Accepted Manuscript in Fisheries Oceanography

Sanz-Fernández, V, Gutiérrez-Estrada, J.C. 2021. Historical changes of Blackspot seabream (*Pagellus bogaraveo*) landing patterns in the Strait of Gibraltar from 1983 to 2016: Environmental and legislation effects. Fisheries Oceanography 30(2), 111-126.

Historical changes of Blackspot seabream (*Pagellus bogaraveo*) landing patterns in the Strait of Gibraltar from 1983 to 2016: environmental and legislation effects

Víctor Sanz-Fernández[1*] and Juan Carlos Gutiérrez-Estrada[1]

[1]Dpto. de Ciencias Agroforestales, Escuela Técnica Superior de Ingeniería, Universidad de Huelva, 21007 Huelva, Spain

[*]Corresponding author. E-mail address: victor.sanz@dcaf.uhu.es (Víctor Sanz-Fernández).

Running Head: Historical changes of Blackspot seabream landing

Abstract

The Blackspot seabream (*Pagellus bogaraveo*) is one of the most important fishery resources in the region of the Strait of Gibraltar. The fishery of this demersal species, carried out by the Spanish and Moroccan artisanal fleets, is highly vulnerable to overexploitation whose effects can be enhanced by environmental and regulatory changes. This study evaluates from a univariate perspective the variation patterns of Blackspot seabream landings (from 1983 to 2016) in the Strait of Gibraltar and investigates the effects environmental factors (sea temperature anomaly and NAO index) and regulatory changes on the landings. For this purpose, we used a wide set of univariate seanonal and non-seasonal approaches like Holt-Winters, autoregressive integrated moving average (ARIMA) models and generalized autoregressive conditional heteroscedasticity (GARCH) models and submodels. The Holt-Winters, autoregressive and ARIMA models were able to detect a strong linear dependence between current landings and previous landings as well as seasonal effects, while the GARCH models indicated the presence of intense uncertainty or volatility around two periods (1993-1998 and 2007-2011), associated to possible effects of underlying biological, environmental-climatic and regulatory factors. Therefore, the use of a combination of univariate modelling techniques has enabled us to establish potential factors associated with the variability in the landings, which could significantly help move the management of this fishery towards an ecosystem-based approach.

Keywords: uncertainty analysis, artisanal fishery, deep-sea, fishing pressure, fishery politics, fish population, long-term series.

Introduction

The thorough understanding of the patterns of variation of fish catches and the possible exogenous causes of these variations are essential requirements for the adoption of ecosystem-based management (Respondek et al., 2014). The acquisition of this knowledge is particularly important for artisanal fisheries associated with local coastal communities because this type of fisheries are less resilients to regulatory changes as well as to the biological changes introduced by environmental variations (Wakefield, 2012; De Boni et al., 2018).

A good example of this is the Blackspot seabream fishery [*Pagellus bogaraveo* (Brünnich, 1768)] in the Strait of Gibraltar. Target of two different small fleets belonging to Spain and Morocco, this species is from biomass landed and ecomomic point of views the most important fishery in this area (Gil, 2006; Czerwinski et al., 2010; Burgos et al., 2013; Palma-Pedraza, 2017; Gil, 2019). From an operationaly point of view, the Spanish fleet is composed by 60 artisanal vessels in Spain and around 102 boats in Morocco (73 longliners and 45 artisanal vessels) with fishing procedures, length-gross ton register and nominal power different (CopeMedII, 2018), but deploying their gears in overlapping operational areas very close the base ports of Tarifa, Algeciras, Conil and Ceuta for the Spanish fleet and Tangier for the Moroccan boats (Gil, 2019).

For both fleets, the fishing gear used in the fishery is the '*voracera'*, although there are important technical differences between both countries. The Spanish '*voracera'* is a longline attached to the boat composed of 2000 meters main line wrapped around a trawler which is attached 90 fishing lines of 1 metre in length, separated from each other by 1.10 meters. Each vessel can use a maximum of 30 lines/day with 100 hooks baited with sardine. From 2006 the legal dimensions of the hooks used are 3.95 ± 0.39 cm long and 1.4 ± 0.14 cm wide (hooks numbers 10, 9.5 and 9) (Order APA/8/2006). On the other hand, the Moroccan '*voracera'* is attached to a buoy, keeping the gear afloat. In the longliner, the main line is between 150-200 m long with a maximum of 50 hooks (numbers 11 to 8) per line, baited with sardine and artificial bait, arranged 1 per 3-4 metres. Each vessel can use a maximum of 20 lines/day. Instead, in the artisanal fleet easch vessel can use a maximum of 25 lines/day with 150-200 hooks (numbers 12, 11 or 9) spaced 1 meter baited with sardine (Gil, 2019; Gil-Herrera et al., 2020).

The catches are carried out in the Strait of Gibraltar which can be considered a small-scale complex ecosystem. The dynamic of this narrow (14 km of sea at the Strait's narrowest point) and deep (depth range between 300 and 900 m) strait that connects the Mediterranean Sea to the Atlantic Ocean is strongly conditioned by the interchange of water masses. Due to physical and chemical differences, the Atlantic water body flows at the surface going into the Mediterranean Sea, while the Mediterranean water body flows at depth going into the Atlantic basin to a greater o lesser extent. The Atlantic flow enters into the Strait of Gibraltar in the form of two water bodies, North Atlantic Central Water (100-700 m) (NACW) and Surface Atlantic Water (depth less than 100 m) (SAW), both characterized by seasonal variations in temperature and salinity. Likewise, the Mediterranean flow is also formed by two water bodies, Levantine Intermediate Water (LIW) and Western Mediterranean Deep Water (WMDW), that as the same as the NACW and SAW show important seasonal changes in temperature and salinity (Sverdrup et al., 1942; Parrilla et al., 1986; García-Lafuente et al., 2000; García-Lafuente et al., 2020). In turn, these oceanographic characteristics are also strongly associated to the particular climatic conditions of this area which are forced by the geomorphological configuration of their coasts. Likewise, its geographical location makes it sensitive to atmospheric variations with ocean-scale teleconnections. For example, different studies show how the North Atlantic Oscilation index (NAO) may have an effect on the Blackspot seabream abundance in the Strait of Gibraltar (Báez et al., 2014; Gutiérrez-Estrada et al., 2017; Sanz-Fernández et al., 2019; Gutiérrez-Estrada et al., 2020).

On the other hand, from a biological point of view, the Blackspot seabream has several biological characteristics that hinder its management. It is protandric hermaphrodite with low productivity, reaching sexual maturity at 4 or 6 years of age (approximately between 30-35 cm) (Buxton & Garratt, 1990). During this phase, sexual inversion occurs. The sexual inversion is from males to females when they reach a length of 32.5 cm, although it is also possible to find individuals that do not follow this pattern (Sobrino & Gil, 2002; Gil, 2019). The process of sexual inversion is conditioned by the abundance of females per class/size and their state of maturity in the population. Therefore at low densities of females in the population the sexual inversion towards them will be greater (Krug, 1998). Additionally, the size at first maturity and the gametogenic development are different depending on whether they are functional male or female (males around 30 cm and females between 35 and 36 cm) and its maximum size around 54 cm at 10 years, which makes the Blackspot seabream is considered a long-lived species, with slow growth rate (Buxton & Garratt, 1990; Sobrino & Gil, 2002; Gil, 2006; Gil et al., 2019).

These bio-ecological and environmental characteristics strongly condition the amount of biomass extracted, the minimum catch length and gear size used which has leds to pass different normatives subjected to continuous modifications to limit catches and landings. This way, the first regulation of the Blackspot seabream fishery was passed in 1995 (Royal Decree 560/1995) which established the minimum catch size at only 25 cm. Three years later the Order of 17 June 1998 established a specific plan for fishing with the '*voracera*' in the area of the Strait of Gibraltar, which established a minimum landing size and different aspects related with the boundaries of the fishing grounds, technical characteristics of the gear and number of vessels authorized. From 1998 to 2012, there was a policy transition where the above aspects have been modified (Orders: 17 June 1998; APA/3323/2002; APA/8/2006; APA/274/2007; APA/445/2008; ARM/521/2009 and ARM/3536/2009). The Order (AAA/1589/2012) established a management plan similar to the determined in 1998, although the maximum number of hooks allowed is increased to 2400, the number of authorized vessels is reduced to 88, the prohibition of simultaneous use of gear is continued and the fishing effort remains at 5 days per week and a minimum size of 33 cm, which is the current minimum landing size (Regulations EU; 1225/2010 and 2017/787). Also the fishing ban and annual total catch (TAC) have been regulated (AAA/1589/2012; Regulation (EU) No 1367/2014).

On the other hand, the regulation of the activity of the Moroccan fleet has been in force since 1992. It only sets out the scope of operation (Tangier and Al Hoceima and below 3 miles in the area between Al Hoceima and Saidia), the minimum landing size is 25 cm and the technical characteristics of the gear that will be used (CopeMed II, 2011).

All these bio-ecological, environmental and regulatory factors interact with each other by means unknown mechanisms which has been recongnized by others authors as the main sources of uncertainty that hinder an adecuate fisheries resources management (Hilborn et al., 2001; Agnew et al., 2009; Fulton et al., 2011; Leitão et al., 2014; Hart & Fay, 2020; Van Beveren et al., 2020). This is because the interactions of these factors lead to misunderstood changes in fish dinamics reflected as variations in the frequency and intensity of fish abundance (Hsieh et al., 2006; Anderson et al., 2008). To understand the source of variability or volatility in fish stocks is a key question because it affects to several decision making by the managers as for example the biological reference points or the capacity to determine the extinction risk for a population (Pimm, 1991; Hilborn et al., 2001). Therefore, for a fishery with the characteristics like Blackspot seabream in the Strait of Gibraltar the analysis and characterization of the catches and the evolution of historical landings as well as the identification of the periods and possible causes that determine the fluctuation of the volatility associated to the fishery are very important aspects that condition its adequate management.

The study of the dynamics of catches, landings and abundance indexes derived from them (catch per unit of effort -CPUE- or landings per unit of effort -LPUE-) is a topic that has been widely investigated in fisheries science (Stergiou et al., 1989; 1991; Potter et al., 2004; Czerwinski et al., 2007). Stergiou et al. (1997) established three basic analysis techniques for detecting patterns of variation in fisheries time series: i) models based on a deterministic approach with linear regressions able to explain changes in the fishing variables in terms of changes in biotic and abiotic variables (multivariate approach); ii) techniques based on univariate time series analysis that rely on the assumption of continuity, that is, that assume that past changes will continue to be reflected in the present and the future as their patterns will continue into the future (univariate approach); and, iii) approaches based on combinations of the aforementioned methodologies.

In the cases of univariate approaches, numerous classical methodologies as such Holt-Winters and the Autoregressive Integrated Moving Average (ARIMA) models have been proposed for the analisys of abundances, catches and landings (Lloret et al., 2000; Tsitsika et al., 2007; Kim et al., 2015). These methods have a fundamental advantage on multivariante approaches which is that they can obtain estimations only from the variable analysed. In this way, it is assumed that each observation can be explained as a linear/non-linear function of their past values. This implies that the variance of data series is equivalent to the co-variances of any external variable sets and therefore a univariate model that explain shifts of historical data has the capacity to detect the external variables influence implicit in the variance of time series (Gutiérrez-Estrada et al., 2007). Obviously a common drawback of these univariate approaches is that the structures of these models don't allow the inclusion of terms such as external factors or variables which hinders to interpretate the effects of those variables that could have an impact on the target variable and which are ultimately the causes of the variability lagged in time or volatility of the variable analysed.

