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Modelling and forecasting monthly fisheries catches: comparison of regression, univariate and multivariate time series methods

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Abstract

In the present work, seven forecasting techniques were evaluated on the basis of their efficiency to model and provide accurate operational forecasts of the monthly commercial landings of 16 species (or groups of species) in the Hellenic marine waters. The development of operational forecasts was based on the following three general categories of forecasting techniques: (a) deterministic simple or multiple regression models incorporating different exogenous variables (seasonal time-varying regression, TVS; multiple regression models, MREG, incorporating time, number of fishers, wholesale value of catch and climatic variables); (b) univariate time series models (Winter's three parameter exponential smoothing, WES; ARIMA); and (c) multivariate time series techniques (harmonic regression, HREG; dynamic regression, DREG; vector autoregressions, VAR). Fits (for 1964–1987) and forecasts (for 1988–1989) obtained by the different models were compared with each other and with those of two naive methods (NM1 and NM12) and an empirical one (i.e. combination of forecasts, EMP) using 32 different measures of accuracy. The results revealed that the univariate ARIMA, closely followed by the multivariate DREG time series model, outperformed the others (NM1, NM12, TVS, MREG, HREG, EMP, VAR and WES) in terms of both fitting and forecasting accuracy. They were characterised by: (a) higher accuracy in terms of all, or most of the standard and relative statistical measures that were usually tied together; (b) unbiased fits and forecasts; (c) much better performance than NM1 and NM12. In addition, ARIMA and DREG models: (d) explained over 80% of the variance of the transformed catches; (e) had residuals that were essentially white noise; (f) in all cases predicted the amplitude and the start and end of the fishing season; and (g) produced forecasts that had mean absolute percentage error values under 28.2% for 11 out of 16 monthly series. The different measures employed also indicated that EMP and WES models outperformed NM1, NM12, TVS, MREG and HREG models. EMP produced forecasts with MAPE values under 23.2% for ten monthly series, whereas WES produced forecasts with MAPE values under 25.3% for eight monthly series. This suggests their potential use in short-term fisheries forecasting. The limitations of the different forecasting techniques, measures of accuracy and data used in the present study are also discussed.

Some of the empirical models built also had interesting biological/oceanographic explanations. Hence, the univariate ARIMA and multivariate DREG and VAR time series models all predicted persistence of catches. The univariate ARIMA and multivariate HREG, DREG and VAR time series models all predicted cycles in the variability of the catches with periods of 1 and 2–3 years. Moreover, MREG, DREG and VAR models indicated that the number of fishers, wholesale

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value of catch and climate may, in a synergistic fashion, affect long-term trends and short-term variation in the catches of at least some species (or groups of species). Finally, DREG and VAR models predicted that variability and replacement of anchovy by sardine catches are not due to chance and wind activity over the northern Aegean Sea may act as a forcing function.

Keywords: Forecasting; Monthly catches; Multiple regression; Seasonal time-varying regression; Exponential smoothing; ARIMA; Dynamic regression; Harmonic regression; Vector autoregression

1. Introduction

Forecasting is an interesting subject, partly because it is difficult to do accurately owing to the uncertainties confronting forecasters (see Getz et al., 1987; Hilborn, 1987), but mainly because it plays a central role in management: it precedes planning which, in turn, precedes decision making (Makridakis et al., 1983). Policy makers establish goals and objectives, seek to forecast uncontrollable events, then select appropriate actions which, hopefully, will result in the realisation of the goals and objectives. One important point worthy of mention here is the distinction between uncontrollable external events (e.g. effect of natural climatic changes on fish abundance and availability) and controllable events (e.g. fishing effort) affecting the fishery variable of interest. The success of a certain managerial scheme depends on both categories of events, but forecasting applies to the former, while decision making and effectiveness of implementation applies to the latter. Planning is the link that integrates them.

Quantitative forecasting can be applied under the following conditions: (a) past quantitative information is available and (b) some aspects of the past pattern will continue into the future. In general, historical fishery time series satisfy condition (a) and have been extensively used for the provision of a variety of information on fishery resources (e.g. description of fishery units: Murawski et al., 1983; Smetanin et al., 1984; Stergiou and Pollard, 1994; state of fisheries resources and management: Fox, 1970; Pauly, 1989; Sparre et al., 1989; Stergiou and Petrakis, 1993). Condition (b) is known as the 'assumption of continuity' (Makridakis et al., 1983) and is an underlying premise of all quantitative forecasting methods, irrespective of their degree of sophistication.

Apart from methods based on biological principles (e.g. Fox, 1970; Shepherd, 1984; Pope and Shepherd, 1985; Borges, 1990), a variety of statistical techniques have also been used/adapted to fisheries forecasting and span a continuum between two extremes: naive/intuitive methods and formal/quantitative methods based on statistical principles. These methods are oriented towards (Stergiou and Christou, 1996) the following:

1. modelling on the basis of deterministic, regression techniques that explain changes in fishery variables (e.g. catch, catch per unit of fishing effort, recruitment) in terms of changes in various biotic (e.g. spawning stock, predators, competitors) and/or abiotic variables (e.g. fishing effort, climate);
2. modelling on the basis of univariate time series techniques that treat the system as a black box, viewed as an unknown generating process, and forecasting is based on projecting past values of a variable and/or past errors into the future;
3. models that synthesise the above mentioned two general approaches (multivariate time series).

From the point of view of the practitioner forecaster, who is mainly accuracy-oriented, the success of a specific method can be judged by comparison with other methods (a naive included).

In a recent study, Stocker and Noakes (1988) compared the performance of stock-recruitment (Ricker's model and a modified Ricker model accounting for environmental data) and time series models (moving average and multivariate transfer function noise) for forecasting the recruitment in five Pacific herring stocks. Stocker and Noakes (1988) found that time series models produced better forecasts for two stocks, a Ricker stock-recruitment model accounting for environmental data produced marginally better forecasts than the other models for two stocks, while all models produced equally good/bad forecasts for one stock. In addition, Noakes et al. (1990) compared the ability of seven models (a simple cycle mean, two forms of Ricker's model, a transfer function noise model, ARIMA models and a model based on age composition data) to produce forecasts for returns of two British Columbia sockeye salmon stocks. They found that simple time series models may provide more accurate forecasts of run size than other 'biological' Ricker-type models. Stergiou (1991a) also compared the ability of four models (ARIMA, Winter's exponential smoothing, time-varying regression corrected for seasonality, and a naive model) to produce one-step-ahead monthly forecasts of the *Trachurus* spp. catches in the Hellenic waters. The results indicated that ARIMA was far superior to the remaining models, and resulted in unbiased, accurate fits and forecasts, with residuals which were essentially white noise. In addition, the measures used did indicate that although fitting accuracy of the exponential smoothing model was not any better than that of the naive one, its forecasting accuracy (mean absolute percentage error 9.8%) was similar to that of ARIMA. All the above mentioned studies clearly indicate that although time series models do not have built-in stock structure, they should not be dismissed. This is especially true of cases for which time series of biological data (e.g. catch-at-length/age) on various species are lacking, as is the case in Hellenic and east Mediterranean waters in general, a fact rendering the application of such 'biological' forecasting models impossible (with the exception of surplus-yield models).

Elsewhere (Stergiou and Christou, 1996) we evaluated the ability of 11 forecasting techniques (time-varying regression; multiple regression models incorporating time, fishing effort, wholesale value of catch and climatic variables; simple averaging; Brown's one parameter exponential smoothing; Holt's two parameter exponential smoothing; ARIMA; harmonic regression; dynamic regression; vector autoregressions; the 'biological' exponential surplus-yield model (Fox, 1970); and an empirical method based on combination of forecasts] on the basis of their efficiency to model and provide accurate operational forecasts (sensu Bocharov (1989): forecast for up to 1 year ahead) of the annual commercial landings of 16 species or groups of species in the Hellenic marine waters (anchovy *Engraulis encrasicolus*; sardine *Sardina pilchardus*; bogue *Boops boops*; red pandora *Pagellus erythrinus*; gadiformes: hake *Merluccius merluccius* and blue whiting *Micromesistius poutassou*; *Trachurus* spp.; *Scomber* spp.; *Mullus* spp.; *Spicara* spp.; total fish, cephalopods, crustaceans; trawl, purse seine, beach seine and 'other coastal boats' catches). In the present study we evaluate the ability of seven forecasting techniques on the basis of their efficiency to model and provide accurate operational forecasts of the monthly commercial landings of the above mentioned 16 species or groups of species. Modelling the annual and/or monthly catches of a single species is important because it may cast light on the factors affecting its fishery dynamics and may provide forecasts of its future catch level. In addition, modelling the combined catch of a group of species is also of primary importance because: (a) it reflects the situation from the fishers' and fishing industry's viewpoints (Mendelssohn and Cury, 1987); and (b) the combined catch derived from a marine region possibly reflects the carrying capacity of the region.

The development of operational forecasts was based on historical time series of landings for the period 1964–1989, inclusive, and the following three general categories of forecasting techniques:

1. deterministic simple or multiple regression models incorporating different exogenous variables (time, number of fishers, wholesale value of catch and climatic variables);
2. univariate time series models (Winters' (Winters, 1960) seasonal exponential smoothing; ARIMA);
3. multivariate time series techniques (harmonic regression; dynamic regression; vector autoregressions).

Fits (for 1964–1987) and forecasts (for 1988–1989) obtained by the different forecasting techniques were compared with each other and with those of two naive methods and an empirical one (i.e. combination of forecasts) using 32 different measures of accuracy.

The present study together with that of Stergiou and Christou (1996) for annual catches represent the largest comparison of fisheries forecasting techniques (overall: 32 annual and monthly catch series analysed by 14 techniques resulting to 307 models). Analogous comparisons have been undertaken in other fields (e.g. hydrology: three techniques applied to 30 monthly riverflow series; Noakes et al., 1985) with the largest and most famous being the M-Competition (Makridakis et al., 1983) in which 1001 yearly, monthly and quarterly time series of microeconomic, macroeconomic, industrial and demographic data were collected and analysed using 20 different forecasting methods.

2. Materials and methods

2.1. Sources of data

Fisheries statistics for Hellenic waters have been recorded on a monthly basis since January 1964 by the National Statistical Service of Hellas Bulletins

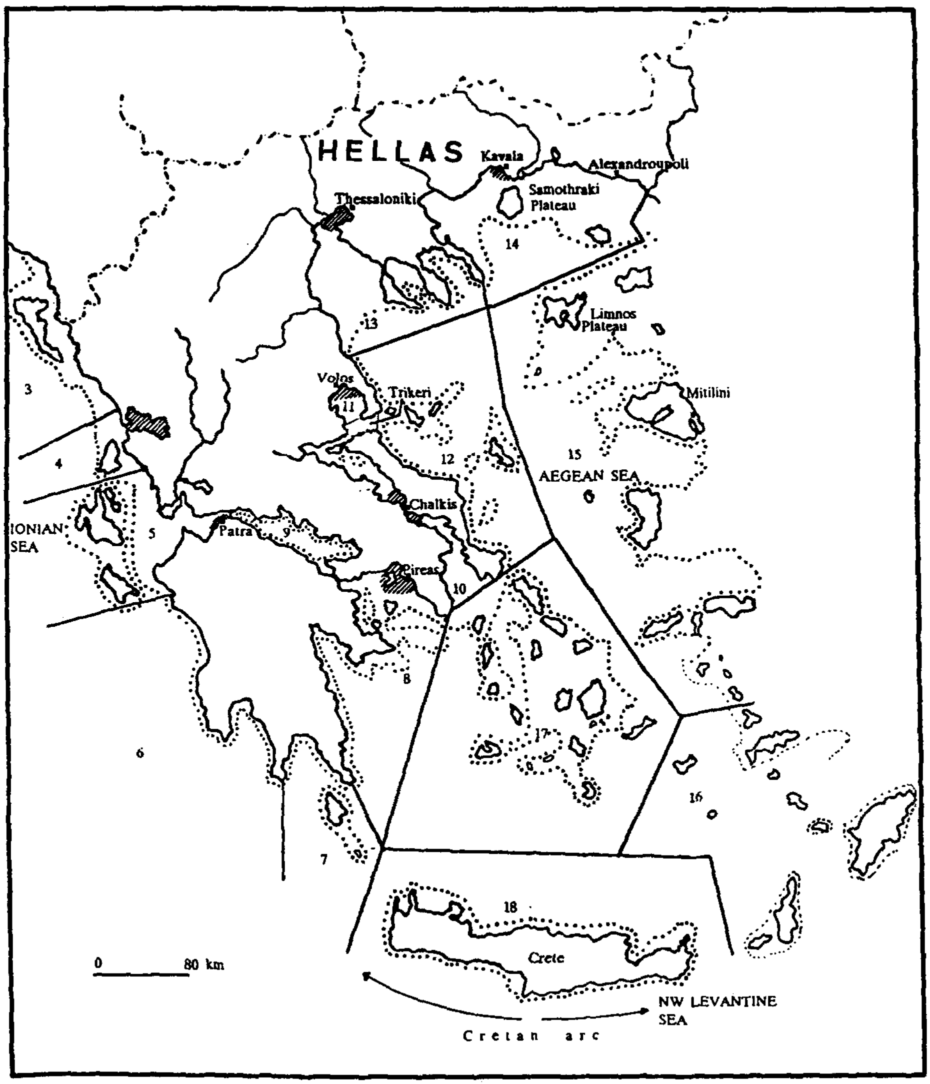


Fig. 1. Map showing the 16 Hellenic fishing subareas. The dotted line represents the 200 m isobath, and hatched areas show areas where anthropogenic eutrophication is locally important.

(NSSH, 1965–1992). For a better evaluation of the available data, the waters fished by the Hellenic vessels have been divided into 18 statistical fishing subareas (Fig. 1). Fishing subareas 1 and 2 (not shown in Fig. 1) refer to the Atlantic Ocean and the northern coast of Africa, respectively. Catch data are collected directly from a sample of fishing vessels (using stratified random sampling) that are surveyed by local customs authorities. For each vessel surveyed, a statistical questionnaire is completed showing the quantities of each major fish species (or group of species) caught during the previous month (or that the vessel did not work during that period).

In general, the Hellenic fishing fleet includes: (a) fishing vessels operating in distant waters (Atlantic Ocean and northern African coast, and thus of no concern to the present study); (b) trawlers operating in Hellenic open-sea waters; (c) purse seiners operating in Hellenic open-sea and coastal waters; (d) beach seiners operating along the Hellenic coasts; (e) 'other coastal boats' (including small ring netters, drifters, liners, etc.) operating along the Hellenic coasts. Since 1969 the catches of the smaller inshore ring netters, drifters and liners (i.e. boats with engine of less than 20 hp) have not been recorded by the local customs authorities.

In the present study an attempt is made to model and forecast the monthly commercial catch weights of 16 species (or groups of species) in Hellenic marine waters using historical fisheries time series for the years 1964–1989. The following time series were considered:

1. total (i.e. all fishing subareas combined) monthly commercial catches of trawlers, beach seiners, purse seiners and 'other coastal boats';
2. total monthly commercial catches of anchovy (*Engraulis encrasicolus*), sardine (*Sardina pilchardus*), bogue (*Boops boops*), red pandora (*Pagellus erythrinus*), gadiformes (hake *Merluccius merluccius* and blue whiting *Micromesistius poutassou*), *Trachurus* spp., *Scomber* spp., *Mullus* spp. and *Spicara* spp.;
3. total monthly commercial catches of fishes, cephalopods and crustaceans.

Anchovy, sardine, bogue, *Scomber* spp., *Trachurus* spp., hake, blue whiting, red pandora, *Mullus* spp. and *Spicara* spp. are the most important fish species in Hellenic marine waters either in terms of abundance (their combined annual catch represents more than 70% of the total Hellenic marine catch: Stergiou and Petrakis, 1993; Stergiou and Pollard, 1994) or in terms of commercial value.

Table 1
Time series of independent variables used for the development of multivariate models. Hellenic waters, 1964–1989

Time series	Symbol	Source
Fishing effort		
No. of fishers (total)	FI	NSSH (1968–1992)
Trawlers	FIT	
Purse seiners	FIP	
Beach seiners	FIB	
Other coastal boats	FIC	
Demersal [a]	FID	
Economic variables		
Value of catch		
Trawlers	VAT	
Purse seiners	VAP	
Beach seiners	VAB	
Other coastal boats	VAC	
Climatic variables		
Sea surface temperature	SST	COADS DATABASE
Air temperature	AIRT	
North–south wind	NSW	
Wind speed cubed	WISC	
Sea-level pressure	SLP	

[a] Sum of corresponding values of trawlers, beach seiners and 'other coastal boats'.

The independent variables used for the development of the models are listed in Table 1. We point out that in contrast to annual data, the only monthly index of fishing effort available is the monthly number of fishers (Stergiou et al., 1994). Monthly climatic data for the Hellenic marine waters are available since the late 1940s in the COADS database, an extensive meteorological database of individual meteorological ship observations, currently re-processed within the framework of the CEOS project (Bakun et al., 1993). In the present study, we used the climatic time series from three 1° squares of the north Aegean Sea (38–39°N, 24–25°E; 38–39°N, 25–26°E; 39–40°N, 25–26°E) because: (a) the North Aegean Sea represents the most important Hellenic fishing and spawning grounds for both demersal and pelagic fishes (Stergiou and Pollard, 1994; Stergiou et al., 1994); (b) the mean monthly number of observations in the selected squares was the highest (25, 16 and

18, respectively) whereas the number of missing values was the lowest (only three to four missing values per square) during the 1964–1989 period. The monthly SST records in the three 1° squares were highly significantly ($P < 0.001$) correlated with each other (for all three combinations: $r > 0.97$, $n = 312$, $P < 0.001$). The same was also true of AIRT ($r > 0.95$, $n = 312$, $P < 0.001$), NSW ($r > 0.62$, $n = 312$, $P < 0.001$), WISC ($r > 0.52$, $n = 312$, $P < 0.001$) and SLP ($r > 0.81$, $n = 312$, $P < 0.001$). Hence, for each climatic variable, the monthly records were averaged over the three 1° squares, weighted by the number of observations.

2.2. *Forecasting models*

2.2.1. *Deterministic multivariate models*

The general form of a linear multiple regression (MREG) model in the time domain is:

$$X_t = a + b_1 Y_{1t} + b_2 Y_{2t} + \cdots + b_k Y_{kt} + e_t$$

for $t = 1$ to N

where X_t is the value of the dependent variable of interest at time t, Y_1 to Y_k are k independent variables and e_t is an error term, at time t, which is assumed to be sampled independently from a normal distribution. MREG models were developed for all monthly catches using a variety of independent variables (Table 1). For all MREG models, the independent variables initially considered for inclusion into the models were: (a) the five climatic variables; (b) fishing effort (i.e. expressed as number of fishers), defined according to the percentage of species' catch caught by the four component fisheries (based on Stergiou and Pollard, 1994). In addition, for the four component fisheries the wholesale value of the catch was also considered for inclusion, whereas for each species (or groups of species) participating in the three complexes, considered for the development of vector autoregression models (see Section 2.2.3), the catches of the remaining species of the complex were also considered for inclusion. The variables that entered into the final models were selected through stepwise variable selection. All MREG models were developed using STATGRAPHICS/PLUS for DOS (STCS, 1993) with default criteria. MREG models in which the forecasted variable, X_t, is a function of one or more independent variables at the same time point, Y_t, are often of no real-time forecasting power when the independent variable(s) is not controllable (e.g. climate) as opposed to controllable ones (e.g. fishing effort) (Stergiou and Christou, 1996). This is the result of the considerable time lag required for the exchange of statistics between the appropriate authorities (Stergiou and Christou, 1996). In contrast, all univariate time series models are of real-time forecasting power. Hence, in the present study MREG models were developed using lagged (by 1 year) independent variables (i.e. catches refer to the 1965–1987 period whereas the independent variables refer to the 1964–1986 period).

A special case of regression models is the seasonal time-varying (TVS) regression. In simple time-varying models the dependent variable of interest, X_t, is regressed against time t:

$$X_t = a + a_1 t + a_2 t^2 + \cdots + a_k t^k + e_t$$

where $t = 1$ to N. The definition for $t = 1$ for the first observed value is arbitrary. When $k = 1$ the above equation refers to a linear trend (i.e. $X_t = a + bt + e_t$), when $k = 2$ to a quadratic trend (i.e. $X_t = a + bt + ct^2 + e_t$) and so on. For TVS models a modified version of the above model can be used that copes with seasonal cycles. This is done by introducing $s - 1$ dummy variables (where s is the length of seasonality; in our case 12 months), D_1 to D_{11}:$D_1 = 1$, if the month is January, and zero otherwise; $D_2 = 1$, if the month is February, and zero otherwise; and $D_{11} = 1$, if the month is November, and zero otherwise.

Each of these 11 dummy variables is equivalent to a new regressor:

$$X_t = a + b_1 D_1 + b_2 D_2 + \cdots + b_{11} D_{11} + a_1 t + a_2 t^2 + \cdots + a_k t^k + e_t$$

and the set of the 11 dummy variables identifies all 12 months (Makridakis et al., 1983).

