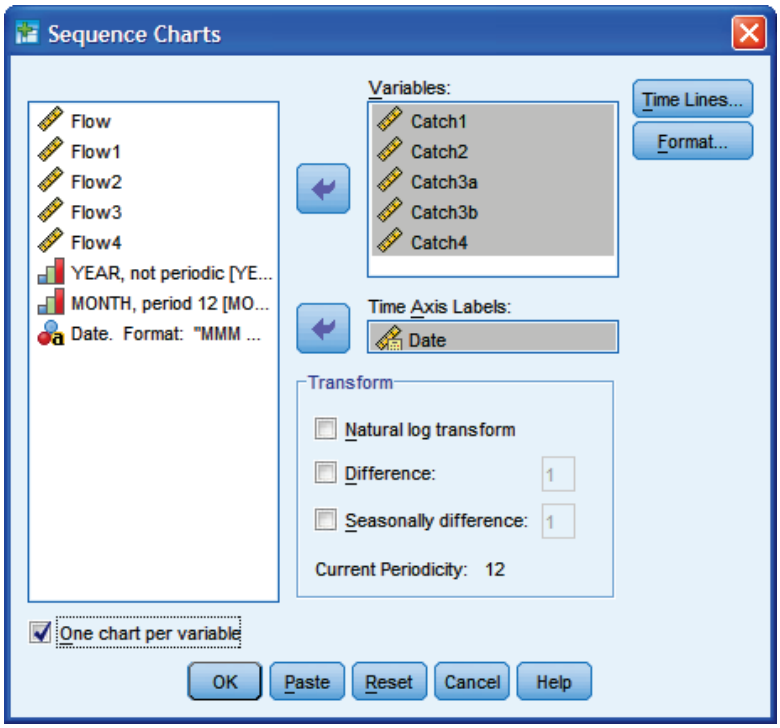
Step 4. Save output as *.spv file.



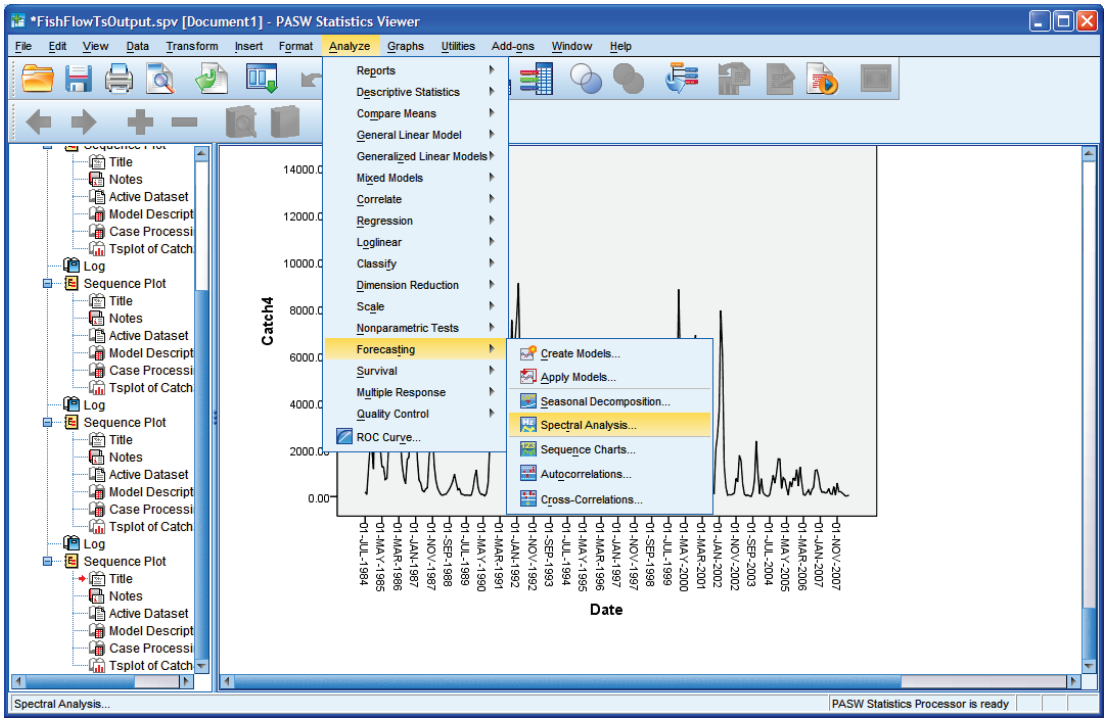
Step 5. Analyse, Forecasting ▶ Sequence charts.



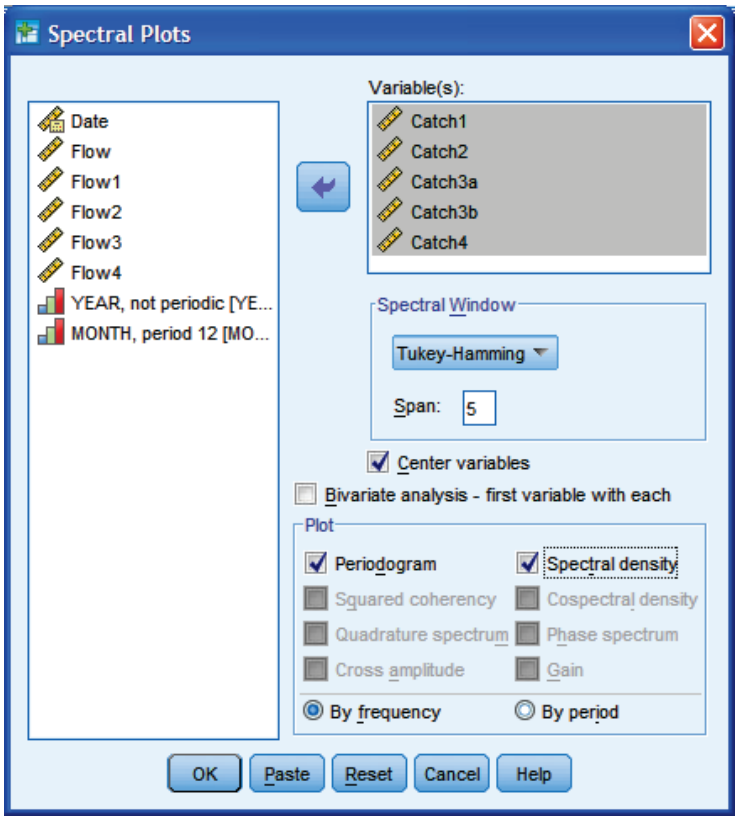
Step 6. Enter variables and time axis labels; check one chart per variable.



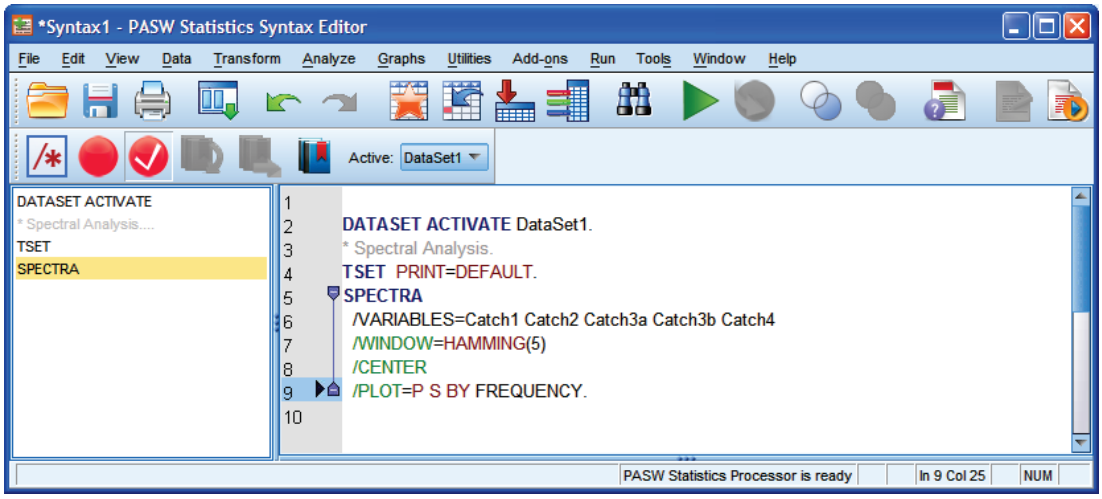
Step 7. Analyse, Forecasting ▶ Spectral analysis.



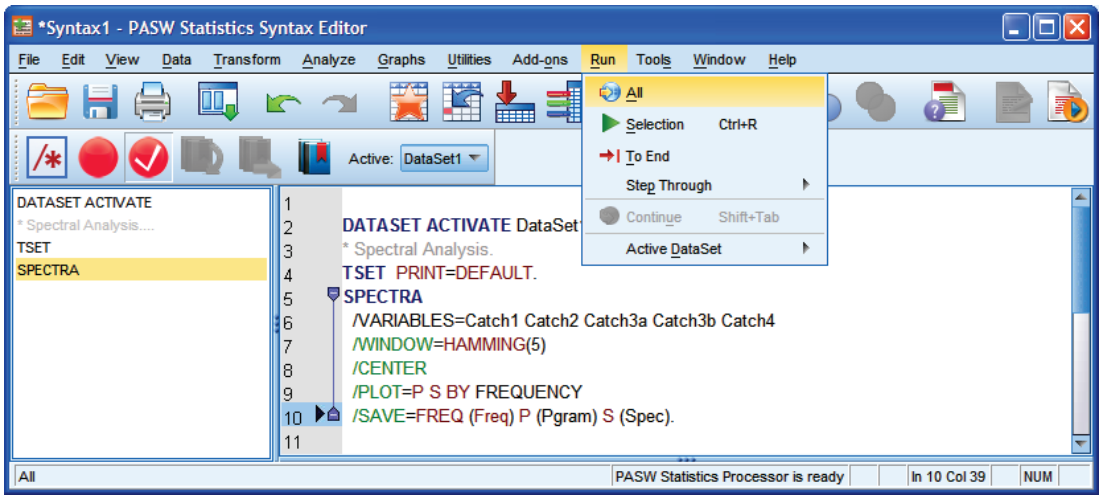
Step 8. Enter variables; check spectral density; select paste (syntax to syntax editor).