To mitigate this problem Bollerslev, (1986) developed a family of models known as generalized autoregressive conditional heteroscedasticity (GARCH) models which can quantify the volatility associated with a time series without the need for include external variables. These models incorporate in their origins, the assumption that the time series are composed by several volatility clusters. In other words, a strong unexpected fluctuation in a time series tend to be followed by periods of similar characteristics, while periods in which the time series are stable are also followed by stability. This way, these kinds of models can collect the inertial behaviour as well as the dynamic behaviour typically detected in the time series. For this reason their use is relatively widespread in the field of finance and economy (Mohammadi & Su 2010; Liu & Shi 2013; Girish, 2016; Ortiz-Arango, 2017). In contrast, their potential application to the analysis of fisheries time series has been overlooked to date.

The main objective of the study is to carry out an evaluation from a univariate perspective of the patterns of variation of Blackspot seabream landings (*Pagellus bogaraveo*) between 1983 and 2016 in the Strait of Gibraltar. For this purpose, we have used different univariate approaches as Holt-Winters models, ARIMA models and GARCH Models. For each technique, we have developed their corresponding sub-variants. Particularly for GARCH models, we explore their applicability to fisheries time series and investigate their capacity to detect the effect of some bioecological and environmental factors (water temperature anomaly and NAO index) and regulatory factors on the increasing/decreasing volatility.

Material and Methods

Study area and databases

This study was based on the landing time series of Blackspot seabream (*Pagellus bogaraveo*) in the Strait of Gibraltar. The fish catching area of interest is the operational fishing area of the Blackspot seabream fleet in the sector between 6º25’W to 5º15’W and 35º45’N to 36º15’N, corresponding to the extreme southeast of International Council for the Exploration of the Sea (ICES) Division IXa (Burgos et al., 2013) (Figure 1). The monthly landings time series for this species correspond to the landings carried out by the fleets from the Spanish ports of Tarifa, Algeciras, Conil and Ceuta and Moroccan port of Tangiers between 1983 and 2016. The main reason why the fleets have their fishing grounds near their base ports, lies in the migration patterns of the species. Different studies, that are carried out on this aspect, indicate that juveniles move from their breeding area to the fishing grounds of the Strait of Gibraltar while adult specimens only show movements within the fishing grounds where the fleet operates. Therefore, all the catches made by both fleets, the Spanish and the Moroccan, come from the waters of the Strait of Gibraltar (Gil et al., 2001; Sobrino & Gil, 2001; Burgos et al., 2013; Gil, 2019).

The trend, seasonality, and random component of the historical series of sets were obtained by applying a classical seasonal breakdown by moving averages. The model chosen for the decomposition was multiplicative (CV = 1.65) because it had a lower coefficient of variation (additive CV = 5,52).

Water temperature anomaly (ºC) and NAO climate index were used as explanatory proxy variables of the results produced by volatility (Báez et al., 2014; Gutiérrez-Estrada et al., 2017; Sanz-Fernández et al., 2019). The data on temperature (°C) were obtained for a monthly period of 33 years 1983-2015 from the Simple Ocean Data Assimilation (SODA) v 3.3.1 (http://www.atmos.umd.edu/~ocean). SODA provides monthly values of different parameters such as sea temperature in a resolution of 1/4ºx 1/4º for 50 depth levels. As Blackspot seabream is a demersal species, the SODA data were filtered to obtain the first 24 depth layers (from 5 to 525 meters). For each layer, the monthly mean water temperature was calculated and therefore, 24 time series of water temperature monthly scaled were obtained.

The historical time series of the monthly NAO index spanning 1983 to 2016 were obtained from the US National Center for Atmospheric Research (https://climatedataguide.ucar.edu/climate-data/hurrell-northatlantic-oscillation-nao-index-station-based). This link provides a NAO time series in a monthly time scale (Hurrell & National Center for Atmospheric Research Staff, 2020).

The significant correlations between the landings time series and environmental and climate time series (water temperature anomaly and NAO climate index) was annual calculated with lags of 0, 1, 2 and 3 years, with the objective of evaluating possible present and past climate and environmental effects.

Exponential smoothing (Holt-Winters), Autoregressive (AR) and Autoregressive integrated moving average (ARIMA) models

A common characteristic of these methods is that in all cases their estimations are dependents of the values of the variables to estimate lagged in time. In the case of Holt-Winters models their predictions are means of past values exponentially weighted such that more recent observations have greater weight or importance than those from further into the past (Holt, 1957; Winters, 1960). Instead, in the autoregressive family models (AR and ARIMA), the pattern of change in a variable in period *t* is explained by its behaviour in the past plus a white noise term (Box & Jenkins, 1976).

All these models have been widely used with notable results in fishery science (Stergiou et al., 1997; Lloret et al., 2000; Gutiérrez-Estrada et al., 2007) particularly the ARIMA models.

Univariate ARIMA models (*p,d,q*) explain the behaviour of a variable over time based on their own past observations and forecasting errors. In this expression, *p* is the number of autoregressive parameters, *d* is the number of differentiations required for the time series to become stationary and *q* is the order of moving average parameters. The Box-Jenkins model is expressed by the following equation:

$$Y_t = \phi_0 + \phi_1 y_{t-1} + L + \phi_p y_{t-p} + a_t - \theta_1 a_{t-1} - L - \theta_q a_{t-q}$$

The coefficients of parameters ϕ and θ are determined by the data (y), through consistent statistics. ARIMA models also enable us to fit seasonal components in the data, and in this case, the model is expressed as ARIMA (p,d,q) $(P,D,Q)^S$, where P is the number of autoregressive parameters in the seasonal component, D is the number of differences required for the time series to become stationary, in the seasonal component, and Q is the order of the moving average in the seasonal component, while S is the series periodicity.

Autoregressive conditional heteroscedasticity (ARCH and GARCH) models

Autoregressive conditional heteroscedasticity (ARCH) models proposed by Engle (1982) were developed to study volatility in inflation in the United Kingdom. In this approach, a model is created to fit the changing variance of a time series, in this case, related to finances. The goal of the author was to indicate the performance of a financial asset that was not autocorrelated but was not independent. In this case, the variance may be described as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + \cdots + \alpha_t y_{t-m}^2$$

They assume that the positive and negative shocks have a similar effect on the volatility of the variable, which is not true, negative shocks being known to have a more pronounced impact on volatility (Black, 1976; Christie, 1982).

In order to address the problems inherent to ARCH models, Bollerslev, (1986) developed the generalized autoregressive conditional heteroscedasticity (GARCH) models. In these models, the conditional variance structure depends not only on the square of the lags periods time series *p*, as in the ARCH model, but also on the lags conditional variances *q* periods. A characteristic of GARCH models is that the residuals follow an ARIMA model.

The GARCH model can be expressed as follows:

$$y_t^2 = \alpha_0 + \sum\nolimits_{i=0}^{\tau} (\alpha_i + \beta_j) y_{t-i}^2 - \sum\nolimits_{i=0}^{\tau} \beta_j (y_{t-j}^2 - \sigma_{t-j}^2) + v_t$$

where $v_t = y_t^2 - \sigma_t^2$ and $\tau = max\ (p, q)$.

GARCH family of models

Since the basic equation proposed by Bollerslev, (1986), numerous variations of the model have been developed to adapt to different conditions of the data series. Among them, given their applicability, we should highlight the exponential weighted moving average (EWMA) models (Best, 1999), the asymmetric power ARCH models (APARCH) (Zing et al., 1993), the integrated generalized autoregressive conditional heteroskedastic (IGARCH) models (Engle, 1982; Bollerslev, 1986), the standard GARCH (sGARCH) models (Bollerslev, 1986), the component sGARCH (csGARCH) models (Lee & Engle, 1999), the fractionally integrated GARCH (FIGARCH) models (Baillie et al., 1996) and the GARCH family (fGARCH) models (Hentschel, 1995). Within the fGARCH models, there are eight notable submodels: full FGARCH (ALLGARCH) (Hentschel, 1995), asymmetric power ARCH (APARCH) (Ding et al., 1993), absolute value GARCH (AVGARCH) (Taylor, 1986), GARCH (Bollerslev, 1986), GJRGARCH (GJR-GARCH) (Glosten et al., 1993), nonlinear asymmetric GARCH (NAGARCH) (Engle & Ng, 1993), nonlinear ARCH (NGARCH) (Higgins & Bera, 1992) and threshold GARCH (TGARCH) (Zakoian, 1994).

Goodness-of-fit measures

For this study, a total of 10 types of accuracy measurements were considered. The total variance in the data that can be explained by a model was analysed using four estimators: the coefficient of determination (r^2), the standard error of prediction (%SEP) (Ventura et al., 1995), the coefficient of efficiency (E_2) (Nash & Sutcliffe, 1970; Kitanidis & Bras, 1980; Legates & McCabe, 1999) and the mean relative variance (ARV) (Griñó, 1992). The error of the model in terms of estimating the study variable (landings) was assessed using the root mean square error (RMSE) and the mean absolute error (MAE). The lag time accumulated by the model during the estimation was assessed with the persistence index (PI) (Kitanidis & Bras, 1980; Anctil & Rat, 2005). Finally, the quantity of information lost by the model during the validation phase was analysed using three different criteria: the Akaike information criterion (AIC) (Akaike, 1974), a bias-corrected version of the AIC (AICc) (Hurvich & Tsai, 1989) and the Bayesian information criterion (BIC) (Qi & Zhang, 2001). Also we calculated the threshold for the maximum error allowed by means the basic naïve model (NF).

Calibration process

The various different models were implemented in Rstudio 1.1.456, an integrated development environment based on the R programing language (R Core Team, 2020). The HoltWinters and AR functions, both from the stats package in R (R Core Team & contributors worldwide, 2018), were used for estimating the exponential smoothing models and the autoregressive models respectively. Lastly, the auto.arima () function (Hyndman & Khandakar, 2008) was used to obtain the best ARIMA model, according to AIC, AICc or BIC, within the order constraints provided. The range of variation of the parameters (p, q, d) (P, Q, D)^s of the ARIMA models was [0-6]. This range (more extensive than usual) ensures that the selection of p and q parameters is optimal.

For building the GARCH models, first, the variance of the time series was modelled individually, varying the parameters (p,q) of the models in the range [1-9]. For this, a function was developed that executed all the possible combinations and selected the best model as indicated by the lowest AIC. Having modelled the variance, an autoregressive moving average model, ARMA (*p*,*q*), was incorporated into the best GARCH, in order to consider the effects of the mean, yielding an ARMA (*p*,*q*) + GARCH (*p*,*q*) model. Depending on the GARCH model, various different probability distributions were explored: normal (*norm*), skew normal (*snorm*), generalized error (*ged*), skew generalized error (*sged*), Student's t (*std*), skew Student's t (*sstd*), normal inverse Gaussian (*nig*), generalized hyperbolic (*ghyp*), Johnson's reparametrized SU (*jsu*) and quasi-maximum likelihood estimation (*qmle*). All of the development of the models was performed using the garchFit () and ugarchfit () functions from the fGarch (Wuertz et al., 2019) and rugarch (Ghalanos, 2017) packages respectively. The best model was identified based on the error measures described above goodness-of-fit measures. Once the best model was selected, the volatility (σ_t-standard deviation) without the effect of the average was presented.