2.2.2. *Univariate time series models*

In general, there are three categories of univariate time series models which can be used for modelling and forecasting: averaging, exponential smoothing and AutoRegressive Integrated Moving Average (ARIMA) models. Averaging and smoothing models do not identify individual components of the basic underlying pattern and forecasts are based on the projection into the future of the basic pattern after eliminating randomness with smoothing. They both improve upon the mean as the forecast for the next period. Averaging models apply equal or unequal weight to average past observations, whereas exponential smoothing models apply unequal exponentially decreasing weights for the averaging of past observations (i.e. recent observations are given relatively more weight in forecasting than older observations). Exponential smoothing models have been widely used in economic forecasting because of their robustness which renders them ideal for short and highly irregular data (Makridakis et al., 1983; Goodrich, 1989; Stellwagen and Goodrich, 1993). In contrast, ARIMA models, although similar to smoothing in that forecasts are developed from historical time series analysis, are based on well-articulated statistical theory (Box and Jenkins, 1976). ARIMA models capture the historic autocorrelations of the data and extrapolate them into the future. They usually outperform exponential smoothing models when the time series of data is long, not highly irregular and the autocorrelations are strong (Stellwagen and Goodrich, 1993). The following univariate time series models were used in the present study: (a) two 'naive' models, NM; (b) the Winters' (Winters, 1960) additive and multiplicative exponential smoothing models, WES; (c) ARIMA models.

A comparison with NM helps us to decide whether or not the improvement achieved from going from a simple model to a sophisticated model is worth the time and cost involved (Makridakis et al., 1983). Two such models were used in the present study. The first one, NM1, uses as a forecast for time $t+1$ (F_{t+1}) the catch one time period ago (X_t). This method is actually an averaging method of order 1. The second one, NM12, deals with seasonality of length 12 months and uses as a forecast for time $t+1$ (F_{t+1}) the catch 12 time periods ago (X_{t-11}). In mathematical terms this is as follows: $F_{t+1} = X_{t-11}$ and $F_{t+12} = X_t$.

WES was applied for the first time to fisheries forecasting by Stergiou (1991a). WES models can handle both trend and seasonality as well as randomness. They are based on three smoothing equations, one for trend, one for stationarity and one for seasonality. In the multiplicative WES model it is assumed that each observation is the product of a deseasonalised value and a seasonal index:

$$S_t = \alpha(X_t/I_{t-L}) + (1-\alpha)(S_{t-1} + b_{t-1})$$
$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}$$
$$I_t = \beta(X_t/S_t) + (1-\beta)I_{t-L}$$

and forecasts are computed based on:

$$F_{t+m} = (S_t + mb_t)I_{t-L+m}$$

In the additive WES model it is assumed that each observation is the sum of a deseasonalised value and a seasonal index:

$$S_t = \alpha(X_t - I_{t-L}) + (1-\alpha)(S_{t-1} + b_{t-1})$$
$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}$$
$$I_t = \beta(X_t - S_t) + (1-\beta)I_{t-L}$$

and forecasts are computed based on:

$$F_{t+m} = (S_t + mb_t + I_{t-L+m})$$

For both categories of WES models, α, β and γ are the general smoothing, seasonal smoothing and trend smoothing coefficients, respectively, with values ranging between 0 and 1; L is the length of seasonality; b_t is the trend component; I is the seasonal adjustment factor; S_t is the smoothed series (smoothed value at time t) that does not include seasonality; and F_{t+m} is the forecast m periods ahead. For all WES models built in the present study the computation of the smoothing coefficients was based on the minimisation of the Bayesian Information Criterion, mean squared error and mean absolute percentage error (see Section 2.3), in that order of importance, and the approach to estimate these values was trial and error. WES models were built using the FORECAST-PRO statistical package for windows (Business Forecast Systems, Inc., Belmont; Stellwagen and Goodrich, 1993).

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 and Jenkins, 1976). They apply to stationary time series (i.e. time series with no systematic change in mean and variance; Box and Jenkins, 1976; Makridakis et al., 1983). First or second order differencing handles problems of non-stationary mean, and logarithmic (or power) transformation of the raw data handles non-stationary variance. The general form of ARIMA models can be described by the following equation:

$$(1-\varphi_1 B^p)(1-\Phi_1 B^P)(1-B^d)(1-B^D)X_t = (1-\theta_1 B^q)(1-\Theta_1 B^Q)e_t$$

where X_t is the value of the variable of interest at time t; B^p is the backward shift operator for which $B^p X_t = X_{t-p}$; φ_1, Φ_1, θ_1 and Θ_1 are the arithmetic coefficients; and e_t is the error term at time t. The general form of the ARIMA models is referred to as:

$$\mathrm{ARIMA}(p,d,q)(P,D,Q)^S$$

where p is the order of the autoregressive term (AR term); d is the degree of differencing involved to achieve stationarity (I term); q is the order of the moving average term (MA term); S is the seasonality (number of periods per season); and P, D, Q are seasonal terms corresponding to p, d, q, respectively. Identification of the appropriate model used (i.e. how many terms to be included in the model) was based on the examination of the autocorrelation (ACF) and partial autocorrelation (PACF) functions (not shown here) of the differenced, log-transformed time series (Box and Jenkins, 1976; Makridakis et al., 1983). Consequently, the initial models were tested for improvement (by considering alternative models and/or overfitting) in terms of BIC, mean squared error, mean absolute percentage error and r^2 values, in that order of importance, whereas the overfitted term(s) had to have coefficients that were more than two standard errors. All ARIMA models were built using the approximate maximum likelihood algorithm of McLeod and Sales (1983).

2.2.3. Multivariate time series models

The following multivariate time series models were used in the present study: (a) dynamic regression, DREG; (b) harmonic regression, HREG; (c) vector autoregressions, VAR.

For DREG models, the ordinary MREG models developed were subsequently examined for inclusion of Cochrane–Orcutt autoregressive error terms (Cochrane and Orcutt, 1949), autoregressive terms of the dependent variable and lagged terms of the independent variable(s). The general form of a dynamic regression (DREG) model including κ autoregressive terms of the dependent variable of interest, X_t, μ lags of an independent variable, Y_t, and λ Cochrane–Orcutt autoregressive error terms, e_t, is:

$$X_t = c + a_1 X_{t-1} + \cdots + a_\kappa X_{t-\kappa} + b_0 Y_t + b_1 Y_{t-1} + \cdots + b_\mu Y_{t-\mu} + \theta_0 e_t + \theta_1 e_{t-1} + \cdots + \theta_\lambda e_{t-\lambda}$$

For all MREG models the test was performed for each of the first 12 lags and the first two seasonal lags of the above mentioned parameters. New terms were included in the models when the Lagrange multiplier test was significant at the level 0.01 (Stellwagen and Goodrich, 1993). All DREG models were developed using FORECAST/PRO for WINDOWS (Stellwagen and Goodrich, 1993).

HREG models incorporate sine and cosine terms to account for periodic variations. This technique was applied for the first time to fisheries by Bulmer (1974). The general form of a HREG model incorporating a set of sine and cosine waves, with known frequencies, f_i (for $i = 1$ to k), is:

$$X_t = \sum_{i=1}^{k} \left[b_{1i}\sin((f_i t/n)2\pi) + b_{2i}\cos((f_i t/n)2\pi) \right] + e_t$$

where X_t is the value of the variable of interest at time t, b_{1i} and b_{2i} are the arithmetic coefficients, estimated using ordinary least squares regression techniques, and e_t is the error at time t. The application of HREG requires that the frequencies f_i are known ahead of time. In the present study the frequencies f_i were estimated using Fast Fourier Transform (FFT), applied to the log-transformed and detrended monthly catches. The frequencies that entered into the final HREG models were selected through stepwise variable selection. FFT and HREG models were developed using STATGRAPHICS/PLUS for DOS (STCS, 1993).

VAR models allow interdependence among a set of variables (called internal variables). Each internal variable is regressed against its own value in each of the n preceding periods, against the values in each of the n preceding periods of all other variables included in the model, and against a constant term and an external variable(s) (Schlegel, 1985). The equations are estimated individually in order to compute the arithmetic coefficients and the constant. Consequently, the reduced form of the system is calculated and forecasts are produced. Although VAR models were applied to fisheries forecasting for the first time by Stergiou (1991b), they are of increasing interest to economic forecasters (Litterman, 1979; Todd, 1984; Schlegel, 1985). The general form of a VAR model including two internal variables, X and Y, n lags, and an external variable Z, is as follows (Schlegel, 1985):

$$\begin{aligned}X_t = {} & c_1 + a_{11}X_{t-1} + a_{21}X_{t-2} + \cdots + a_{n1}X_{t-n} \\ & + b_{11}Y_{t-1} + b_{21}Y_{t-2} + \cdots + b_{n1}Y_{t-n} \\ & + d_1 Z_t + e_1 \\ Y_t = {} & c_2 + a_{12}X_{t-1} + a_{22}X_{t-2} + \cdots + a_{n2}X_{t-n} \\ & + b_{12}Y_{t-1} + b_{22}Y_{t-2} + \cdots + b_{n2}Y_{t-n} \\ & + d_2 Z_t + e_2\end{aligned}$$

where X_{t-n} is the value of the variable of interest n periods before time t; c is a constant; a, b and d are the arithmetic coefficients of the model; and e_1 and e_2 are the error terms. The arithmetic parameters of the equations are estimated using ordinary least squares regression. In the present study, VAR models were used to model and forecast the monthly catches of the following three complexes: (a) sardine, anchovy, *Trachurus* spp. and *Scomber* spp.; (b) trawlers, beach-seiners, purse-seiners and 'other coastal boats'; (c) fish, cephalopods and crustaceans. The above mentioned complexes were selected because: (a) VAR models take into account interactions between variables; (b) the replacement of sardine by anchovy and/or other small- and medium-sized pelagic fish species has been observed throughout the Mediterranean Sea (Spanish, Adriatic, Hellenic and Moroccan waters: Stergiou, 1989) and elsewhere (e.g. Daan, 1980); (c) the replacement of pelagic fisheries by demersal fisheries as well as changes in the relative importance of the major component fishery groups have been observed in various regions of the world ocean (e.g. Caddy and Sharp, 1986). Hence, three VAR models were fitted, one including three internal variables and two including four internal variables (the above mentioned complexes), involving lag lengths ranging from 1 to 36 lags (= months) as well as various external variables. VAR models were developed using TSP for DOS (Hall et al., 1990).

2.2.4. Empirical (EMP) models

An empirical approach to forecasting is by combining the forecasts from the different models used. In this case the forecast at time $t+1$, F_{t+1}, can be the unweighted mean of the F_{t+1} of all and/or of the best fitting/forecasting models. The success achieved by combining forecasts produced by different methods has been documented for economic (e.g. Armstrong and Lusk, 1983) as well as fisheries time series (Noakes et al., 1990).

2.3. Measures of accuracy

There are many measures of forecasting accuracy that one may use to compare different models (Makridakis et al., 1983). The following general categories of statistical measures were used in the present study:

1. standard statistical measures (mean and median error, ME and MDE, respectively; mean and median absolute error, MAE and MDAE, respectively; mean and median squared error, MSE and MDSE, respectively; root MSE, RMSE; minimum and maximum values of errors, absolute errors and squared errors; standard deviation of errors, absolute errors and squared errors, SDE, SDAE and SDSE, respectively);
2. relative statistical measures (mean and median percentage error, MPE and MDPE, respectively; mean and median absolute percentage error, MAPE and MDAPE, respectively; minimum and maximum values of percentage errors and absolute percentage errors; standard deviations of percentage errors and absolute percentage errors, SDPE and SDAPE, respectively; number of data points predicted with APE smaller than an arbitrary percentage, here 10% and 20%);
3. other statistical measures (Theil's (Theil, 1966) U-statistic, U, and bias component, B; McLaughlin's (McLaughlin, 1975) batting average, MBA; Ljung and Box's (Ljung and Box, 1978) Q statistic). A detailed description of all of the above mentioned measures has been presented in Stergiou and Christou (1996).

Apart from the above mentioned measures, the Bayesian information criterion, BIC, was also used to compare MREG and DREG models as well as the

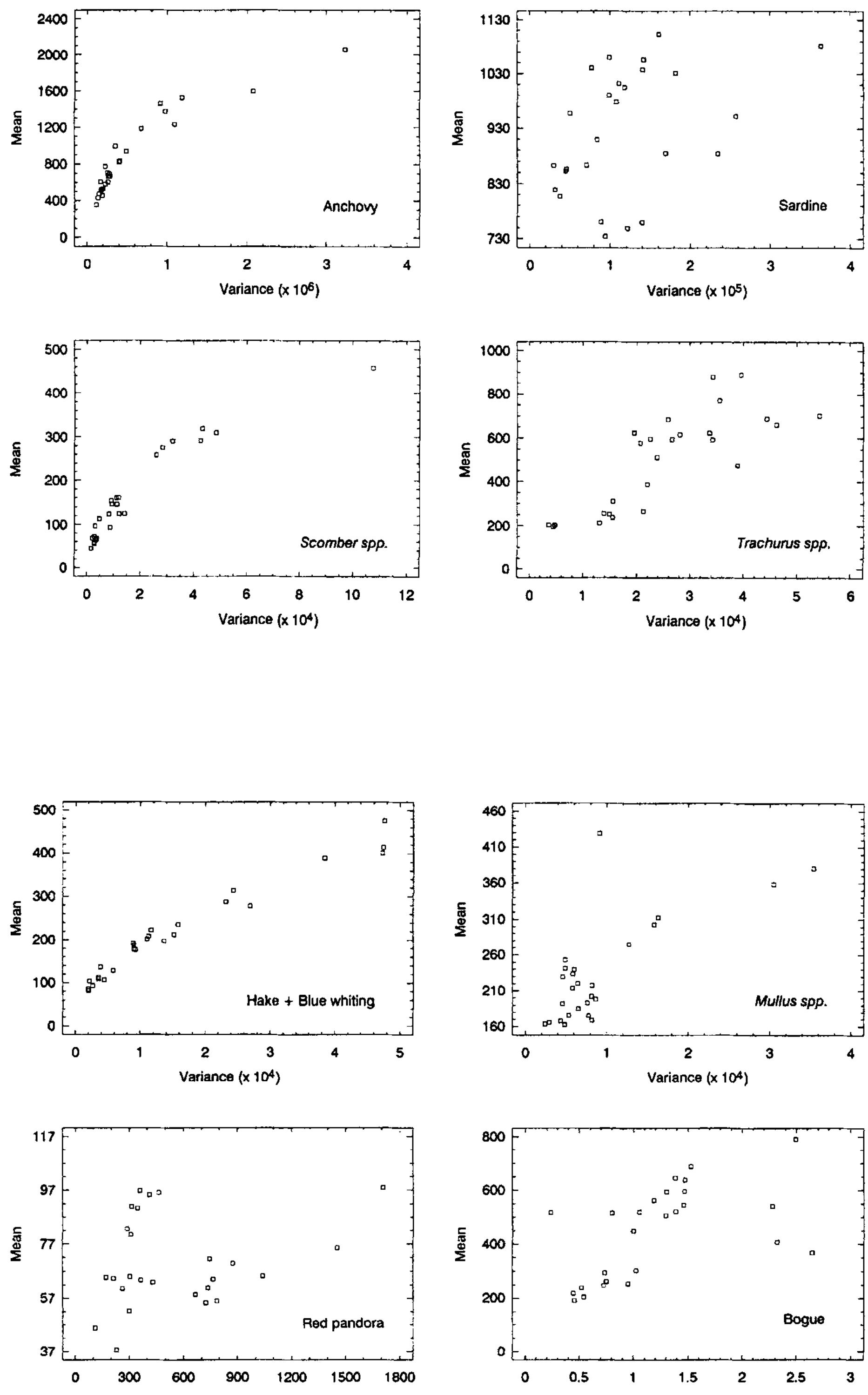


Fig. 2. Variance-mean plots for the 16 monthly fisheries time series, Hellenic waters, 1964–1989.

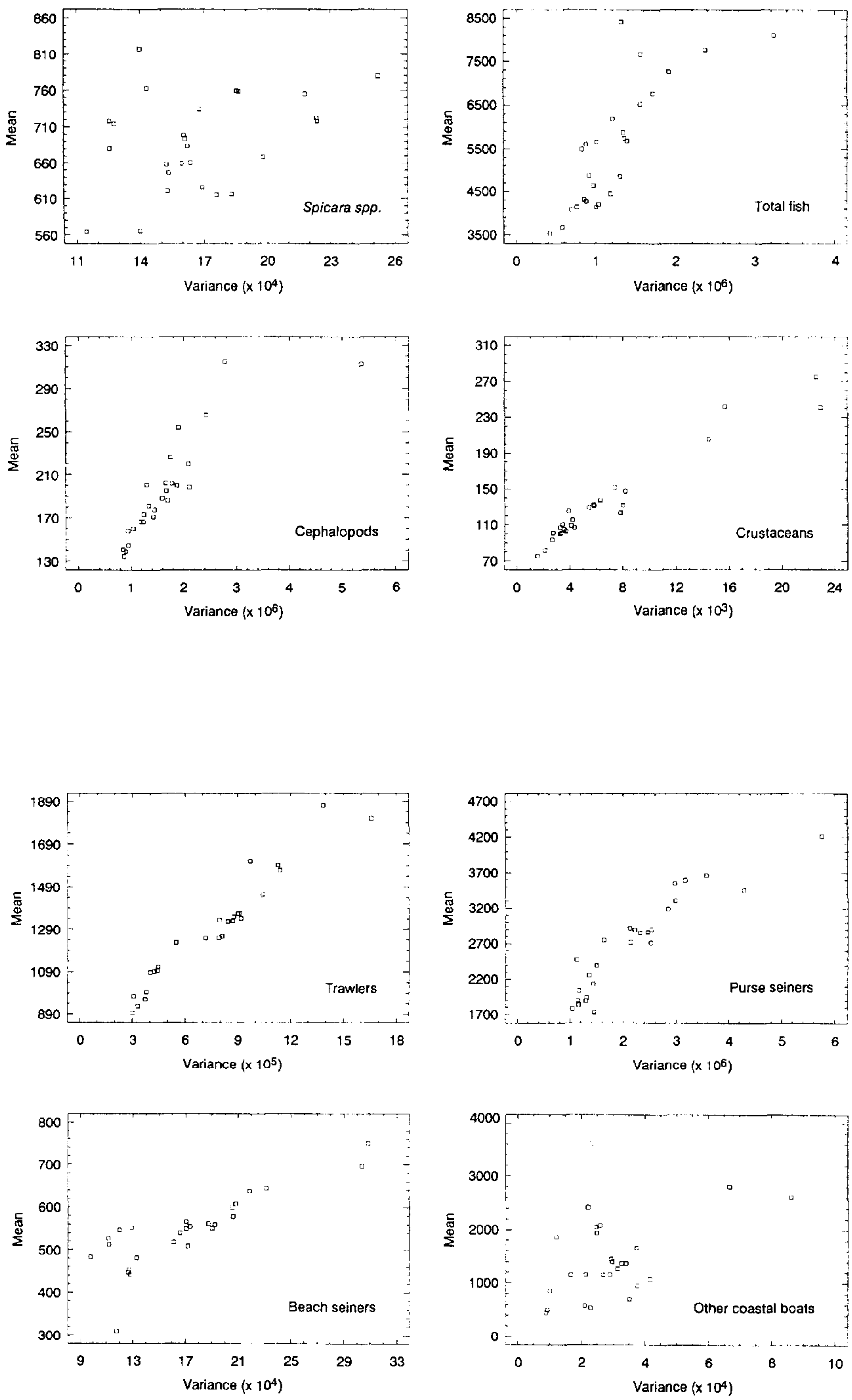


Fig. 2 (continued).

