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LOLIGINID AND OMMASTREPHID STOCK PREDICTION IN GREEK WATERS USING TIME SERIES ANALYSIS TECHNIQUES

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ABSTRACT

Time series of loliginid and ommastrephid landings were analysed taking into account spatio-temporal descriptors of sea surface temperature (SST). The data are based on fisheries statistics recorded from the three most important fishing ports in the Northern Aegean Sea (1984–1999) and NOAA satellite images processed using GIS and image analysis tools. Autocorrelation (AC) and partial autocorrelation (PAC) functions were estimated leading to the identification and construction of seasonal ARIMA models, suitable for explaining the time series and forecasting future abundance values. The performance of the models was tested by comparing the predicted against the observed data of the last year (1999) and by examining the distribution and the AC of the residuals. The analysis provided results characterizing the different fishing patterns in each geographic area, as well as new series containing seasonally adjusted values, trend, cycle and error components of the model. Time series of several statistical parameters describing spatio-temporal variations of the SST were estimated and analysed aiming at the detection of anomalies and possible stock-environment relationships. Cross-correlation analysis between SST parameters and stock biomass indexes showed significant correlation coefficients, before and after compensation of the seasonal fluctuations by seasonal differencing. The results suggest that SST can be a leading indicator for stock prediction of the target species in the survey area.

Studies on the biology and fisheries of the cephalopods in general and in particular of those species having a resource potential in the Mediterranean are rather limited compared with those of the adjacent NE Atlantic waters or other sea basins and oceans of the world, e.g., Pacific, Antarctic. Furthermore the currently available information on the exploitation and study of the cephalopods in the Mediterranean comes mainly from the western basin while in the eastern basin there is only scattered information on the species exploited (Worms, 1983).

With a total length of coastline in Greece over 15,000 km, fisheries production should play an important role in the national economy. Nevertheless, the fishery sector accounted for 0.31% of the Greek National Product (GNP) over the 1980–87 period and 2% of the mean revenues from the agricultural sector that made up 13.7% of GNP (Stergiou, 1993). Despite the fact that various attempts have been made to describe and assess the state of, and to model and forecast, fisheries production in Greek waters from commercial fisheries catch statistics (Stergiou et al., 1997 and references therein) very few concern cephalopods (Stergiou, 1987, 1988, 1989) and most cover the period before 1985.

The cephalopod categories of interest presented in this study are the fished species of long-finned squids (Loliginidae) and short-finned squids (Ommastrephidae). Concerning loliginid squids the species taken into consideration is the European squid *Loligo vulgaris* Lamarck, 1798, a species with commercial importance occurring throughout the Mediterranean and the eastern Atlantic (Roper et al., 1984). The other commercially important loliginid species, the veined squid *Loligo forbesi* Steenstrup, 1856 does not comports in the Cyclades plateau in the South Aegean Sea (Koutsoubas et al., 1999).

Concerning Ommastrephid squids, the species taken into consideration is the broadtail squid *Illex coindetii* (Verany, 1839), a species with commercial importance which extends across the Mediterranean and Atlantic (Roper et al., 1984). Concerning the remaining ommastrephid species, the European flying squid *Todarodes sagittatus* (Lamarck, 1798) presents a scattered distribution in the study area (D'Onghia et al., 1996) while the lesser flying squid *Todaropsis eblanae* (Ball, 1841) is not only absent in the Greek fish markets but also has a negligible contribution in the cephalopod catch in research surveys conducted recently in the Greek Seas (Koutsoubas et al., 1999 and references therein).

A very comprehensive sourcebook providing the foundation for cephalopod management strategies has been published by Caddy (1989). It summarizes the dynamics of 30 populations of invertebrates from tropical, temperate, and Arctic ecosystems. The book also includes an analytical contribution by Fogarty concerning fishery forecasting models (Forecasting Yield and Abundance of Exploited Invertebrates).

Forecasting models are very attractive for scientists and policy makers, especially during critical management periods. They facilitate the comprehension of relationships among biological and environmental interactions and can improve the efficiency of fisheries management. However, their reliability depends on several assumptions concerning the stationarity of the system parameters, which characterize the system 'biological resources-environment-fishing activity', as well as the quality of the available time series.

Two different strategies have been developed for forecasting the commercial catch in a fisheries management approach: deterministic models based primarily on the population dynamics theory (Schaefer, 1984; Fox, 1970) and stochastic models originating from the econometric and business literature. Stochastic models were first applied to ecological problems by Moran (1949). It is widely accepted that the stochastic models have an advantage over the deterministic, especially due to the fact that the causal relationships of the latter involve unobservable variables or unknown lagged processes (Cohen and Stone, 1987).

Several types of stochastic models have been developed, both in the time domain (ARIMA, uni- or multivariate transfer function noise models) and in the frequency domain (spectral and wavelet analysis) for estimating the system parameters. ARIMA and transfer function noise models result in similar precision and accuracy in the short-term forecasting of the commercial harvest (Tsai and Chai, 1992). Generally, it is widely accepted that stochastic models provide more reliable forecasts compared to the deterministic models (Cohen and Stone, 1987).

Modelling of fishery landings using temperature as the main environmental predictor has been repeatedly used to uncover the role of the environment in the distribution and abundance of the target populations (Cushing, 1981; see reviews in Stergiou, 1987,1989). Satellite technology provided accurate estimations of the sea surface temperature (SST) in high spatial and temporal resolution over the last two decades, allowing both short- and long-term prediction of biomass density or production.