Finally, a multiple change point analysis was applied to the volatility series estimated by the best ARMA (*p*,*q*) + GARCH (*p*,*q*) model, with the objective of detecting abrupt variations in the mean of the series that allow to identify transitions between different periods. This was done by using the function cpt.mean () from the R changepoint package, version 2.2.2 (Killick & Eckley, 2014; Killick et al., 2016). The exact algorithm used was segment neighborhood algorithm (Auger & Lawrence, 1989; Bai & Perron, 1998) because our series presented a non-normal distribution (Shapiro-Wilk normality test, p-value < 0.05), therefore the statistical test of distribution of the data was the non parametric cumulative sum (CUSUM) (Page, 1954). No traditional penalty was applied to the algorithm as they are not appropriate for the cusum test statistic (Killick et al, 2016). The maximum number of segment/regime (number of changepoints + 1) to search was 5, thus selecting 4 change points.

Results

Analysis of the landings time series for Blackspot seabream

The Blackspot seabream fishery started in 1983 with two peaks, both of them in June 1997 and 2009 with a total of 283.5 tonnes (Figure 2a, 2b). In March 1999 and 2000, the lowest landings were recorded totalling 2.02 tonnes. The mean landing during the entire period was 34.82 ±1.27 (standard error) tonnes /month. The landing time series of Blackspot seabream was characterised by a marked seasonal component (Figure 2c, 2d).

The port with the largest historical volume captured was Tarifa, with 10308.2 tonnes, followed by Algeciras and Tangier with 1924.3 and 1438.1 tonnes respectively. Algeciras, Conil and Tarifa showed a downward trend in captured volume throughout the historical record. A clear upward trend is detected for Tangier (Figure 3). Regarding the annual contribution to the landings by port, Tarifa was the most important fishing port between 1983 and 2009 (78.92% of the total landings). After 2009, there is a change in the trend, towards a more balanced contribution to the landings across the ports. Tangier has caught up with Tarifa in terms of volume landed ($\text{Tarifa}_{\text{2010-to-date}}$=37.71%; $\text{Tangier}_{\text{2010-to-date}}$=44.71%).

Exponential smoothing, autoregressive and ARIMA models

Three exponential smoothing additive models and three exponential smoothing multiplicative models were calibrated: simple exponential smoothing ($\beta = \gamma = 0$), Holt's linear trend ($\gamma = 0$) and Winter's seasonal ($\beta \neq \gamma \neq 0$). Given the error statistics obtained, we can clearly state that the most appropriate modelling technique for the series was Winter's seasonal, which provided the most acceptable level of error both additive and multiplicative method (Table 1).

In the case of the autoregressive approach, the lag time and variance explained by all the models were statistically acceptable with similar levels of error but the best fit was obtained using the Burg and Yule-Walker method (Table 1). Finally, we built 93 ARIMA models, resulting from different combinations of the parameters. Table 1 and Figure 4 shows the results of the best ARIMA model (103) $(011)^{12}$.

GARCH family of models

A total of 123 GARCH models were calibrated. To estimate the landings using the GARCH family of models, an ARMA model (1,3) was incorporated in the models in order to take into account the effects of the mean. The ARMA model (1,3) was selected as the ARIMA model (103) $(011)^{12}$ provided the best results.

Comparing the GARCH modelling techniques, the mean values of the error statistics obtained for the best models during the validation period were: RMSE= 18.75 (t), MAE = 13.41 (t), %SEP= 53.85, E_2 = 0.46, ARV = 0.53, PI = 0.26, AIC = 2.55, AICc =2.62, BIC = 2.55 and r^2 = 0.47. In this case, the probability distributions with the best results were *sstd*, *nig* and *jsu*, with absolute frequencies of 4, 3 and 3 respectively.

Analysis of the good of fit measurements indicates that the models with the shortest lag time in the fit and that explained the highest percentages of variance during the validation period was the APARCH model with the *sstd* distribution (Table 1; Figure 5).

The estimated volatility for the best ARMA (1,3) and GARCH (p,q) model (APARCH-SSTD-) is shown in the Figure 6. We found a variation of between 16.26 and 59.41 tonnes between

1983 and 2016. The maximum values were found in the summer. In contrast, the minimum value was observed in the spring, specifically in May 2005. Finally, the model indicated that volatility did not have a trend and again indicated two clearly marked cycles, the first one approximately from 1993 to 1999 and the second from 2007 to 2011.

The application of multiple change point analysis revealed the existence of 4 change points and 5 different periods. The change points detected were November 1992, July 1998, March 2007 and January 2011, therefore the periods were: January 1983 - November 1992, December 1992 - July 1998, August 1998 - March 2007, April 2007 - January 2011 and finally February 2011 - December 2016 (Figure 6). The average volatility of each period was: 21.47 (tonnes), 33.46 (tonnes), 21.48 (tonnes), 27.13 (tonnes) and 21.12 (tonnes), respectively. Therefore, the periods with the highest average volatility were December 1992 - July 1998 and April 2007 - January 2011, which coincide with the cycles clearly marked and detected by the model.

After grouping and analysing the accuracy measurements, the best univariate models with various different approaches for characterising changes over time in Blackspot seabream landings between 1983 and 2016 explained a mean of 57% of the variability associated with the time series and acceptable mean PI of 0.41. The autoregressive and ARIMA models provided the best results. These models showed the shortest time lag and the highest coefficients of persistence, lost the least information (24%) and explained the greatest variance (61%).

Correlations of landings with water temperature anomaly and NAO index

Table 2 shows the number of total significant correlations of water temperature anomaly (ºC) and Blackspot seabream landings. The highest number of significant correlations was obtained with a lag of 1 year (C=137) followed by a lag of 2 years (C=127). In the lag = 1 year the predominant correlations were positive, while in the lag = 2 year were negative. Analyzing the years, it could be observed that the greatest number of correlations was concentrated within two time periods: 1985-1993 and 1998-2011. The depth range with the highest number of correlations was [125-185] m.

On the other hand, Table 3 shows the significant correlations between landings and the NAO index. This index showed correlations without a lag = 0 year and with a lag =1, 2 and 3 years. Significant correlations negative were obtained in 1991, 1997, 1998, 2000 and 2009.

Discussion

There is no ideal form universally applicable of fisheries management. Neither is there a strict rule as to how a set of data should be meta-analysed, especially in a field such as fisheries analysis where the sources of information are subject to strong uncertainties. But what is clear is that it is fundamental detect the periods of high variability of fish stocks to adquire a better understranding of the relationships between bio-ecological, environmental and regulatory factors and fish resources which allow detecting and identifying the sustaible exploitation alternatives, opening the way to an ecosystem based management. Thus, this paper present a study aimed at analyse the variation patterns of Blackspot seabream landings in the Strait of Gibraltar in order to detect analogies as a consequence of regulatory changes and some bio-ecological and two environmental factors as water temperature anomaly and NAO index.

In this sense, a significant step is the approach type to apply to analyse the time series (univariate, multivariate or a mixed approach). Each one of these approaches has their advantages and disadvantages and their use can be force by the specific time series feature to analyse. For example, Stergiou (1989, 1991), Stergiou et al. (1997), Czerwinski et al. (2007) or Gutiérrez-Estrada et al. (2007) among others, indicate that the univariate approaches assume that the co-variance due to all possible external factors involved in the time series is contanined in the time series itself. This *a priori* allows reduce the theorical ecological framework that supports the time series variability in relation to the possible external factors, which facilities fit a model to the time series. However, this will hinder the achievement of functional relationships between the time series analyse and external factors. On the other hand, if a particular time series as the change of variability patters lagged in time or volatility wants be analysed (as in this study), then a specific approach that allow carry out this analysis must be select. This explains the selection of a univariate approach and particularly the selection of GARCH models in this study.

Exponential smoothing (Holt-Winters), AR and ARIMA models

The original equation of the Holt-Winters model was developed to analyse time series characterised by the presence of linear trends and influenced by a seasonal factor. Gutiérrez-Estrada et al. (2004) indicated that Holt-Winters models are very sensitive to autocorrelation effects. Due to this, the best PI values did not exceed 0.4, which clearly indicates the autoregressive nature of the time series and the difficulty of differentiating it from a simplistic model. This situation has previously been noted by other authors (Mini et al., 2015). Winter's seasonal multiplicative model was slightly better than its additive analogue, possible due to multiplicative method is able to capture the effect of exogenous factors that cause an increase in the time series as a consequence of the action of these factors on the interaction between seasonality and trend.

In our study, the AR models explained a relatively high percentage of the variance (59-62%). This good fit indicates the existence of linear dependence between the current and past landings, highlighting the highly autoregressive nature of the time series. That is, the current pattern of landings is constrained by the history of these landings. This would explain the good results obtained with ARIMA models. The structure of the ARIMA model with the best fit has a clearly autoregressive ($p = 1$) and seasonal nature (S=12), but also a strong moving average component (q=3). This may be interpreted as the landings being partially independent of the population density which, in turn, can be attributed to changes in the particular conditions of each annual class or to variations in catches and fishery activity (Becerra-Muñoz et al., 2003; González & Lorenzo, 1995; Manjarrés-Martínez et al., 2010). On the other hand, the values P=0 and Q=1 suggest a partial linear relationship between the seasonally differenced rates of change and the prior error term, which also could be interpreted as density-independent effect and a dependence of external factors at least in over a period of time. For example, the existence of the seasonal parameter could be related to the success of recruitment of the species. In other fisheries such as the Japanese anchovies, *Engraulis japonicus*, in the South Korean Sea, the seasonal variability in their catches per unit of effort, taken by the ARIMA seasonal model, is interpreted as a consequence of the strength of recruitment and the growth of individuals recruited from previous months (Kim et al., 2015).

These external factors affect to the species accessibility and vulnerability which finaly will be reflected on fishery activity and landing. In turn, this helps to explain why the ARIMA models generally performed better than the Holt-Winters models, as has also been indicated by other authors. For example, Becerra-Muñoz et al. (2003) analysed the spatial patterns of *Chirostoma sp* and *Chapalichthys encaustus* in Lake Chapala (Mexico) using ARIMA models. They found that human pressure, in this case due to domestic pollution, strongly determined the structure of the ARIMA models. Similarly, Manjarrés-Martínez et al. (2010) detected that the structure of the ARIMA models significantly depended on the lack of a regular component in the catch per unit effort of *Scomberomorus cavalla*, determined by the effect of wind on abundance in the Colombian Caribbean Sea.

Successful application of the Holt-Winters, AR and ARIMA models to the catch time series supports the view that current catches are determined by catches in the past. This helps to understand the changes over time and biological determinants of commercially-exploited fish populations. Taboada & Anadón (2016) used the "ghost of overexploitation past" hypothesis proposed by Connell, (1980), with the intention of explaining the decrease in anchovy catches in the Bay of Biscay as the consequence of past fishing. Kim et al., 2015 also indicated through the application of ARIMA models, that the incremental changes in the catch per unit effort of *Engraulis japonicus* in the South Korean Sea, depends on their variations in previous years.