Step 9. Syntax editor.

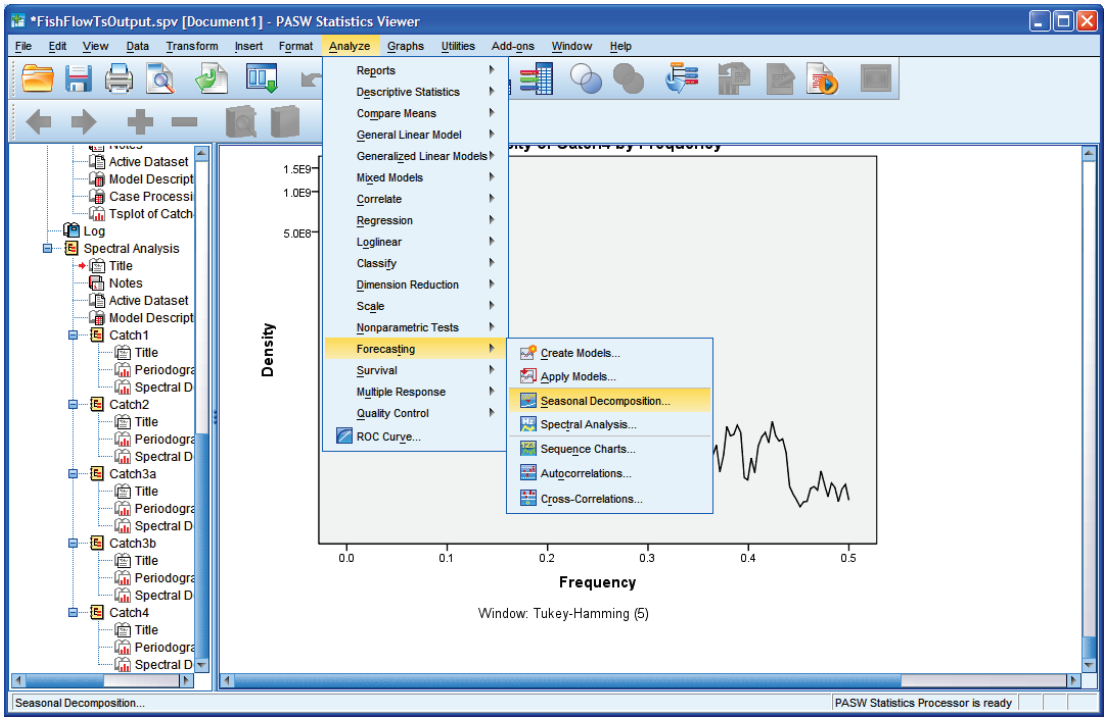


Step 10. Customise syntax to SAVE and label computed spectra variables to active data set; Run all.

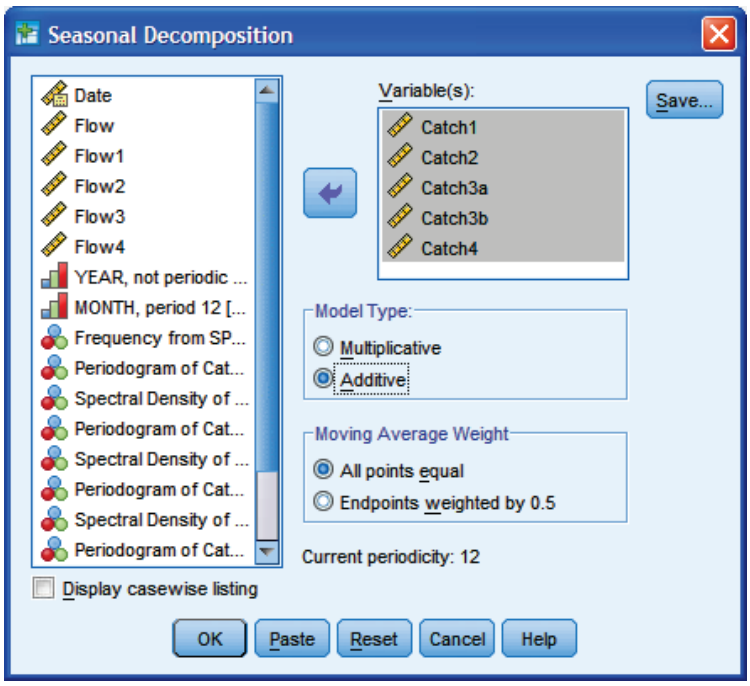


Step 11. Close syntax.

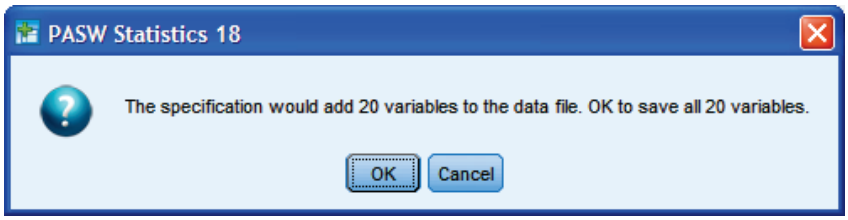
Step 12. Analyse, Forecasting ▶ Seasonal decomposition.



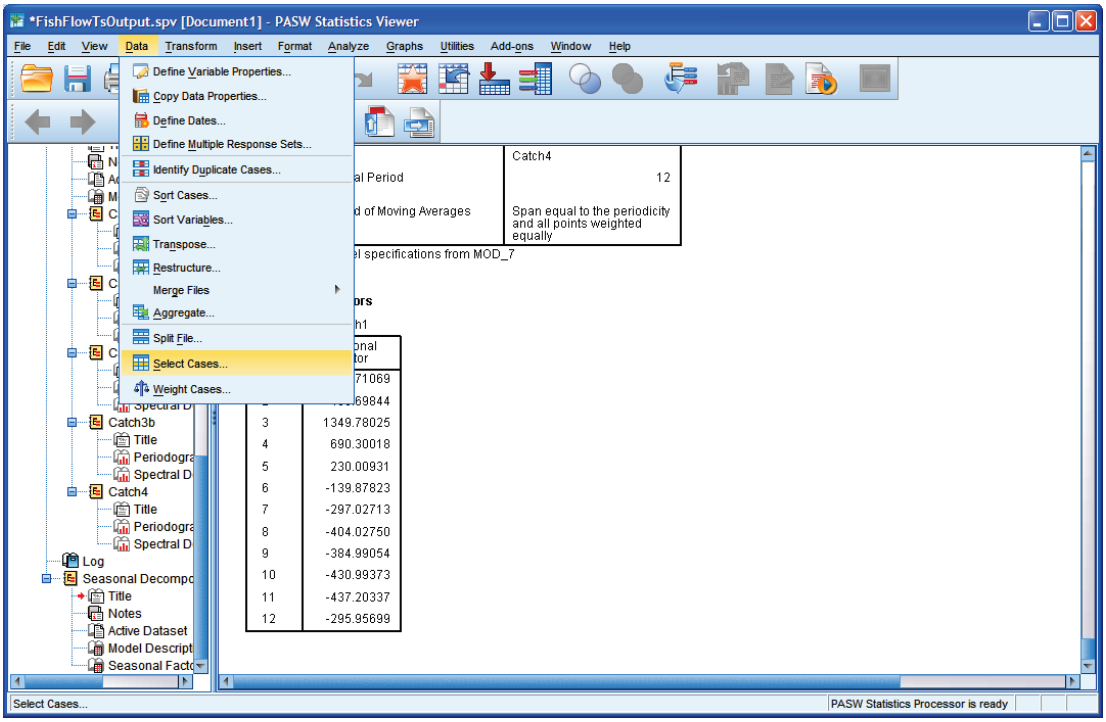
Step 13. Enter variables; model type is additive.



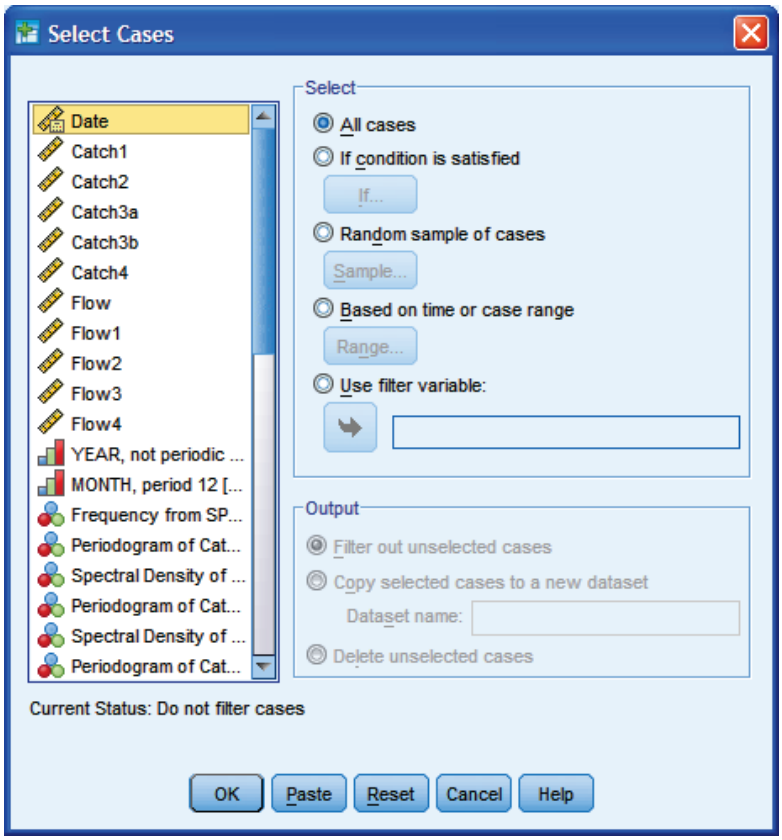
Step 14. Select OK.