Table 2
Multiple regression (MREG) models between the log-transformed monthly catches of the 16 species or groups of species, Ln(C), and various independent variables, Hellenic waters, January 1964–December 1987. All independent variables refer to the 1964–1986 period, whereas all dependent variables refer to the 1965–1987 period (i.e. lagged by 12 months). For all regressions ($n = 276$), t is time ($t = 1$ to 276). The r^2, BIC and Ljung–Box test, $LB(18)$, values are also shown; significant ($P < 0.05$) LB(18) values are marked with an asterisk

Species	MREG model	r^2	BIC	$LB(18)$
Anchovy	$\mathrm{Ln}(C) = 424.67 - 0.21\mathrm{Ln}(\text{sardine}) + 0.21\mathrm{Ln}(\textit{Scomber}) - 0.23\mathrm{Ln}(\mathrm{NSW}) - 61.94\mathrm{Ln}(\mathrm{SLP}) + 1.36\mathrm{Ln}(\mathrm{FIP}) + 0.005t$	0.84	241	167.1 *
Sardine	$\mathrm{Ln}(C) = -156.86 + 0.08\mathrm{Ln}(\textit{Scomber}) + 0.20\mathrm{Ln}(\textit{Trachurus}) - 0.15\mathrm{Ln}(\text{anchovy}) - 0.09\mathrm{Ln}(\mathrm{WISC}) + 22.74\mathrm{Ln}(\mathrm{SLP})$ $+ 0.72\mathrm{Ln}(\mathrm{FIP}) + 0.008t - 0.00002t^2$	0.70	251	197.2 *
Scomber spp.	$\mathrm{Ln}(C) = -14.07 + 0.34\mathrm{Ln}(\text{sardine}) + 0.43\mathrm{Ln}(\textit{Trachurus}) + 1.17\mathrm{Ln}(\mathrm{SST}) + 1.19\mathrm{Ln}(\mathrm{FIP}) + 0.006t$	0.84	43	177.1 *
Trachurus spp.	$\mathrm{Ln}(C) = 3.15 + 0.10\mathrm{Ln}(\text{anchovy}) + 0.16\mathrm{Ln}(\text{sardine}) + 0.15\mathrm{Ln}(\textit{Scomber}) + 0.00006t^2 - 0.0000002t^3$	0.88	100	472.9 *
Gadiformes	$\mathrm{Ln}(C) = -436.50 - 4.51\mathrm{Ln}(\mathrm{SST}) + 1.19\mathrm{Ln}(\mathrm{AIRT}) + 64.55\mathrm{Ln}(\mathrm{SLP}) + 0.40\mathrm{Ln}(\mathrm{FID}) + 0.005t$	0.75	68	265.9 *
Mullus spp.	$\mathrm{Ln}(C) = -355.64 - 1.07\mathrm{Ln}(\mathrm{SST}) + 0.37\mathrm{Ln}(\mathrm{AIRT}) + 0.13\mathrm{Ln}(\mathrm{NSW}) + 51.50\mathrm{Ln}(\mathrm{SLP}) + 0.68\mathrm{Ln}(\mathrm{FID}) + 0.000003t^2$	0.65	61	265.9 *
Red pandora	$\mathrm{Ln}(C) = -174.65 - 0.59\mathrm{Ln}(\mathrm{SST}) + 0.15\mathrm{Ln}(\mathrm{NSW}) + 25.31\mathrm{Ln}(\mathrm{SLP}) + 0.57\mathrm{Ln}(\mathrm{FID}) - 0.000005t^2$	0.51	21	318.4 *
Bogue	$\mathrm{Ln}(C) = 3.96 + 0.64\mathrm{Ln}(\mathrm{AIRT}) - 0.07\mathrm{Ln}(\mathrm{WISC}) + 0.005t$	0.73	106	866.3 *
Spicara spp.	$\mathrm{Ln}(C) = -676.27 - 2.75\mathrm{Ln}(\mathrm{SST}) + 0.28\mathrm{Ln}(\mathrm{NSW}) + 98.99\mathrm{Ln}(\mathrm{SLP}) + 0.51\mathrm{Ln}(\mathrm{FI}) - 0.001t$	0.68	269	291.6 *
Total fish	$\mathrm{Ln}(C) = 5.47 + 0.62\mathrm{Ln}(\mathrm{AIRT}) - 0.10\mathrm{Ln}(\mathrm{NSW}) - 0.08\mathrm{Ln}(\mathrm{WISC}) + 0.12\mathrm{Ln}(\mathrm{FI}) + 0.06\mathrm{Ln}(\text{cephalopods})$ $+ 0.07\mathrm{Ln}(\text{crustaceans}) + 0.003t$	0.82	727	285.0 *
Cephalopods	$\mathrm{Ln}(C) = -178.29 - 2.02\mathrm{Ln}(\mathrm{SST}) - 0.90\mathrm{Ln}(\mathrm{AIRT}) + 0.32\mathrm{Ln}(\mathrm{NSW}) + 0.23\mathrm{Ln}(\mathrm{WISC}) + 25.56\mathrm{Ln}(\mathrm{SLP})$ $+ 0.60\mathrm{Ln}(\mathrm{FI}) + 0.46\mathrm{Ln}(\text{fish}) + 0.62\mathrm{Ln}(\text{crustaceans})$	0.88	53	211.4 *
Crustaceans	$\mathrm{Ln}(C) = -225.23 - 1.80\mathrm{Ln}(\mathrm{SST}) + 0.88\mathrm{Ln}(\mathrm{AIRT}) - 0.11\mathrm{Ln}(\mathrm{WISC}) + 32.67\mathrm{Ln}(\mathrm{SLP}) + 0.56\mathrm{Ln}(\text{fish})$ $+ 0.49\mathrm{Ln}(\text{cephalopds})$	0.78	39	129.9 *
Trawl	$\mathrm{Ln}(C) = 5.01 + 0.35\mathrm{Ln}(\text{seine}) - 0.96\mathrm{Ln}(\mathrm{SST}) + 0.31\mathrm{Ln}(\mathrm{VAT}) - 0.01t$	0.80	488	50.6 *
Purse seine	$\mathrm{Ln}(C) = 4.48 - 0.26\mathrm{Ln}(\text{coastal}) - 0.98\mathrm{Ln}(\mathrm{SST}) + 1.55\mathrm{Ln}(\mathrm{AIRT}) - 0.24\mathrm{Ln}(\mathrm{NSW}) - 0.15\mathrm{Ln}(\mathrm{WISC})$ $+ 0.52\mathrm{Ln}(\mathrm{VAP}) - 0.004t$	0.86	648	126.3 *
Beach seine	$\mathrm{Ln}(C) = -258.11 + 0.40\mathrm{Ln}(\text{trawl}) - 0.32\mathrm{Ln}(\mathrm{VAB}) - 0.91\mathrm{Ln}(\mathrm{SST}) + 37.39\mathrm{Ln}(\mathrm{SLP}) + 1.03\mathrm{Ln}(\mathrm{FIB})$ $+ 0.007t$	0.92	104	38.9 *
Coastal boats	$\mathrm{Ln}(C) = 2.29 + 0.47\mathrm{Ln}(\mathrm{VAC}) - 0.003t$	0.73	333	804.5 *

Table 3

Arithmetic coefficients of the independent variables of the seasonal time-varying (TVS) multiple regression models between the log-transformed monthly catches of the 16 species or groups of species and 12 dummy variables ($D1$ to $D12$) as well as time t ($t = 1$ to 288), ($\mathrm{Ln(Catch)} = c + a_1 D1 + a_2 D2 + \cdots + a_{12} D12 + a_{13} t + \cdots + a_k t^k$), $n = 288$), Hellenic waters, January 1964–December 1987. c is a constant, $D12$ is a dummy variable that takes the value of 1 for the months/years 1964–1969, inclusive, and the value of 0 for the months/years following 1969. The r^2 and Ljung–Box test, $LB(18)$, values are also shown; significant ($P < 0.05$) $LB(18)$ values are marked with an asterisk

Species	Arithmetic coefficients of TVS model															r^2	$LB(18)$
	c	$D1$	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$	$D11$	$D12$	t	t^2		
Anchovy	3.81	0.16	0.29	1.47	2.05	2.59	2.81	2.74	2.56	2.24	1.42	0.54		0.005		0.88	222.2 *
Sardine	5.82	−0.32	−0.23	0.43	0.83	0.93	0.85	0.70	0.75	0.86	0.95	0.60		0.005	−0.000015	0.67	615.7 *
Scomber spp.	1.64	−0.40	−0.22	1.03	1.70	2.45	2.59	2.49	2.51	2.49	1.94	0.88		0.008		0.83	503.5 *
Trachurus spp.	4.57	0.04	0.08	0.40	0.65	0.94	0.90	0.96	0.88	0.79	0.65	0.32		0.006		0.83	1227.2 *
Gadiformes	4.62	0.03	0.01	0.04	0.09	0.15	−1.37	−1.49	−1.65	−1.80	0.16	0.08		0.005		0.92	333.2 *
Mullus spp.	5.85	−0.13	−0.19	−0.13	−0.10	−0.11	−0.88	−0.87	−0.78	−0.65	0.37	0.26		−0.008	0.000030	0.83	490.4 *
Red pandora	4.85	−0.02	−0.09	−0.07	0.03	0.08	−0.61	−0.63	−0.63	−0.66	0.28	0.15		−0.007	0.000019	0.68	495.8 *
Bogue	4.89	0.04	0.03	0.31	0.40	0.60	0.62	0.67	0.66	0.54	0.48	0.21		0.005		0.77	1178.5 *
Spicara spp.	7.08	−0.11	−0.15	−0.16	−0.34	−0.47	−1.81	−1.96	−1.94	−1.58	0.29	0.14		−0.001		0.91	183.7 *
Total fish	7.93	−0.07	−0.10	0.14	0.34	0.52	0.37	0.31	0.25	0.25	0.49	0.26		0.003		0.86	647.6 *
Cephalopods	5.25	−0.04	0.09	0.27	0.11	−0.25	−2.24	−2.52	−2.68	−2.38	−0.09	0.04		0.002		0.91	773.9 *
Crustaceans	4.54	−0.15	−0.08	0.08	0.30	0.60	−0.82	−1.43	−1.87	−1.09	0.24	0.23		0.002		0.83	434.2 *
Trawl	7.81	−0.08	−0.09	−0.07	−0.11	−0.15	−3.63	−3.87	−3.50	−3.02	0.13	0.14		−0.002		0.78	424.9 *
Purse seine	6.23	−0.31	−0.17	0.72	1.18	1.55	1.68	1.55	1.54	1.47	1.17	0.68		0.003		0.91	85.1 *
Beach seine	6.87	−0.05	−0.18	−0.27	−0.45	−0.60	−5.86	−6.40	−6.53	−4.52	0.20	0.12		−0.001	0.000004	0.89	179.9 *
Coastal boats	5.32	0.02	0.03	0.14	0.19	0.27	0.36	0.30	0.26	0.28	0.17	0.10	1.23	0.009		0.90	873.1 *

different versions of WES and ARIMA models fitted to the monthly catches. BIC provides a combined measure of goodness-of-fit (as measured by MSE) and model parsimony (i.e. number of variables). The following equation was used for its computation (Stellwagen and Goodrich, 1993):

$$\mathrm{BIC} = (\mathrm{MSE})\, t^{\frac{n}{2t}}$$

where t is the number of data points and n is the number of variables fitted to the model. This version of BIC is scaled the same as the standard forecast error and can very loosely be interpreted as an estimate of out-of-sample error (Stellwagen and Goodrich, 1993). BIC is meaningful only for comparing different versions from the same family of models and for the same time series and the model with the minimum BIC value is selected as the most appropriate.

2.4. Model fitting and forecasting

All models were fitted to the 1964–1987 period and the different measures of accuracy were computed and compared for the untransformed time series. NM1, NM12 and WES models were fitted to the original catches. All remaining models were fitted to the log-transformed catches. Logarithmic transformation was justified by examining the mean–variance plots of the monthly catches that were obtained by dividing the series into 26 years, calculating the variance and mean of each year and plotting the variance vs. the mean (Fig. 2).

Since good fitting does not necessarily imply good forecasting, the ability of all models to produce forecasts was tested by using the arithmetic values of the parameters of the estimated models to develop one-step-ahead monthly forecasts for the years 1988 and 1989. Forecasts were then compared with the actual catches in 1988 and 1989 using the above mentioned 32 measures of accuracy. The two (all methods) × (all measures) matrices, one for fitting and another one for forecasting, were subjected to principal component analysis (PCA; based on correlation matrix). PCA was conducted using the PRIMER algorithms of Plymouth Marine Laboratory (Clarke and Warwick, 1989).

PCA identified four groups of methods of similar performance, in terms of both fitting and forecasting. Each of the four groups was assigned an integer rank from 1 to 4 to indicate fitting and forecasting performance from worst to best. Consequently, all models included in the groups were assigned the rank of the group and rank averages (× 100) were then computed for each model.

3. Results

3.1. Model fitting

The MREG models fitted to the 16 monthly catch series through stepwise variable selection are shown in Table 2. The r^2 values of the models ranged from 0.51, for red pandora catches, to 0.92, for beach seine catches. For all models the Ljung–Box test indicated highly significant error autocorrelation (Table 2).

The TVS models between the log-transformed monthly catches and the 11 dummy variables (D_1 to D_{11}) as well as time t and/or t^2 for the 16 monthly time series are shown in Table 3. The TVS model fitted to the 'other coastal boats' catches included an additional dummy variable (D_{12}) which takes the value of 1 for the months/years 1964–1969 inclusive, and the value of 0 for the months/years following 1969 (during which the number of boats with engine less than 20 hp, and their corresponding catch, is not recorded by NSSH). The r^2 values of the TVS models were high, ranging from 0.67 for sardine, to 0.92 for gadiformes (Table 3). For all models the Ljung–Box test indicated highly significant error autocorrelations (Table 3).

The final values of the smoothing coefficients of WES models are shown in Table 4. The additive WES model was used for four catch series whereas the multiplicative WES model was used for the remaining 12 monthly catches (Table 4). The r^2 values of the models were high, ranging from 0.70 for sardine catches, to 0.96 for trawl catches (Table 4). For all WES models the Ljung–Box test indicated significant error autocorrelations (Table 4).

The frequencies identified, through FFT analysis, in the variability of the log-transformed and detrended monthly catches of the 16 species or groups

Table 4
Arithmetic values of the coefficients (α, β, γ) of the Winter's exponential smoothing (WES) models fitted to the monthly catches of the 16 species or groups of species, together with the type of model used (A, additive; M, multiplicative) and the corresponding r^2 and BIC values, Hellenic waters, January 1964–December 1987. For all models, the Ljung–Box(18) values were over 51 ($P < 0.01$)

Species	Type	α	β	γ	r^2	BIC
Anchovy	M	0.400	0.175	0.002	0.90	265
Sardine	M	0.019	0.375	0.002	0.70	209
Scomber spp.	M	0.077	0.411	0.001	0.80	64
Trachurus spp.	M	0.165	0.423	0.001	0.91	86
Gadiformes	M	0.125	0.302	0.003	0.92	41
Mullus spp.	M	0.135	0.546	0.0001	0.88	36
Red pandora	A	0.369	0.159	0.001	0.78	13
Bogue	M	0.226	0.541	0.000	0.88	67
Spicara spp.	M	0.071	0.626	0.000	0.94	102
Total fish	M	0.369	0.415	0.001	0.92	492
Cephalopods	A	0.085	0.415	0.004	0.92	37
Crustaceans	A	0.145	0.686	0.007	0.83	36
Trawl	M	0.004	0.549	0.009	0.96	184
Purse seine	A	0.199	0.368	0.001	0.91	486
Beach seine	M	0.000	0.987	0.000	0.94	101
Coastal boats	M	0.448	0.974	0.038	0.94	150

of species during the 1964–1987 period are shown in Table 5. Overall, seven frequencies were identified in the variability of the monthly catches (23.8, 12.1, 8.3, 1, 0.5, 0.25 and 0.2 years: Table 5). All catch series displayed a dominant annual cycle whereas cycles with frequencies less than 1 year represent harmonics generated by non-sinusoidal periodic variability. The arithmetic coefficients of the HREG models fitted to the monthly catches, using the estimated frequencies (as well as time t, t^2 and/or t^3), as independent variables, and stepwise variable selection, are shown in Table 6. The r^2 values of HREG models ranged from 0.68 for sardine catches, to 0.92 for gadiform catches (Table 6). For all models, the Ljung–Box test indicated significant error autocorrelation (Table 6).

Table 5
Frequencies identified through FFT analysis applied to the log-transformed and detrended monthly catches of the 16 species or groups of species, Hellenic waters, January 1964–December 1987

Species	Frequency in years						
	23.8	12.1	8.3	1	0.5	0.25	0.2
Anchovy				+			
Sardine				+	+		
Scomber spp.				+	+		
Trachurus spp.		+		+			
Gadiformes				+	+	+	+
Mullus spp.				+	+	+	+
Red pandora			+	+	+	+	+
Bogue		+		+			
Spicara spp.				+	+		
Total fish		+		+	+		
Cephalopods				+	+		
Crustaceans	+			+	+		
Trawl				+	+	+	+
Purse seine				+	+		
Beach seine				+	+		
Coastal boats	+		+	+			

The final ARIMA models fitted to the monthly catches of the 16 species or groups of species (Table 7) were characterised by the smallest BIC, MSE and MAPE values, the highest r^2 values and had arithmetic coefficients that were significantly ($P < 0.05$) different from 0. Overall, ten general ARIMA models were identified (Table 7). The r^2 values of the models ranged from 0.84 for red pandora catches, to 0.96 for cephalopod catches (Table 7). The Ljung–Box test indicated significant error autocorrelation for four models only (*Trachurus* spp., *Scomber* spp., bogue and purse seine: Table 7).

The monthly MREG models presented in Table 2 were tested for significant improvement by including Cochrane–Orcutt autoregressive error terms, lagged dependent variables as well as lagged independent

Table 6
Arithmetic coefficients of the harmonic multiple regression (HREG) models between the log-transformed monthly catches of the 16 species or groups of species and the various frequencies identified in their variability, using FFT analysis, as well as time t ($t = 1$ to 288), Hellenic waters, January 1964–December 1987. c is a constant. The r^2 and Ljung–Box, $LB(18)$, values are also shown; significant ($P < 0.01$) $LB(18)$ values are marked with an asterisk

Species	Arithmetic coefficients of HREG models															r^2	$LB(18)$
	c	$x = 2\pi(0.0032)t$		$x = 2\pi(0.01)t$		$x = 2\pi(0.083)t$		$x = 2\pi(0.167)t$		$x = 2\pi(0.4167)t$		$\cos[2\pi(0.33)t]$	t	t^2	t^3		
		$\sin(x)$	$\cos(x)$	$\sin(x)$	$\cos(x)$	$\sin(x)$	$\cos(x)$	$\sin(x)$	$\cos(x)$	$\sin(x)$	$\cos(x)$						
Anchovy	5.38					−0.41	−1.38						0.01			0.86	189.8 *
Sardine	6.38					−0.29	−0.41	−0.35	−0.11				0.004		−0.00000004	0.68	560.7 *
Scomber spp.	3.10					−0.78	−1.28	−0.38	−0.20				0.01			0.83	437.4 *
Trachurus spp.	5.17		0.21			−0.21	−0.44							0.00007	−0.0000002	0.90	274.6 *
Gadiformes	4.15					0.67	0.58	−0.52	0.08	0.21	0.16	−0.30	0.01			0.92	283.9 *
Mullus spp.	5.58					0.14	0.39	−0.34		0.10	0.08	−0.15	−0.01	0.00003		0.83	422.5 *
Red pandora	4.70			−0.11	0.07	0.18	0.26	−0.28		0.10	0.07	−0.15	−0.01	0.00002		0.72	287.3 *
Bogue	5.20	0.16	0.11			−0.16	−0.30						0.01			0.83	484.1 *
Spicara spp.	6.23					0.51	0.86	−0.54								0.83	297.1 *
Total fish	8.13	0.05	0.05			−0.10	−0.17	−0.18					0.003			0.86	250.3 *
Cephalopods	4.45					1.05	0.99	−0.72					0.002			0.86	375.3 *
Crustaceans	4.44					0.60	0.41	−0.70	0.09				−0.002	0.00002		0.79	272.2 *
Trawl	6.32					1.25	1.49	−1.09		0.33	0.32	−0.49				0.77	370.4 *
Purse seine	7.15					−0.45	−0.82	−0.29	−0.11				0.003			0.91	63.3 *
Beach seine	4.75					2.00	2.58	−1.79								0.84	207.9 *
Coastal boats	7.03				−0.17	−0.08	−0.14						−0.01	0.00004		0.71	1178.6 *

Table 7
Arithmetic coefficients of the autoregressive integrated moving average (ARIMA) models fitted to the log-transformed monthly catches of 16 species or groups of species, Hellenic waters, January 1964–December 1987. n is the number of data points fitted. The r^2, BIC and Ljung–Box, $LB(18)$, values are also shown; significant ($P < 0.05$) $LB(18)$ values are marked with an asterisk

Species	ARIMA model	Arithmetic coefficients							n	r^2	BIC	$LB(18)$
		φ_1	φ_2	θ_1	Φ_{12}	Θ_{12}	Θ_{24}	c				
Anchovy	(1,0,0)(0,1,2)	0.599				0.653	0.249	0.025	276	0.92	164	22.4
Sardine	(1,0,0)(1,0,1)	0.506			0.973	0.578		0.092	288	0.87	170	25.8
Scomber spp.	(1,0,0)(0,1,1)	0.623				0.806		0.035	276	0.91	32	32.8*
Trachurus spp.	(1,1,0)(0,1,1)	−0.186				0.836		−0.0002	275	0.93	74	51.7*
Gadiformes	(1,0,1)(0,1,1)	0.851		0.499		0.926		0.009	276	0.94	32	10.6
Mullus spp.	(1,0,0)(0,1,2)	0.760				0.467	0.128	0.003	276	0.93	27	25.6
Red pandora	(1,1,1)(1,1,1)	0.644		0.941	0.228	0.857		0.0001	275	0.84	12	25.4
Bogue	(1,0,1)(0,1,1)	0.874		0.265		0.693		0.006	276	0.92	57	39.9*
Spicara spp.	(1,0,1)(0,1,1)	0.763		0.550		0.456		−0.005	276	0.94	110	9.1
Total fish	(2,0,0)(0,1,1)	0.599	0.183			0.762		0.007	276	0.94	412	15.3
Cephalopods	(1,0,0)(0,1,1)	0.532				0.511		0.012	276	0.96	29	24.1
Crustaceans	(1,0,0)(0,1,1)	0.565				0.670		0.014	276	0.88	26	28.7
Trawl	(0,0,1)(0,1,1)	−0.363				0.669		−0.016	276	0.86	392	16.2
Purse seine	(1,1,0)(0,1,1)	−0.339				0.792		−0.002	275	0.92	473	36.5*
Beach seine	(0,0,0)(0,1,1)					0.446		−0.005	276	0.93	91	7.3
Coastal boats	(0,1,0)(1,0,1)				0.973	0.826		0.0002	287	0.94	148	14.3

variables. All Lagrange multiplier tests performed, indicated that Cochrane–Orcutt autoregressive error terms at various lags and/or various lags of the dependent and/or independent variables were statistically ($P > 0.05$) significant. Indeed, all DREG models fitted to the 16 monthly catches were characterised by much smaller BIC and higher r^2 values (Table 8) than those corresponding to the monthly MREG models (Table 2). In addition, the Ljung–Box test did not indicate error autocorrelation for all models, with the exception of the sardine one (Table 8), whereas the corresponding MREG models did suffer from significant ($P < 0.05$) error autocorrelation (Table 2). The r^2 values of DREG models ranged from 0.80 for sardine, to 0.96 for cephalopods. The inclusion of autoregressive error and lagged dependent and/or independent variables resulted in exclusion of other independent variables which were originally entered into the monthly MREG models. Such an exclusion of independent variables was true of all models with the exception of the anchovy, *Trachurus* spp. and 'other coastal boats' ones (Table 8).