In the case of the Blackspot seabream, the fact that past landings are twice as high as recent landings, may suggest that past high fishing pressure exerted on the fraction of the adult and mature population has prevented the stock from recovering, resulting in fewer current landings and increasing the likelihood of sudden collapse in the event of recruitment failure. This hypothesis seems reasonable given that this species is highly sensitive to the effects of overexploitation (Lorance et al., 2011). In fact, nowadays this species is classified as a near threatened by the International Union for the Conservation of Nature's (IUCN) Red List of Threatened Species (Carpenter & Russell, 2014). The pattern of dependence of landings may also be applied to the biomass, and this would be in agreement with the results of Gutiérrez-Estrada et al. (2017) who obtained a realistic simulated time series showing changes over time in total biomass with a discrete biomass model and high levels of correlation between past and present biomass with autoregressive modelling.

Volatility and the GARCH family of models

In general, the GARCH family provided acceptable percentage of explained variances. Regarding the probability functions, the APARCH, FGARCH/ALLGARCH, FGARCH/APARCH and FGARCH/TGARCH models worked well with the following distributions: *sstd*, *jsu*, *sstd*, *ghyp/jsu* and *nig*, respectively, yielding results notably close to those of the Holt-Winters and ARIMA models. Nzombe, (2017) compared the results of the symmetric models GARCH (1,1) and GARCH-M with asymmetric models EGARCH, APARCH and TGARCH (or GJR) to model the volatility of fish populations of fishing companies in West Cape listed in the Johannesburg Stock Exchange. For this, they used various different probability distributions (as *norm* and *sstd*) and combinations of model parameters. On the other hand, Lai et al. (2005) used GARCH models to explain the white noise generated after the application of ARIMA models, used to demonstrate the presence of seasonality in the catches in the fisheries of Western Australia. These authors concluded that the combined use of ARIMA-GARCH models is a good tool for describing catch data and making estimations in some cases.

The relatively good fit of the APARCH models for estimating Blackspot seabream landings is not surprising, as these models are really a version of the ARCH models that also include an asymmetric term which is able to respond to the positive and negative volatility of the variable (Black, 1976; Engle & Ng, 1993). In this way, APARCH models are able to capture the positive and negative effects of external factors on increases or decreases in landings. This could indicate that the fluctuations in landings attributable to external factors are only important in some periods. In the current study, we have detected how Blackspot seambream landings are significantly correlated with environmental factors in periods where volatility is the most important. This also support the results reported by Gutiérrez-Estrada et al. (2020). In this study the authors developed two new indexes (the significant effect of the environmental parameter –EF- and the relative weight index –RW-) that allow improve the interpretability of the environmental effects on abundance of fish stocks applied to the same data set. In this case the EF index showed that the significant effect of temperature was centred on the two periods in which the volatility was highly variable (1993-1998 and 2007-2011). On the other hand, this would support the hipothesys that landing time series could reflect, at least a part of the underlying population dynamics. Similar conclusions were obtained by Rouyer et al. (2008). These authors indicated that general trends of catch or CPUE indices cannot be used alone to document any potential change in biomass or depletion fish population when tried to explain the interplays among the population dinamics of large pelagic fisheries and environmental factors. Likewise, Rouyer et al. (2008) reported that the identification of the fluctuation periods is a key issue because the bias in catches and CPUEs strongly affect biomass and fish mortality from classical stock assessment models.

Báez et al. (2014) analysed the potential effect of previous three years of SST and NAO EOF index on the variation in relative abundance of Blackspot seabream in the Strait of Gibraltar and found an overall significant statistical correlations between these variables. Also, Borges et al. (2003) highlighted NAO index influences the Iberian coastal upwelling by modulating the intensity and latitudinal position of the trade winds belt, which may affect the recruitment dynamics of the fishing populations. In this sense, negative NAO are usually associated with weak recruitment events of pelagic species which implies that negative NAO years, catches are expected to decrease as there are fewer individuals in the population (Santos et al., 2012). On the other hand, in positive phases, coinciding with periods of drought, there is a strengthening of recruitment and catches may increase in coming years, which could mitigate the decline in biomass as a result of overfishing (Gutiérrez-Estrada et al., 2017). However these findings contrast with the results of our study which indicate that the effects of NAO on landings would only be concentrated in some particular years. These years coincide with the most volatile years in terms of landings (between 1993-1998 and 2007-2011, approximately), which would support the results of Gutiérrez-Estrada et al. (2017) and Sanz-Fernández et al. (2019). These authors reported that the Blackspot seabream abundance has low resilience to climatic-oceanic variability when the potential biomass is at low levels. Under these conditions, small environmental changes can hinder the population recovery, which will be reflected in the volatility of landings Again, these periods coincide with those in which the EF and RW indexes for SST and NAO are significant in Gutiérrez-Estrada et al., (2020) which reinforce the idea that it is very difficult establish causal relations between atmospheric indexes as NAO and parameters of the dynamic of commercially exploited fish population.

On the other hand, the NAO index has been also related with the abundance variability of zooplankton (Heat et al., 1999; Pershing et al., 2005), which could determine the strength of recruitment of the Blackspot seabream in the Strait of Gibraltar. If spawning occurs at the same time as the maximum abundance of zooplankton, the survival of the larvae would increase leading to strong recruitment. By contrast, if there is a mismatch between the two moments then recruitment would be weakened (match-mismatch hypothesis) (Cushing, 1990). This has been put forward as an explanation for the variability of fish recruitment, as in the case of North Sea cod (*Gadus morhua*), between the years 1960-1980, in which the NAO index was predominantly negative and the abundance of phytoplankton and zooplankton decreased (Colebrook, 1986).

In the case of this species, the effect of low biomass levels on volatility can be increased by its biological nature. The Blackspot seabream is protandric hermaphrodite specie with slow growth rate, larger size at sexual maturity, high age at first sexual maturity and high fecundity. This life-history traits are associated with vulnerability to fishing (Anderson et al., 2008). A recent stock report indicates that a large part of the landings are immature fish with a size significantly below the minimum landing size (CopeMed II, 2012). During the first block of greater volatility (1993-1998) the minimum landing size was 25 cm while in the second period (2007-2011), the length varied from 25, 30 to 35 cm in EU and international waters of VI, VII, VIII and IX (Council Regulation (EU) No 3094/86; Council Regulation (EU) No 1359/2008; Council Regulation (EU) No 1225/2010). The current minimum landing size is 33 cm in EU and international waters of VI, VII, VIII and IX (Council Regulation (EU) No 2017/787), which is below the size of the age class with the highest reproductive effort. This cause a truncation of the age structure, which reduce the capacity of population to buffer environmental events (Hutchings and Reynolds, 2004; Perreti et al., 2017). The age-truncation (AT) effect hipothesys suggests that when new recruits composed most of the stock, the juvenescent population is more likely to track variable environmental process directly (Murphy, 1967; Anderson et al., 2008). This implies that younger and smaller fish are more susceptible to changes in the environment and therefore it is expected that periods with a high volatility will be associated to lower catch size. The AT effect will be reinforce in those species like Blackspot seabream in which the impact of fishing effort is focused mainly on females and individuals bigger than 35 cm. This can lead to unstable population dynamics which could explain much of the volatility detected in the Blackspot seabream time series. This way, Gutiérrez-Estrada et al., (2017) and Gil (2019) reported two periods in which the mean size of total length of landigns dropped significantly. The first one period between 1994 and 1998 and second one between 2010 and 2011. Again both time periods were characterized by high volatilities detected by GARCH models.

Furthermore, the Blackspot seabream fishery has been affected by changes in fishing pressure, through greater operational efficiency of the fleet, with initially fairly permissive legislation moving towards clearly more restrictive regulations on the Spanish government, seeking to reduce the intensity of fishing and catches detected in the fisheries time series. The first restrictive measure was put in place in 1998, at the time of the highest landings until then, and this could explain the notable landing volatility between 1993 and 1998. Nonetheless, the 1998 regulations were not tightly enforced and landings significantly increased between 2008 and 2010 (Orders: 17 June 1998, APA/3323/2002, APA/8/2006, APA/274/2007, APA/445/2008, ARM/521/2009, ARM/2687/2009, ARM/3536/2009). Therefore, regulatory transitions also coincide with the periods in which they occur an increase in landing volatility periods and continues until the implementation of new, much more restrictive, regulations at the beginning of 2012 (Order AAA/1589/2012). The increase in volatility starting mainly from 2008 coincides with the change in the relative importance of the ports in terms of biomass landed, from the base of the Spanish fleet (Tarifa) to a Moroccan port (Tangier). This could have a strong impact on the volatility of the time series because the Moroccan legislation is considerably more lax concerning landings of this species in the Strait of Gibraltar. Therefore, from a political perspective, the Spanish and Moroccoan government should evaluate the regulatory framework (effective number of vessels, gears, fishing effort, etc.) and landings very cautiously and simultaneously to avoid large fluctuations in landings.

Conclusions

A broad management approach is required for managing a commercially-exploited species in a context of marked socioeconomic, climatic and ocean variability and, as is the case of the Blackspot seabream, complex biology. Undoubtedly, the success of ecosystem based management approach relies on fishery managers having accurate information concerning potential changes in fish catches over time. For this reason, in this study, we have assessed the suitability of three different univariate modelling methods (exponential smoothing, ARIMA and the GARCH family of models) to characterise and analyse the monthly Blackspot seabream landings in the Strait of Gibraltar between 1983 and 2016.

This analysis can be of direct use in fisheries management and planning of this shared marine resource (for example, detecting short-term variations in volatility could be integrated into a protocol that indicates managers that some factor is unbalancing catches). In this sense the univariate techniques have been able to quantify and detect the trend, seasonality and volatility behaviours of landings time series. In relation to this last aspect, to out knowledge this is the first time that a volatility analiys is carried out directly on time series of catches or landings. With this approach to study the time series of the landings of Blackspot seabream (*Pagellus bogaraveo*) between 1983 and 2016 in the Strait of Gibraltar, decisions on their management could be taken taking into account the uncertainty associated to landings behaviour, which would undoubtedly allow the application of the sustainable management and planning principles to short and longer term.

Acknowledgements

The authors wish to express their gratitude to Dr. Juan Gil-Herrera (Oceanography Spanish Institute, Cádiz, Spain) and Dr. Said Benchoucha and Sana el Arraf (National Institute of Fisheries Research - INRH-Tangier, Morocco) for providing the data set of Blackspot seabream landings in the Spanish and Moroccan ports. Víctor Sanz-Fernández is financed by the Spanish Ministry of Science, Innovation and Universities with a FPU fellowship (FPU17/04298).

Compliance with ethical standards

Conflict of Interest: There are no conflict of interests to declare.

Author Contribution

The two authors contributed extensively to the research and contributed to development of concepts presented in this paper. Dr. Juan Carlos Gutiérrez Estrada designed the study. Víctor Sanz Fernández Fernández programmed the R script that allows the adjustment of the all models. Both authors interpreted the data, reviewed the literature and wrote the initial manuscript, as well as commented on and approved the final version.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Agnew, D. J., Pearce, J., Pramod, G., Peatman, T., Watson, R., Beddington, J. R., & Pitcher, T. J. (2009). Estimating the Worldwide Extent of Illegal Fishing. *PLoS ONE*, 4, e4570.