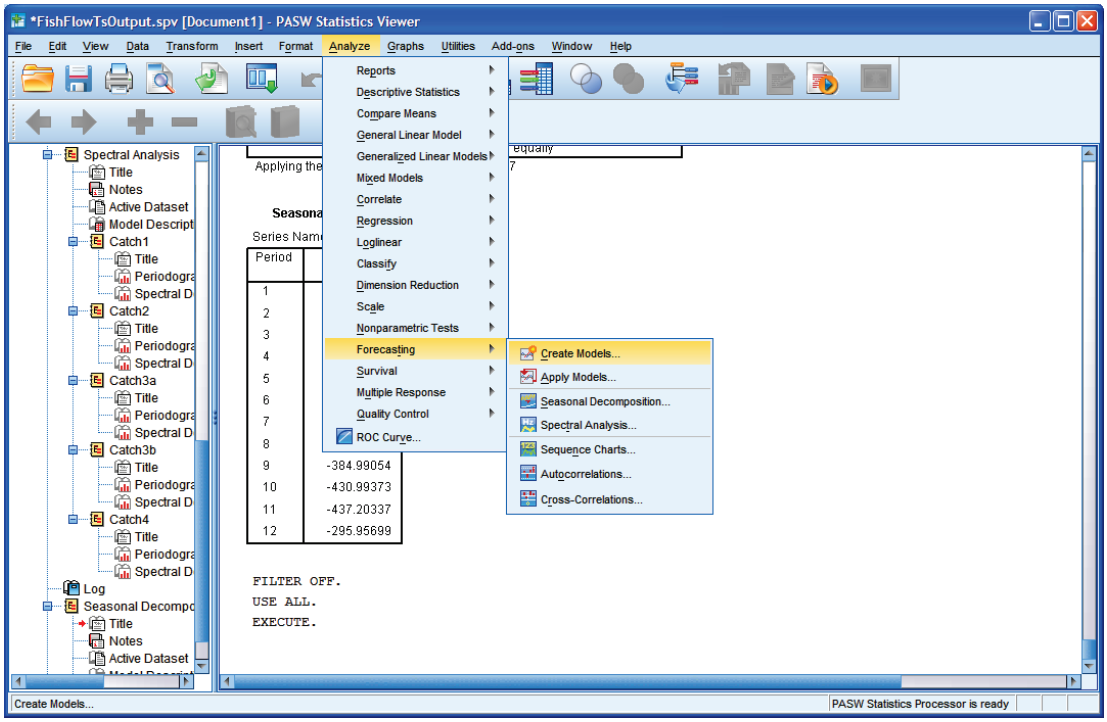
Step 15. Data, Select cases.



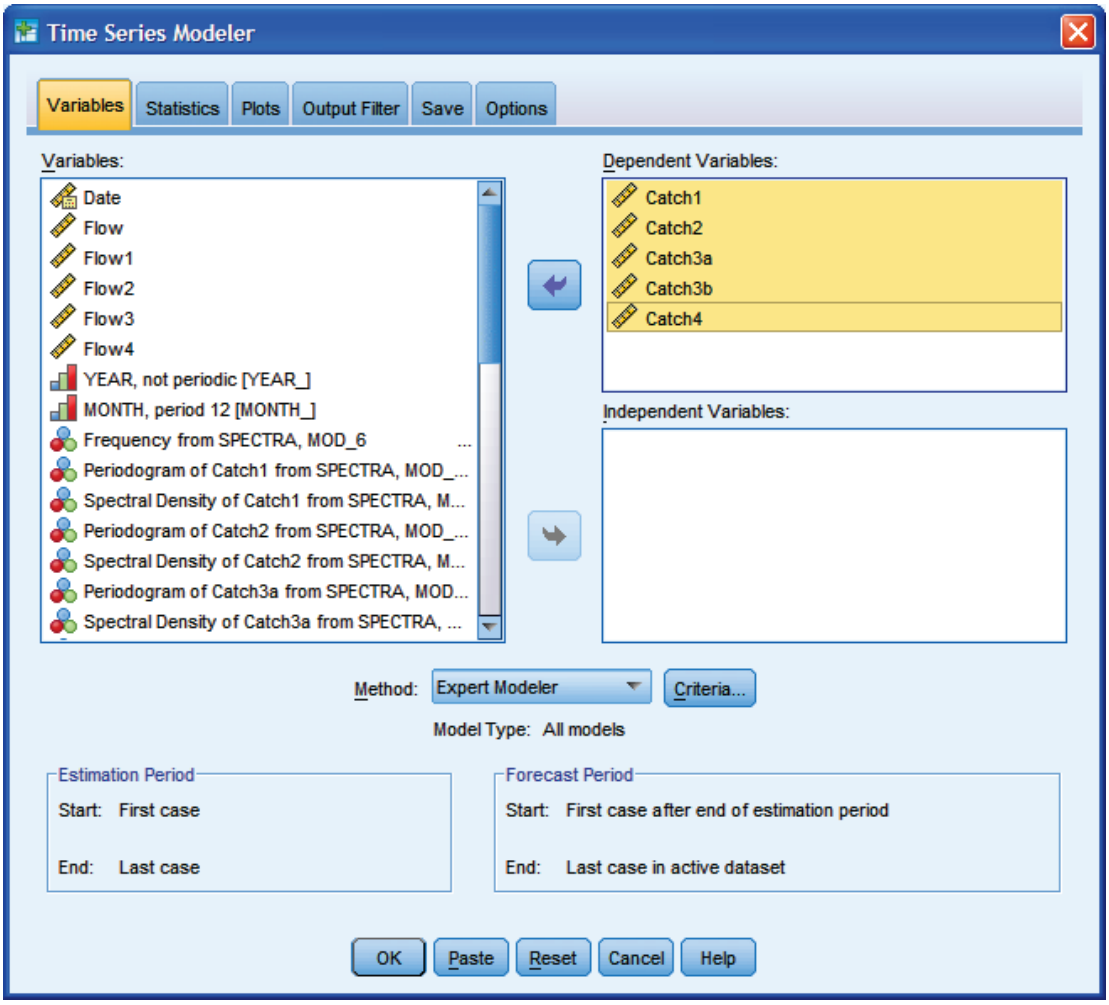
Step 16. Select all cases.



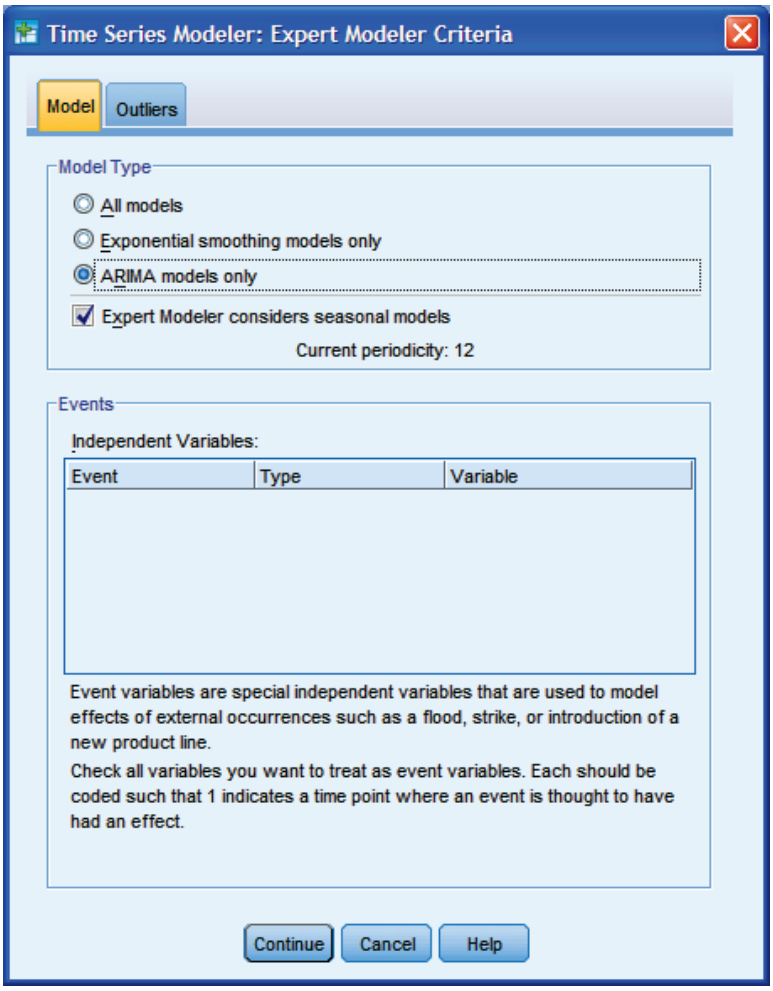
Step A1. Analyse, Forecasting ▶ Create models.