Different VAR models including 36 lags (months) and a variety of external parameters were fitted to the monthly catches of the three complexes. However, many of the coefficients of the lagged internal variables had large standard errors. Hence, the final models selected included six lags only (1, 2, 3, 12, 24 and 36 months: Tables 9 and 10). The r^2 values of the models ranged from 0.83 for sardine catches to 0.95 for cephalopod catches (Tables 9 and 10). The Ljung–Box test indicated significant error autocorrelation for three models only (anchovy, *Trachurus* spp. and total fish: Tables 9 and 10).

3.2. Model accuracy

The initialising period for the different models used ranged from zero months, for TVS and HREG, to 60 months (January 1964–December 1968), for the DREG model of purse seine catches. Hence, all measures of accuracy (for the untransformed series) were estimated for the common fitting period of January 1969 to December 1987. The accuracy measures for the fits and forecasts of the 16 monthly catches, obtained by the different forecasting methods, are not shown here.

Overall, ARIMA models produced the most accurate fits in terms of MAPE for six monthly series, DREG for three series, DREG and ARIMA produced equally accurate fits for two series, VAR for four series and, finally, TVS for one series. In addition, NM1 produced the worst fits for 11 monthly series,

Table 8
Dynamic regression (DREG) models between the log-transformed monthly catches of the 16 species or groups of species, Ln(C), and various independent variables including Cochrane–Orcutt autoregressive terms, Hellenic waters, January 1964–December 1987. n is number of data points fitted. The r^2, BIC and Ljung–Box, $LB(18)$, values are also shown; significant ($P < 0.05$) $LB(18)$ values are marked with an asterisk

Species	DREG model	n	r^2	BIC	$LB(18)$
Anchovy	$\mathrm{Ln}(C) = 285.5 - 0.21\mathrm{Ln(sardine)} + 0.29\mathrm{Ln}(\mathit{Scomber}) - 0.15\mathrm{Ln(NSW)} - 41.48\mathrm{Ln(SLP)} + 0.77\mathrm{Ln(FIP)} + 0.004t - 0.14\mathrm{Ln}(\mathit{Scomber})_{t-1} - 0.19\mathrm{Ln}(\mathit{Scomber})_{t-2} + 0.50\mathrm{Ln}(C)_{t-1}$	274	0.89	204	27.4
Sardine	$\mathrm{Ln}(C) = -62.32 + 0.07\mathrm{Ln}(\mathit{Scomber}) - 0.000003t^2 + 9.25\mathrm{Ln(SLP)}_{t-1} + 0.34\mathrm{Ln}(C)_{t-12} + 0.37\mathrm{Ln}(C)_{t-24} + 0.43e_{t-1} - 0.18e_{t-24}$	228	0.80	174	39.2 *
Scomber spp.	$\mathrm{Ln}(C) = -10.30 + 0.43\mathrm{Ln(sardine)} + 1.07\mathrm{Ln(SST)} + 0.84\mathrm{Ln(FIP)} + 0.006t + 0.27\mathrm{Ln}(C)_{t-12} + 0.54e_{t-1}$	263	0.90	36	27.4
Trachurus spp.	$\mathrm{Ln}(C) = 2.36 + 0.07\mathrm{Ln(sardine)} + 0.09\mathrm{Ln}(\mathit{Scomber}) + 0.00005t^2 - 0.000000t^3 + 0.33\mathrm{Ln}(C)_{t-12} + 0.07\mathrm{Ln(anchovy)}_{t-1} + 0.57e_{t-1} + 0.21e_{t-9}$	255	0.94	73	23.8
Gadiformes	$\mathrm{Ln}(C) = 0.20 + 0.37\mathrm{Ln}(C)_{t-12} + 0.61\mathrm{Ln}(C)_{t-24} + 0.35e_{t-1} + 0.21e_{t-2} - 0.30e_{t-24}$	228	0.94	39	19.1
Mullus spp.	$\mathrm{Ln}(C) = -58.35 + 8.45\mathrm{Ln(SLP)} + 0.000004t^2 + 0.57\mathrm{Ln}(C)_{t-12} + 0.39\mathrm{Ln}(C)_{t-24} + 0.59e_{t-1} - 0.24e_{t-24}$	228	0.93	28	26.7
Red pandora	$\mathrm{Ln}(C) = -1.77 + 0.27\mathrm{Ln(FID)} + 0.39\mathrm{Ln}(C)_{t-12} + 0.44\mathrm{Ln}(C)_{t-24} + 0.64e_{t-1} + 0.18e_{t-6} - 0.24e_{t-24}$	228	0.82	12	26.7
Bogue	$\mathrm{Ln}(C) = 0.60 + 0.20\mathrm{Ln(AIRT)} + 0.17\mathrm{Ln}(C)_{t-10} + 0.37\mathrm{Ln}(C)_{t-12} + 0.28\mathrm{Ln(C)}_{t-24} + 0.51e_{t-1} + 0.20e_{t-2} + 0.15e_{t-5}$	247	0.91	63	27.6
Spicara spp.	$\mathrm{Ln}(C) = 0.81 - 0.22\mathrm{Ln(SST)} + 0.61\mathrm{Ln}(C)_{t-12} + 0.36\mathrm{Ln}(C)_{t-24} + 0.33e_{t-1} - 0.19e_{t-24}$	228	0.95	107	15.2
Total fish	$\mathrm{Ln}(C) = 0.77 - 0.10\mathrm{Ln(FI)} + 0.55\mathrm{Ln}(C)_{t-12} + 0.47\mathrm{Ln}(C)_{t-24} + 0.66e_{t-1} - 0.24e_{t-24}$	228	0.93	471	22.2
Cephalopods	$\mathrm{Ln}(C) = 1.46 - 0.39\mathrm{Ln(SST)} + 0.50\mathrm{Ln}(C)_{t-12} + 0.43\mathrm{Ln}(C)_{t-24} + 0.49e_{t-1}$	251	0.96	31	25.5
Crustaceans	$\mathrm{Ln}(C) = 0.38 + 0.13\mathrm{Ln(cephalopods)} + 0.49\mathrm{Ln}(C)_{t-12} + 0.31\mathrm{Ln}(C)_{t-24} + 0.47e_{t-1}$	251	0.89	29	19.1
Trawl	$\mathrm{Ln}(C) = 1.20 + 0.15\mathrm{Ln(seine)} - 0.36\mathrm{Ln(VAT)} + 0.0005t + 0.85\mathrm{Ln}(C)_{t-12} + 0.31\mathrm{Ln}(C)_{t-24} + 0.33e_{t-1}$	251	0.87	409	22.4
Purse seine	$\mathrm{Ln}(C) = 0.40 + 0.35\mathrm{Ln}(C)_{t-12} + 0.61(C)_{t-24} + 0.42e_{t-1} - 0.32e_{t-24}$	228	0.93	469	14.8
Beach seine	$\mathrm{Ln}(C) = -1.07 + 0.22\mathrm{Ln(trawl)} - 0.31\mathrm{Ln(VAB)} + 0.27\mathrm{Ln(FIB)} + 0.005t + 0.95\mathrm{Ln}(C)_{t-12} - 0.28e_{t-12}$	252	0.94	90	26.0
Coastal boats	$\mathrm{Ln}(C) = 0.37 + 0.04\mathrm{Ln(VAC)} + 0.89\mathrm{Ln}(C)_{t-1} + 0.26e_{t-24} + 0.21e_{t-12}$	251	0.95	161	21.9

Table 9
Vector autoregression (VAR) models between the log-transformed monthly catches of anchovy, sardine, *Trachurus* spp. and *Scomber* spp., Hellenic waters, January 1964–December 1987 (number of data points fitted 252). The r^2 and Ljung–Box, $LB(18)$, values are also shown; significant ($P < 0.05$) $LB(18)$ values are marked with an asterisk

VAR model	r^2	$LB(18)$
$\mathrm{Ln(anchovy)} = 12.14 + 0.58\mathrm{Ln(anchovy)}_{t-1} - 0.035\mathrm{Ln(anchovy)}_{t-2} - 0.21\mathrm{Ln(anchovy)}_{t-3}$ $+ 0.24\mathrm{Ln(anchovy)}_{t-12} - 0.05\mathrm{Ln(anchovy)}_{t-24} + 0.23\mathrm{Ln(anchovy)}_{t-36} - 0.25\mathrm{Ln(sardine)}_{t-1}$ $+ 0.10\mathrm{Ln(sardine)}_{t-2} - 0.09\mathrm{Ln(sardine)}_{t-3} - 0.15\mathrm{Ln(sardine)}_{t-12} + 0.04\mathrm{Ln(sardine)}_{t-24}$ $+ 0.09\mathrm{Ln(sardine)}_{t-36} - 0.04\mathrm{Ln}(Trachurus)_{t-1} + 0.22\mathrm{Ln}(Trachurus)_{t-2} - 0.13\mathrm{Ln}(Trachurus)_{t-3}$ $- 0.02\mathrm{Ln}(Trachurus)_{t-12} - 0.05\mathrm{Ln}(Trachurus)_{t-24} + 0.11\mathrm{Ln}(Trachurus)_{t-36} - 0.1\mathrm{Ln}(Scomber)_{t-1}$ $- 0.03\mathrm{Ln}(Scomber)_{t-2} + 0.08\mathrm{Ln}(Scomber)_{t-3} + 0.15\mathrm{Ln}(Scomber)_{t-12} - 0.06\mathrm{Ln}(Scomber)_{t-24}$ $+ 0.07\mathrm{Ln}(Scomber)_{t-36} - 1.56\mathrm{Ln(SLP)} + 0.11\mathrm{Ln(WTOT)}$	0.90	82.9 *
$\mathrm{Ln(sardine)} = -58.08 - 0.03\mathrm{Ln(anchovy)}_{t-1} + 0.13\mathrm{Ln(anchovy)}_{t-2} - 0.06\mathrm{Ln(anchovy)}_{t-3} - 0.06\mathrm{Ln(anchovy)}_{t-12}$ $+ 0.05\mathrm{Ln(anchovy)}_{t-24} + 0.03\mathrm{Ln(anchovy)}_{t-36} + 0.27\mathrm{Ln(sardine)}_{t-1} - 0.11\mathrm{Ln(sardine)}_{t-2}$ $+ 0.03\mathrm{Ln(sardine)}_{t-3} + 0.20\mathrm{Ln(sardine)}_{t-3} + 0.20\mathrm{Ln(sardine)}_{t-12} + 0.19\mathrm{Ln(sardine)}_{t-24}$ $+ 0.17\mathrm{Ln(sardine)}_{t-36} + 0.16\mathrm{Ln}(Trachurus)_{t-1} - 0.13\mathrm{Ln}(Trachurus)_{t-2} + 0.12\mathrm{Ln}(Trachurus)_{t-3}$ $+ 0.007\mathrm{Ln}(Trachurus)_{t-12} - 0.17\mathrm{Ln}(Trachurus)_{t-24} + 0.05\mathrm{Ln}(Trachurus)_{t-36}$ $+ 0.03\mathrm{Ln}(Scomber)_{t-1} - 0.12\mathrm{Ln}(Scomber)_{t-2} - 0.02\mathrm{Ln}(Scomber)_{t-3} + 0.05\mathrm{Ln}(Scomber)_{t-12}$ $- 0.004\mathrm{Ln}(Scomber)_{t-24} - 0.02\mathrm{Ln}(Scomber)_{t-36} + 8.66\mathrm{Ln(SLP)} - 0.07\mathrm{Ln(WTOT)}$	0.83	40.5
$\mathrm{Ln}(Trachurus) = -48.93 - 0.0006\mathrm{Ln(anchovy)}_{t-1} + 0.004\mathrm{Ln(anchovy)}_{t-2} - 0.06\mathrm{Ln(anchovy)}_{t-3}$ $+ 0.03\mathrm{Ln(anchovy)}_{t-12} + 0.02\mathrm{Ln(anchovy)}_{t-24} + 0.05\mathrm{Ln(anchovy)}_{t-36} - 0.007\mathrm{Ln(sardine)}_{t-1}$ $- 0.08\mathrm{Ln(sardine)}_{t-2} + 0.06\mathrm{Ln(sardine)}_{t-3} - 0.02\mathrm{Ln(sardine)}_{t-12} + 0.04\mathrm{Ln(sardine)}_{t-24}$ $+ 0.03\mathrm{Ln(sardine)}_{t-36} + 0.54\mathrm{Ln}(Trachurus)_{t-1} + 0.09\mathrm{Ln}(Trachurus)_{t-2} + 0.11\mathrm{Ln}(Trachurus)_{t-3}$ $+ 0.17\mathrm{Ln}(Trachurus)_{t-12} + 0.03\mathrm{Ln}(Trachurus)_{t-24} + 0.09\mathrm{Ln}(Trachurus)_{t-36} + 0.01\mathrm{Ln}(Scomber)_{t-1}$ $- 0.007\mathrm{Ln}(Scomber)_{t-2} - 0.07\mathrm{Ln}(Scomber)_{t-3} + 0.05\mathrm{Ln}(Scomber)_{t-12} - 0.01\mathrm{Ln}(Scomber)_{t-24}$ $- 0.06\mathrm{Ln}(Scomber)_{t-36} + 7.02\mathrm{Ln(SLP)} + 0.02\mathrm{Ln(WTOT)}$	0.94	68.7 *
$\mathrm{Ln}(Scomber) = -37.46 + 0.10\mathrm{Ln(anchovy)}_{t-1} - 0.25\mathrm{Ln(anchovy)}_{t-2} + 0.04\mathrm{Ln(anchovy)}_{t-3}$ $+ 0.11\mathrm{Ln(anchovy)}_{t-12} + 0.03\mathrm{Ln(anchovy)}_{t-24} + 0.24\mathrm{Ln(anchovy)}_{t-36} - 0.15\mathrm{Ln(sardine)}_{t-1}$ $- 0.08\mathrm{Ln(sardine)}_{t-2} + 0.14\mathrm{Ln(sardine)}_{t-3} + 0.17\mathrm{Ln(sardine)}_{t-12} + 0.25\mathrm{Ln(sardine)}_{t-24}$ $+ 0.21\mathrm{Ln(sardine)}_{t-36} + 0.09(Trachurus)_{t-1} + 0.06\mathrm{Ln}(Trachurus)_{t-2} - 0.17\mathrm{Ln}(Trachurus)_{t-3}$ $- 0.05\mathrm{Ln}(Trachurus)_{t-12} + .024\mathrm{Ln}(Trachurus)_{t-24} + 0.10\mathrm{Ln}(Trachurus)_{t-36}$ $+ 0.38\mathrm{Ln}(Scomber)_{t-1} + 0.01\mathrm{Ln}(Scomber)_{t-2} + 0.03\mathrm{Ln}(Scomber)_{t-3} + 0.16\mathrm{Ln}(Scomber)_{t-12}$ $- 0.02\mathrm{Ln}(Scomber)_{t-24} - 0.09\mathrm{Ln}(Scomber)_{t-36} + 4.16\mathrm{Ln(SLP)} + 0.44\mathrm{Ln(WTOT)}$	0.90	55.2

Table 10
Vector autoregression (VAR) models between the log-transformed monthly catches of (a) total fish, cephalopods and crustaceans, and (b) trawl, purse seine, beach seine and 'other coastal boats', Hellenic waters, January 1964–December 1987 (252 data points fitted). The r^2 and Ljung–Box, $LB(18)$, values are also shown; significant ($P < 0.05$) $LB(18)$ values are marked with an asterisk

VAR model	r^2	$LB(18)$
Fish / cephalopods / crustaceans		
$\mathrm{Ln(fish)} = -49.81 + 0.57\mathrm{Ln(fish)}_{t-1} + 0.005\mathrm{Ln(fish)}_{t-2} - 0.10\mathrm{Ln(fish)}_{t-3} + 0.36\mathrm{Ln(fish)}_{t-12} - 0.04\mathrm{Ln(fish)}_{t-24} + 0.18\mathrm{Ln(fish)}_{t-36} - 0.06\mathrm{Ln(cephalopods)}_{t-1} + 0.03\mathrm{Ln(cephalopods)}_{t-2} + 0.04\mathrm{Ln(cephalopods)}_{t-3} + 0.02\mathrm{Ln(cephalopods)}_{t-12} + 0.03\mathrm{Ln(cephalopods)}_{t-24} - 0.01\mathrm{Ln(cephalopods)}_{t-36} - 0.01\mathrm{Ln(crustaceans)}_{t-1} - 0.06\mathrm{Ln(crustaceans)}_{t-2} + 0.04\mathrm{Ln(crustaceans)}_{t-3} + 0.02\mathrm{Ln(crustaceans)}_{t-12} + 0.009\mathrm{Ln(crustaceans)}_{t-24} + 0.001\mathrm{Ln(crustaceans)}_{t-36} + 0.05\mathrm{Ln(NW)} + 7.09\mathrm{Ln(SLP)} + 0.06\mathrm{Ln(WTOT)}$	0.91	98.5 *
$\mathrm{Ln(cephalopods)} = -29.60 - 0.20\mathrm{Ln(fish)}_{t-1} + 0.17\mathrm{Ln(fish)}_{t-2} + 0.19\mathrm{Ln(fish)}_{t-3} + 0.40\mathrm{Ln(fish)}_{t-12} - 0.08\mathrm{Ln(fish)}_{t-24} - 0.20\mathrm{Ln(fish)}_{t-36} + 0.18\mathrm{Ln(cephalopods)}_{t-1} - 0.02\mathrm{Ln(cephalopods)}_{t-2} + 0.02\mathrm{Ln(cephalopods)}_{t-3} + 0.37\mathrm{Ln(cephalopods)}_{t-12} + 0.38\mathrm{Ln(cephalopods)}_{t-24} + 0.09\mathrm{Ln(cephalopods)}_{t-36} - 0.12\mathrm{Ln(crustaceans)}_{t-1} + 0.03\mathrm{Ln(crustaceans)}_{t-2} - 0.07\mathrm{Ln(crustaceans)}_{t-3} + 0.11\mathrm{Ln(crustaceans)}_{t-12} + 0.06\mathrm{Ln(crustaceans)}_{t-24} - 0.05\mathrm{Ln(crustaceans)}_{t-36} - 0.07\mathrm{Ln(NW)} + 3.83\mathrm{Ln(SLP)} + 0.12\mathrm{Ln(WTOT)}$	0.95	54.6
$\mathrm{Ln(crustaceans)} = -30.35 + 0.02\mathrm{Ln(fish)}_{t-1} + 0.01\mathrm{Ln(fish)}_{t-2} + 0.08\mathrm{Ln(fish)}_{t-3} + 0.01\mathrm{Ln(fish)}_{t-12} + 0.03\mathrm{Ln(fish)}_{t-24} + 0.01\mathrm{Ln(fish)}_{t-36} - 0.11\mathrm{Ln(cephalopods)}_{t-1} + 0.05\mathrm{Ln(cephalopods)}_{t-2} - 0.02\mathrm{Ln(cephalopods)}_{t-3} + 0.08\mathrm{Ln(cephalopods)}_{t-12} + 0.05\mathrm{Ln(cephalopods)}_{t-24} + 0.06\mathrm{Ln(cephalopods)}_{t-36} + 0.26\mathrm{Ln(crustaceans)}_{t-1} - 0.09\mathrm{Ln(crustaceans)}_{t-2} - 0.03\mathrm{Ln(crustaceans)}_{t-3} + 0.43\mathrm{Ln(crustaceans)}_{t-12} + 0.10\mathrm{Ln(crustaceans)}_{t-24} + 0.10\mathrm{Ln(crustaceans)}_{t-36} - 0.04\mathrm{Ln(NW)} + 3.98\mathrm{Ln(SLP)} + 0.23\mathrm{Ln(WTOT)}$	0.88	47.9