Akaike, H. (1974). A new look at the statistical identification model. *IEEE Transactions on Automatic Control*, 19, 716-723.

Anctil, F., & Rat, A. (2005). Evaluation of neural network streamflow forecasting on 47 watersheds. *Journal of Hydrologic Engineering*, 10, 85-88.

Anderson, C. N. K., Hsied, C. H., Sadin, S. A., Hewitt, R., Hollowed, A., Beddington, J., May, R. M. & Sugihara, G. (2008). Why fishing magnifies fluctuations in fish abundance. *Nature*, 452, 835-839.

Auger, I. E., & Lawrence, C. E. (1989). Algorithms for the Optimal Identication of Segment Neigh-borhoods. *Bulletin of Mathematical Biology*, 51, 39-54.

Báez, J. C., Macías, D., de Castro, M., Gómez-Gesteira, M., Gimeno L., & Real, R. (2014). Assessing the response of exploited marine populations in a context of rapid climate change: the case of blackspot seabream from the Strait of Gibraltar. *Animal Biodiversity and Conservation*, 37, 35-47.

Bai, J., & Perron P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, 66, 47-78.

Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally Integrated Generalized Conditional Heteroskedasticity. *Journal of Econometrics*, 74, 3-30.

Becerra-Muñoz, S., Buelna-Osben, H. R., & Catalán-Romero, J. M. (2003). Spatial patterns of ARIMA modeled rates of change of atherinids (Chirostoma spp.) and goodeid *Chapalichthys encaustus* from Lake Chapala, México. *Ecological Modelling*, 165, 237-250.

Best, P. (1999). *Implementing Value At Risk*. Bidles Ltd., England.

Black, F. (1976). Studies of stock price volatility changes. In: Proceedings of the 1976 Meeting of the Business and Economic Statistics Section, American Statistical Association, Washington D.C, 177-181.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31, 307-327.

Borges, M. F., Santos, A. M. P., Crato, N., Mendes, H., & Mota, B. (2003). Sardine regime shifts off Portugal: a time series analysis of catches and wind conditions. *Scientia marina*, 67, 235-244.

Box, G. E. P., & Jenkins, G. (1976). *Time Series Analysis, Forecasting and Control*. Holden-Day, San Francisco, CA, 1970.

Burgos, C., Gil, J., & del Olmo, A. (2013). The Spanish blackspot seabream (*Pagellus bogaraveo*) fishery in the Strait of Gibraltar: spatial distribution and fishing effort derived from a small-scale GPRS/GSM based fisheries vassel monitoring system. *Aquatic Living Resources*, 26, 399-407.

Buxton, C.D., & Garratt, P. A. (1990). Alternative reproductive styles in seabreams (Pisces: *Sparidae*). *Environmental Biology of Fishes*, 28,113-124.

Carpenter, K. E., & Russell, B. (2014). *Pagellus bogaraveo*. The IUCN (International Union for the Conservation of Nature's) Red List of Threatened Species: e.T170244A1300216 (2014).

Christie, A. (1982). The Stochastic Behavior of Common Stock Variances. *Journal of Financial Economics*, 10, 407-432.

Connell, J. H. (1980). Diversity and the coevolution of competitors, or the Ghost of Competition Past. *Oikos*, 35, 131-138.

Colebrook, J. M. (1986). Environmental influences on long-term variability in marine plankton. *Hydrobiologia*, 142, 309-325.

CopeMed II. (2011). Report of the first joint assessment exercise on red seabream (*Pagellus bogaraveo*) of the Strait of Gibraltar area between Spain and Morocco. CopeMed II – ArtFiMed Technical Documents Nº23 (GCP/INT/028/SPA – GCP/INT/006/EC). Málaga, 2011. 31pp.

CopeMed II. (2012). Report of the Second meeting of the CopeMed II Working Group between Spain and Morocco on blackspot seabream (*Pagellus bogaraveo*) of the Strait of Gibraltar area. CopeMed II Technical Documents Nº26 (GCP/INT/028/SPA – GCP/INT/006/EC). Málaga, 2012. 37pp.

CopeMed II. (2018). Report of the Joint COPEMED II – GFCM data preparation meeting on Blackspot seabream (*Pagellus bogaraveo*) in the Strait of Gibraltar. Cádiz (Spain), 19-21 March 2019. Documents Nº51 (GCP/INT/028/SPA - GCP/INT/006/EC). 19 pp.

Cushing, D. H. (1990). Plankton production and year-class strength in fish populations: an update of the match/mismatch hypothesis. *Advances in Marine Biology*, 26, 249-293.

Czerwinski, I. A., Gutiérrez-Estrada, J. C., & Hernando-Casal, J. A. (2007). Short term forecasting of halibut CPUE: linear and non-linear Univariate approaches. *Fisheries Research*, 86, 120-128.

Czerwinski, I. A., Gutiérrez-Estrada, J. C., Casimiro-Soriguer-Escofet, M., Hernando, J. A. (2010). Hook selectivity models assessment for black spot seabream. Classic and heuristic approaches. *Fisheries Research*, 102, 41-49.

De Boni, A., Roma, R., & Ottomano Palmisano, G. (2018). Fishery policy in the European Union: A multiple criteria approach forassessing sustainable management of Coastal Development Plans in Southern Italy. *Ocean & Coastal Management*, 163:11-21.

Ding, Z., Granger, C. W .J., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1, 83-106.

Engle, R. (1982). Autorregresive Conditional Heterocedasticity with Estimates of the Variance of the U.K. Inflation. *Econometrica*, 50, 987-1008.

Engle, R. F., & Ng, V. K. (1993). Measuring and Testing the Impact of News on Volatility. *The Journal of Finance*, 48, 1749-1778.

Fulton, E. A., Smith, A. D. M., Smith, D. C., & van Putten, I. E. (2011). Human behaviour: the key source of uncertainty in fisheries management. *Fish and Fisheries*, 12, 2-17.

García-Lafuente, J., Vargas, J. M., Plaza, F., Sarham, T., Candela, J., & Bascheck, B. (2000). Tide at the Eastern section of the Strait of Gibraltar. *Journal of Geophysical Research*, 105, 14197-14213.

García Lafuente J., Sánchez Garrido J.C., García A., Hidalgo M., Sammartino S. & Laiz, R. (2020). Biophysical processes determining the connectivity of the Alboran Sea Fish Populations. In:Alboran Sea, Ecosystems and Marine Resources (J.C. Báez; J.T. Vázquez; J.A. Camiñas & M. Malouli, Eds.). Springer. In press.

Ghalanos, A. (2017). rugarch: Univariate GARCH Models. R package version: 1.3-8. https://CRAN.R-project.org/package=rugarch.

Gil, J., Silva, L., & Sobrino I. (2001). Results of two Tagging Surveys of red seabream (*Pagellus bogaraveo* Brünnich, 1768) in the Spanish South Mediterranean Region. *Thalassas*, 17: 43-46.

Gil, J. (2006). Biología y pesca del voraz [*Pagellus bogaraveo* (Brünnich, 1768)] en el Estrecho de Gibraltar. PhD Thesis, University of Cádiz, Spain.

Gil, J. (2019). Stock Annex: Blackspot seabream (Pagellus bogaraveo) in Subarea 9 (Atlantic Iberian waters). Working Document to the 2019 Report of the ICES Working Group on the Biology and Assessement of Deep-Sea Fisheries Resources (WGDEEP).

Gil-Herrera, J., Gutiérrez-Estrada, J. C., Benchoucha, S., Pérez-Gil, L., Sanz-Fernández, V., el Arraf, S., Burgos, C., Malouli, M., & Farias, C. (2020). The Blackspot seabream fishery in the Strait of Gibraltar: lessons and future perspective of shared marine resource. In: Alboran Sea, ecosystems and marine resources (Eds. Báez, J.C., Vázquez, J.T., Camiñas, J.A., and Malouli, M.), Springer (In press).

Girish, G. P. (2016). Spot electricity price forecasting in Indian electricity market using autoregressive-GARCH models. *Energy Strategy Reviews*, 11-12, 52-57.

Glosten, L. R. Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48, 1779-1801.

González, J. M., & Lorenzo, J. M. (1995). Análisis y predicción de las capturas de salmonete de roca *Mullus surmuletus* (Linnaeus 1758) en aguas de Gran Canaria (Islas Canarias) mediante un modelo ARIMA. *Boletín del Instituto Español de Oceanografía*, II, 61-76.

Griñó, R. C. (1992). Neural networks for univariate time series forecasting and their application to water demand prediction. *Neural Network World*, 2, 437-450.

Gutiérrez-Estrada, J. C., de Pedro-Sanz, E., López-Luque, R., & Pulido-Calvo, I. (2004). Comparison between traditional methods and artificial neural networks for ammonia concentration forecasting in an ell (*Anguilla anguilla* L.) intensive rearing system. *Aquacultural Engineering*, 31, 183-203.

Gutiérrez-Estrada, J. C., Silva, C., Yáñez, E., Rodríguez, N., Pulido-Calvo, I. (2007). Monthly catch forecasting of Anchovy *Engraulis ringens* in the north area of Chile: non-linear univariate approach. *Fisheries Research*, 86, 188-200.

Gutiérrez-Estrada, J. C., Gil-Herrera, J., Pulido-Calvo, I., & Czerwinski, I.A. (2017). Is it possible to differentiate between environmental and fishery effects on abundance- biomass variation? A case study of blackspot seabream (*Pagellus bogaraveo*) in the Strait of Gibraltar. *Fisheries Oceanography*, 26, 455-475.

Gutiérrez-Estrada, J. C., Sanz-Fernández, V., Pulido-Calvo, I., & Gil-Herrera, J. (2020). Improving the interpretability of the effects of environmental factors on abundance of fish stocks. *Ecological Indicators*, 117, 106533.

Hart, A. R., & Fay, G. (2020). Applying tree analysis to assess combinations of Ecosystem-Based Fisheries Management actions in Management Strategy Evaluation. *Fisheries Research*, 225, 105446.

Heath, M. R., Backhaus, J. O., Richardson, K., McKenzie, E., Slagstad, D., Beare, D., Dunn, J., Fraser, J. G., Gallego, A., Hainbucher, D., Hay, S., Jonasdottir, S., Madden, H., Mardaljevic, J., & Schacht, A. (1999). Climate fluctuations and the spring invasión of the North Sea by *Calanus finmarchicus*. *Fisheries Oceanography*, 8, 163-176.

Hentschel, L. (1995). All in the family Nesting symmetric and asymmetric GARCH models. *Journal of Financial Economics*, 39, 71-104.

Higgins, M. L., & Bera, A. K. (1992). A Class of Nonlinear Arch Models. *International Economic Review*, 33, 137-158.

Hilborn, R., Maquire, J., Parma, A. M. & Rosenberg, A. A. (2001). The precautionary approach and risk management: can they increase the probability of successes in fishery management? *Canadian Journal of Fisheries and Aquatic Sciences*, 58, 99-107.

Holt, C. C. (1957). Forecasting Seasonals and Trends by Exponentially Weighted Moving Averages. ONR Memorandum, Vol. 52, Carnegie Institute of Technology, Pittsburgh. Available from the Engineering Library, University of Texas, Austin.

Hurrell, J. & National Center for Atmospheric Research Staff (Eds). Last modified 24 Apr 2020. "The Climate Data Guide: Hurrell North Atlantic Oscillation (NAO) Index (station-based)". Retrieved from https://climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-station-based.

