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Improving the interpretability of the effects of environmental factors on abundance of fish stocks

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Abstract

Adequately assess the environmental effects on commercially exploited fish stocks is one of the main challenges faced by stock managers in their attempt to achieve ecosystemic management. In this study, we have developed a methodology which allows simulate the evolution of abundance or biomass of a fish population and calculate two indexes (the significant effect of the environmental parameter *–EF-* and the relative weight index *–RW-*) that improve the interpretability of the environmental effects on abundance of fish stocks. This methodology, based on the assumption that under the premise of environmental invariability the variation in the abundance of a population is linearly dependent on its abundance in the past, have been integrated into a decision support system namely SFish SubClass 1.1, specifically designed to disaggregate the effects of different environmental factors on a commercially exploited fish population. We have applied our model to the fishery of *Pagellus bogaraveo* in a complex environmental area (Strait of Gibraltar). The results show that the developed methodology provides plausible simulations. The relative weight index (*RW*) indicated the time and the significance (*EF*) of each environmental parameter and showed that the most influential variables were salinity, sea temperature and salinity flux.

Keywords: Ecosystemic approach, Computational simulation; Time series; ARIMA models; oceanic parameters; Atmospheric parameters

1. Introduction

The way in which the environmental factors modulate the abundance of fish populations is a key interaction to analyse if we seek to manage fisheries from a holistic or ecosystem point of view (García and Cochrane, 2005; Jørgensen et al., 2007). This approach considers the effects of multiple forcing agents and analyses fisheries considering the ecological interdependencies between species occurring in the ecosystem and their relationship with the environment, as well as the technological interdependencies between fleets and the impact that they have on habitats (Pauly et al., 2003). These principles are integrated in the Marine Strategy Framework Directive (MSFD: 2008/56/EC) enacted by the European Union which requires to the member states to assess the environmental status of jurisdictional marine waters by means the evaluation of several qualitative descriptors.

In practice, the application of this approach is hindered by several sources of uncertainty associated with the assessment and management of fishery resources (Skern-Mauritzen et al., 2015) some of which are inherent to several ecosystem indicators established in the MSFD. For example, the MSFD number 1 descriptor determines that the quality and occurrence of species abundance must be in line with prevailing physiographic, geographic and climatic conditions. This implies that in order to determine the impacts and pressures that the environmental conditions on exploited populations, it’s necessary to have an in-depth understanding of the species biology just like characterize the relationships between the abundance of fish populations and the environmental conditions.

The characterization of environmental conditions and the response of fish populations to the change of these conditions can be approached using various methodologies and modelling techniques that can be integrated into more complex systems known as Expert Systems (ESs) and Decision Support Systems (DSSs). As a general rule, these types of systems integrate a great variety of models (qualitative, quantitative, discrete or continuous, physical, statistical, etc.) through which it is possible to establish and simulate statistical functional relationships between different variables (Silliman, 1967; King and Paulik, 1967; Paulik, 1969; Francis, 1974; Fonteneau, 1975; Takeuchi and Taneishi, 1976; Tillman and Stadelman, 1976; Hammond and Lackey, 1976; Sissenwine, 1977; Grant et al., 1981; Crutchfield, 1986; Hilborn and Walters, 1987; Kleiber and Baker, 1987; Castro and Erzini, 1988; Erzini, 1990; Erzini and Castro, 1998; Christensen and Pauly, 1992; Walters et al., 1997, 2000; Moeseneder et al., 2015; Schiavina et al., 2015; Begley, 2005; Erzini et al., 2006; Taylor et al., 2007). This allows the comparison of the responses of the system analyzed under different environmental conditions or management scenarios (Sterman et al., 2014).