Trawl / purse-seine / beach-seine / 'other coastal boats'		
$\mathrm{Ln(Trawl)} = -44.33 + 0.10\mathrm{Ln(trawl)}_{t-1} - 0.04\mathrm{Ln(trawl)}_{t-2} - 0.04\mathrm{Ln(trawl)}_{t-3} + 0.48\mathrm{Ln(trawl)}_{t-12} + 0.10\mathrm{Ln(trawl)}_{t-24} + 0.19\mathrm{Ln(trawl)}_{t-36} - 0.04\mathrm{Ln(purse)}_{t-1} - 0.09\mathrm{Ln(purse)}_{t-2} + 0.23\mathrm{Ln(purse)}_{t-3} - 0.07\mathrm{Ln(purse)}_{t-12} + 0.10\mathrm{Ln(purse)}_{t-24} + 0.003\mathrm{Ln(purse)}_{t-36} - 0.03\mathrm{Ln(seine)}_{t-1} + 0.01\mathrm{Ln(seine)}_{t-2} + 0.04\mathrm{Ln(seine)}_{t-3} + 0.35\mathrm{Ln(seine)}_{t-12} - 0.51\mathrm{Ln(seine)}_{t-24} + 0.31\mathrm{Ln(seine)}_{t-36} + 0.001\mathrm{Ln(other)}_{t-1} - 0.21\mathrm{Ln(other)}_{t-2} - 0.24\mathrm{Ln(other)}_{t-3} + 0.09\mathrm{Ln(other)}_{t-12} + 0.14\mathrm{Ln(other)}_{t-24} + 0.03\mathrm{Ln(other)}_{t-36} + 5.89\mathrm{Ln(SLP)} - 0.15\mathrm{Ln(NW)} + 0.52\mathrm{Ln(WTOT)}$	0.87	41.5
$\mathrm{Ln(purse)} = -13.47 + 0.01\mathrm{Ln(trawl)}_{t-1} - 0.01\mathrm{Ln(trawl)}_{t-2} - 0.01\mathrm{Ln(trawl)}_{t-3} + 0.01\mathrm{Ln(trawl)}_{t-12} + 0.003\mathrm{Ln(trawl)}_{t-24} - 0.01\mathrm{Ln(trawl)}_{t-36} + 0.29\mathrm{Ln(purse)}_{t-1} - 0.03\mathrm{Ln(purse)}_{t-2} - 0.09\mathrm{Ln(purse)}_{t-3} + 0.29\mathrm{Ln(purse)}_{t-12} + 0.26\mathrm{Ln(purse)}_{t-24} + 0.18\mathrm{Ln(purse)}_{t-36} - 0.01\mathrm{Ln(seine)}_{t-1} - 0.02\mathrm{Ln(seine)}_{t-2} + 0.03\mathrm{Ln(seine)}_{t-3} - 0.003\mathrm{Ln(seine)}_{t-12} - 0.02\mathrm{Ln(seine)}_{t-24} + 0.02\mathrm{Ln(seine)}_{t-36} - 0.05\mathrm{Ln(other)}_{t-1} - 0.31\mathrm{Ln(other)}_{t-2} + 0.44\mathrm{Ln(other)}_{t-3} - 0.02\mathrm{Ln(other)}_{t-12} - 0.15\mathrm{Ln(other)}_{t-24} + 0.06\mathrm{Ln(other)}_{t-36} + 1.90\mathrm{Ln(SLP)} + 0.03\mathrm{Ln(NW)} + 0.14\mathrm{Ln(WTOT)}$	0.93	39.2
$\mathrm{Ln(seine)} = -99.71 - 0.10\mathrm{Ln(trawl)}_{t-1} - 0.03\mathrm{Ln(trawl)}_{t-2} - 0.01\mathrm{Ln(trawl)}_{t-3} + 0.14\mathrm{Ln(trawl)}_{t-12} + 0.08\mathrm{Ln(trawl)}_{t-24} + 0.07\mathrm{Ln(trawl)}_{t-36} - 0.01\mathrm{Ln(purse)}_{t-1} + 0.09\mathrm{Ln(purse)}_{t-2} - 0.06\mathrm{Ln(purse)}_{t-3} + 0.04\mathrm{Ln(purse)}_{t-12} + 0.06\mathrm{Ln(purse)}_{t-24} - 0.12\mathrm{Ln(purse)}_{t-36} + 0.12\mathrm{Ln(seine)}_{t-1} + 0.03\mathrm{Ln(seine)}_{t-2} + 0.05\mathrm{Ln(seine)}_{t-3} + 0.44\mathrm{Ln(seine)}_{t-12} + 0.24\mathrm{Ln(seine)}_{t-24} + 0.08\mathrm{Ln(seine)}_{t-36} - 0.07\mathrm{Ln(other)}_{t-1} + 0.44\mathrm{Ln(other)}_{t-2} - 0.17\mathrm{Ln(other)}_{t-3} - 0.31\mathrm{Ln(other)}_{t-12} - 0.16\mathrm{Ln(other)}_{t-24} + 0.16\mathrm{Ln(other)}_{t-36} + 14.18\mathrm{Ln(SLP)} - 0.05\mathrm{Ln(NW)} + 0.22\mathrm{Ln(WTOT)}$	0.93	34.5
$\mathrm{Ln(other)} = -58.84 - 0.01\mathrm{Ln(trawl)}_{t-1} - 0.01\mathrm{Ln(trawl)}_{t-2} - 0.01\mathrm{Ln(trawl)}_{t-3} - 0.01\mathrm{Ln(trawl)}_{t-12} - 0.003\mathrm{Ln(trawl)}_{t-24} - 0.0002\mathrm{Ln(trawl)}_{t-36} - 0.06\mathrm{Ln(purse)}_{t-1} - 0.07\mathrm{Ln(purse)}_{t-2} + 0.10\mathrm{Ln(purse)}_{t-3} + 0.04\mathrm{Ln(purse)}_{t-12} + 0.07\mathrm{Ln(purse)}_{t-24} + 0.04\mathrm{Ln(purse)}_{t-36} + 0.02\mathrm{Ln(seine)}_{t-1} + 0.006\mathrm{Ln(seine)}_{t-2} + 0.02\mathrm{Ln(seine)}_{t-3} - 0.002\mathrm{Ln(seine)}_{t-12} + 0.0003\mathrm{Ln(seine)}_{t-24} - 0.0008\mathrm{Ln(seine)}_{t-36} + 0.83\mathrm{Ln(other)}_{t-1} + 0.06\mathrm{Ln(other)}_{t-2} - 0.09\mathrm{Ln(other)}_{t-3} + 0.062\mathrm{Ln(other)}_{t-12} + 0.008\mathrm{Ln(other)}_{t-24} - 0.013\mathrm{Ln(other)}_{t-36} + 8.24\mathrm{Ln(SLP)} + 0.06\mathrm{Ln(NW)} + 0.19\mathrm{Ln(WTOT)}$	0.95	33.7

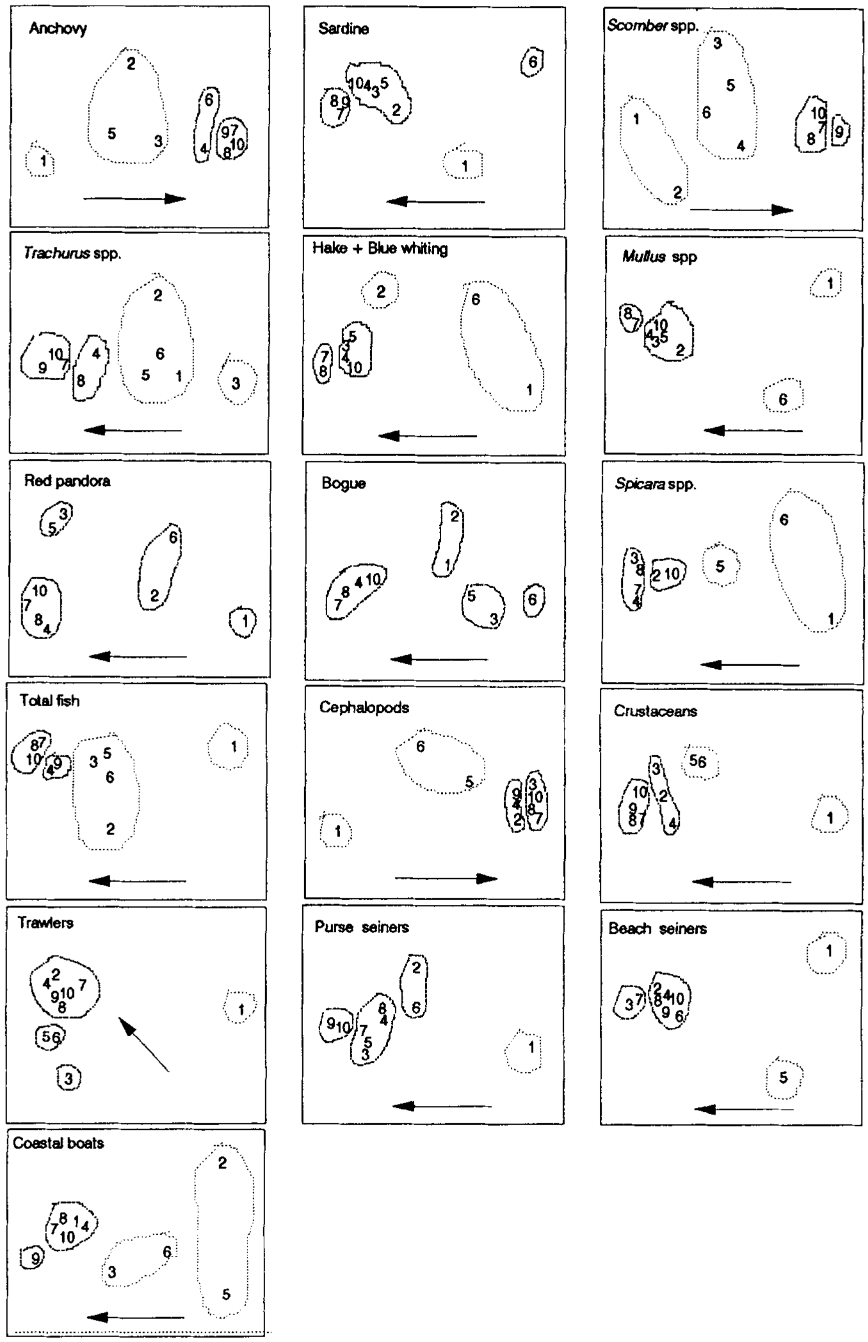


Fig. 3. Results of principal component (PC) analysis performed on the (measures) × (methods) fitting matrices for the 16 monthly times series, January 1964–December 1987. 1, NM1; 2, NM12; 3, TVS; 4, WES; 5, HREG; 6, MREG; 7, DREG; 8, ARIMA; 9, VAR; 10, EMP. Arrows indicate increasing fitting performance. Vertical and horizontal axes represent PC1 and PC2, respectively.

Table 11
Percentage of variance explained by the two first principal component axes for the (methods)×(measures) fitting and forecasting matrices of the 16 species or groups of species (see Figs. 3 and 4)

Species	Fitting	Forecasting
Anchovy	77.4	81.7
Sardine	85.5	93.6
Scomber spp.	74.5	73.9
Trachurus spp.	83.8	96.1
Gadiformes	79.8	84.9
Mullus spp.	81.7	86.3
Red pandora	80.2	74.1
Bogue	74.1	90.7
Spicara spp.	76.9	89.3
Total fish	90.6	82.4
Cephalopods	79.5	81.9
Crustaceans	86.3	77.0
Trawl	85.3	81.7
Purse seine	79.6	66.9
Beach seine	87.0	69.9
Coastal boats	81.6	90.7

MREG for three series and TVS and HREG for one series each.

ARIMA, DREG, VAR and, to a lesser extent, WES and EMP were generally characterised either by the best, or intermediate, relatively tied together, measures. They produced unbiased fits (very low B values, usually zero) and outperformed NM1 (in terms of U and MBA values, less than 1 and more than 300, respectively). In addition, all DREG models, 12 out of 16 ARIMA models and eight out of 11 VAR models were characterised by transformed errors which were essentially white noise (Tables 7–10) as opposed to WES (Table 4), HREG (Table 6) and MREG models (Table 2).

The above mentioned observations were clearly depicted in the results of PCA performed on the 16 (methods) × (measures) fitting matrices (Fig. 3). PCA identified four general groups of methods, characterised by increasing fitting accuracy (general improvement in all, or most, accuracy measures; Fig. 3). The first two axes explained more than 74.1% of the variance per species (or group of species) (Table 11). The average of ranks (×100) per method are shown in Table 12. It is evident that all methods performed better than NM1. In addition, VAR, DREG, ARIMA and, to a lesser extent, EMP and WES were superior than the remaining methods, and had average ranks (×100) higher than the total average rank (×100). In addition, MREG performed worse than NM12 whereas HREG had an average rank (×100) equal to that of NM12 (Table 12).

With respect to forecasting performance, ARIMA models produced the most accurate forecasts in terms of MAPE for five monthly series, DREG for two series, NM12 for two series, EMP for two series, and WES, NM1, TVS, HREG and MREG for one series each. In addition, NM1 produced the worst fits for seven monthly series, MREG for three series, HREG for two series and DREG, TVS, NM12 and VAR for one series each.

The forecasts obtained from the ARIMA, DREG and, to a lesser extent, WES and EMP models were generally characterised either by the lowest, or intermediate, generally tied together error values. All the above mentioned models produced unbiased forecasts (very low values of B, usually zero) and outperformed NM1 (U and MBA values less than 1 and more than 300, respectively) for all monthly series with the exception of: (a) *Trachurus* spp. (for ARIMA and WES models), anchovy (for ARIMA, DREG and EMP models), red pandora and 'other coastal boats' catches (for all models) for which U values were more than 1, MBA values less than 300 and bias was higher; (b) for trawl and bogue catches for which their performance was marginally better than that of NM1 (in terms of U and MBA).

Table 12
Average rank (×100) fitting and forecasting performance of the models fitted to the monthly catches of the 16 species or groups of species, Hellenic waters, January 1964–December 1989

Performance	Model									
	NM1	NM12	TVS	WES	HREG	MREG	DREG	ARIMA	VAR	EMP	AVERAGE
Fitting	133	233	260	313	233	187	380	373	380	347	280
Forecasting	207	287	300	340	287	233	333	367	240	353	295
Sum	340	520	560	653	520	420	713	740	620	700	575

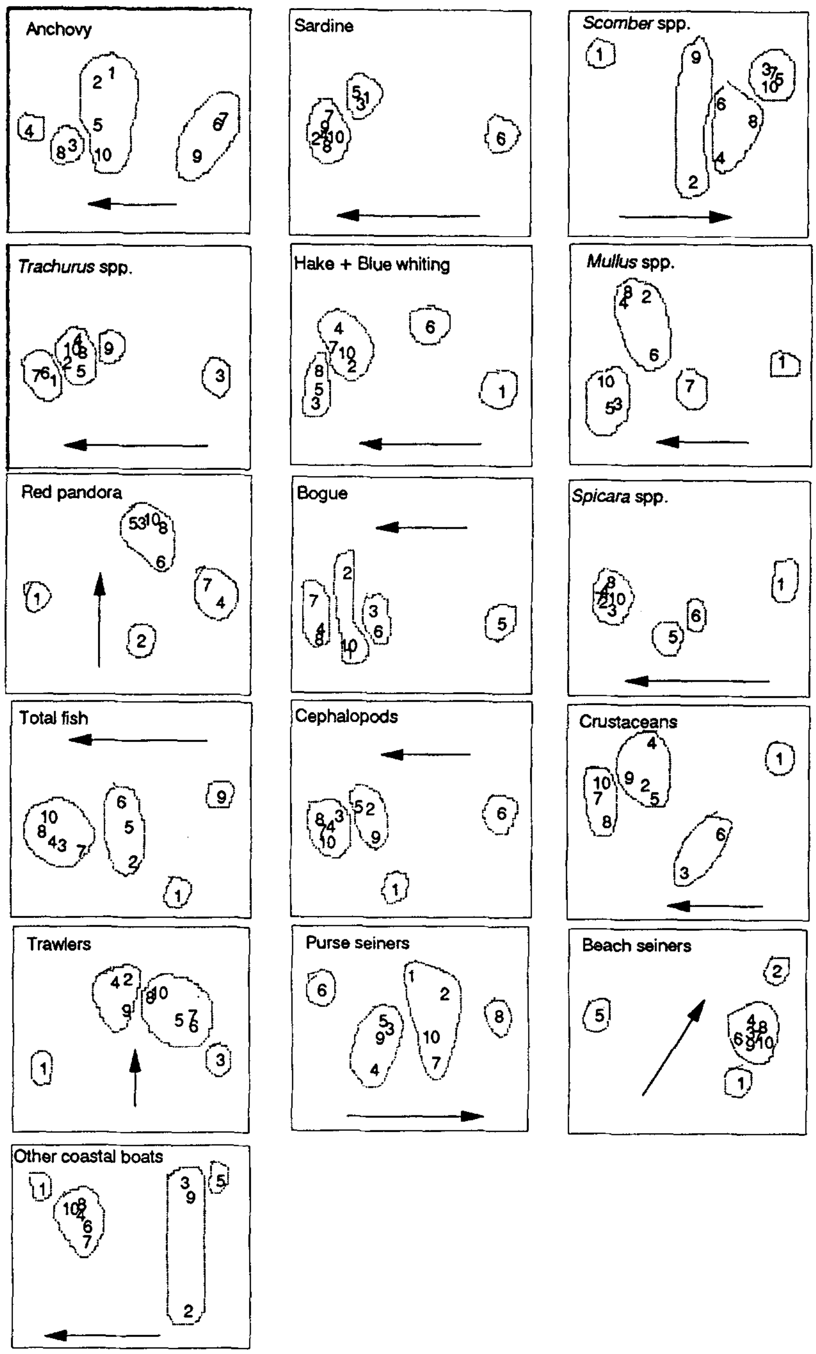


Fig. 4. Results of principal component analysis performed on the (measures) × (methods) forecasting matrices for the 16 monthly times series, January 1988–December 1989. 1, NM1; 2, NM12; 3, TVS; 4, WES; 5, HREG; 6, MREG; 7, DREG; 8, ARIMA; 9, VAR; 10, EMP. Arrows indicate increasing fitting accuracy. Vertical and horizontal axes represent PC1 and PC2, respectively.

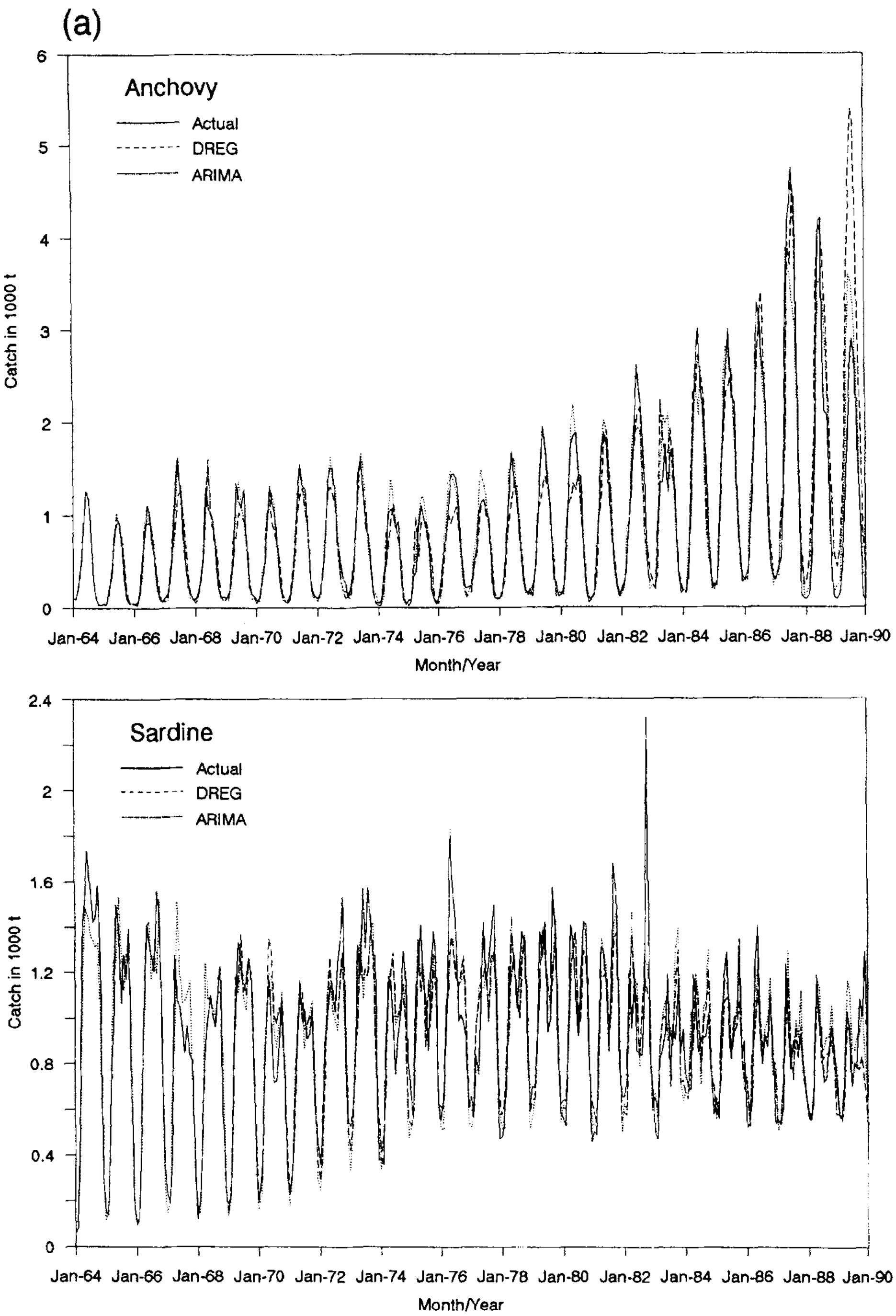


Fig. 5. Actual monthly catches of the 16 species or groups of species in Hellenic waters during 1964–1989 together with fits (for January 1964–December 1987) and forecasts (for January 1988–December 1989) produced by the two best fitting and forecasting methods, ARIMA and DREG.