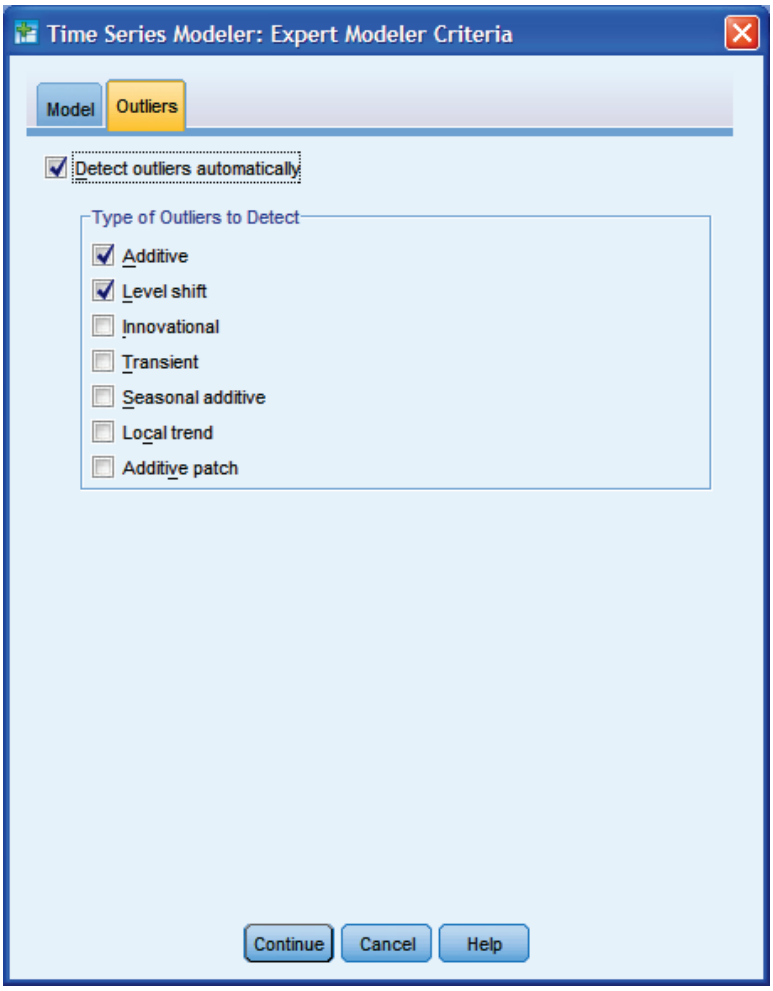
Step A2. Variables (tab): enter dependent variables (univariate ARIMA model, Type A); choose Expert Modeler and criteria.



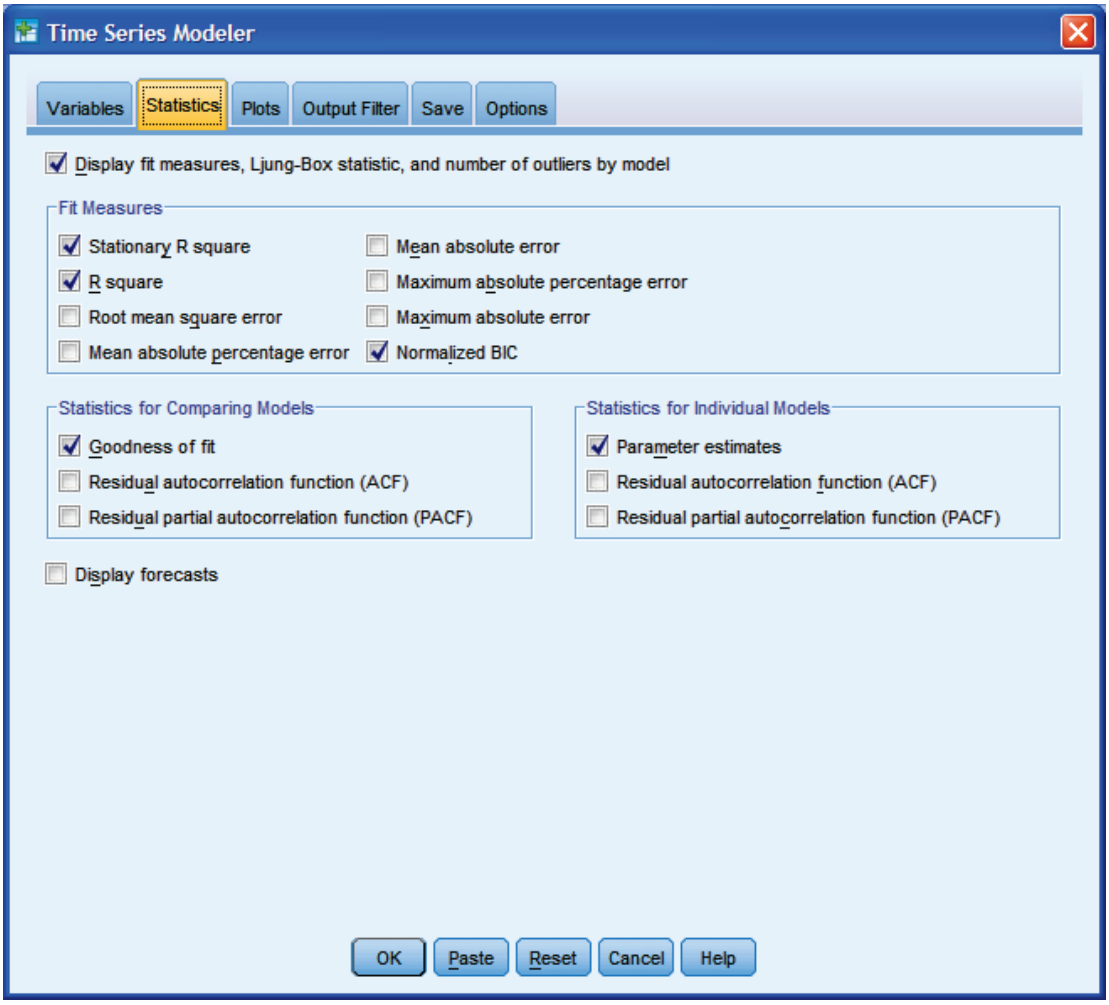
Step A3. Model: select ARIMA models only; check Expert Modeler considers seasonal models.



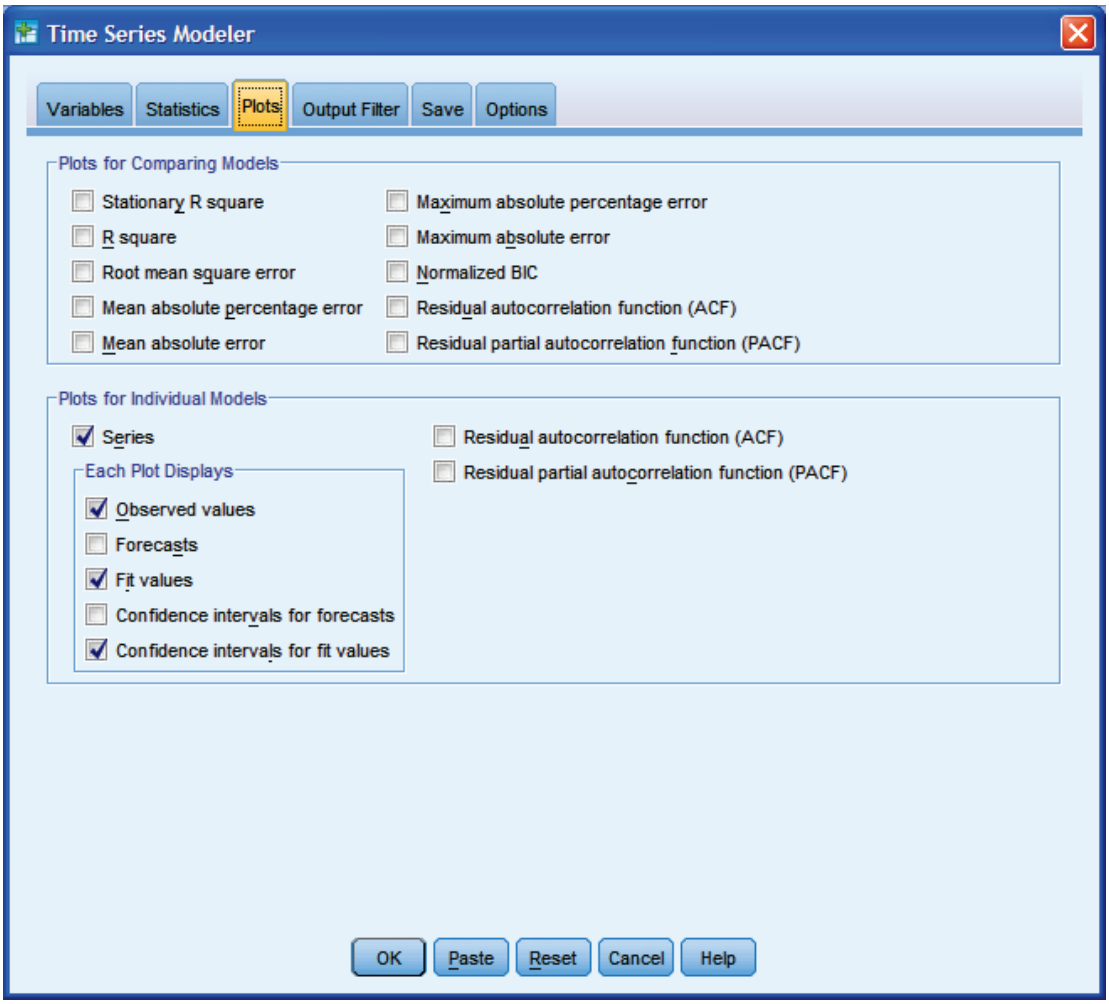
Step A4. Outliers: select detect outliers automatically; select additives and level shift types.