The developed models are based on ARIMA uni- and multivariate time series analysis techniques and the response variable is the landings of the oliginid and ommastrephid squids in Greek waters, aiming to contribute towards the rational management and protection of this fishery resource.

STUDY AREA, SOURCE OF DATA AND PRE-PROCESSING

The study area in this paper is the North Aegean Sea (northern and north-eastern part of the Aegean; major fishing areas 13, 14 and 15 – Fig. 1), where more than 50% of the total cephalopod catch in Greek Seas is reported.

Two sources of data were used concerning the registration of the fishing activity in the present study. Monthly landings data from the most important fishing ports in Greece have been provided by the Fishing Development Corporation (ETANAL S.A), while annual commercial catch estimates have been provided by the Greek National Statistical Service (GNSS).

The Greek waters are divided by the GNSS, in order to achieve better monitoring of the resources, into 14 major fishing areas. Areas 13 and 14 represent the northern part of the study area, while area 15 covers the north-eastern part of the Aegean Sea (Fig. 1). The most important commercial ports of the areas under study are Thessaloniki, Kavala and Alexandroupolis (Fig. 1). Monthly landings were grouped into fishing periods starting from July and ending in June, to avoid splitting the higher winter landings over two different years.

Processed satellite images provided from the National Oceanic and Atmospheric Administration (NOAA) have been transformed into Sea Surface Temperature (SST) using GIS tools (Valavanis, et al., 2000). The daily SST images cover the studied area between the years 1984 and 1999. Spatially averaged temperature means were calculated, for each month and major fishing area, taking into account weekly means, weighted according to the number of valid pixels per image.

For statistical reasons the time series needs to be stationary, that is, it should have a constant mean, variance, and autocorrelation through time. Therefore, the series usually needs to be differenced first until it is stationary in the mean and log transformed for stabilising the variance. In general,

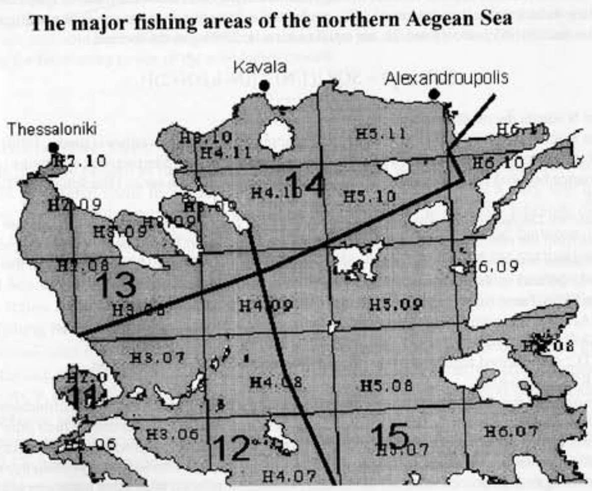


Figure 1 The major fishing areas in the northern Aegean Sea. The map shows the statistical divisions 13, 14 and 15 of the northern and north-eastern part of the Aegean according to the National Statistical Service of Greece. Small divisions marked with four digits were used for the analysis of the SST data.

verified by plotting the original or the transformed time series and estimating the autocorrelation function for consecutive time windows.

Due to the lack of accurate estimates of the fishing effort the landings have not been standardized as LPUE and therefore incorporate any change in the level of the fishing pressure. Fortunately, the transformation of the original time series to the differenced time series of landings minimizes the effect of possible changes in the effort time series. Moreover, if it is assumed that the annual change in fishing effort is much lower compared to the trend of effort accumulated over longer time periods, the prediction of short period components includes much less bias. However, it should be recognized that the mathematical proof of stationarity is not sufficient for accepting stability of the ecosystem parameters.

Time-Series Analysis

The statistical procedures mentioned in the present study were implemented using the SPSS for Windows software, SPSS Trends routines (SPSS Inc., 1993).

Exploratory Analysis.—The time series were first analysed to identify systematic patterns (frequency components or trends) which are not salient in the time series. Autocorrelation and Crosscorrelation Functions (ACF, CCF) as well as Spectral and Cross-Spectral densities were estimated for these purposes. All estimated correlation functions (correlograms) were plotted with the 95% confidence intervals of consecutive lags in the specified range. The sample autocorrelations had been used in the earlier part of the analysis to check the stationarity of the data set and also to have a measure of the dependence considering the data as a time series.

Seasonal dependency was proved by comparing the results of the Partial Autocorrelation Function (PACF), which considerably reduces the dependence on the intermediate elements, within the lag, and the results of the ordinary ACF (Box and Jenkins, 1976; see also McDowall et al., 1980). The software routines applied validate the significance of the correlation coefficients r_k by comparing their values to the standard error of r_k, under the assumption that the series is a white noise process and that all autocorrelations are equal to zero, according to the formula:

$$\mathrm{StdErr}(r_k) = \mathrm{SQR}\{(1/N) * [(N-k)/(N+2)]\},$$

where N equals the number of samples.

The spectral density estimates are computed by applying Hamming windows (Banks, 1990) with weights mentioned in the figures. The cross-spectral density can be interpreted as a measure of the covariance between the respective frequency components in the two series (Blackman and Tukey, 1958).

Seasonal Decomposition Procedure.—The goal of the Seasonal Decomposition procedure is to extract from the observed signal a seasonal component and a combined trend – cycle component. The residual is considered as an 'error' component. In the present study the seasonality of the time series is defined by the 12 mo periodicity, which is dominant in the signal.