An very common approach used in most of these works is to attempt to establish cause-effect statistical relationships between fish stock abundance indexes as catch per unit of effort (CPUE) or landings per unit of effort (LPUE) and environmental and climatic factors by means different regression techniques (Lorance and Dupouy, 2001; Casini et al, 2005; Haggarty and King, 2006; Czerwinski et al., 2007; Gutiérrez-Estrada et al., 2007, 2009; Yáñez et al., 2010). These indexes (CPUE or LPUE) are generally obtained from commercial capture series and therefore do not always reflect the variations in actual abundance of the populations analyzed (Paloheimo and Dickie, 1964; Bannerot and Austin, 1983; Harley et al., 2001; Branch et al., 2011; Pauly et al., 2013; Campbell, 2015). For example, if the stock is not homogeneous, that is not all equally vulnerable to fishing, CPUE will only be an abundance reflect in very special circumstances (Ricker, 1975). Therefore it would be desirable to have alternative and complementary methods that facilitate the adequate characterization of the effect of changing environmental conditions on abundance, which is a fundamental preliminary step in the implementation of an approach based on ecosystem (Klyashtorin, 2001; Garcia and Cochrane, 2005).

An alternative to the calculation of correlations between observed and predicted values by statistical models in which the input variables are environmental factors and the output variables are indices of abundance, such as CPUE or LPUE, is the dynamic simulation of the evolution of fish populations based on biological parameters (Castro and Erzini, 1988; Cochrane and Starfield, 1992).

For example Probst et al. (2013) simulated the evolution of a cod stock over a 120-year period with the aim of identifying viable size-based indicators (SBIs) for the assessment of stock abundance. Likewise, Gutiérrez-Estrada et al. (2017) and Sanz-Fernández et al. (2019) obtained realistic simulations of the evolution of the abundance and biomass of blackspot seabream (*Pagellus bogaraveo*) in the Strait of Gibraltar based on the information available on the biology of this species. From the simulated series these authors extracted time series of residues that were correlated with environmental and climatic parameters, which allowed them to identify more or less favourable environmental periods with respect to the increase or decrease of the predicted abundance of this blackspot seabream population. The advantage of this type of approach is that the statistical correlations or functional relationships obtained do not depend on CPUE or LPUE time series. However, due to the nature of the time series of residues, they present the disadvantage of the difficulty in interpreting the correlations obtained (Sanz-Fernández et al., 2019).

The methodology proposed in this study allows to assess variation in the abundance or biomass during the exploitation period without the need for CPUEs and LPUEs time series. It is specifically designed to disaggregate the effects of the fishing component of the changes dependent on the environmental variations and allows to interpret, in an easy way, the weight and the time effect of each environmental parameter considered by means two adimensional indexes called Environmental Significant Effect (*EF*) and Relative Weight (*RW*). This methodology has been implemented in a software called SFish SubClass 1.1.

To test the operability of these indexes, we used all data sets available on the fishery and biology of blackspot seabream as well as those environmental factors potentially impacting on the abundance of this population. This species was selected because is the most important commercially-exploited fish species in the extreme southeast of International Council for the Exploration of the Sea (ICES) Division IXa (Strait of Gibraltar).

2. The SFish Subclass 1.1 software

Sfish Subclass 1.1 is a toolbox that combines a graphical interface developed in Microsoft Visual Basic 6.0 (VB 6.0) with an independent calculation engine implemented in R 3.4.0. (Figure 1). That is, Sfish has two components: (i) the main core that simulates the population dynamics (compiled in VB 6.0) and; (ii) the statistical core that takes advantage of the power and flexibility of R.

2.1. *Fish population dynamic with SFish*

SFish program integrate a discrete dynamic model of biomass-abundance which operates under three basic assumptions: (1) over a sufficiently long period of time, the biomass of a non-exploited fish population tends to reach a dynamic equilibrium that oscillates around an mean value (persistence principle); (2) the environmental conditions under which the parameters of the general growth model were calculated remain constant throughout the simulation; and (3) under the premise of environmental invariability, the variation in the abundance of a population is linearly dependent on the abundance of the resource in the past and hence, it can be modelled through an autoregressive process of non-seasonal order p and seasonal order P.