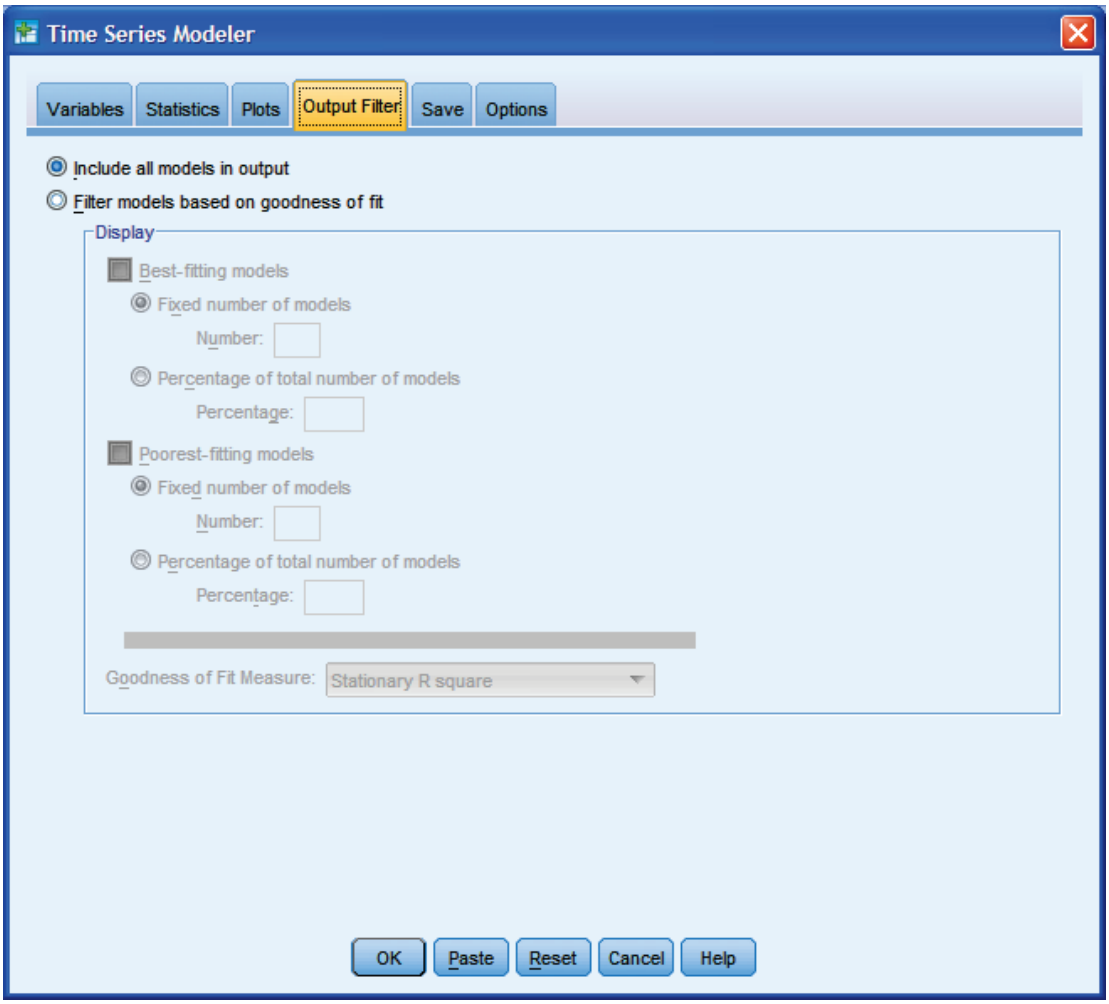
Step A5. Statistics: select display fit measures, …; check stationary R-square, R-square, normalized BIC, goodness-of-fit, and parameter estimates.



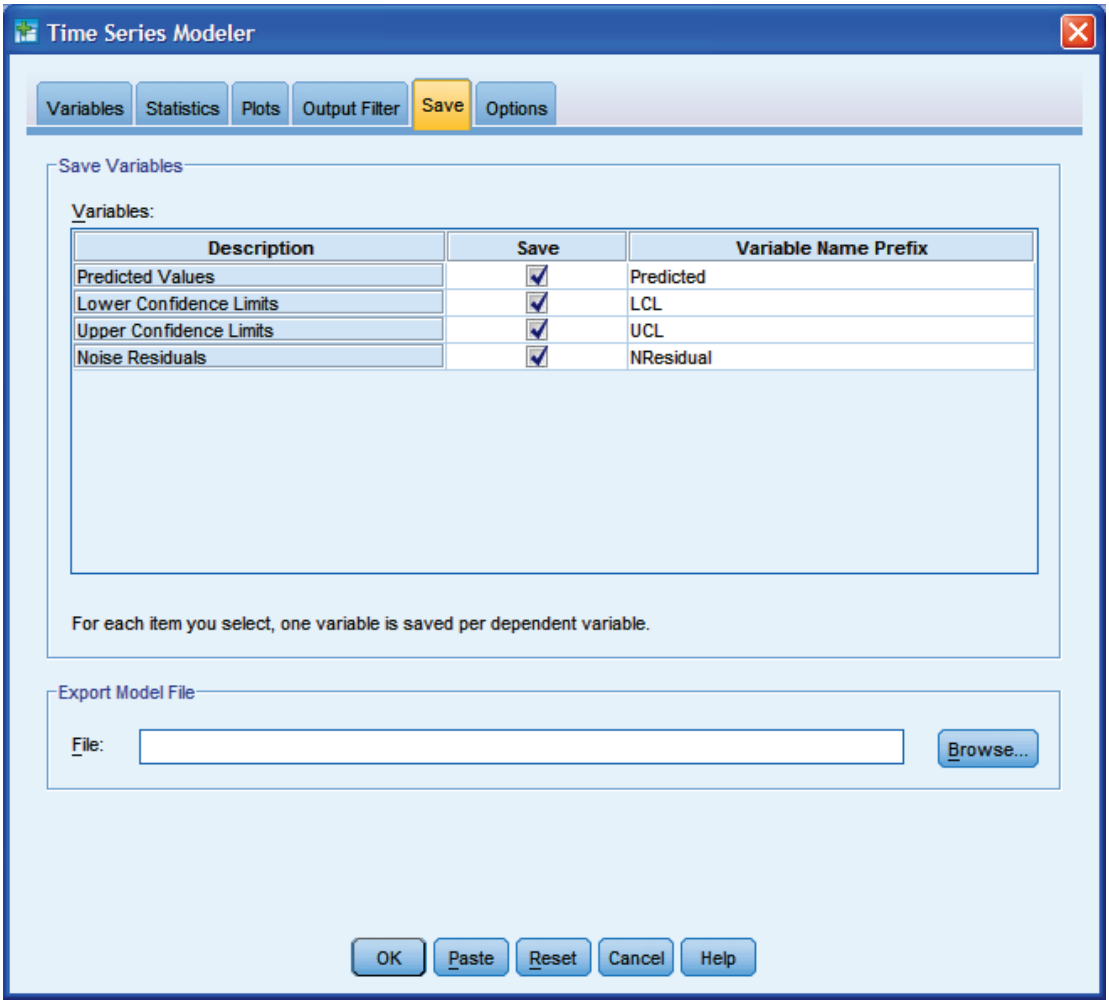
Step A6. Plots: check series, observed values, fit values, and confidence intervals for fit values.



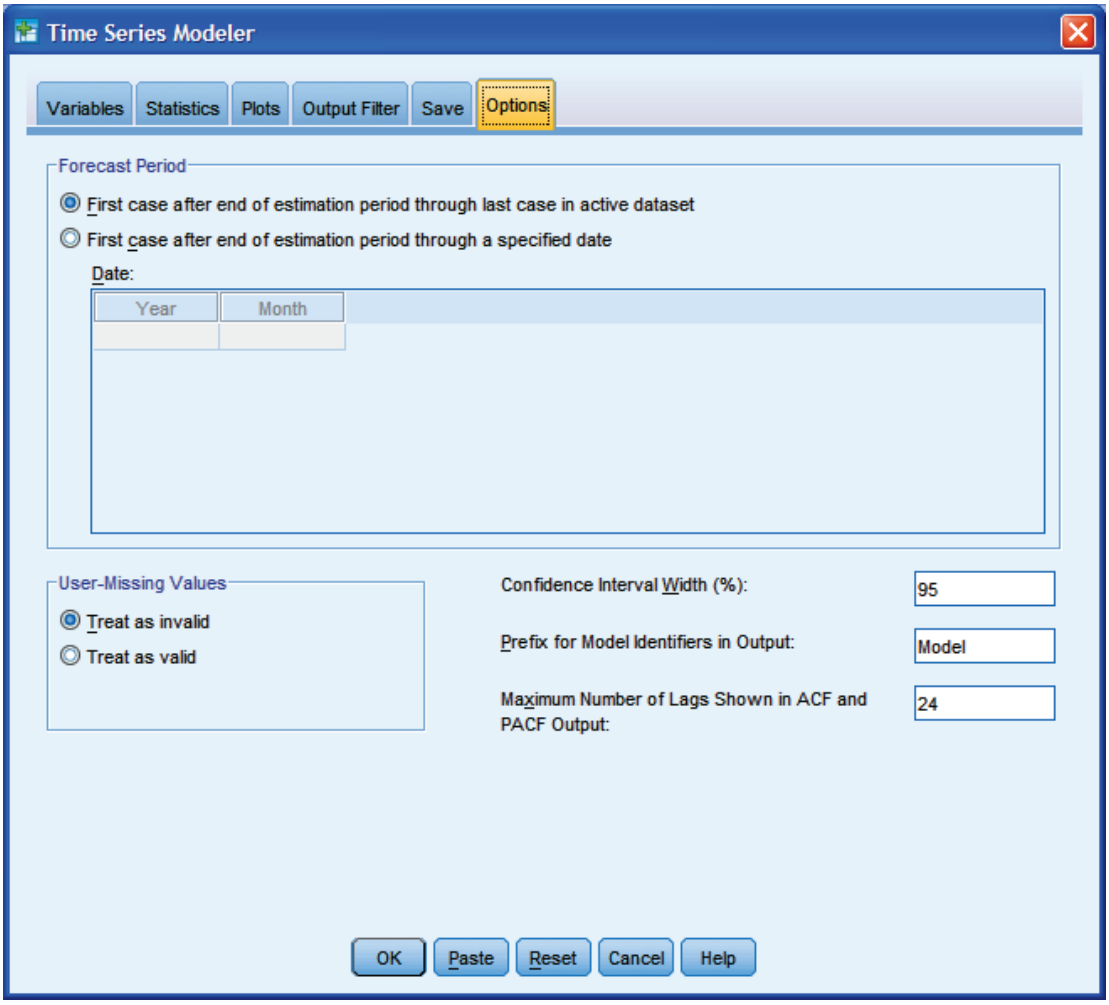
Step A7. Output filter: select include all models in output.