The SPSS Trend routine estimates these components or a combination of them:

- SAF: seasonal adjustment factor, which contains the seasonality of the time series
- SAS: seasonal adjusted series (the original series minus the seasonality)
- STC: de-seasoned trend and cycle (the trend component plus the cycle) and
- ERR: the residuals.

The new generated components were normally further analysed, checking their distributions and their auto- and cross-correlograms. The residuals were analysed in order to ensure their pure randomness (white noise properties) and that they were not correlated to other potential predictors. The characteristics of the STCs, which include the trend and the non-seasonal periodicity, were also investigated for autocorrelation, trends and possible correlation with other parameters. In the end all these parameters were cross-checked as potential ARIMA predictors.

ARIMA Models.—The development of ARIMA models is based on the methodology described in the classical work of Box and Jenkins (1976). The procedure is applied separately to the landings and SST time series, as a univariate time series approach, taking into account only the mathematical properties of the data, without involving the biological or the physical background of the system. This kind of analysis supposes that other 'external factors' do not participate in the process development or that there contribution is stochastic. For each developed ARIMA model the standard three-steps procedure has been followed, namely model identification, parameter estimation and finally the diagnosis of the simulation and its verification (Makridakis, 1990).

As mentioned above, the input series for ARIMA needs to be differenced to achieve stationarity. The order of differencing is reflected in the d parameter. The general model introduced by Box and Jenkins (1976) can be summarized by the use of the following three types of parameters: the autoregressive parameters (p), the number of differencing passes (d), and moving average parameters (q). In the notation introduced by Box and Jenkins, a model described as (0, 1, 2) means that it contains 0 (zero) autoregressive (p) parameters and 2 moving average (q) parameters which were computed for the series after it was differenced once. Similarly the required parameters sp, sd and sq of the seasonal ARIMA process are determined according to the results of the corresponding ACF and PACF. The approach used consequently was to estimate the seasonal model first, then study the residuals of this model to get a clearer view of the non-seasonal model involved. If the identification of the seasonal model was correct, these residuals showed the non-seasonal portion of the model.

After the identification of the tentative model, its parameters were estimated applying maximum-likelihood methods. The final results include: the parameter estimates, standard errors, estimate of residual variance, standard error of the estimate, log likelihood, Akaike's information criterion (AIC), Schwartz's Bayesian criterion (SBC). The minimizing of SBC and AIC were used, taking into account both how well the model fitted the observed series, and the number of parameters used in the fit (SPSS manual, Trends, Release 6.0).

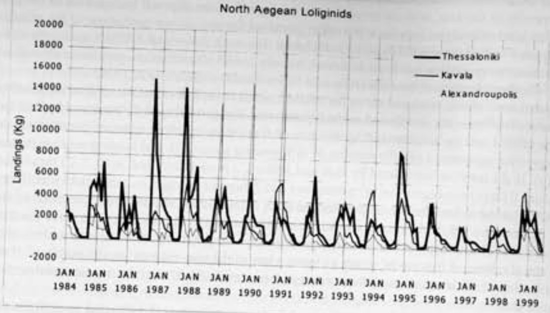
In all cases, if not mentioned otherwise, the data from 1984 to 1998 were used for evaluating (fitting) the model, except in the case of Alexandroupolis Ommastrephids, where landings data were not available before October 1992. The data of the last 12 mo (1998–1999) were used for testing the forecasting power of the established models.

Results

Exploratory Time Series Analysis

The monthly pattern of the landings for the two groups showed the typical catch oscillations for cephalopods in a finer spatial resolution, characterized by a very low catch during the June–July and August period. The time series of the monthly landings of the three important fishing ports of the northern Aegean Sea, for the period between 1984 and 1999, were plotted (Fig. 2). Concurrent monthly measurements of the spatially averaged Sea Surface Temperature (SST) showed a similar oscillation in the corresponding time series. As an example the SST time series of the area 13 is plotted, corresponding to the fishing port of Thessaloniki (Fig 3).

Periodicities Observed in the Time Series.—Time series of landings by species group and fishing ports were pre-processed in order to fulfill the stationarity requirements and their ACF and PACF were estimated for both un-differenced and first order seasonal differenced data (Fig. 4). Comparing the estimated coefficients to the plotted 95% confidence intervals, a series of important conclusions can be made. The exponentially declining ACF and the significant correlation at lag one in PACF indicate an autoregressive process of order one. Interpreting the same pattern of the correlograms it is concluded that the inherent moving average process in the time series is of order 1 or 2. Furthermore, from the correlograms based on the seasonal differenced data, the autoregressive



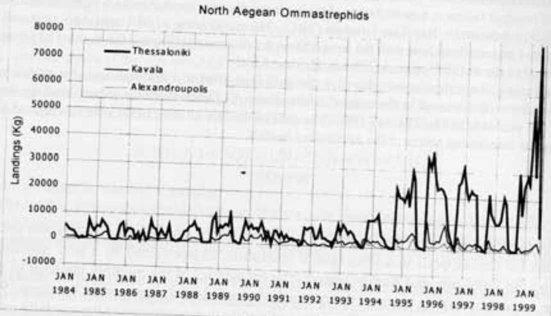


Figure 2. Time series of loliginid (above) and ommastrephid (below) monthly landings (Kg) for the major three fishing ports of North Aegean Sea. (Source: ETANAL S.A)

process and the moving average process are confirmed to be of order 1 and 1 (or 2) respectively.