SFish is composed of three main algorithms: *Distribution*, *Generation* and *Catch*. The *Distribution* algorithm (Algorithm 1) estimates a density function $\hat{f}(L)$ of biomass-abundance calculated from C kernels each of which is associated with an age class and assuming that the frequency distribution by size of C age classes approximates a normal distribution. Therefore, each kernel is a function of the normal or Gaussian type (Equation 1):

$$K(z) = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{z^2}{2}\right)} \qquad (1)$$

$$z = \frac{(L_j - X_{ij})}{h_j}; z \in (-\infty, +\infty)$$

where X_{ij} is the size of specimen i of the age class j and h_j is the bandwidth (interval) equivalent to the standard deviation (σ_j) associated with each age class, which can be calculated from the age t as follows (Equation 2):

$$h_j \approx \sigma_j = a_\sigma + b_\sigma L_j + \varepsilon \qquad (2)$$

$$t_{year}=1;\ t_{month}=0.083$$

where a_σ and b_σ are constant and species-specific parameters. Likewise, the size (L) at age t varies according to the general species growth model defined by the von Bertalanffy equation (Equation 3):

$$L = L_\infty\left(1 - e^{(-k(t-t_0))}\right) + \varepsilon \qquad (3)$$

where L_∞ is the asymptotic average maximum body size, k is a growth rate coefficient that determines the shape of the growth curve and t_0 is the hypothetical age at which the species has zero length (Beverton and Holt, 1957). The epsilon (ε) denotes the belief that residuals would be distributed normally about the expected growth line.

Hence, the L density function is defined as (Equation 4):

$$\hat{f}(L) = \frac{1}{n}\sum_{j=1}^{n} K_{h_j}(L_j) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{h_j}K\left(\frac{L_j - X_{ij}}{h_j}\right) \tag{4}$$

From $\hat{f}(L)$, the *Distribution* algorithm estimates the total biomass at a time t (TB_t) knowing the length-weight relationship and establishing the initial biomass of age class 0+ at time t=0 (B_{0,t_0}) (Equation 5):

$$TB_t = \sum_{j=0}^{C}\sum_{i=0}^{L_\infty}\hat{f}(L_j)N_j\left(dX_{ij}{}^{g}\right) \tag{5}$$

$$\forall\, j > 0\ N_j = N_{j-1}e^{-M_j(\Delta t)}$$

where N_j is the estimated abundance of the age class j, d and g are parameters that establish the specific length-weight relationship for each species and population, and M_j is the natural mortality rate whose value depending on the growth phase (Chen and Watanabe, 1989) (equation 6):

$$M_j = \begin{cases} \dfrac{k}{1-e^{-k(t-t_0)}}, & t \le t_M \\ \dfrac{k}{a_0 + a_1(t-t_M) + a_2(t-t_M)^2}, & t > t_M \end{cases} \tag{6}$$

$$\begin{cases} a_0 = 1 - e^{-k(t_M - t_0)} \\ a_1 = ke^{-k(t_M - t_0)} \\ a_2 = -\frac{1}{2}k^2e^{-k(t_M - t_0)} \end{cases}$$

$$t_M = -\frac{1}{k}ln\left|1 - e^{-kt_0}\right| + t_0$$

where t_M is the age at end of the reproductive span.

The *Generation* algorithm (Algorithm 2) re-adjusts the abundance of age class 0+ by including new recruits and increases the values of existing age classes. In this algorithm, the recruitment (R) can be estimated from the stock-recruitment relationship estimated from the Beverton and Holt (R_{BH}) or Ricker (R_R) equations (Equation 7):

$$\begin{cases} R_{BH} = \dfrac{S}{\alpha + \beta S} \\ R_R = a_R S e^{-b_R S} \end{cases} \tag{7}$$

where S is the measure of spawning stock size, β determines the asymptotic limit, α is a parameter that determines the relative steepness near the origin, a_R is the recruits-per-spawner at low stock levels and b_R relates to the rate of decrease of recruits-per-spawner when *S* increases. In addition, this algorithm includes the possibility of incorporating new individuals in different lots over the course of the reproductive period. SFish processes each lot as different subclasses into the new class 0+ (Figure 2).