Step A8. Save: check predicted values, lower confidence limits, upper confidence limits, and noise residuals.

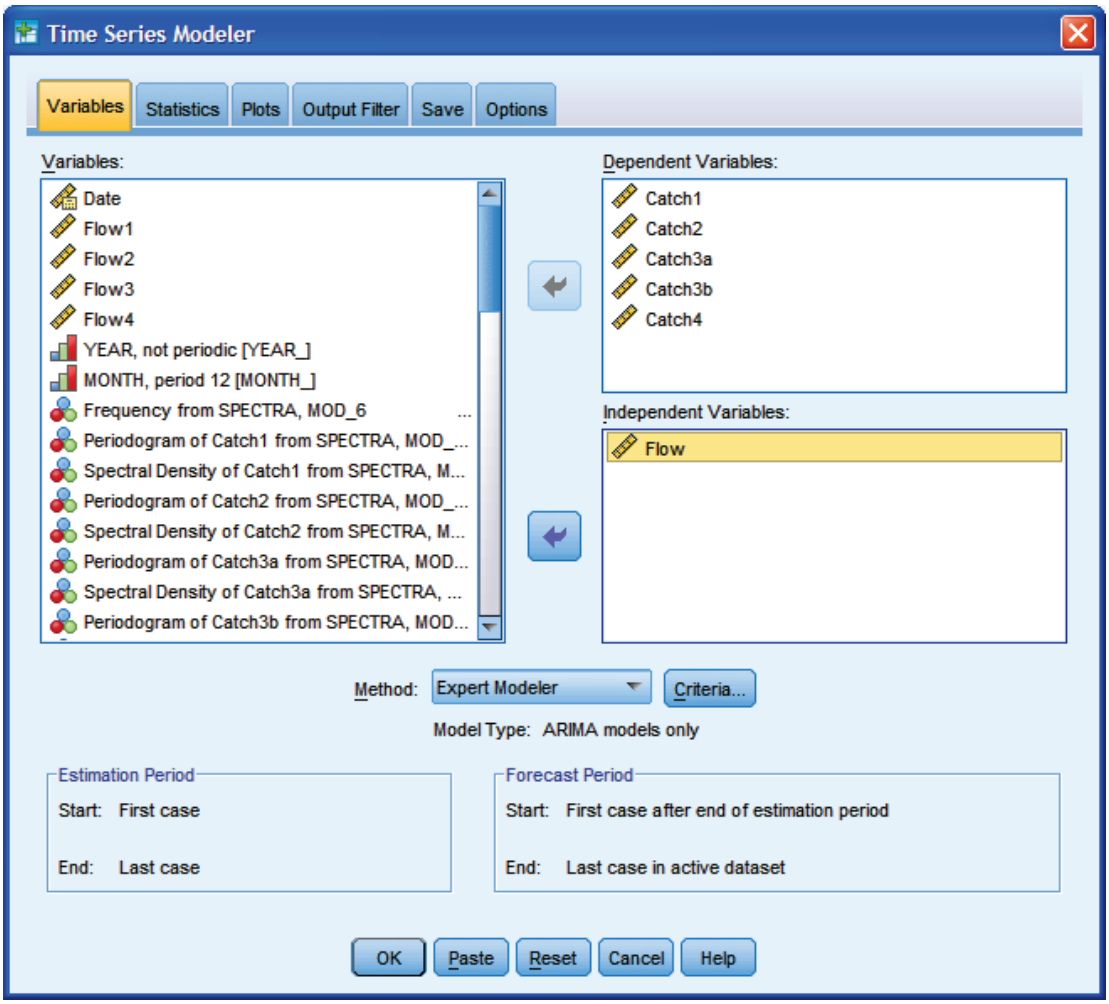


Step A9. Options: select first case after end of estimation period through last case in active dataset; OK.



Step B1. Repeat step A1.

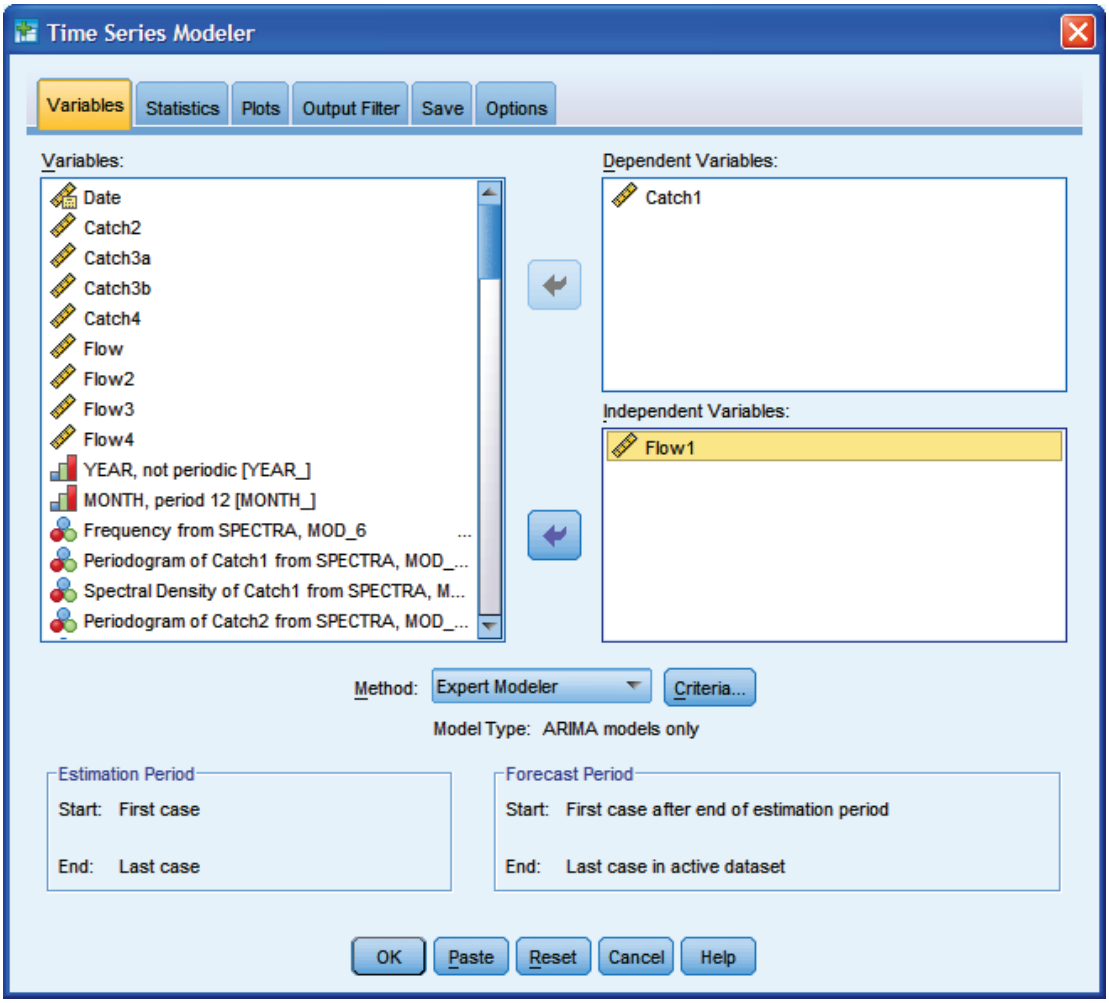
Step B2. Variables: enter dependent variables, and independent variable (transfer function model, Type B); choose Expert Modeler and criteria.



Step B3. Repeat steps A3-A9.

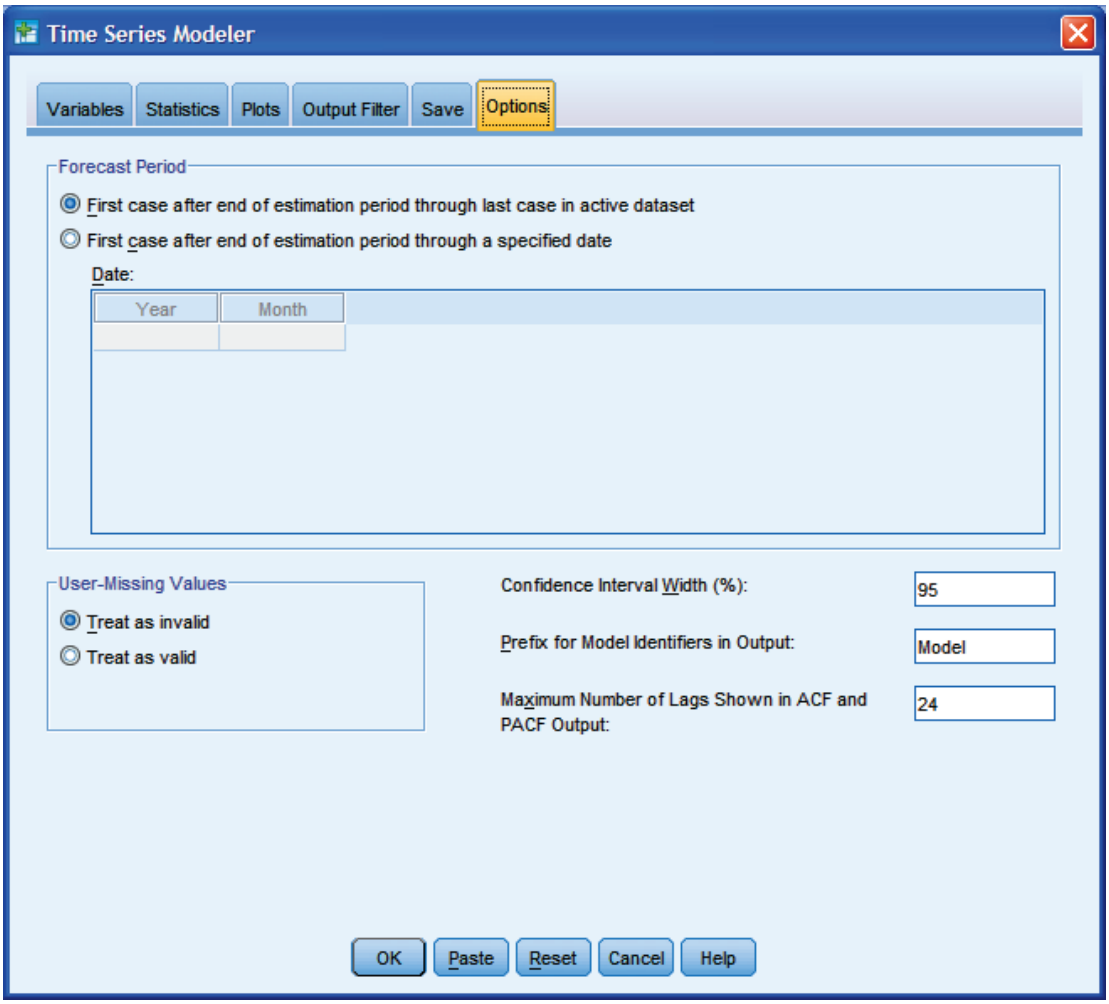
Step C1. Repeat step A1.