The frequency components contributing to the observed periodicities were estimated by applying spectral analysis techniques. Two main unequal components were encountered at 6 and 12 mo, which were stronger in the Ommastrephids and Loliginids time series respectively. Less significant lower frequencies were also encountered between 14 and 16 mo (Fig. 5).

The mean SST values of the major areas were significantly positively correlated at 0 lag and no differences were encountered between the SST patterns in the different major areas, at least averaging at low spatial resolution.

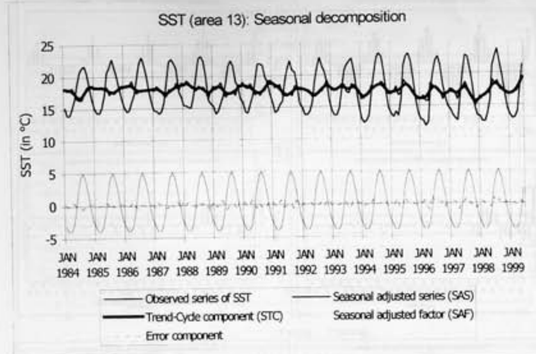


Figure 3. SST time series from major fishing area 13 and the seasonal decomposition.

Correlations Between Time Series.—Cross-Correlograms (CCFs) were calculated between 'yearly' SST values and corresponding annual catch. The spatially averaged SST of the Januarys or Februarys or Marches, etc was selected as the 'yearly' representative temperature in each CCF. Finally, a CCF was estimated for each target species, month and major fishing area, namely in the two areas of the northern part (major fishing areas 13: Thermaikos Gulf, 14: Kavala and Alexandroupolis) and in the eastern part of the Aegean Sea (fishing area: 15). Only correlograms with statistically significant coefficients are listed in Table 1. The results showed a clearly different behaviour of the catch in the studied species in the different major fishing areas. Loliginid local catch was mainly positively correlated with the mean SST observed in area 13, while the Ommastrephids catch was negatively correlated correspondingly with the mean SST of area 14.

Cross-spectral analysis of the same data set showed how well the SST and the catch time-series correlate as a function of frequency. The cross-spectral amplitude based on the yearly differences of SST and the catch values served as a measure of the covariance between the frequency components of the two time series. Thus we can conclude from the plot (Fig. 6), that the frequencies corresponding to an interval of 2 yrs between the two time series covary.

Seasonal Decomposition

Monthly landings in all fishing ports showed a strong seasonal periodicity (Fig. 2), which may cover any other weaker periodicity or trend included in the time series. Standard Seasonal Decomposition procedures were used to investigate the significance and the meaning of other components. The series of each fishing port were decomposed into a seasonal factor, a cycle component, a combined trend and the remaining 'error'. Taking into account that seasonality did not increase with the level of the landings an additive model is selected (Makridakis, 1990).

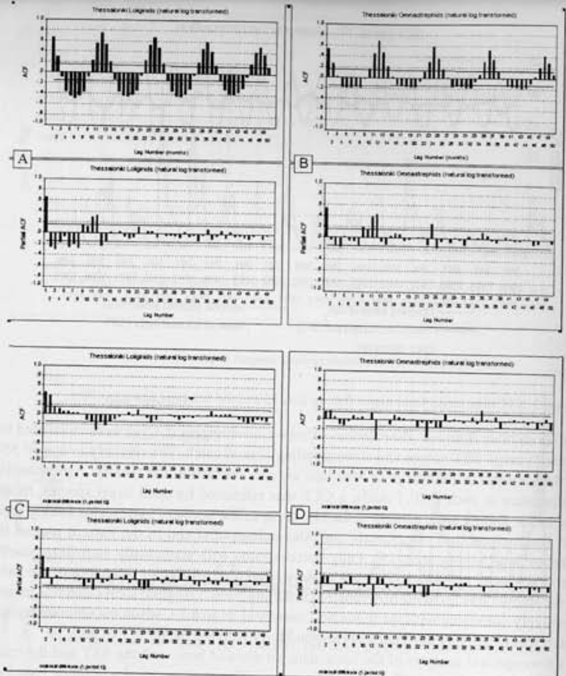


Figure 4. A and B: Autocorrelation function (ACF) and Partial autocorrelation function (Partial ACF) of loliginid (A) and ommastrephid (B) natural log transformed landings at Thessaloniki Port. The lag distance is in months. C and D: The same plots as above but after seasonal differencing for loliginids (C) and ommastrephids (D).

The two components, the seasonal adjustment factor—SAF and the de-seasoned trend and cycle—STC were estimated for each month and target species. The SAF pattern differed between the species groups and showed a larger variation among the fishing ports for the Ommastrephids. The SAF plots portray the well-known rapid decrease of the landings during July and August, as well as a possibly second maximum of the Ommastrephids landings during May.