Hurvich, C. M., & Tsai, C. L. (1989). Regression and time series model selection in small samples. *Biometrika*, 76, 297-307.

Hsieh, C. H., Reiss, C. S., Hunter, J. R., Beddington, J. R., May, R. M. & Sugihara, G. (2006). Fishing elevates variability in the abundance of exploited species. *Nature*, 44, 859-862.

Hutchings, J. A. & Reynolds, J. D. (2004). Marine fish population collapses: consequences for recovery and extinction risk. *Biosciences*, 13, 297-309.

Hyndman, R. J., & Khandakar, Y. (2008). Automatic time series forecasting: the forecast package for R. *Journal of Statistical Software*, 26, 1-22.

Kim, J. Y., Jeong, H, C., Kim, H., & Kang, S. (2015). Forecasting the monthly abundance of anchovies in the South Sea of Korea using a univariate approach. *Fisheries Research*, 161, 293-302.

Killick, R., & Ecke, I. A. (2014). Changepoint: An R Package for Changepoint Analysis. *Journal of Statistical Software*, 58, 1-19.

Killick, R., Haynes, K., Eckley, I. A., Fearnhead, P., & Lee, J. (2016). Changepoint: Methods for Changepoint Detection. R package version: 2.2.2. https://CRAN.R-project.org/package=changepoint.

Kitanidis, P. K., & Bras, R. L. (1980). Real time forecasting with a conceptual hydrological model. 2. Applications and results. *Water Resources Research*, 16, 1034-1044.

Krug, H. M. (1998). Variation in the reproductive cycle of the blackspot seabream, *Pagellus bogaraveo* (Brünnich, 1768) in the Azores. Arquipelago. *Ciencias biologicas e marinhas*, 16A: 37-47.

Lai, E. K. M., Cheng, Y. W., & McAleer, M. (2005). Predicting Monthly Catch for Some Western Australia Coastal Finfish Species with Seasonal ARIMA - GARCH models. In Modelling Western Australian Fisheries with Techniques of Time Series Analysis: Examining Data from a Different Perspective. Project No. 1999/155. Dr M. Craine. Published by the Department of Fisheries Research Division, Western Australian Marine Research Laboratories, PO Box 20 NORTH BEACH, Western Australia 6920.

Lee, G. J., & Engle, R. F. (1999). A permanent and transitory component model of stock return volatility. In Cointegration Causality and Forecasting A Festschrift in Honor of Clive WJ Granger. Oxford University Press.

Legates, D. R., & McCabe Jr. (1999). Evaluating the use of ‘goodness-of-fit’ measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, 35, 233-241.

Leitão, F., Alms, V., & Erzini, K. (2014). A multi-model approach to evaluate the role of environmental variability and fishing pressure in sardine fisheries. *Journal of Marine Systems*, 139, 128-138.

Liu, H., & Shi, J. (2013). Applying ARMA-GARCH approaches to forecasting short-term electricity prices. *Energy Economics*, 37, 152-166.

Lloret, J., Lleonart, J., & Solé, I. (2000). Time series modelling of landings in Northwest Mediterranean Sea. *ICES Journal of Marine Science*, 57, 171-184.

Lorance, P. (2011). History and dynamics of the overexploitation of the blackspot sea bream (*Pagellus bogaraveo*) in the Bay of Biscay. *ICES Journal of Marine Science*, 68, 290-301.

Manjarrés-Martínez, L. M., Gutiérrez-Estrada, J. C., Mazenet-González, J., & Soriguer, M. C. (2010). Seasonal patterns of three fish species in a Caribbean coastal gill-next fishery: Biologically induced or climatic-related aggregations? *Fisheries Research*, 106, 358-367.

Mini, K. G., Kuriakose, S., & Sathianandan, T. V. (2015). Modeling CPUE series for the fishery along northeast coast of India: A comparison between the HoltWinters, ARIMA and NNAR models. *Journal of the Marine Biological Association of India*, 57, 75-82.

Mohammadi, H., & Su, L. (2010). International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models. *Energy Economics*, 32, 1001-1008.

Murphy, G. I. (1967). Vital statistics of the Pacific sardine (*Sardinops caerulea*) and the pupulation consequences. *Ecology*, 48, 731-736.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models. I. A discussion of principles. *Journal of Hydrology*, 10, 282-290.

Nzombe, J. (2017). Modelling and Forecasting Volatility in the Fishing Industry: A Case Study of Western Cape Fisheries. (Master Thesis). University of the Witwatersrand, South Africa.

Ortiz-Arango, F. (2017). Pronóstico de precios de petróleo: una comparación entre modelos GARCH y redes neuronales diferenciales. *Investigación Económica*, 300, 105-126.

Page, E. S. (1954). Continuous Inspection Schemes. *Biometrika*, 41, 100-115.

Palma-Pedraza, S. (2017). Análisis de la pesquería del voraz *Pagellus bogaraveo* (Brünnich, 1768) que se desarrolla en el estrecho de Gibraltar. Undergraduate dissertation, University of Cádiz, Spain.

Parrilla, G., Kinder, T. H., & Preller, R. H. (1986). Deep and Intermediate Mediterranean Water in the western Alboran Sea. *Deep Sea Research Part A. Oceanographic Research Papers*, 33, 55-88.

Pershing, A. J, Greene, C. H, Jossi, J. W, O'Brien, L, Brodziak, J. K. T, Bailey, B. A. (2005) Interdecadal variability in the Gulf of Maine zooplankton community, with potential impacts on fish recruitment. *ICES Journal of Marine Science*, 62, 1511-1523.

Perreti, C. T., Fogarty, M. J., Friedland, K. D., Hare, J. A., Lucey, S. M., McBride, R. S., Miller, T. J., Morse, R. E., O'Brien, L., Pereira, J. J., Smith, L. A., & Wuenschel, M. J. (2017). Regime shifts in fish recruitment on the Northeast US Continental Shelf. *Marine Ecology Progress Series*, 574, 1-11.

Pimm, S.L. (1991). The balance of nature? Ecological issues in the conservation of species and communities. University of Chigaco Press, 448 pp.

Potter, E. C. E., Crozier, W. W., Schön, P-J., Nicholson, M. D., Maxwell, D. L., Prévost, E., Erkinaro, J., Gudbergsson, G., Karlsson, L., Hansen, L. P., MacLean, J. C., Ó Maoiléidigh, N., & Prusov, S. (2004). Estimating and forecasting pre-fishery abundance of Atlantic salmon in the Northeast Atlantic for the management of mixed-stock fisheries. *ICES Journal of Marine Science*, 61, 1359-1369.

Qi, M., & Zhang, G. P. (2001). An investigation of model selection criteria for neural network time series forecasting. *European Journal of Operational Research*, 132, 666-680.

R Core Team: R (2020). A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, version 3.6.3, available at: https://www.R-project.org/.

R Core Team., & Contributors worldwide. (2018). The R Stats Package. R package version: 3.6.3.

Respondek, G., Gröger, J., Floeter, J., & Temming, A. (2014). Variability of fishing effort for the German brown shrimp (*Crangon crangon*) fishing fleet: influencing factors, and seasonal and spatial patterns. *ICES Journal of Marine Science*, 71, 1805-1817.

Rouyer, T., Fromentin, J. -M., Ménard, F., Cazelles, B., Briand, K. Pianet, R., Planque, B., & Stenseth, N.C. (2008). Complex interplays among population dynamics, environmental forcing, and exploitation in fisheries. *PNAS*, 105, 5420-5425.

Santos, M. B., González-Quirós, R., Riveiro, I., Cabanas, J. M., Porteiro, C., & Pierce, G. J. (2012). Cycles, trends, and residual variation in the Iberian sardine (*Sardina pilchardus*) recruitment series and their relationship with the environment. *ICES Journal of Marine Science*, 69, 739-750.

Sanz-Fernández, V., Gutiérrez-Estrada, J. C., Pulido-Calvo, I., Gil-Herrera, J., Benchoucha, S., & el Arraf, S. (2019). Environment or catches? Assessment of the decline in blackspot seabream (*Pagellus bogaraveo*) abundance in the Strait of Gibraltar. *Journal of Marine Systems*, 190, 15-24.

Sobrino, I., & Gil, J. (2001). Studies on age determination and growth pattern of the red (blakspot) seabream (*Pagellus bogaraveo* Brünnich, 1768) from the Strait of Gibraltar (ICES IXa/SW Spain): Application to the species migratory pattern. NAFO SCR 01/87. 5 pp.

Sobrino, I., & Gil, J. (2002). Estudio de la pesquería del voraz (*Pagellus bogaraveo*) en aguas del Estrecho de Gibraltar. Informe final de resultados. Convenio de colaboración entre el Instituto Español de Oceanografía, Red Eléctrica de España y la Cofradía de Pescadores de Tarifa.

Stergiou, K. I. (1989). Modelling and forecasting the fishery for pilchard (*Sardina pilchardus*) in Greek waters using ARIMA time series models. *ICES Journal of Marine Science*, 46, 16-23.

Stergiou, K. I. (1991). Short-term fisheries forecasting: comparison of smoothing, ARIMA and regression techniques. *Journal of Applied Ichthyology*, 7, 193-204.

Stergiou, K. I., Chritou, E. D., & Petrakis, G. (1997). Modelling and forecasting monthly fisheries catches: comparison of regression, univariate and multivariate time series methods. *Fisheries Research*, 29, 55-95.

Sverdrup, H. U., Johnson M. W., & Fleming R. H. (1942). The Oceans: Their physics, chemistry and general Biology. Pentice-Hall, Englewood Cliffs, NJ, 1087 pp.

Taboada, F. G., & Anadón, R. (2016). Determining the causes behind the collapse of a small pelagic fishery using Bayesian population modeling. *Ecological Applications*, 26, 886-898.

Taylor, S. J. (1986). Modelling financial time series. Wiley. ISBN: 978-9812770844.

Tsitsika, E. V., Maravelias, C. D., & Haralabous, J. (2007). Modeling and forecasting pelagic fish production using univariate and multivariate ARIMA models. *Fisheries Science*, 73, 979-988.

Van Beveren, E., Duplisea, D. E., Marentette, J. R., Smith, A., & Castonguay, M. (2020). An example of how catch uncertainty hinders effective stock management and rebuilding. *Fisheries Research*, 224, 105473.

Ventura, S., Silva, M., Pérez-Bendito, D., & Hervás, C. (1995). Artificial neural networks for estimation of kinetic analytical parameters. *Analytical Chemistry*, 67, 1521-1525.

Wakefield, J. (2012). Common fisheries policy reform and sustainability. European Policy Analysis. Retrieved from. http://www.sieps.hemsida.eu/sites/default/files/2012_6epa.pdf.

Winters, P.R. (1960). Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*, 6, 324-342.

Wuertz, D., Setz, T., Chalabi, Y., Boudt, C., Chausse, P., & Miklovac, M. (2019). FGarch. Rmetrics - Autoregressive Conditional Heteroskedastic Modelling. R Package. https://cran.r-project.org/web/packages/fGarch/fGarch.pdf.

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18, 931-955.

Zing, Z., Granger, C. W. J., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1, 83-106.