Step C2. Variables: enter dependent variables, and independent variable (transfer function model, Type C); choose Expert Modeler and criteria.

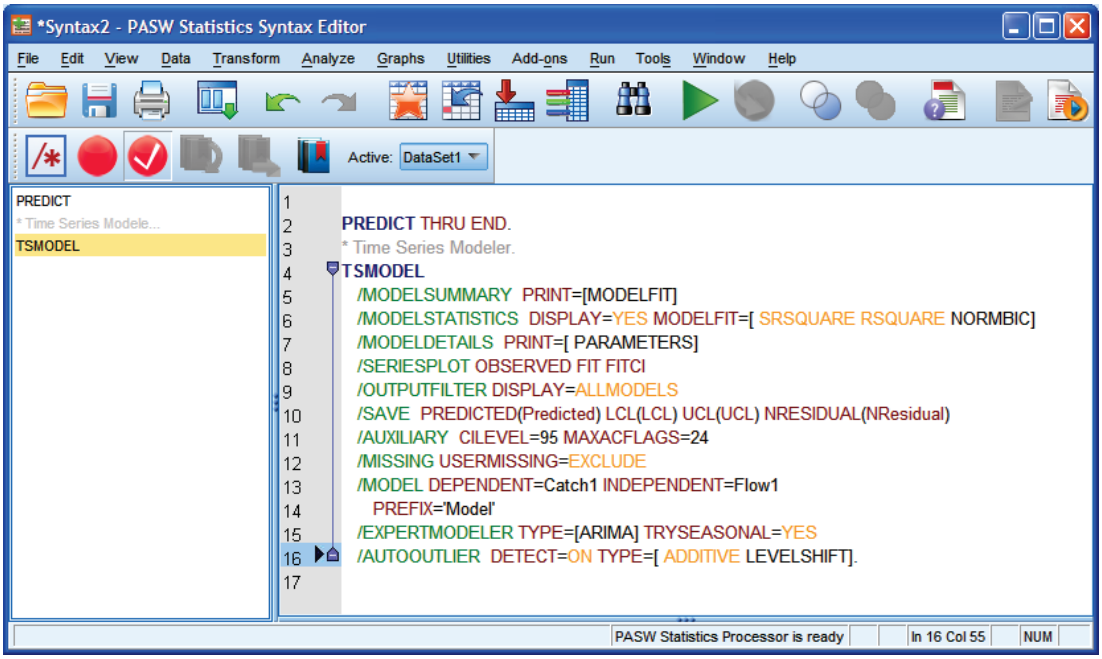


Step C3. Repeat steps A3-A8.

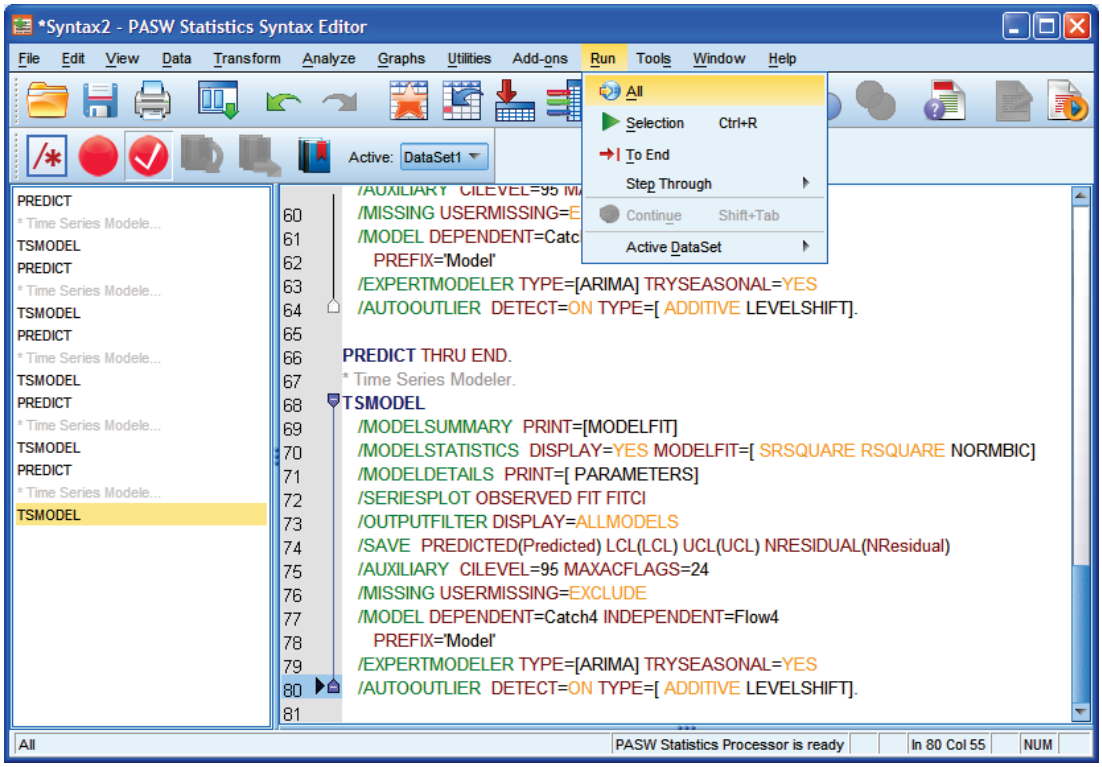
Step C4. Options: paste (syntax to syntax editor).



Step C5. Copy, paste, and customise syntax to simultaneously run transfer function models (Type C) for each dependent and predictor series combination.



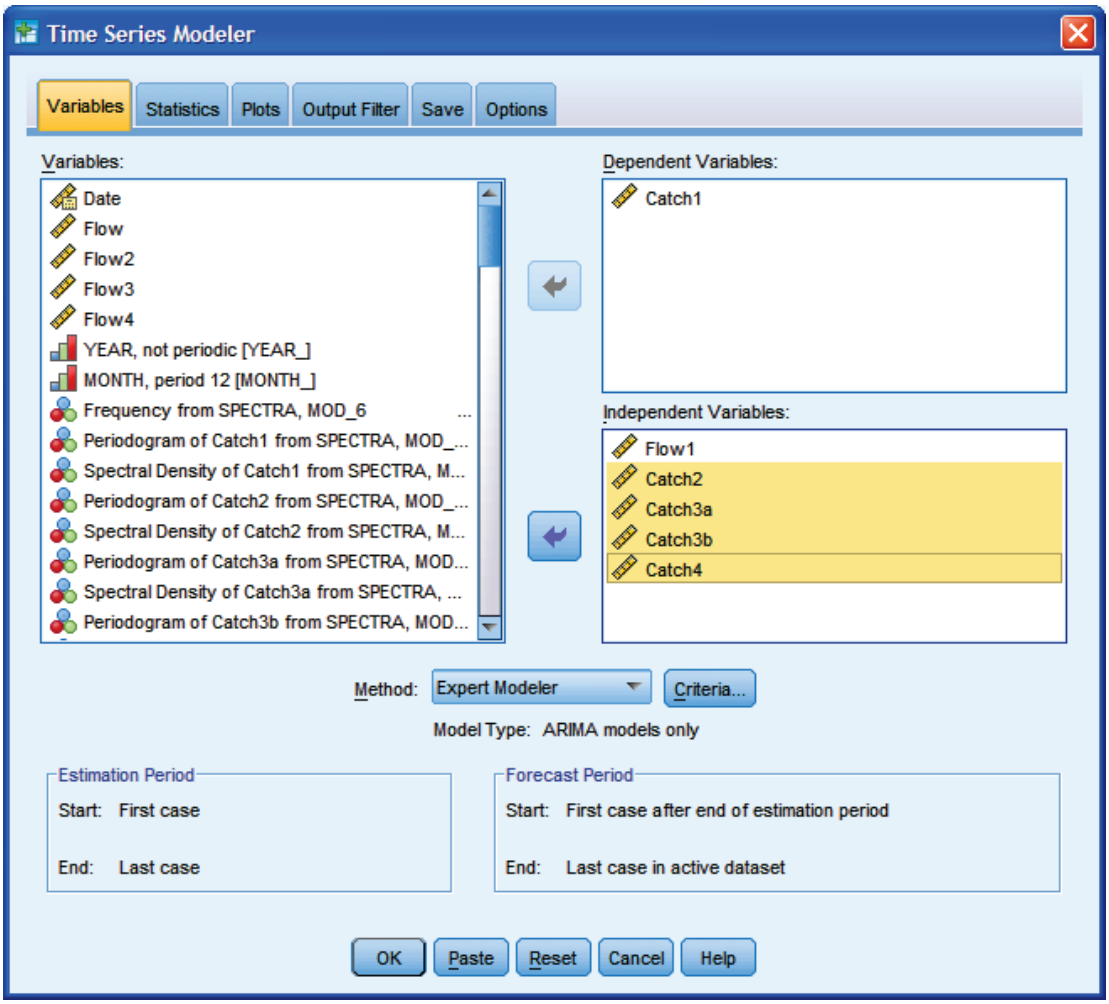
Step C6. Run all.