The next component, STC, contains the trend component plus the cycle and therefore its analysis could give indications for trends longer than 12 mo. The STCs from seasonal

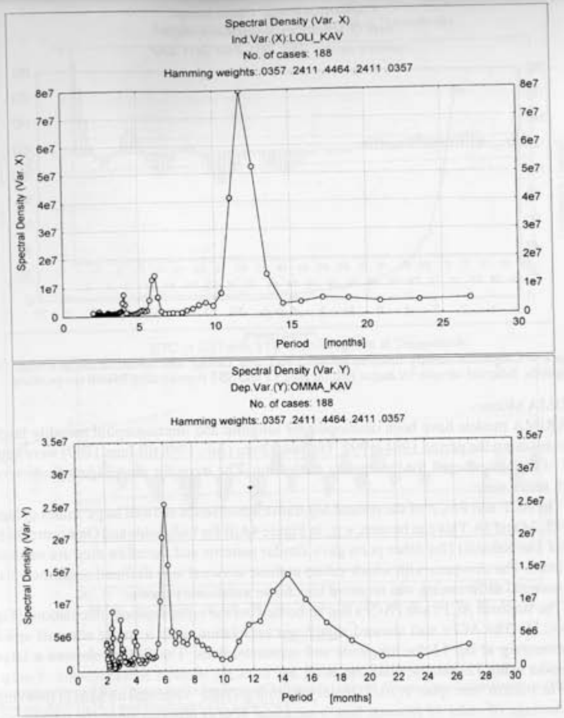


Figure 5. Spectral densities of loliginid (above) and ommastrephid (below) monthly landings time series. The difference in the frequency components is noteworthy.

decomposed time series of both monthly landings and SST were further analysed, investigating their ACF and CCF characteristics (Fig. 7,8).

Loliginid landings showed significant positive correlations with the SST at time lags of 0, 12 and 24 mo (the positive lag axis implies always the effect of SST on the landings). The coefficient at 24 mo was slightly stronger compared to that at 12 mo. On the contrary, Ommastrephids showed negative correlations at 0 and 12 mo lags.

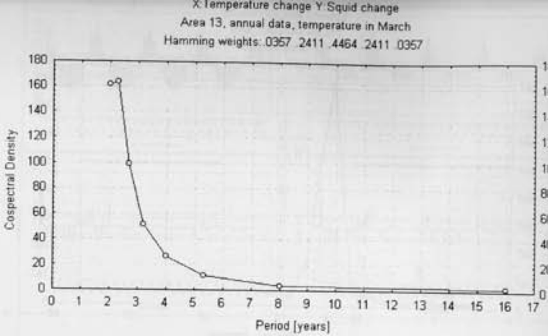


Figure 6. Cospectral density function between SST year change and annual landings change for loliginids. Selected sample for major fishing area 13 and SST representing March temperature.

ARIMA Models

ARIMA models have been developed for loliginid and ommastrephid monthly landings covering the period 1984–1999. The last 12 mo (July 1998 till June 1999) were kept out of fitting and used for forecasting evaluation. The steps for model identification of each series were:

(a) The ACF and PACF of the natural log transformed series showed large values at lags 12, 24 and 36. This can be seen, e.g., in Figure 4A,B for Loliginids and Ommastrephids of Thessaloniki (the other ports gave similar patterns and therefore they are omitted here). The slowness with which values at those seasonal lags declined confirmed that seasonal differencing was required to achieve a stationary mean.

(b) The seasonal ACFs and PACFs had smoothed out the rapid seasonal fluctuations (Fig 4C,D). The ACFs still showed significant correlation, with a single seasonal spike emerging at lag 12 for loliginids and ommastrephids. The PACFs showed a large spike at lag 12 and a smaller one at lag 24.

(c) The pattern 'one spike in ACF, rapidly declining PACF' indicated an MA(1) (Moving Average of order 1) process, here a *seasonal* MA(1) process, since the pattern appeared at the seasonal lags. The tentative seasonal model was (0,1,1) since the data were from seasonal differenced series.

(d) After the coefficients of the seasonal model had been estimated, the ACF and PACF plots of the residuals of these seasonal models (not shown here) were examined. Their ACFs started large and then died out, while their PACFs also died out somewhat more quickly. The non-seasonal model could therefore be ARIMA (1,0,1) in all cases except for ommastrephids of Thessaloniki where the non-seasonal model of ARIMA (1,1,1) performed best.

(e) The combined tentative models incorporating both non-seasonal and seasonal parameters in the ARIMA(p-d-q) format were ARIMA$(1,0,1)(0,1,1)_{12}$ or ARIMA $(1,1,1)(0,1,1)_{12}$. The coefficients and the summary statistics of these univariate ARIMA models are given in Table 2.

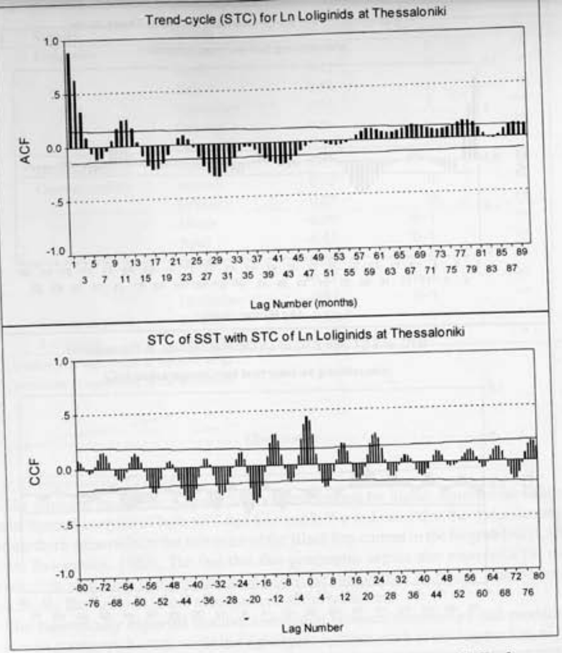


Figure 7. Autocorrelation function (ACF) of the Trend-cycle component (STC) after seasonal decomposition of the Thessaloniki landings of loliginids (above). Cross-correlation function (CCF) between SST (STC) and landings (STC) (below).