Figure Captions

Figure 1. Operational ground in the Strait of Gibaltar of the Spanish (blue) and Moroccan (red) "voracera" fleet. This figure is a modification of maps 9 to 17 included in "Empresa Pública para el Desarrollo Agrario y Pesquero de Andalucía, S.A. 2010. Análisis de la pesquería de voraz y especies asociadas en el Estrecho de Gibraltar".

Figure 2. Classical seasonal decomposition by moving averages time series (1983-2016) of Blackspot seabream monthly landings (tonnes). a) Time series data, b) trend, c) seasonal and d) random.

Figure 3. Time series (1983-2016) of Blackspot seabream monthly landings (tonnes) by main ports. Algeciras, Ceuta, Conil, Tarifa and Tangier.

Figure 4. a) Time series of Blackspot seabream monthly landings (tonnes) during 1983-2016 with the fit provided by the best ARIMA model (103) $(011)^{12}$, landings observed are represented in green and landings estimated by the model in red. b) Landings observed and estimated variation and linear regression of the best ARIMA model (103) $(011)^{12}$.

Figure 5. Time series of Blackspot seabream monthly landings (tonnes) during 1983-2016 with the fit provided by the best ARMA (1,3) + GARCH family models. a) Fitting of the APARCH model (1,6) ("Asymetric Power Arch Model") with probability Skew Student-t Distribution (SSTD), landings observed are represented in green and landings estimated by the model in red. b) Landings observed and estimated variation and linear regression of the best ARMA (1,3) + APARCH model (1,6) with probability Skew Student-t Distribution (SSTD).

Figure 6. Time series of landings volatility estimated (tonnes) by the best model of the ARMA (1,3) + GARCH family. APARCH model (1,6) ("Asymetric Power Arch Model") with probability Skew Student-t Distribution (SSTD). Red lines are the periods detected by means the multiple change point analysis.

Table 1. Best models obtained according to the different approximations depending on the goodness-of-fit measures. Probability distributions: *sstd* = Skew Student-t.

Model	RMSE (t)	MAE (t)	%SEP	E_2	ARV	PI	AIC	AIC_C	BIC	r^2	Parameters estimation method	Probability distribution
Naïve	21.800	15.450	62.590	0.278	0.721	0.000	2.677	2.682	2.677	0.407	-	-
AR	15.865	11.561	43.545	0.618	0.381	0.498	2.408	2.547	2.410	0.610	Burg	-
^{m} Winter's seasonal	16.960	12.152	47.610	0.562	0.438	0.411	2.465	2.532	2.466	0.579	-	-
ARIMA (103)(011)^{12}	16.096	11.568	46.220	0.606	0.393	0.454	2.417	2.438	2.418	0.610	-	-
ARMA (1,3) + APARCH (1,6)	18.626	13.522	53.484	0.473	0.527	0.269	2.546	2.627	2.548	0.474	-	*sstd*

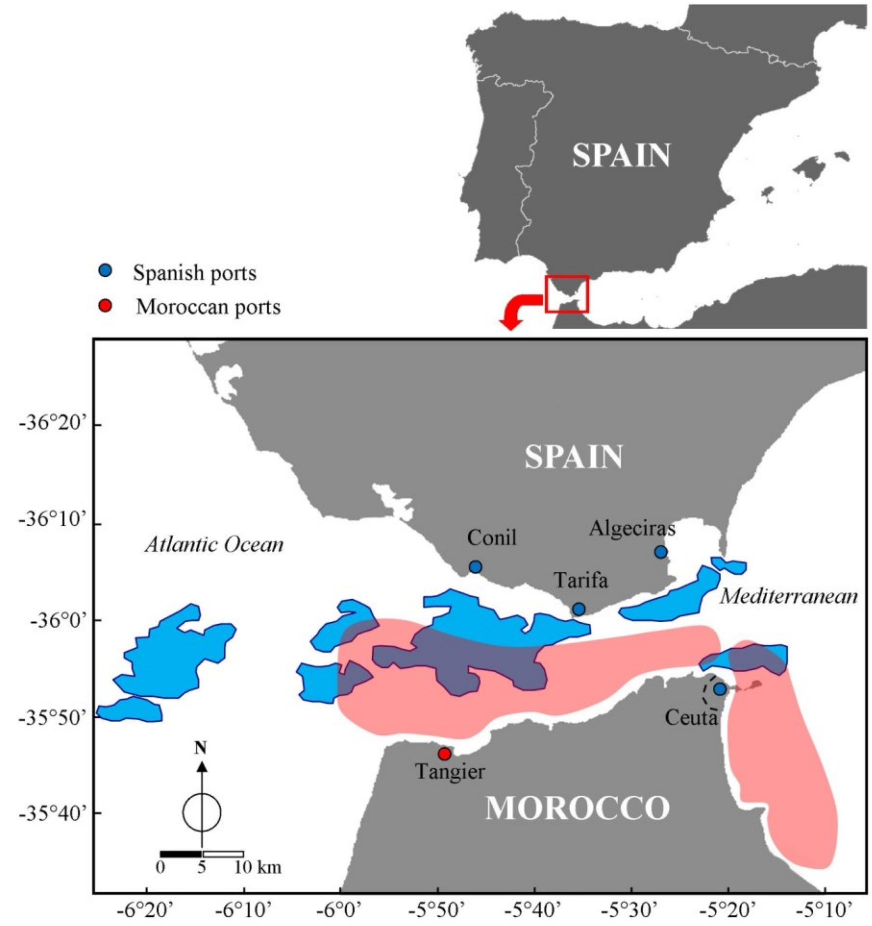
m = multiplicative.

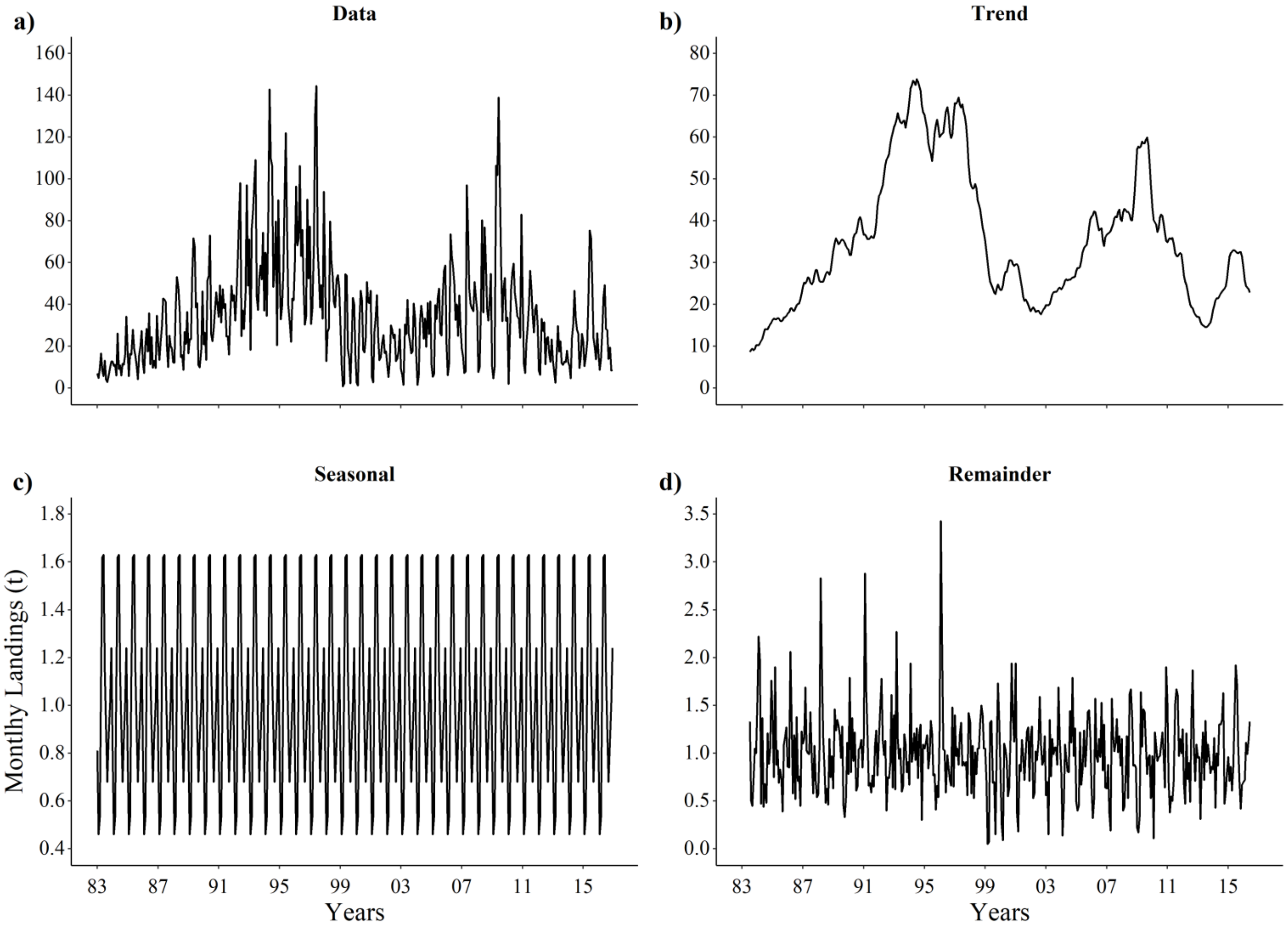
Table 2. Number of significant annual correlations (C) between the time series of Blackspot seabream monthly landing (tonnes) (1983-2016) and water temperature anomaly (ºC) by depth range (5-525) m. No lagged and lagged 1, 2 and 3 years. Signification limit of C ($N = 12$ and P level of 0.05) = 0.576.