Step C7. Close syntax.

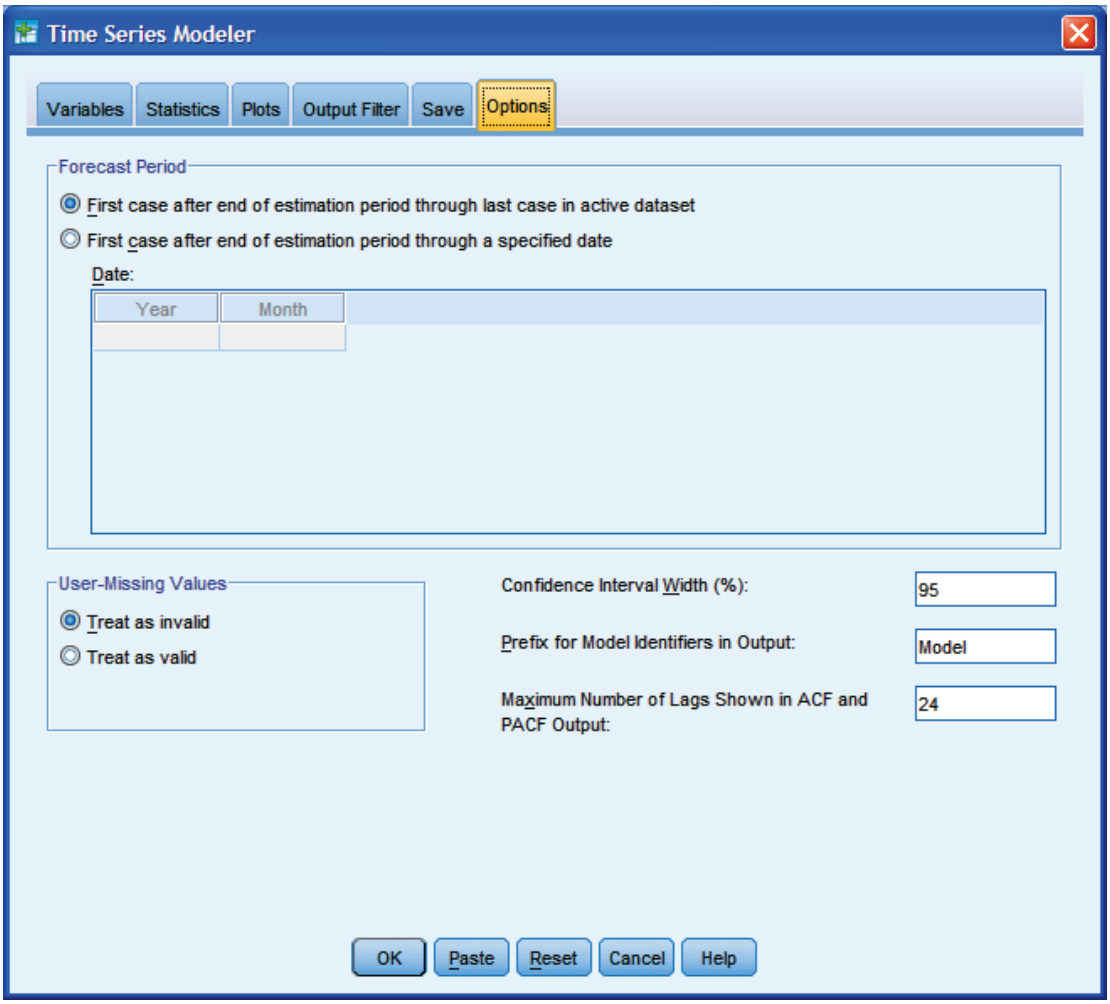
Step D1. Repeat step A1.

Step D2. Variables: enter dependent variables, and independent variable (transfer function model, Type D); choose Expert Modeler and criteria.

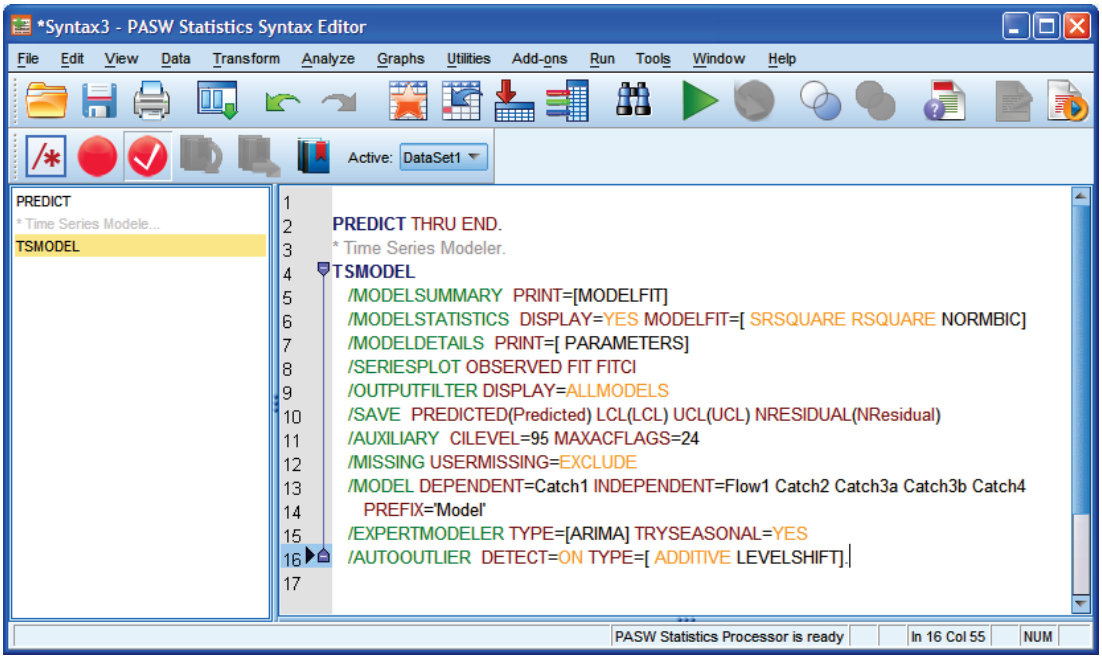


Step D3. Repeat steps A3-A8.

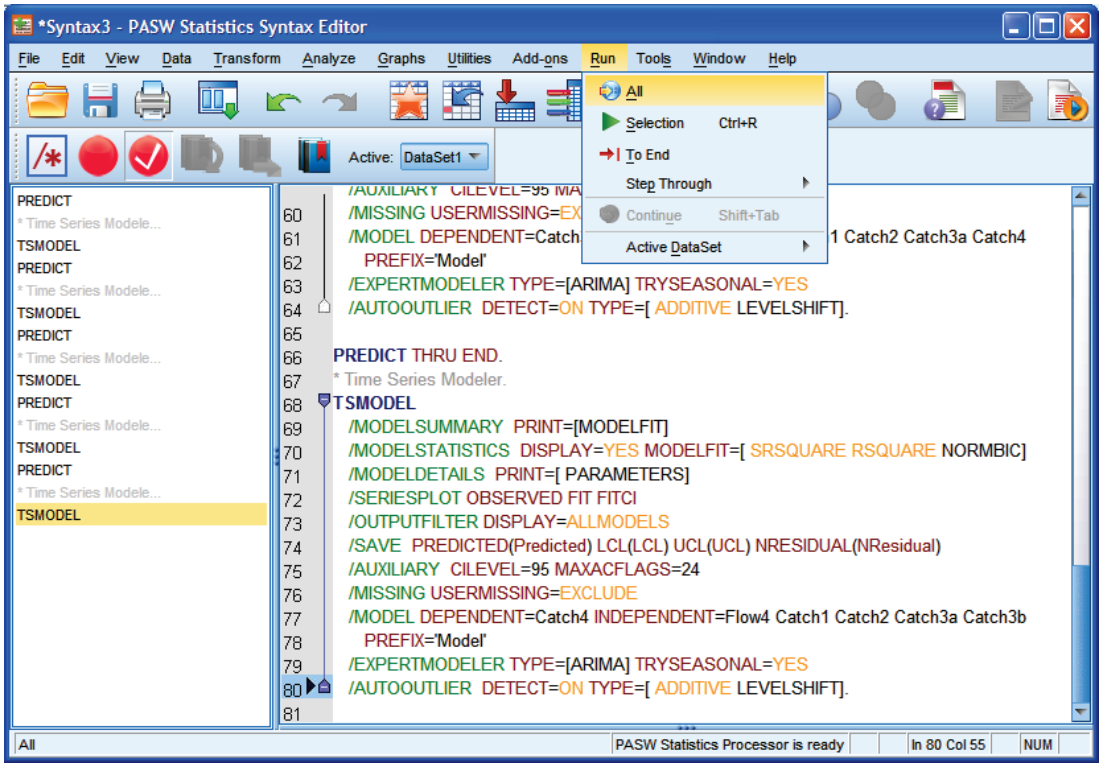
Step D4. Options: paste (syntax to syntax editor).



Step D5. (following page) Copy, paste, and customise syntax to simultaneously run transfer function models (Type D) for each dependent and predictor series combination



Step D6. Run all.



Step D7. Close syntax; save *.sav and *.spv files.