(f) New multivariate ARIMA models were developed, incorporating the SST parameters (mean, minimum and maximum values as well as STC and the residuals of the seasonal decomposition). The covariate that best improved each of the initial (univariate) ARIMA model in terms of reduction of the standard error and the residual variance is presented in Table 2. The STC and the SAS of the maximum value of SST gave the best results for loliginids in all Ports. For ommastrephids, different parameters of SST (min, max and mean) for each Port model gave the best results.

(g) The plots of the observed series (natural log transformed) along with their model fit and confidence intervals are shown in Figure 9 for Thessaloniki. The ACF and PACF of the model residuals (not shown) did not provide any significant pattern; i.e., the residuals had a stochastic character.

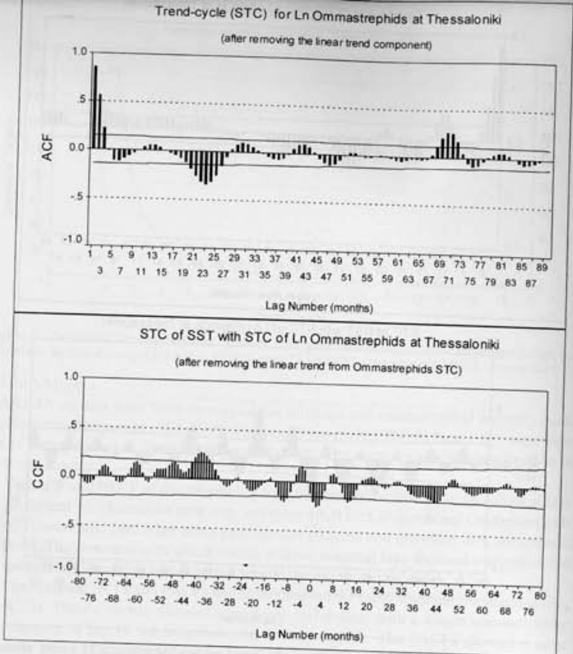


Figure 8. Autocorrelation function (ACF) of the Trend-cycle component (STC) after seasonal decomposition of the Thessaloniki landings of ommastrephids (above). Cross-correlation function (CCF) between SST (STC) and landings (STC) (below).

(h) The observed values of the forecasting period 1998–99 (also shown in Fig. 9) fall within the confidence intervals of the ARIMA models.

(i) The predicted values, for both the fit and forecast periods, were compared to the observed ones and the estimated adjusted r^2 varied between 0.96 and 0.99 (Table 2).

for a given month. Northern Aegean (area 13, 14)

Area	Species	Month	Correlation	Lag (year)	Significance
13	Loliginids	March	0.62	0	**
		April	0.43	2	*
		June	−0.48	1	*
		September	0.54	1	**
		October	0.66	1	**
		December	0.36	3	*
	Ommastrephids	September	0.69	1	**
14	Ommastrephids	January	−0.70	0	**
		February	−0.67	0	**
		March	−0.59	0–1	**
		April	−0.55	0–1	**
		October	−0.63	0	**
		November	−0.57	0–1	**
		December	−0.61	0–1	**
15	Ommastrephids	January	0.60	2	**
	Loliginids	January	0.42	0	*

**: Correlation is significant at the 0.01 level
* : Correlation is significant at the 0.05 level

Discussion

The Environmental Component

The northern part of the Aegean Sea is characterized by higher commercial fisheries yield. Spatial analysis of both SST and Chlorophyll-*a* indicates that the water surface in the northern areas reflects the influence of the Black Sea current in the Aegean Sea (Carter, 1956; Balopoulos, 1982). The fact that this geographic region also represents the most productive area for Cephalopods emphasizes the importance of taking environmental conditions into account in the management of the resources.

The theoretically expected positive correlation between temperature and production concerns nutrient rich areas, while in oligotrophic systems, such as the Aegean Sea, higher production may be interpreted as being due to the occurrence of water masses rich in nutrients (Haese, 1996).

Some of the positive correlations encountered between Loliginids and SST in area 13 are based on the higher catch values in the years 1988, 1993 and 1995 simultaneously with increased monthly SST means during February and/or March of the same years (Table 1). During this period the area is dominated by an increased flow from four large river systems (Balopoulos, 1982) and cold, less saline, surface water originating from the Black Sea (Georgopoulos, 1984). The second time period with higher crosscorrelations between landings and SST for both species groups was encountered during September–October. This period is characterized by large scale changes in the northern part of the Aegean Sea, which is now warmer compared to the eastern part (Georgopoulos, 1984). Both seasons coincide with the major pre-spawning and spawning periods of the squids and may influence their natural mortality during this sensitive life period. It is worth