Finally, the *Catch* algorithm (Algorithm 3) for the simuluation frequency considered (in this case the frequency is a month) subtracts the monthly real catches recorded (TC_t) from the function of simulated biomass. For that, SFish adjust a specific density function to each capture period.

2.2. *Extracting the environmental component. EF and RW indexes*

If it is assumed that throughout the simulation the environmental conditions remain at levels similar to those found in the period in which the growth model was obtained (i.e., if the model does not incorporate extra-compensatory effects), then the variation in abundance and biomass at time *t*+1 depends exclusively on the abundance and the catch made at time *t*, and therefore the abundance or biomass series over time can be fitted by an autoregressive model. Under these conditions, deviations between the simulated biomass series and the autoregressive fit to these data (the residual series) must be the consequence of factors exogenous to the explicit biological and fishery-related parameters. In this way, it is possible to find patterns of correlation between the residual series and time series of environmental parameters (Gutiérrez-Estrada et al., 2017).

These patterns can be detected by analysis of the correlation indices obtained between the residual series of autoregressive integrated moving average (ARIMA) models and the anomalies of the various environmental parameters. From these three factors (residual, anomaly and correlation), a total of eight rules determine the positive or negative effects of environmental parameters on biomass (Table 1). For each period p of ARIMA forecasting, it is possible to calculate the degree of compliance of each rule *R* as:

$$C^R = \frac{\sum_1^p F^R}{p} \tag{8}$$

where F^R=1 if the first two premises of the antecedents (residual and anomaly) are met and F^R=0 otherwise. From C^R it is possible to calculate the significant effect (*EF*) of environmental parameter *e* at time *t* as:

$$EF_p^e = \left(\sum_{R=1}^{8} \delta^* C^R\right)(1 - \delta_p^2) \tag{9}$$

where EF_t^e is an adimensional index that oscillates between 1 (favours an increase in biomass), -1 (favours the decrease in biomass) and, therefore, the value 0 indicates a lack of effect on biomass, $\delta^*$are the significant correlations between environmental parameter *e* and the residuals of the best ARIMA model for a forecasting period establish and δ_p^2 is the explained variance by the ARIMA model for forecasting period *p*. This period can oscillate between 12 and 24 months. Therefore, from EF_p^e is possible to calculate the relative weight (*RW*) of each environmental parameter e on the fraction of non-explained variance as:

$$RW^e = \frac{\sum_{t=1}^{n} |EF_p^e|}{n} \tag{10}$$

Sfish optimally adjusts auto-regressive models connecting the main interface to a script encoded in R (ARIMAScript.r). This script is a modification of the script described by Sanz-Fernández et al. (2016) which uses the *auto.arima* function proposed by Hyndman and Khandakar (2008). This function finds the best ARIMA model according to the uncorrected and corrected Akaike information criteria and the Bayesian information criterion. The level of significance of the model parameters was studied using the *coeftest* function (Hothorn et al., 2017). In the development of the R script, the following packages were also used: *forecast* (Hyndman et al., 2017), *lmtest* (Hothorn et al., 2017), *stats* and *tseries* (Trapletti et al., 2017).

2.3. Databases of biological and environmental variables

This study was based on catches of blackspot seabream to the south of the Iberian Peninsula from the Strait of Gibraltar to Cape St. Vincent, ICES Division IXa in the area bound by the coordinates: 5º85' W to 5º31' W and 35º77' N to 36º18' N (Burgos et al., 2013). The historical time series of monthly landings of blackspot seabream correspond to landings from the Spanish ports of Tarifa, Algeciras, Conil, and Ceuta and the Moroccan port of Tangier between 1983 and 2016.