The above patterns were reflected to the results of PCA performed on the 16 (methods) × (measures) forecasting matrices (Fig. 4). PCA identified four general groups of methods, characterised by increasing forecasting accuracy (general improvement in all, or most, measures; Fig. 4). The first two axes ex-

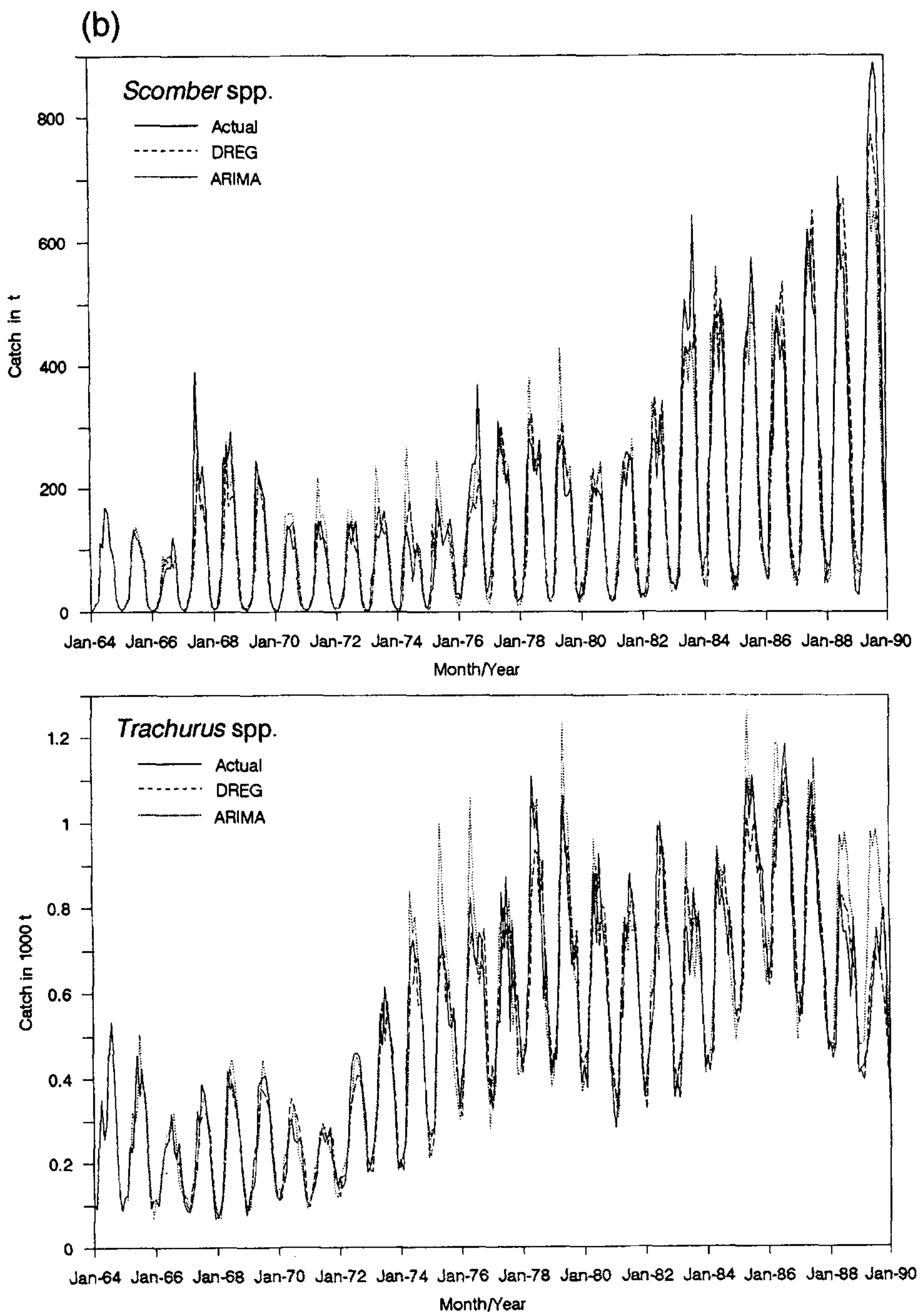


Fig. 5 (continued).

plained more than 66.9% of the variance per species (or groups of species; Table 11). The average ranks (× 100) per forecasting method are shown in Table 12. It is evident that all methods performed better than NM1. ARIMA ranked first, closely followed by EMP, WES and DREG and all had average ranks

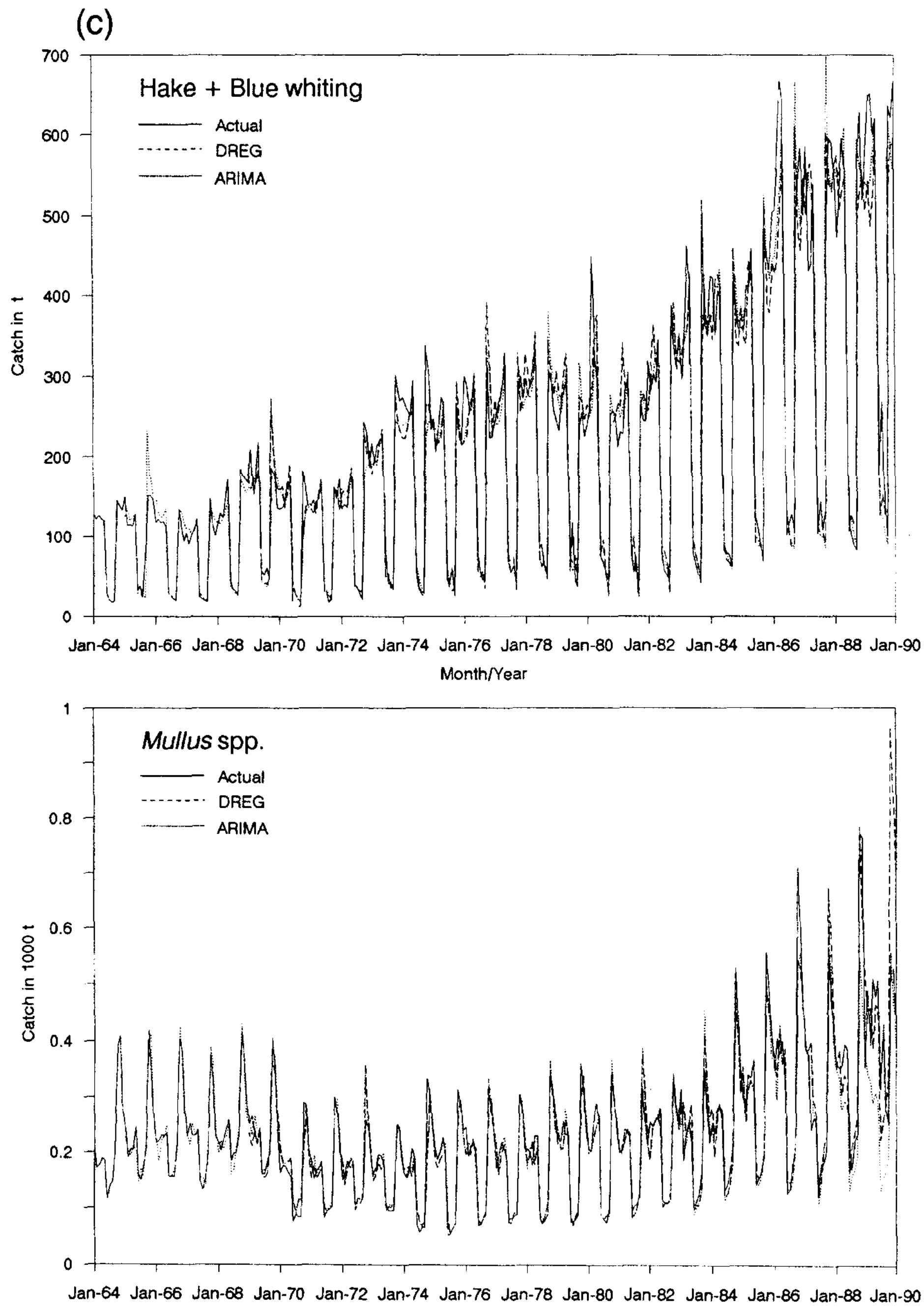


Fig. 5 (continued).

(× 100) higher than the total average rank (× 100). TVS had an average rank (× 100) higher than that of NM12 and the total average rank. In contrast, VAR and MREG had average ranks (× 100) that were lower than that of NM12 and the total average rank. HREG had an average rank (× 100) similar to that of

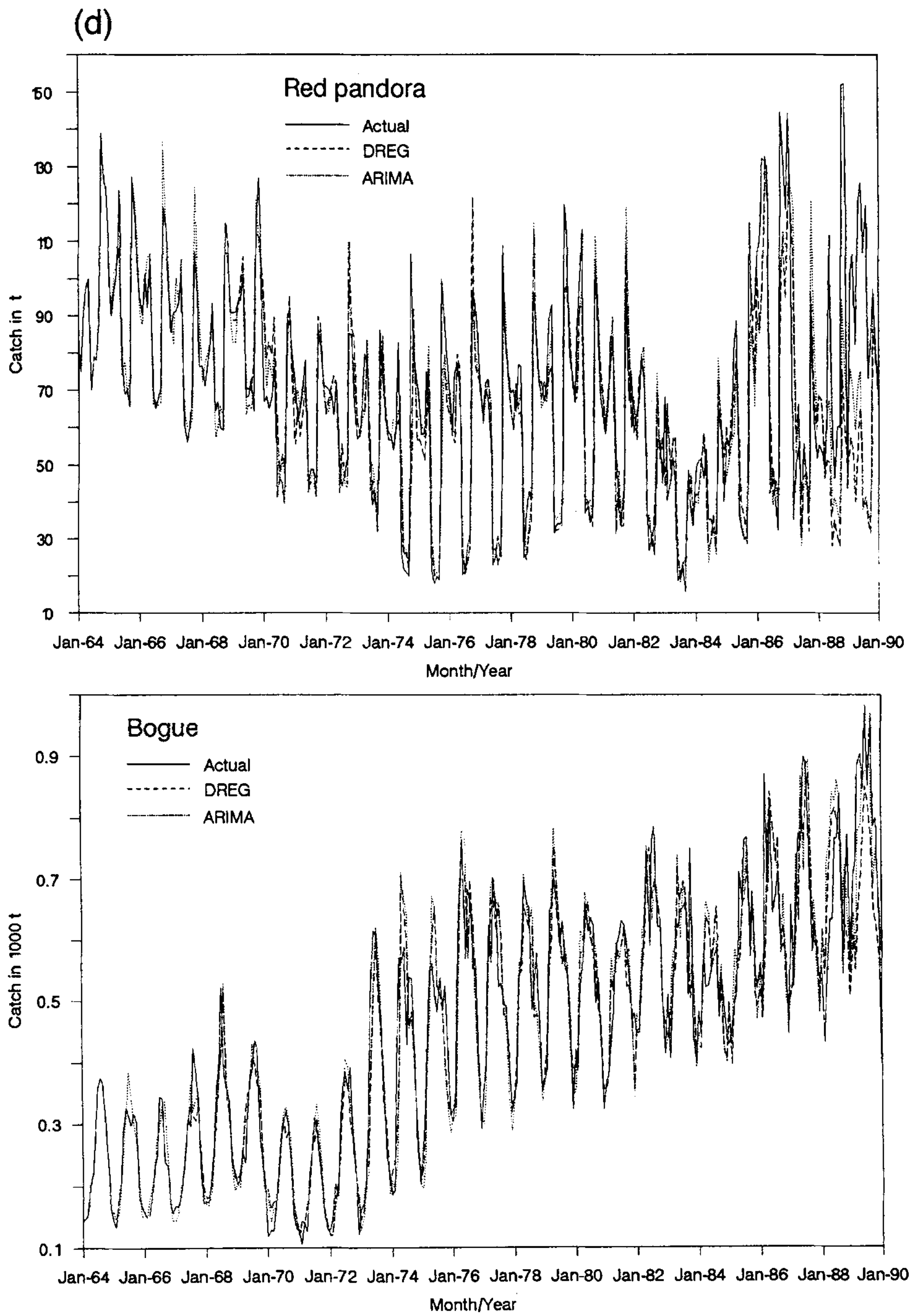
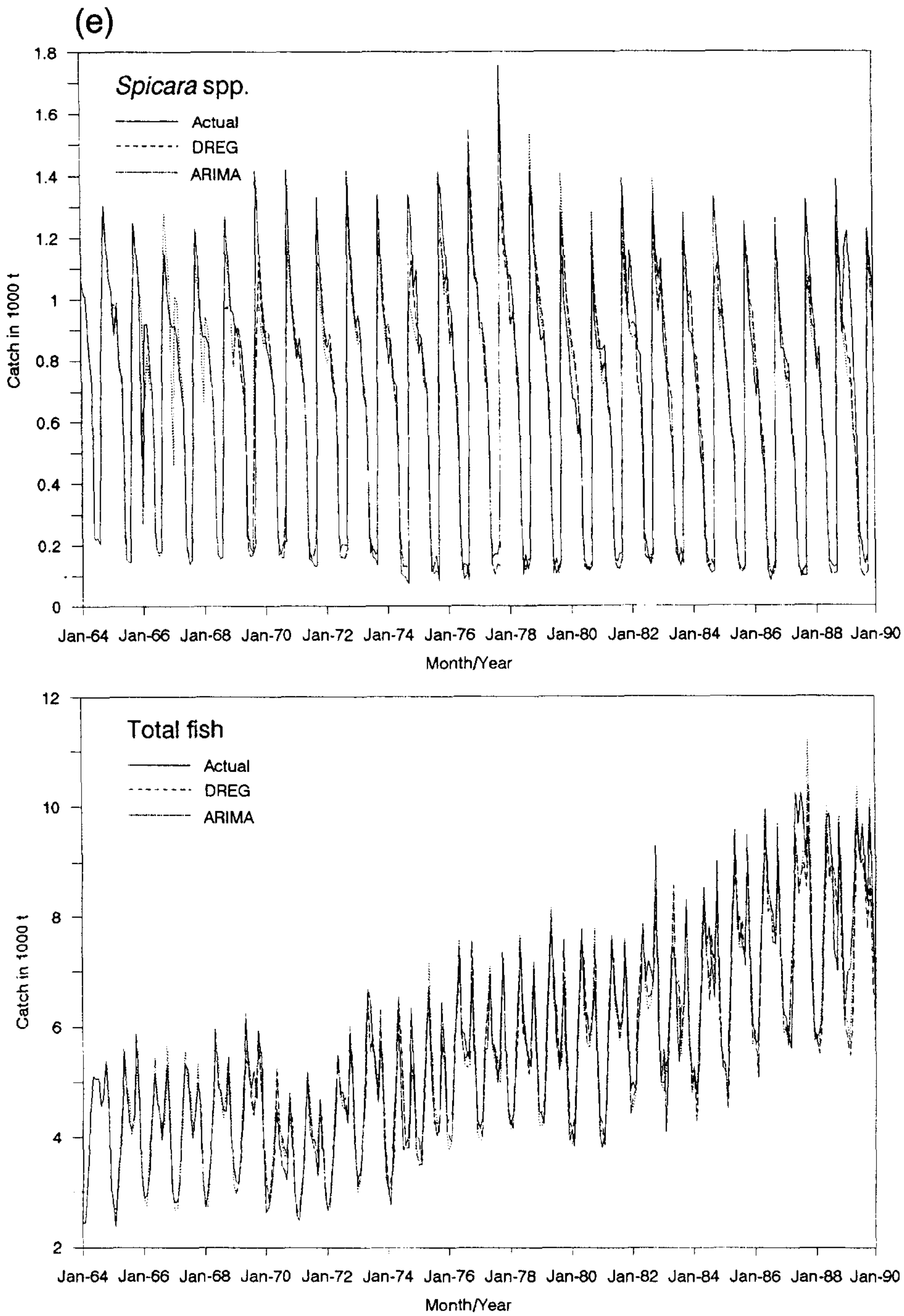


Fig. 5 (continued).

NM12, which was marginally lower than the total average rank. The sum of the average ranks (×100) for both fitting and forecasting is also shown in Table 12. ARIMA ranked first, followed by DREG, EMP and, to a lesser extent, WES and VAR. All the above mentioned methods had summed average ranks



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($\times 100$) that were higher than the sum of the average ($\times 100$).

The actual monthly catches of the 16 species (or groups of species) for 1964–1989 as well as fits and forecasts for those years, estimated from the ARIMA and DREG models, are plotted in Fig. 5. For all

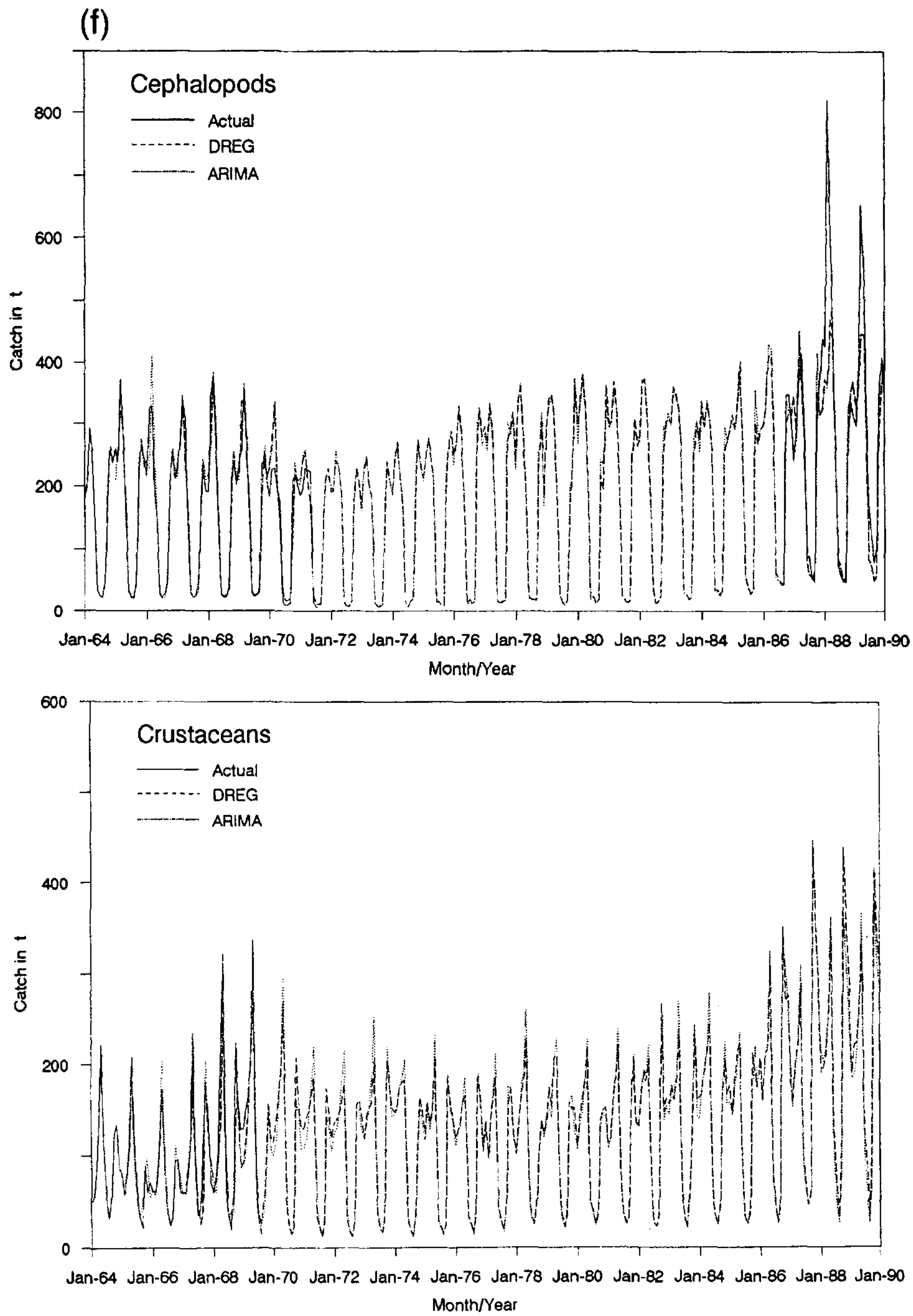


Fig. 5 (continued).

series, the amplitude and the duration of the between- and within-year fluctuations were reasonably described whereas fits and forecasts for most series were satisfactory (Fig. 5). In general, all methods produced the worst fits for anchovy, beach seine, trawl and *Scomber* spp. catches (lower MAPE val-