A. Univariate ARIMA							
Species		Loliginids			Ommastrephids		
Port		Thessaloniki	Kavala	Alex/polis	Thessaloniki	Kavala	Alex/polis
ARIMA model:		(1-0-1) $(0\text{-}1\text{-}1)_{12}$	(1-0-1) $(0\text{-}1\text{-}1)_{12}$	(1-0-1) $(0\text{-}1\text{-}1)_{12}$	(1-1-1) $(0\text{-}1\text{-}1)_{12}$	(1-0-1) $(0\text{-}1\text{-}1)_{12}$	(1-0-1) $(0\text{-}1\text{-}1)_{12}$
Number of residuals		162	162	162	161	162	57
Standard error		**0.646**	**0.656**	**0.985**	**1.009**	**1.086**	**1.023**
B (coefficient)	AR1	0.6502	0.6044	0.5915	0.3161	0.75105	0.25717
	MA1	0.2626	0.1737	0.1146	0.9749	0.36091	0.25717
	SMA1	0.5978	0.7938	0.4506	0.9044	0.77247	–0.58512
Standard error of B	AR1	0.1280	0.1290	0.1241	0.0753	0.09637	0.26203
	MA1	0.1620	0.1582	0.1562	0.0420	0.13499	0.18566
	SMA1	0.0703	0.0696	0.0771	0.0997	0.06978	0.15156
Approximated probability.	AR1	0.0000	0.0000	0.0000	0.0000	0.00000	0.15633
	MA1	0.0107	0.0274	0.0464	0.0000	0.00829	0.01717
	SMA1	0.0000	0.0000	0.0000	0.0000	0.00000	0.00030
Adjusted r^2	Fit	**0.9912**	**0.9890**	**0.9636**	**0.9838**	**0.9739**	0.09949
	Forecast	**0.9985**	**0.9961**	**0.9798**	**0.9934**	**0.9902**	**0.9721**
							0.9684
B. Multivariate ARIMA							
Covariate		STC of SST-max	STC of SST-min	STC of SST-max	SAS of SST-min	STC of SST-max	SST-max
Number of residuals		162	162	162	161	162	57
Standard error		**0.631**	**0.652**	**0.970**	**0.939**	**1.075**	**0.996**
B (coefficient)	AR1	0.6132	0.5328	0.4953	0.2970	0.7825	0.3358
	MA1	0.2687	0.1017	0.0331	0.9738	0.4035	–0.5791
	SMA1	0.6313	0.8199	0.4940	0.8892	0.7800	0.1242
	Covariate	0.3260	0.1073	0.4929	–0.3034	–0.3621	–0.2398
Standard error of B	AR1	0.1498	0.1440	0.1467	0.0767	0.0886	0.1770
	MA1	0.1831	0.1678	0.1730	0.0486	0.1284	0.1525
	SMA1	0.0685	0.0698	0.0765	0.0908	0.0696	0.1635
	Covariate	0.1128	0.0881	0.1963	0.0896	0.1815	0.1007
Approximated probability	AR1	0.0001	0.0003	0.0009	0.0002	0.0000	0.0633
	MA1	0.0444	0.0545	0.0486	0.0000	0.0020	0.0004
	SMA1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0510
	Covariate	0.0044	0.1103	0.0130	0.0009	0.0477	0.0209
Significance level of covariate		*0.9956*	*0.8897*	*0.9870*	*0.9991*	*0.9523*	*0.9791*
Adjusted r^2	Fit	**0.9916**	**0.9890**	**0.9649**	**0.9843**	**0.9745**	**0.9745**
	Forecast	**0.9978**	**0.9952**	**0.9833**	**0.9910**	**0.9897**	**0.9634**

(*) AR1: Autoregressive coefficient of order 1, MA1: Moving average coefficient of order 1, SMA1: Seasonal moving average coefficient of order 1, AIC: Akaike' s information criterion, SBC: Schwarz' s Bayesian criterion.

mentioning that the temperature in September–October covaries with the next year landings, as it is indicated by the significance of the CCF at 1 yr lag.

The environmental character of area 14 is strongly affected by the cold Black Sea surface layer, 5–25 m thin, coming out through the Straits of Dardanelles (Theocharis et al., 1987). The increased catch of ommastrephids coincides with the occurrence and strength of the nutrient rich surface layer from the Black Sea, as was concluded from the high negative CCF coefficients in Table 1. However, it is not evident from the results that the Black Sea water is the only possible factor affecting the squid catches. As mentioned in Table 1, the temperature is cross-correlated with the loliginid landings in area 13 and with the ommastrephid landings in area 14. This could imply that other factors such as the spatial and bathymetric characteristics of the areas play an important role. A possible explanation of this spatial difference is that ommastrephids are expected to live in deeper pelagic zones than the loliginids (Roper et al., 1984) and therefore were better represented in the catch of an open area, such as area 14.

Positive correlations between temperature and cephalopod landings have also been published (see Stergiou, 1987), without interpretations concerning the causality of the

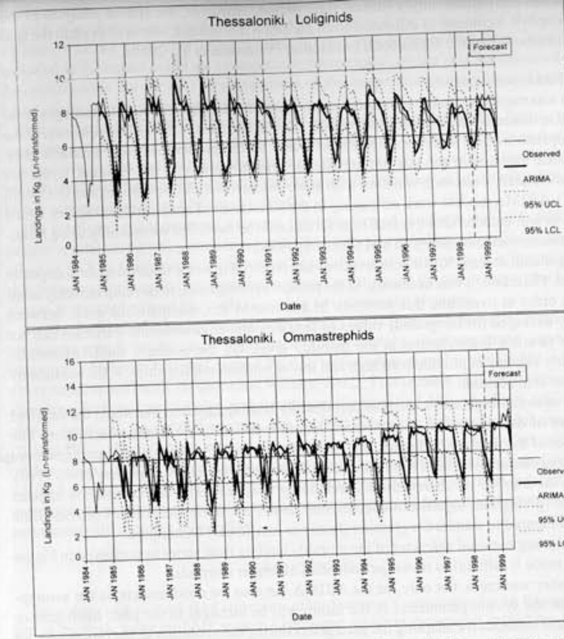


Figure 9. ARIMA fitted models with 95% upper (UCL) and lower (LCL) confidence levels of the Thessaloniki natural log transformed monthly landings of loliginids (above, ARIMA(1-0-1)$(0\text{-}1\text{-}1)_{12}$) and ommastrephids (below, ARIMA (1-1-1)$(0\text{-}1\text{-}1)_{12}$). The dotted vertical line indicates the start of the forecasting period (July, 1998).

temperature effect on the abundance. Pierce et al. (1995) studying fishery landings of the Northeast Atlantic and Mediterranean loliginid landings found similar trends in adjacent countries over the period 1980-1992, suggesting the possibility of a large-scale climatic influence on the cephalopod abundance.