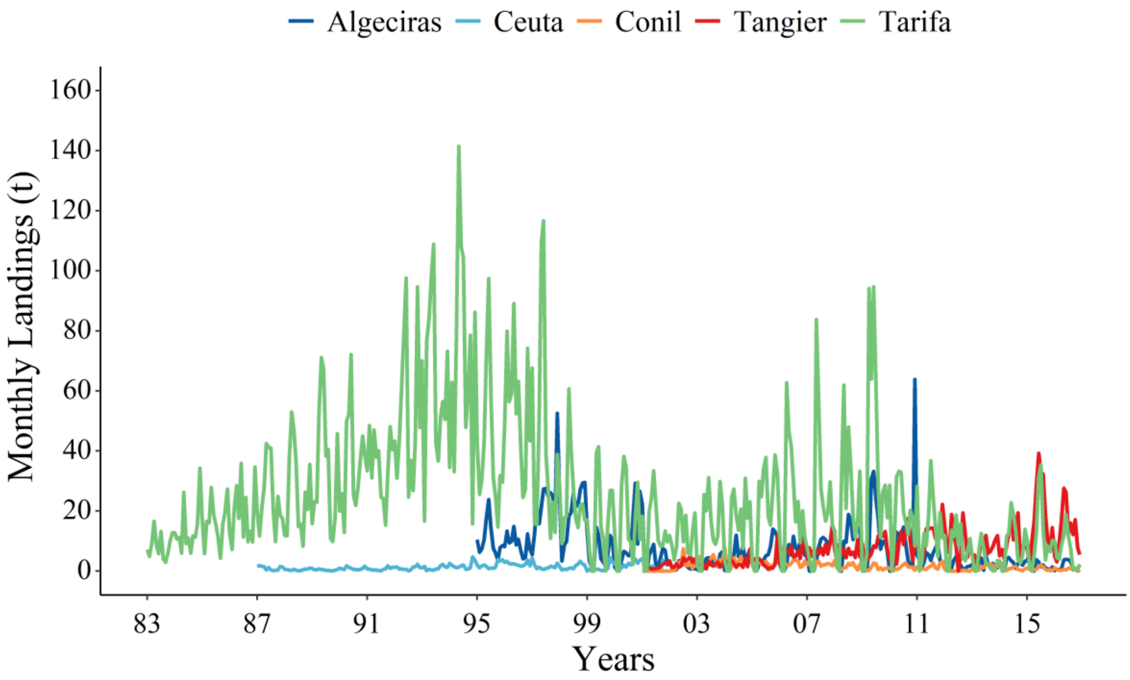
Year	Temperature anomaly (t-0 year)		Temperature anomaly (t-1 year)		Temperature anomaly (t-2 years)		Temperature anomaly (t-3 years)	
	$C > 0.576$	$C < -0.576$	$C > 0.576$	$C < -0.576$	$C > 0.576$	$C < -0.576$	$C > 0.576$	$C < -0.576$
1983	0	0						
1984	0	0	4	0				
1985	0	0	11	0	0	0		
1986	0	0	0	0	0	0	0	0
1987	0	0	0	1	6	0	0	0
1988	0	1	2	0	0	7	0	0
1989	9	0	0	2	0	0	0	4
1990	2	0	1	0	0	0	1	0
1991	0	3	0	2	3	2	2	0
1992	0	3	0	0	0	0	5	0
1993	0	0	0	4	0	0	9	0
1994	0	0	1	0	0	2	1	0
1995	0	5	0	0	2	0	4	3
1996	3	0	0	0	3	0	0	1
1997	2	0	4	0	0	5	0	0
1998	0	14	2	0	2	0	0	0
1999	0	0	0	7	1	0	0	0
2000	5	2	0	0	0	20	2	0
2001	0	10	0	0	0	0	0	6
2002	0	0	4	3	0	3	0	0
2003	3	0	0	5	2	0	9	3
2004	0	16	12	0	0	5	1	0
2005	16	0	0	17	14	0	0	4
2006	4	0	6	0	0	0	5	0
2007	0	0	24	0	1	0	0	8
2008	0	2	0	0	8	0	6	0
2009	6	0	0	0	1	14	9	0
2010	0	0	12	0	0	9	0	0
2011	0	10	0	7	5	0	0	10
2012	0	2	0	0	0	0	0	0
2013	0	0	1	1	0	6	0	3
2014	0	0	1	1	0	3	0	9
2015	3	1	0	0	1	2	2	2
2016			10	2	0	0	3	6
Total	53	69	85	52	49	78	59	59

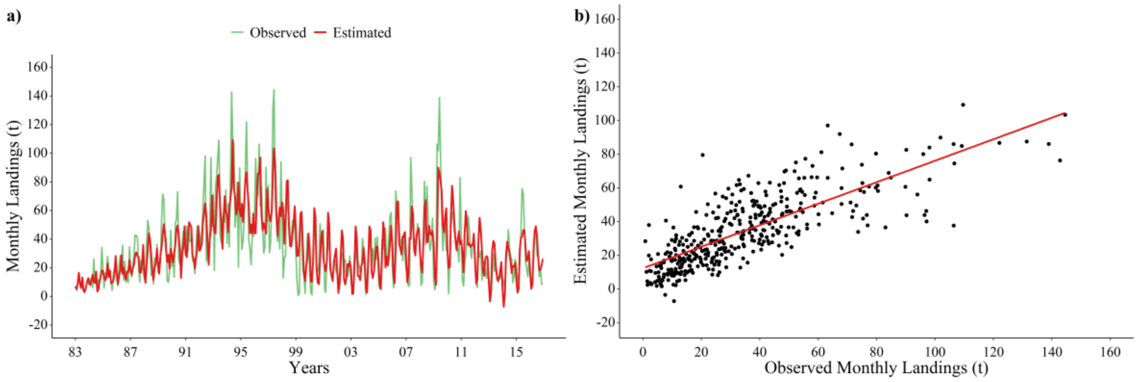
Table 3. Significant annual correlations between the time series of Blackspot seabream monthly landing (tonnes) (1983-2016) with the monthly NAO index. No lagged and lagged 1, 2 and 3 years. Signification limit of correlation (N = 12 and P level of 0.05) = 0.576. Significant correlations in bold.

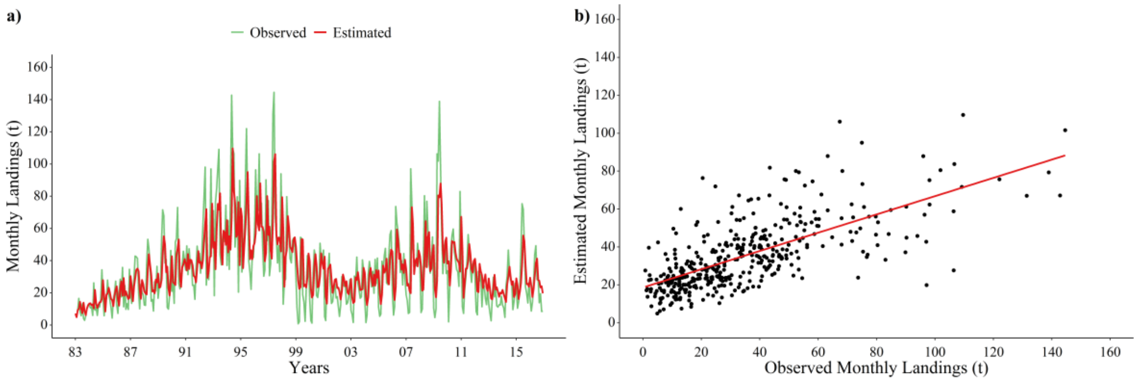
Year	NAO (t-0 year)	NAO (t-1 year)	NAO (t-2 years)	NAO (t-3 years)
1983	-0.195			
1984	0.364	-0.087		
1985	-0.114	0.150	0.122	
1986	0.052	0.225	-0.143	0.272
1987	0.089	0.335	0.173	-0.251
1988	-0.460	0.207	0.439	0.255
1989	-0.310	-0.022	-0.215	-0.024
1990	-0.295	-0.571	-0.531	0.168
1991	0.426	0.292	-0.097	**-0.599**
1992	0.114	0.287	-0.315	-0.390
1993	-0.092	-0.263	-0.105	-0.110
1994	-0.200	-0.561	-0.352	-0.365
1995	-0.314	0.234	-0.251	-0.245
1996	-0.001	0.000	0.025	0.007
1997	**-0.614**	-0.253	-0.412	0.145
1998	-0.214	**-0.644**	-0.017	-0.464
1999	0.260	-0.041	-0.451	-0.042
2000	0.038	0.125	0.040	**-0.715**
2001	0.142	-0.206	0.113	-0.407
2002	0.117	-0.235	-0.301	-0.208
2003	-0.201	0.148	0.012	-0.465
2004	0.003	-0.542	-0.166	-0.029
2005	0.047	0.042	-0.238	-0.112
2006	0.315	0.117	0.162	-0.265
2007	-0.179	0.039	-0.124	-0.153
2008	-0.312	-0.005	0.231	0.221
2009	-0.143	**-0.580**	-0.478	0.097
2010	-0.150	-0.462	-0.342	-0.057
2011	-0.389	0.331	-0.263	0.084
2012	-0.304	-0.150	-0.065	0.057
2013	0.548	-0.536	0.177	0.244
2014	-0.555	0.502	-0.509	-0.171
2015	-0.552	-0.452	0.264	-0.563
2016	-0.571	-0.341	-0.455	0.284

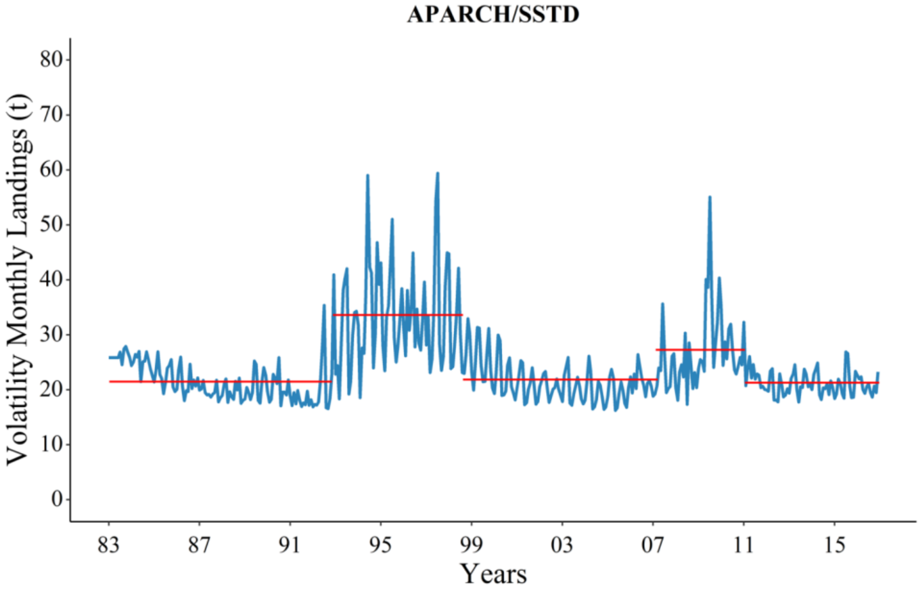

SPAIN
Spanish ports
Moroccan ports
-36°20'
-36°10'
-36°0'
-35°50'
-35°40'
SPAIN
Atlantic Ocean
Conil
Algeciras
Tarifa
Mediterranean
Ceuta
Tangier
MOROCCO
N
0
5
10 km
-6°20'
-6°10'
-6°0'
-5°50'
-5°40'
-5°30'
-5°20'
-5°10'


a)
Data
160
140
120
100
80
60
40
20
0
b)
Trend
80
70
60
50
40
30
20
10
0
c)
Seasonal
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
Montlhy Landings (t)
83
87
91
95
99
03
07
11
15
Years
d)
Remainder
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
83
87
91
95
99
03
07
11
15
Years


Algeciras
Ceuta
Conil
Tangier
Tarifa
Monthly Landings (t)
160
140
120
100
80
60
40
20
0
83
87
91
95
99
03
07
11
15
Years


a)
Observed
Estimated
Monthly Landings (t)
160
140
120
100
80
60
40
20
0
-20
83
87
91
95
99
03
07
11
15
Years
b)
Estimated Monthly Landings (t)
160
140
120
100
80
60
40
20
0
-20
0
20
40
60
80
100
120
140
160
Observed Monthly Landings (t)


a)
Observed
Estimated
Monthly Landings (t)
160
140
120
100
80
60
40
20
0
83
87
91
95
99
03
07
11
15
Years
b)
Estimated Monthly Landings (t)
160
140
120
100
80
60
40
20
0
0
20
40
60
80
100
120
140
160
Observed Monthly Landings (t)


APARCH/SSTD
Volatility Monthly Landings (t)
80
70
60
50
40
30
20
10
0
83
87
91
95
99
03
07
11
15
Years