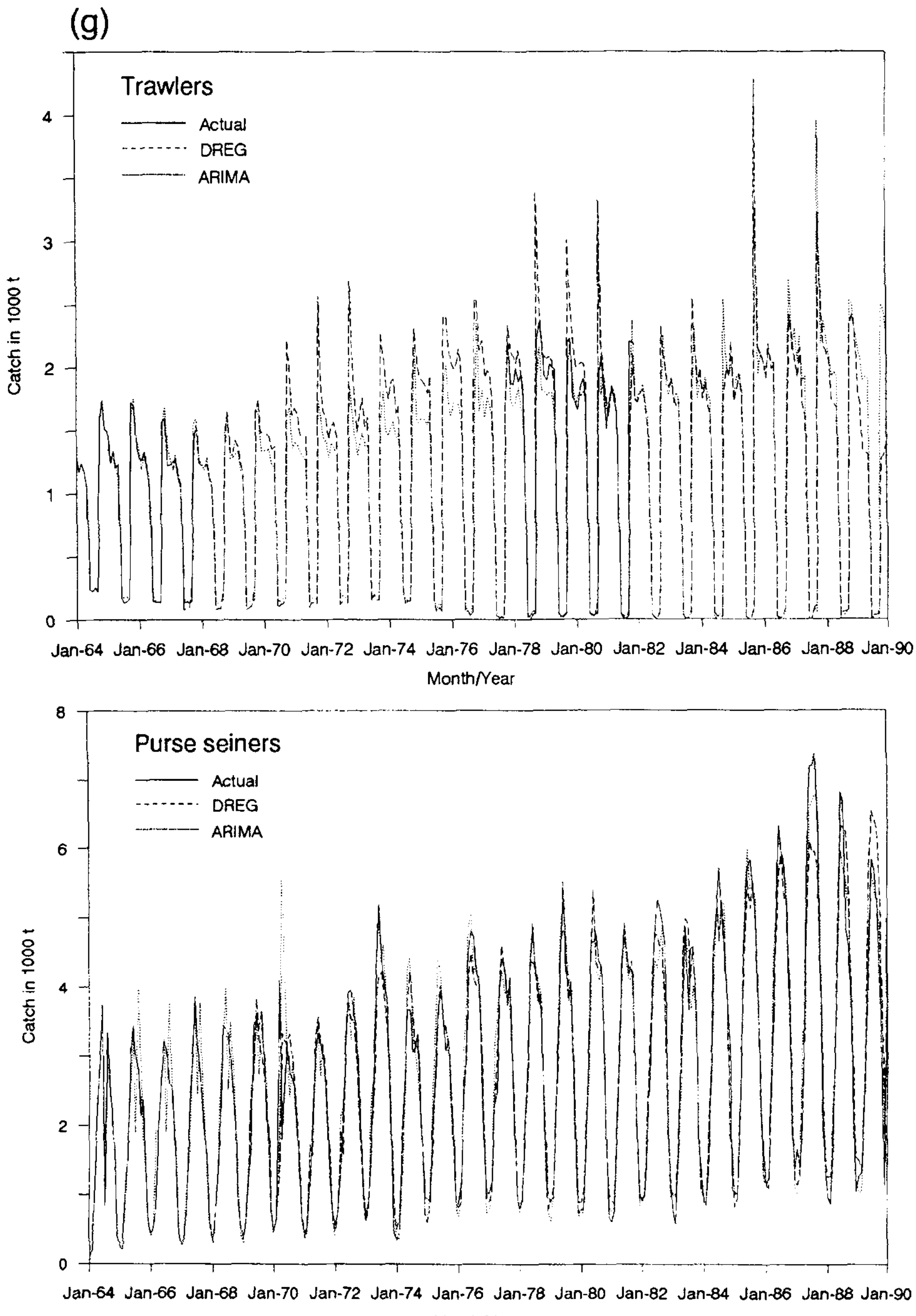
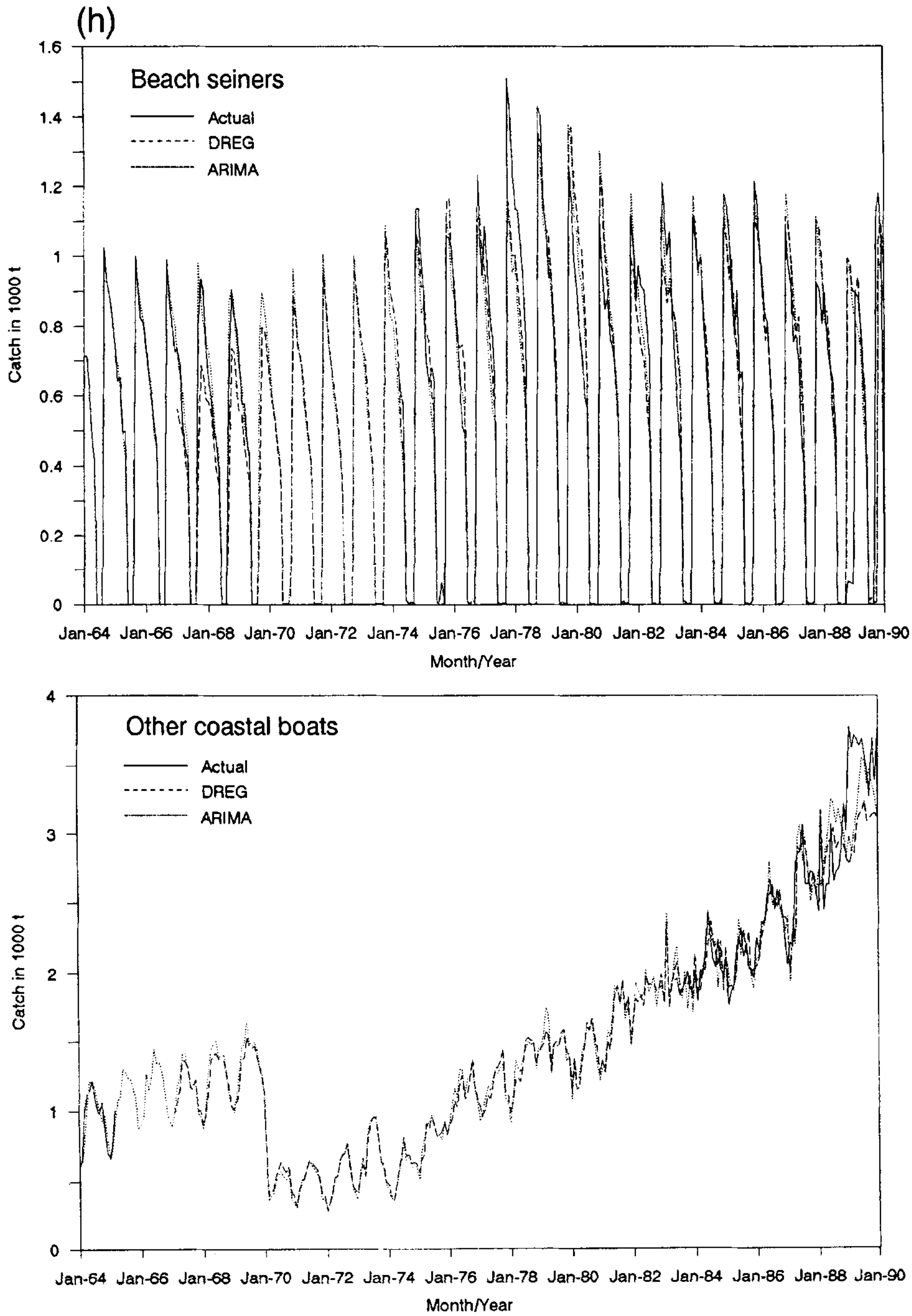


Fig. 5 (continued).

ues achieved by any method: 26.5%, 29.9%, 35.4% and 33.3%, respectively) whereas fits for the remaining time series were accurate (for all remaining time series, the lower MAPE and MDAPE values achieved by any method were less than 20.5% and less than 14.3%, respectively). The low fitting accuracy for the beach seine and trawl catches must be attributed to the low level of the catches in June–September



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(Fig. 5), which in most cases approached zero, a fact leading to very high MAPE values. Indeed, the lowest MDAPE values achieved by any method was 10% for beach seine catches and 10.5% for trawl catches. In addition, the low fitting accuracy in the case of anchovy and *Scomber* spp. must be also attributed to the relatively low level of winter catches and, to a much lesser extent, to the fact that the occurrence of the peak in the summer catches varied temporally from June to September, for *Scomber* spp., and from June to August, for anchovy (Fig. 5). Indeed, the lowest MDAPE values achieved by any method was 16.1% for anchovy catches and 20.6% for *Scomber* spp. catches.

Similarly, all methods generally produced the worst forecasts for beach seine (MAPE: 338.0–4621.4%) and, to a much lesser extent, for trawl (MAPE: 53.4–203.9%), anchovy (MAPE: 48.4–172.7%), *Scomber* spp. (MAPE: 30.1–79.7%) and red pandora (MAPE: 31.7–47.2%) whereas forecasts for the remaining species were relatively accurate (the lower MAPE achieved by any method ranged from 8.2% for 'other coastal boats' to 19.5% for cephalopods). The low forecasting accuracy in the case of the beach seine and trawl catches must be attributed to the following facts: (a) beach seine and trawl catches in June–September were very low, approaching 0 (Fig. 5); (b) the beach seine catch in October 1988 (68 t) was one order of magnitude lower than those in October 1987 and 1989 (923 t and 1182 t, respectively); (c) the trawl catch in December 1989 (299 t) was about 1/8 of that in 1988 (2435 t). The relatively low accuracy of the forecasts in the case of anchovy and *Scomber* spp. must be attributed, as also mentioned for fits, to their low catch level in the winter (Fig. 5). In addition, for anchovy the summer peak in the catches in 1987 occurred in August (4755 t), whereas the August catches in 1988 and 1989 were lower by about 50% (2116 t and 2709 t, respectively).

4. Discussion

4.1. Model fitting and forecasting performances

In the present study, the ability of seven models to produce accurate forecasts for the monthly catches of 16 species (or groups of species) was compared with each other and with those of two naive methods and an empirical one. The fitting and forecasting performances of the different models was evaluated using 32 measures of accuracy. Overall, 108 monthly models were built (without taking into account the naive and EMP ones), belonging to three different families of forecasting techniques: deterministic regression and univariate and multivariate time series models. All models were built with equal care.

The results revealed that the univariate ARIMA, closely followed by the multivariate DREG time series models, outperformed the remaining ones (NM1, NM12, TVS, MREG, HREG, EMP, VAR and WES) in terms of both fitting (1964–1987) and forecasting (1988–1989) accuracy. They were characterised by: (a) higher accuracy in terms of all, or most, standard and relative statistical measures, that were usually tied together; (b) unbiased fits and forecasts; (c) much better performance than NM1. In addition, ARIMA and DREG models: (d) explained more than 80% of the variance of the transformed catches (Tables 7 and 8); (e) had residuals that were essentially white noise (Tables 7 and 8); (f) in all cases predicted the amplitude and the start and end of the fishing season (Fig. 5); (g) produced forecasts that, with the exception of those for anchovy, red pandora, *Scomber* spp., trawl and beach seine catches, had MAPE values less than 28.2%.

The different measures employed also indicated that EMP and WES models outperformed NM1, NM12, TVS, MREG and HREG ones. EMP produced forecasts with MAPE values less than 23.2% for ten monthly series, whereas WES produced forecasts with MAPE values less than 25.3% for eight monthly series. This suggests their potential use in short-term fisheries forecasting. Although WES models had transformed errors that were significantly ($P < 0.05$) autocorrelated (Table 4), a fact indicating that future errors may be predicted from past ones, smoothing models, in general, are not purported to explain all autocorrelations in the data.

ARIMA, DREG and WES models are well adapted for handling trends, autocorrelated data (with the exception of WES) and seasonal cycles. DREG models differ from ARIMA in two aspects: (a) they include explanatory variables, a feature that may often result to increased fitting and forecasting accuracy; (b) they do not include moving average terms that are useful for inducing data smoothing just like that of exponential smoothing. Indeed, all 16 monthly time series displayed significant ($P < 0.05$) trends, strong and significant autocorrelations and a pronounced seasonal cycle (Fig. 5). In general, the seasonal ARIMA and, and to a lesser extent, WES models have been successfully used for modelling and forecasting:

1. the fisheries of a wide variety of species differing in their biology and behaviour (lobsters: Boudreault et al., 1977; Saila et al., 1979; tuna: Mendelssohn, 1981; sardine: Stergiou, 1989; Moura and Alfonso dos Santos, 1989; anchovy: Stergiou, 1990a);
2. the fisheries of groups of species (combined purse seine catch: Moura and Alfonso dos Santos, 1989; *Mullus* spp.: Stergiou, 1990b);
3. other time series (e.g. Makridakis et al., 1983; Gardner, 1985; Noakes et al., 1985; Noakes et al., 1988; Goodrich, 1989).

In addition, EMP may incorporate the particular strengths of different models and, hence, lead to more accurate monthly forecasts. The potential use of EMP for short-term forecasting has been stressed for fisheries (Noakes et al., 1990) and other time series (e.g. Armstrong and Lusk, 1983; McLeod et al., 1987).

It is worth pointing out that although VAR models ranked first in terms of fitting performance, their forecasting performance was very poor (Table 12). Nevertheless, given their excellent fitting performance and the fact that VAR produced accurate forecasts (MAPE between 11 and 16%) for three (sardine, total fish and 'other coastal boats') out of 11 monthly series, their application to fisheries modelling and forecasting should not be dismissed, especially for fisheries variables exhibiting strong and justified interactions (e.g. anchovy–sardine complex, predator–prey relationships). In general, the model that explains the historical data best does not necessarily produce the most accurate forecasts for many reasons: (a) the future may not be described by the same probability model as the past; (b) the model may involve too many independent variables (i.e. overfitting) which account for noise or other features in the data that are not likely to extend into the future; (c) the errors involved in overfitted models may be damaging to forecasting accuracy (Goodrich, 1989). In addition, it must be pointed out that both model fitting and forecasting may fail after a certain period of time, even if the parameters of the model

Table 13
MAPE values of annual forecasts for 1988 and 1989 estimated from the sum of the individual monthly forecasts for the 2 years

Species	Model								
	NM12	TVS	WES	HREG	MREG	DREG	ARIMA	VAR	EMP
Anchovy	29.3	20.3	12.3	23.6	62.9	69.2	18.4	56.4	30.2
Sardine	2.7	4.1	2.0	6.5	43.8	8.4	2.6	4.0	3.7
Scomber spp.	17.7	15.5	16.4	15.4	19.6	13.1	12.7	13.7	13.8
Trachurus spp.	15.8	87.1	22.1	19.4	4.4	5.1	23.7	33.1	22.2
Gadiformes	9.3	9.0	7.0	9.0	2.6	7.6	7.7		5.2
Mullus spp.	15.9	2.2	24.4	2.2	18.6	7.1	25.7		9.3
Red pandora	17.8	19.9	42.6	17.6	29.0	39.2	29.4		24.5
Bogue	12.5	11.4	9.5	41.6	11.4	9.6	8.0		7.4
Spicara spp.	9.6	18.5	11.7	9.2	10.2	13.4	14.8		10.0
Total fish	6.1	4.3	3.5	4.9	8.1	5.7	2.3	14.1	2.1
Cephalopods	9.8	22.6	12.2	24.2	48.4	14.6	14.4	8.8	4.5
Crustaceans	13.1	36.3	12.5	15.8	29.3	13.3	20.2	14.9	11.1
Trawl	15.5	49.9	8.6	29.8	38.8	33.1	15.9	19.2	16.7
Purse seine	12.4	19.8	19.7	20.0	33.2	11.4	4.2	22.6	16.7
Beach seine	52.0	43.3	37.8	44.3	45.2	37.5	40.4	32.0	37.3
Coastal boats	14.6	7.9	8.4	11.5	7.7	8.4	8.0	7.4	5.6

are readjusted each year, and different variables (external and/or lagged) may have to be taken into account from time to time (e.g. Dement'eva, 1987).

4.2. Comparison of annual and monthly models

The monthly MREG models, as opposed to their DREG counterparts, were characterised by transformed errors that were significantly ($P < 0.05$) autocorrelated, a fact indicating that future errors may be predicted from past ones. However, this was not true of the annual MREG models (Stergiou and Christou, 1996). This, combined with the facts that (a) MREG and HREG models produced the best fits for annual catches and exponential smoothing models and, to a lesser extent, HREG models produced the best forecasts for annual catches (Stergiou and Christou, 1996) and (b) ARIMA, DREG, WES and VAR models produced the best fits (and forecasts, with the exception of VAR) for monthly catches, probably indicates that MREG and HREG models may be better suited for capturing the longer term trends, univariate time series models (averaging, exponential smoothing and ARIMA models) for capturing short-term variations, and multivariate time series models (HREG, DREG and VAR) probably for capturing both types of variations.

The MAPE values of the annual forecasts for 1988 and 1989, estimated from the sum of the individual monthly forecasts for the two years, are shown in Table 13. A comparison of the MAPE values from monthly forecasts with those derived from annual forecasts (Stergiou and Christou, 1996) indicates that, with the exception of *Mullus* spp., red pandora, *Spicara* spp., crustaceans and trawl catches for which MAPE was marginally better from annual forecasts, MAPE is improved considerably when annual forecasts are estimated from monthly forecasts.

4.3. Measures of accuracy

The complementary use of different measures (standard, relative and other statistical measures) is highly recommended when two or more forecasting models are to be compared because most measures suffer from certain limitations. For example, ME is not a very useful measure since positive and negative errors cancel one another (Makridakis et al., 1983). Hence, although NM1 produced forecasts of the monthly *Spicara* spp. catches with the smallest ME (1.6 t), it was clearly the worst model for this series. The more inaccurate a forecast is, the more sectors related to fisheries may be affected by decisions made on the basis of the incorrect forecast. In this case, MSE is useful because it gives relatively more weight to large errors. In addition, its minimisation is often the objective of many optimisation procedures. However, MSE is of limited value when the methods compared use different procedures in the fitting stage (e.g. regression: MSE minimisation by giving equal weight to all observations; ARIMA: non-linear minimisation). MAE is very useful in rolling simulation analysis (Stellwagen and Goodrich, 1993). In general, the comparison of the values of standard statistical measures (e.g. ME, MAE, MSE) between series is meaningless inasmuch as their values are proportional to the scale of the variable. In contrast, the values of relative statistical measures (e.g. MPE and MAPE) are comparable between series and more meaningful to the practitioner than standard statistical measures. For instance, it is more meaningful to know that ARIMA produced forecasts for the monthly catches of sardine that had MAPE 11% than to know that ME was −21 t and/or MSE was 18 937. However, MAPE values can be very high when the observed values are very low (Noakes et al., 1985). In this case MDAPE may be more appropriate because median errors decrease the influence of a single or a few large errors. Hence, the APE of the monthly beach seine forecasts ranged, depending on the model, from 0 to 76 450%, MAPE from 338 to 4621% and MDAPE from 7.7 to 56.5%. U and its alternative MBA are also very useful measures because they provide a measure of comparison of a given method with a naive method, and, at the same time, by squaring the errors, more weight is given at large errors (Makridakis et al., 1983). B is also very useful because, in general, it is useful to know if forecasts consistently overestimate or underestimate the actual values of the variable in concern. If forecasts constantly miss the actual values in the same direction, the problems caused by the decisions based on the forecasts will be compounded over time, rather than being compensated for by misses in the other direction. The Ljung–Box Q is also useful because it provides information on the pattern left in the errors. U, MBA, B and Q are generally meaningful by themselves. Finally, there were gains from model selection criteria, such as BIC, that definitely rejected for instance monthly MREG models (Table 2) when compared with their DREG counterparts (Table 8).

4.4. Model limitations

It is clear that all models developed here suffer from certain limitations. First, catches and number of fishers refer to aggregate nation-wide data, whereas climatic variables refer to certain specific areas of the north Aegean Sea (which account, however, for the major part of the total Hellenic catch). Second, the number of fishers may differ from fishing subarea to fishing subarea. Third, for the development of the multivariate models we used the monthly values of the five climatic variables and assumed that the relationship between climatic variables and catches is linear. It is known, however, that many biological processes are affected by environmental parameters that probably operate on either shorter or longer time scales. In addition, non-linear relationships allow for an 'optimal response' of a biological variable to an environmental variable (e.g. Mendelssohn and Cury, 1987; Mendelssohn and Cury, 1989; Roy et al., 1992).

One important aspect of multivariate models that has to be hitherto considered is multicollinearity [1] between the different regressors (or linear combination of them) in the right side of the equations (e.g. Makridakis et al., 1983; Zar, 1984; Schlegel, 1985). From a strictly statistical viewpoint, multicollinearity leads to high standard errors of the partial regression coefficients and may lead to increased roundoff error in the computation of regression statistics (Makridakis et al., 1983; Zar, 1984). However, predictability and fitting increases along with the expansion of the model (Fewster, 1987) and, actually, multicollinearity is ignored if it is of low magnitude (Makridakis et al., 1983; Zar, 1984; Hall et al., 1990). In practice, there is no need for a special test for multicollinearity; large standard errors of the coefficients themselves are good indicators (Hall et al., 1990). The TVS, HREG, MREG and DREG models presented in this study were all developed using stepwise regression that does not allow the construction of highly multicollinear models (e.g. Intrilligator, 1978; Freund and Minton, 1979). The above mentioned models were all characterised by coefficients that had low standard errors (all t-statistic values were more than 2). In contrast, the VAR models built included some lagged terms that had coefficients with relatively high standard errors (t-statistic values greater than 1). This is inevitable for VAR models (Schlegel, 1985).

The models that generally performed best (annual catches—exponential smoothing, NM1, EMP, HREG: Stergiou and Christou, 1996; monthly catches—ARIMA, DREG, WES, EMP) produced annual and monthly forecasts that were, with few exceptions (annual models—anchovy, *Trachurus* spp. and beach seine catches: Stergiou and Christou, 1996; monthly models—anchovy, *Scomber* spp., red pandora and beach seine catches), accurate; in other words, forecasts were close to the catches recorded by NSSH (having a MAPE less than 20% in most cases). This indicates that the above mentioned models, which were fitted to the annual or monthly catches of the 16 species (or groups of species) during 1964–1987, were efficient in capturing the main characteristics of the 16 time series and, hence, in producing accurate forecasts for 1988 and 1989. Yet, whether the forecasts produced are close to the actual rather than the recorded (by NNSH authorities) catches is another matter, depending exclusively on the accuracy of the annual and monthly NSSH records. Although NSSH commercial landings and fishing effort data are the best figures available for Hellenic waters, they do suffer from various biases, especially so the inshore ones (i.e. beach seine and 'other coastal boats' effort and catches) (Stergiou et al., 1994). Reliable records of commercial landings and discards (the latter is not monitored by NSSH) is one important key to success for fisheries forecasting. Fishing effort affects commercial landings to a great extent and collecting reliable fishing effort data is another important key to success for short-term fisheries forecasting. More accurate forecasts will require additional measures of fishing effort (e.g.

[1] Multicollinearity refers to more than two regressors; two regressors are collinear or not.

days spent at sea) that will reflect better the effort expended on fishing on both spatial and temporal scales.