SST satellite imagery covers large geographic areas for a relatively long period of time (1984–today) which is very attractive for model development, however the sea surface temperature can not explicitly describe the ecological environment. It is suggested that more complicated 3-dimensional multivariate information is needed, if particular points in the cephalopod life cycle are to be linked to environmental conditions. Unfortunately, other environmental time series data, such as Chlorophyll content are not available in the period. However, the spatial analysis of the Chlorophyll-a content, as estimated from the SeaWiFS images, seems to explain the spatial distribution of the cephalopod production (Valavanis et al., 2000).

The Modeling Approach

As was mentioned in the introduction, stochastic models have several advantages compared to deterministic or biological models (Cohen and Stone, 1987). The selection of the appropriate model, however, depends seriously on the properties of the available data. Classical regression models are statistically inappropriate if the residual terms are autocorrelated, a common situation with autocorrelated series (Bowerman and O'Conell, 1987). ARIMA models work efficiently in the simulation of autocorrelated series, whilst weak or non-autocorrelated annual time series could be modelled successfully using Multi-Regression methods (Stergiou and Christou, 1996).

In general, at least 50–100 observations are required in order to develop an acceptable model. Therefore, it was necessary, in the present investigation, to develop monthly models in order to overcome this problem. In addition to this, comparisons made between yearly averaged (or integrated) values of landings and environmental variables can not detect possible interrelations at the monthly level. On the contrary, models based on monthly values can provide both high and low-resolution relationships, if the seasonality is taken into account.

For seasonal time series, such as the monthly landings used in the study, the required amount of data increases, because each month is much like a single observation. The number of the January, February, etc., observations becomes critical and perhaps more historical data are needed to simulate a suitable seasonal model (Montgomery et al., 1990). When the number of observations is relatively low, the serial autocorrelation appears weaker (giving less significant coefficients), and Time Series techniques provide little gain compared to standard regression (linear or non-linear) techniques.

The strong seasonal character of the monthly landing time series as portrayed in Figure 5 also made it difficult to reveal periodicities of longer intervals.

Another weakness, not only for the ARIMA but also for most models, is the assumption that the system parameters in the future will be identical to the past. Intelligent or automatic methods for adapting the parameters during the evolution of the process do not exist in multivariate ARIMA models. Despite these problems, ARIMA models are in general the most efficient prediction method available today (Montgomery et al., 1990).

The performance of the univariate ARIMA model expressed the autoregressive character of the landings time series, namely the dependence of the landings at $t = 0$ on landings in the years t-1 and t-2. The model confirmed a short-term persistence or latency in the system, which hindered high frequency changes of the landings. This latency indicated that driving parameters, including fishing effort, did not change in the short term and that the environment may affect the resources contributing to the formation of good or bad year classes in time periods, longer than 1 or 2 yrs. This is in accordance with the estimated Cospectral density, which is higher during the first 2–3 yr intervals (Fig. 6).

The hypothesis concerning the role of the environment was tested by developing multivariate ARIMA models, which included the SST parameters. The incorporation of the SST data into the ARIMA models did not improve the goodness of fit greatly. This may be partly due to the lack of consistent timing in the relationship between SST and landings at the monthly level (Table 1). Additionally, the contribution of the SST in the prediction performance varied from model to model and the reduction of the residual variance was not more than 13.5% (Table 2). This may indicate that other factors not included in the model could act synergetic to the response, and/or that the extracted SST descriptors were not the best representatives of the temperature variability and possibly better spatio-temporal resolution is required.

Due to the lack of CPUE data the authors minimized the effect of the fishing effort variation, by differencing the landings data. It is obvious that this procedure does not produce time series equivalent to abundance indices. However, especially for short-term periods, the contribution of abundance variations in the transformed time series should be higher compared to those of fishing activity.

The relationship encountered between the transformed landings and SST data may suggest a relation between abundance and SST, without excluding a possible secondary effect of SST on fishing activity. However, it is difficult to imply a cause-effect relationship between landings and temperature, without investigating the sensitivity of the earlier phases in the cephalopod life cycle to certain environmental changes.

Standardization of commercial catches (CPUE) could provide a powerful method for estimating trends in the stock abundance. Unfortunately, there are many aspects of fishermen's behavior that will cause CPUE to be not proportional to abundance even on a very small spatial scale (Hilborn and Walters, 1992). Furthermore unbiased estimates of abundance indices require large samples of spatially stratified data, which are difficult to obtain, especially in pelagic species, due to their schooling behavior (Paloheimo and Dickie, 1964). For all these reasons the analysis was concentrated on the transformed (differenced) landings and catch data. Apart from the proven efficiency of multivariate ARIMA models, which can support the important practical approach of forecasting, a more analytical interpretation of the relations among the biological and environmental parameters still requires more effort.

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