4.5. Biological explanations of models

Although many practitioners would argue that forecasting models must not always be 'biologically' meaningful, an empirically developed forecasting model is more appealing if it has a sound biological/oceanographic and/or other explanation. The ARIMA, VAR, DREG, MREG and HREG models presented here have interesting explanations (persistence, periodicity and long-term trends of catches) that are found in agreement with those of the annual models (Stergiou and Christou, 1996).

4.5.1. Catch persistence

In the monthly VAR models fitted to the different complexes (Tables 9 and 10), the response variables were the catches of the individual components at time t and the predictors were, apart from the external variables and the catches of the remaining components of the complex, the autoregressive terms at months $t-1$, $t-2$, $t-3$, $t-12$, $t-24$ and $t-36$ for all monthly catches. The same was also true of the monthly DREG models (Table 8) in which the catch of a species (or groups of species) at month t was partially predicted by autoregressive terms at months $t-12$ and $t-24$, with the exceptions of anchovy and 'other coastal boats' catches (autoregressive term at month $t-1$) and *Scomber* spp., *Trachurus* spp. and beach seine catches (autoregressive term at month $t-12$). Finally, in the case of ARIMA models (Table 7), the catch of a species (or groups of species) at month t was partially predicted by the autoregressive terms at months $t-12$ and $t-13$, and to a lesser extent at months $t-1$ and $t-14$. Hence, all the above mentioned models predicted persistence of catches. In other words, all else being equal, once catches were high they tended to remain high for 2–3 successive months and years. Persistence may indicate that environmental conditions favouring the formation of good year classes (and/or large schools) and/or other factors (e.g. microeconomics) affecting the fisheries of the species (or groups of species) of concern tend to persist. The same was also true of the annual ARIMA, VAR and MREG models (Stergiou and Christou, 1996).

4.5.2. Catch periodicity

The autoregressive terms at month $t-12$ for ARIMA, DREG and MREG models as well as the results of FFT all indicate that the monthly catches of the 16 species (or groups of species) exhibited a strong seasonal cycle. Indeed, the monthly catches of the pelagic (or semipelagic) species anchovy, sardine, *Trachurus* spp., *Scomber* spp. and bogue as well as the monthly catches of all fish combined and of purse seiners and 'other coastal boats' (Fig. 5) all increased from a minimum in January to a maximum in May–September, depending on species (or groups of species), and declined thereafter. This marked seasonal cycle is most likely related to the seasonal offshore and inshore migrations of small- and medium-sized pelagic fishes and the nature of the purse seine fishery. The area where purse seiners operate is mainly determined by the fact that catches must be brought to fishing docks early in the morning to be supplied to the market in time. Hence, fishing does not operate far out into the open sea but is rather restricted to coastal areas where dense schools of small- and medium-sized pelagic fishes migrate on a seasonal basis between spring and autumn for spawning (Stergiou et al., 1993; Stergiou et al., 1994). In contrast, in the winter, small- and medium-sized pelagic fishes are more dispersed and distributed mainly offshore (Stergiou et al., 1994). The monthly catches of the demersal and/or inshore gadiformes, *Mullus* spp., red pandora, *Spicara* spp. as well as the total cephalopod, crustacean, trawl and beach seine catches (Fig. 5), however, unlike their pelagic/semipelagic counterparts, were all consistently very low from June to September, when trawling (which accounts for the major part of their catch) and beach seining are prohibited in Hellenic waters (Stergiou and Petrakis, 1993).

In addition, the autoregressive terms at months $t-24$ and $t-36$ in the monthly VAR (Tables 9 and 10) and DREG models (Table 8) may also indicate a 2–3 year periodicity in the catches of the 16 species (or groups of species). This is consistent with the frequencies identified in the variability of the annual catches of the 16 species (or groups of species; Stergiou and Christou, 1996) and the cycles with frequencies less than 8 years could be generally considered with some confidence since they are less than 1/3 of the length of the time series. Cycles of

2–4 years have also been identified in the air temperature in Athens and in different biotic (zooplankton, phytoplankton, fish egg and larval abundance, fish catches) and abiotic variables (air temperature and pressure, sea temperature and salinity) in different areas of the Mediterranean, Black and Azov Seas (Stergiou, 1992). Similar cycles have also been identified in the physical environment and marine populations in other areas of the world and have been generally related to short-term ocean–atmosphere interactions (e.g. surface heat-exchange phenomena: Zupanovic, 1968; Colebrook and Taylor, 1984; advection: Kort, 1970; Mysak, 1986).

4.5.3. Long-term trends in catches

The monthly catches of the 16 species (or groups of species) displayed long-term trends and, as mentioned above, year-to-year variability. There is a lack of long-term studies on the ecology and population dynamics of the examined species or groups of species in the Hellenic Seas. Hence, the factors responsible for their catch trends and variability cannot be conclusively determined. Changes in catches do not necessarily reflect changes in stock strength, especially so for schooling fishes such as the pelagic and semi-pelagic ones (e.g. anchovy, sardine, *Trachurus* spp., *Scomber* spp., bogue). Theoretically, fishing effort, microeconomics and climate may in a synergetic fashion mediate such patterns. Long-term eutrophication of the Black Sea waters and/or locally of Hellenic waters may also partially account for long-term catch trends but our data cannot justify for such an effect (Stergiou and Georgopoulos, 1993; Stergiou and Christou, 1996). The possible effects of fishing effort and microeconomics have been discussed for the 16 annual series (Stergiou and Christou, 1996). The role of climate is discussed below.

The annual MREG and VAR models (Stergiou and Christou, 1996) and the monthly DREG (Table 8) and VAR models (Tables 9 and 10) built in the present study point to a probable catch–climate relationship at least for the catches of anchovy (−NSW and −SLP regressors), sardine (−SLP regressor), *Mullus* spp. (−SLP regressor), bogue (+AIRT regressor), *Spicara* spp. (−SST regressor) and cephalopods (−SST regressor), if more credit is to be given to those climatic variables that consistently entered the annual and monthly MREG, DREG and VAR models with the same sign. From the above mentioned six catch–climate relationships identified through empirical modelling only the one referring to anchovy and sardine has a biological explanation that is consistent with previous hypotheses and observations (see next paragraphs). For the remaining species it is uncertain how these climatic variables mediate catch variations and, hence, these relationships must be also justified from further field, or other, studies.

The annual VAR model for the anchovy/sardine complex points to a negative relationship (negative coefficient) between sardine and anchovy catches at lag 2 years (Stergiou and Christou, 1996). The same was also true of the monthly VAR model (Table 9), which points to a negative relationship between anchovy and sardine (at lags 1, 3 and 12 months), and of the monthly anchovy DREG model (Table 8), which also points to a negative relationship between anchovy and sardine at lag 12 months. The above mentioned negative relationships imply a replacement of Hellenic sardine by anchovy catches and vice versa, a fact suggested by various authors for the Mediterranean Sea (Stergiou, 1989; Stergiou, 1992) and other areas of the world (e.g. Daan, 1980). *Trachurus* spp. and *Scomber* spp. may also be implicated in such a replacement as shown by the negative relationships between anchovy, sardine, *Scomber* spp. and *Trachurus* spp. at various lags in the monthly VAR model (Table 9).

Replacement of sardine by anchovy cannot be attributed to competition for food at the larval/juvenile stages since spawning and larval emergence periods for these species do not overlap in time (Stergiou, 1992). The same is also true of the California sardine and anchovy (MacCall, 1983). The fact that both the annual MREG models (Stergiou and Christou, 1996) and the monthly MREG, DREG and VAR models (Tables 2, 8 and 9) of anchovy and sardine catches included NSW and/or SLP suggests that wind activity may mediate such a replacement either by (a) involving changes in recruitment rates, and/or by (b) involving changes in the relative availability of anchovy and sardine to purse seiners, and/or in the relative fishing effort expended on each species, rather than to changes in the abundance of anchovy and sardine themselves. A detailed account of mechanisms through which NSW can mediate such changes is given in Stergiou (1992).

4.6. General conclusions

Some general conclusions can be drawn from the comparison between the results of the present study and those of Stergiou and Christou (1996), concerning annual models, as well as from the discussion and facts presented so far.

1. The use of different models, including a naive one and an empirical one, and the evaluation of their fitting and forecasting performances based on different measures of accuracy are highly recommended. The selection of the 'best' model(s) can be based on the analysis of the fitting and forecasting (measures) × (methods) matrices, using multivariate techniques (e.g. PCA).
2. In general, MREG and HREG models may be better suited for capturing the longer term trends, univariate time series models (averaging, exponential smoothing and ARIMA) for capturing short-term variations, and multivariate time series models (HREG, DREG and VAR) probably for capturing both types of variations. The model that explains the historical data best does not necessarily produce the most accurate forecasts.
3. Although multicollinearity may be circumvented in multivariate models such as MREG and DREG, it is inevitable for VAR models.
4. Forecasting accuracy is higher for monthly than annual data and improves considerably when annual forecasts are estimated from monthly forecasts.
5. Multivariate models should be ideal for use in the following two cases.
   5.1. When independent explanatory variables have been shown, through experimental and/or long-term field studies, to significantly affect the fishery variable concerned (e.g. recruitment, catch, CPUE, spawning biomass). When this is not true, as is the case for the Hellenic and many other Mediterranean fisheries, it is quite likely that spurious correlations may arise, especially so when the number of independent variables is high. We believe that when a sound biological hypothesis supporting the inclusion of one or more explanatory variables into the models is lacking, more credit should be given to variables entering into different empirical models with a consistent manner (e.g. appearance of a variable for a particular species in different multivariate models with a coefficient having a consistently negative or positive value).
   5.2. Should real-time forecasting be objective, multivariate models are meaningful only when reliable forecasts of the independent variables are available or their values are provided to forecasters in real-time (e.g. real-time provision of climatic data through satellites). In cases that (5.1) and (5.2) are not satisfied, the univariate time series models are probably the most appropriate.

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References

Armstrong, J.S. and Lusk, E.J., 1983. Commentary on Makridakis time series competition (M-competition). J. Forecasting, 2: 259–311.

Bakun, A., Christensen, V., Curtis, C., Cury, P., Durand, M.H., Husby, D., Mendelssohn, R., Mendo, J., Parrish, R., Pauly, D. and Roy, C., 1993. The Climate Eastern Ocean system Project. Naga (ICLARM), 15 (4): 26–30.

Bocharov, L.N., 1989. Problems of fishery forecasts in Far Eastern Seas from the point of view of systems analysis. Sov. J. Mar. Biol., 14: 1–8.

Borges, M.F., 1990. Multiplicative catch-at-age analysis of scad (*Trachurus trachurus*) from western Iberian waters. Fish. Res., 9: 333–353.

Boudreault, F.R., Dupont, N. and Sylvain, J.N., 1977. Modeles lineaires de prediction des debarquement de homard aux Iles-de-la-Madeleine (Golfe du Saint-Laurent). J. Fish. Res. Board Can., 34: 379–383.

Box, G.E.P. and Jenkins, G.M., 1976. Time Series Analysis, Forecasting and Control. Holden-Day, San Francisco, CA.

Bulmer, M.G., 1974. A statistical analysis of the 10-year cycle in Canada. J. Anim. Ecol., 43: 701–718.

Caddy, J.F. and Sharp, G.D., 1986. An ecological framework for marine fishery investigations. Fish. Tech. Pap. 283, FAO, Rome, 152 pp.

Clarke, K.R. and Warwick, R.M., 1989. Lecture notes prepared for the training workshop on the statistical treatment and interpretation of marine community data. FAO/ IOC/UNEP, Athens, September, 1989, Part II.

Cochrane, D. and Orcutt, G.H., 1949. Application of least squares regression to relationships containing autocorrelated error terms. J. Am. Stat. Assoc., 44: 32–61.

Colebrook, J.M. and Taylor, A.H., 1984. Significant time scales of long-term variability in the plankton and the environment. Rapp. P.-v. Reun. Cons. Int. Explor. Mer, 183: 20–26.

Daan, N., 1980. A review of replacement of depleted stocks by other species and the mechanisms underlying such replacement. Rapp. P.-v. Reun. Cons. Perm. Int. Explor. Mer, 177: 405–421.

Dement'eva, T.F., 1987. A method for correlation of environmental factors and year-class strength of fishes. J. Icthyol., 27: 55–59.

Fewster, P.H., 1987. Regression modeling of perturbation in some vegetation types. Coenoses, 2: 67–74.

Fox, W.W., 1970. An exponential surplus-yield model for optimizing exploited fish populations. Trans. Am. Fish. Soc., 99: 80–88.

Freund, R.J. and Minton, P.D., 1979. Regression Methods: A Tool for Data Analysis. M. Dekker, New York.

Gardner, E.S. Jr., 1985. Exponential smoothing: the state of the art. J. Forecasting, 4: 1–38.

Getz, W.M., Francis, R.C. and Swartzman, G.L., 1987. On managing variable marine fisheries. Can. J. Fish. Aquat. Sci., 44: 1370–1375.

Goodrich, R.L., 1989. Applied Statistical Forecasting. Business Forecast Systems Inc., Belmont, MA, USA, 254 pp.

Hall, R.E., Johnston, J. and Lilien, D.M., 1990. Micro TSP User's Manual for Time Series Analysis, Regression and Forecasting. QMS Quantitative Micro Software, Irvine, CA.

Hilborn, R., 1987. Living with uncertainty in resource management. N. Am. J. Fish. Manage., 7: 1–5.

Intrilligator, M.D., 1978. Econometric Models, Techniques and Applications. Prentice-Hall, Englewood Cliffs, NJ.

Kort, V.G., 1970. Large-scale interaction between the ocean and the atmosphere using the North Pacific as an example. Oceanology, 10: 171–183.

Litterman, R.B., 1979. Techniques of forecasting using vector autoregressions. Working Pap. 115, Federal Reserve Bank of Minneapolis.

Ljung, G.M. and Box, G.E.P., 1978. On a measure of lack of fit in time series models. Biometrika, 67: 297–303.

MacCall, A.D., 1983. Variability of pelagic fish stocks off California. Fish. Rep. 291, FAO, Rome, pp. 101–112.

Makridakis, S., Wheelwright, S. and McGee, V., 1983. Forecasting: Methods and Applications. John Wiley and Sons, New York.

McLaughlin, R.L., 1975. The real record of the economic forecasters. Buss. Econ., 10: 28–36.

McLeod, A.I. and Sales, P.R.H., 1983. An algorithm for approximate likelihood calculation of ARMA and seasonal ARMA models. Algorithm AS 191. Appl. Stat., 1983: 211–223.

McLeod, A.I., Noakes, D.J., Hipel, K.W. and Thompstone, R.M., 1987. Combining hydrologic forecasts. J. Water Resourc. Planning Manage., 113: 29–41.

Mendelssohn, R., 1981. Using Box–Jenkins models to forecast fishery dynamics: identification, estimation and checking. Fish. Bull. US, 78: 887–896.

Mendelssohn, R. and Cury, P., 1987. Fluctuations of a fortnightly abundance index of the Ivorian coastal pelagic species and associated environmental conditions. Can. J. Fish. Aquat. Sci., 44: 408–421.

Mendelssohn, R. and Cury, P., 1989. Temporal and spatial dynamics of a coastal pelagic species, *Sardinella maderensis* off the Ivory Coast. J. Fish. Res. Board Can., 46: 1686–1687.

Moura, O. and Alfonso dos Santos, G., 1989. Purse seine fishery: a stochastic approach. ICES Symposium on Multispecies Models Relevant to Management of Living Resources. Netherlands Congress Centre, Hague, 2–4 October 1989, ICES, Hague, 30 pp.

Murawski, S.A., Lange, A.M., Sissenwine, M.P. and Mayo, R.K., 1983. Definition and analysis of multispecies otter-trawl fisheries of the northeast coast of the United States. J. Cons. Int. Explor. Mer, 41: 13–27.

Mysak, L.A., 1986. El Nino, interannual variability and fisheries in the Northwest Pacific Ocean. Can. J. Fish. Aquat. Sci., 43: 464–497.

Noakes, D.J., McLeod, A.I. and Hipel, K.W., 1985. Forecasting monthly riverflow time series. Int. J. Forecasting, 1: 179–190.

Noakes, D.J., Hipel, K.W., McLeod, A.I., Jimenez, C. and Yakowitz, S., 1988. Forecasting annual geophysical time series. Int. J. Forecast., 4: 103–115.

Noakes, D.J., Welch, D.W., Henderson, M. and Mansfield, E., 1990. A comparison of preseason forecasting methods for returns of two British Columbia sockeye salmon stocks. N. Am. J. Fish. Manage., 10: 46–57.

NSSH (National Statistical Service of Hellas), 1965–1992. Statistical Year-Book. 26 issues (for the years 1964–1989), Athens, Hellas.

Pauly, D., 1989. Biology and management of tropical marine fisheries. Res. Manag. Optimiz., 6: 253–271.

Pope, J.G. and Shepherd, J.G., 1985. A comparison of the performance of various methods for tuning VPAs using effort data. J. Cons. Int. Explor. Mer, 42: 129–151.

Roy, C., Cury, P. and Kifani, S., 1992. Pelagic fish recruitment success and reproductive strategy in upwelling areas: environmental compromises. S. Afr. J. Mar. Sci., 12: 135–146.

Saila, S.B., Wigbout, J. and Lermit, R.J., 1979. Comparison of some time series models for the analysis of fisheries data. J. Cons. Perm. Int. Explor. Mer, 39: 44–52.

Schlegel, G., 1985. Vector autoregressive forecasts of recession and recovery: is less more?. Econ. Rev., IIQ/, 1985: 2–12.

Shepherd, J.G., 1984. Status quo catch estimation and its use in fisheries management. ICES CM, 1984/G:5: 14 pp.

Smetanin, M.M., Strel'nikov, A.S. and Tereshchenko, V.G., 1984. Applying information theory to analysis of catch dynamics in incipient ecosystems. J. Ichthyol., 1984: 1–7.

Sparre, P., Ursin, E. and Venema, S.C., 1989. Introduction to tropical fish stock assessment. Part 1 — Manual. Fish. Tech. Pap. 301(1), FAO, Rome, 337 pp.

STCS, 1993. Statgraphics plus reference manual. Manugistics.

Stellwagen, E.A. and Goodrich, R.L., 1993. Forecast pro for windows. BFS Business Forecast Systems Inc., Belmont, MA, USA.

Stergiou, K.I., 1989. Modeling and forecasting the fishery of pilchard, *Sardina pilchardus*, in Hellenic waters using ARIMA time series models. J. Cons. Int Explor. Mer, 46: 16–23.

Stergiou, K.I., 1990a. An autoregressive model of the anchovy *Engraulis encrasicolus* fishery in the eastern Mediterranean. Fish. Bull., U.S., 88: 411–414.

Stergiou, K.I., 1990b. Prediction of the Mullidae fishery in the eastern Mediterranean 24 months in advance. Fish. Res., 9: 67–74.

Stergiou, K.I., 1991a. Short term fisheries forecasting: comparison of smoothing. ARIMA and regression techniques. J. Appl. Ichthyol., 7: 193–204.

Stergiou, K.I., 1991b. Describing and forecasting the sardine–anchovy complex in the eastern Mediterranean using vector autoregressions. Fish. Res., 11: 127–141.

Stergiou, K.I., 1992. Variability of the monthly catches of anchovy, *Engraulis encrasicolus*, in the Aegean Sea. Fish. Bull. U.S., 90: 211–215.

Stergiou, K.I. and Christou, E.D., 1996. Modelling and forecasting annual fisheries catches: comparison of regression and univariate and multivariate time series methods. Fish. Res., 25: 105–138.

Stergiou, K.I. and Georgopoulos, D., 2. The distribution of phytoplankton pigments and the fishery of anchovy (*Engraulis encrasicolus*) in the Hellenic Seas. Naga (ICLARM), 16: 34–37.

Stergiou, K.I. and Petrakis, G., 1993. Description, assessment of the state and management of the demersal and inshore fisheries resources in the Hellenic Seas. Fresenius Environ. Bull., 2: 312–319.

Stergiou, K.I. and Pollard, D., 1994. A spatial analysis of the commercial fisheries catches from the Hellenic Aegean Sea. Fish. Res., 20: 109–135.

Stergiou, K.I., Papaconstantinou, C., Kleanthous, M. and Fourtouni, A., 1993. The relative abundance and distribution of small pelagic fishes in the Aegean Sea. Fresenius Environ. Bull., 2: 357–362.

Stergiou, K.I., Christou, E. and Petrakis, G., 1994. Operational forecasting of Hellenic fisheries catches. Final Report (Contract No Med92/019, EU), Stergiou and Co., Athens, June 1994, 1, 184 pp.

Stocker, M. and Noakes, D.J., 1988. Evaluating forecasting procedures for predicting Pacific herring (*Clupea harengus pallasi*) recruitment in British Columbia. Can. J. Fish. Aquat. Sci., 45: 928–935.

Theil, H., 1966. Applied Economic Forecasting. North-Holland, Amsterdam.

Todd, R.M., 1984. Improving economic forecasting with Bayesian Vector Autoregressions. Quarterly Review, Federal Reserve Bank of Minneapolis, Fall 1984, pp. 18–29.

Winters, P.R., 1960. Forecasting sales by exponentially weighted moving averages. Manage. Sci., 6: 324–342.

Zar, J.H., 1984. Biostatistical Analysis. 2nd edn., Prentice-Hall, Englewood Cliffs, NJ.

Zupanovic, S., 1968. Causes of fluctuations in sardine catches along the eastern coast of the Adriatic Sea. Anali Jandranskog Inst., 4: 401–489.