The environmental database was composed by historical series of oceanographic and environmental data and climate indices available for the Strait of Gibraltar. The data on temperature (ºC), salinity (PSU), salt flux (kg m^{-2} s^{-1}), heat flux (W m^{-2}) and current speed (m s^{-1}) were obtained for the period between 1983 and 2015 from the Simple Ocean Data Assimilation v 3.3.1 reanalysis data set (http://www.atmos.umd.edu/~ocean). This data set contains monthly ocean data remapped in 3D to a horizontal 1/2º x 1/2º Mercator coordinate grid with 50 vertical levels (Carton et al., 2018).

Data on chlorophyll-a concentration (mg m^{-3}) between 2003 and 2015 were obtained from monthly images from NASA's MODIS satellite (http://coastwatch.pfeg.noaa.gov/erddap/griddap) (Esaias et al., 1998). On the other hand, the historical time series of the NAO index from 1983 to 2015 were downloaded from the US National Center for Atmospheric Research (https://climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-station-based). Further, the monthly AO index from 1983 to 2015 was downloaded from the US National Oceanic and Atmospheric Administration's National Weather Service (http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/monthly.ao.index.b50.current.ascii) (Thompson and Wallace, 2000).

3. SFish application: the case of blackspot seabream in the Strait of Gibraltar

3.1. Blackspot seabream fishery and its environmental context

Blackspot seabream is a demersal species which lives at depths of 400 to 700 m. This species is the target of an artisanal longline fleet known as the "*voracera*" (Báez et al., 2009; Czerwinski et al., 2009). Due to its high commercial and gastronomic value, blackspot seabream has attracted great interest and become economically important for the area of the Strait of Gibraltar (Burgos et al., 2013). This fishery started in the early 1980s. Since then, the catches of this species in the main fishing ports of Spain and Morocco have shown marked variability, characterized by two cycles with peaks around 1994-5 and 2009 (Gutiérrez-Estrada et al., 2017).

The biological cycle of this species in the Strait of Gibraltar is sufficiently well known. Among the studies on blackspot seabream biology in this area, we should highlight those carried out by the Spanish Oceanographic Institute (IEO) (Gil and Sobrino, 2001; Gil, 2006, 2010) and Czerwinski et al. (2008). On the other hand, the fishery (resource management, fishery procedures, catches, landings, etc.) are broadly described in several publications (Gil and Sobrino, 2001; Gil, 2006, 2010; Czerwinski et al, 2009, 2010; Burgos et al., 2013).

From an environmental point of view, the oceanographic conditions in which the biological parameters (growth and reproduction models) were obtained (Table 2) are determined by an oceanic current scheme that links the Atlantic Ocean with the Mediterranean sea. This system is characterized by an important interchange of water mass between the Atlantic Ocean and the Mediterranean Sea, with an outward flow from the Mediterranean sea which moves at a slower velocity in relation to the inward flow from the Atlantic ocean at the surface (García-Lafuente et al., 2000) (Figure 3). These two water masses have different physical and chemical properties. Specifically, the Atlantic Waters (moving towards the Mediterranean Basin) have mean temperatures that oscillate between 16 and 20ºC and a very constant mean salinity of around 36.2 g/l. On the other hand, the Mediterranean waters (moving towards the Atlantic Ocean) are characterized by lower temperatures (around 12.9ºC) and salinities between 38.2 and 38.4 g/l (Parrilla et al., 1986).

These average conditions undergo medium and long-term changes that are reflected as significant variations in the temperature and salinity anomalies in the depth range considered (Figure 3). The temperature and salinity anomalies have been particularly important in some periods at all levels of the water column. For example, the middle of 1990s, sea temperature anomalies significantly higher were detected in the most shallow layers of the sea, and the increase in the sea surface temperature was very clear between the years 2010 and 2012. Similarly, significantly low anomalies were observed in several periods at all depths, and this was particularly evident for some years (2002, 2008 and 2010) at depths lower than 130 m. A similar anomaly pattern was detected for the salinity (Figure 3). In this case, there was notable variation in salinity in the surface layers between 1990 and 1993 and between 2006 and 2010. Further, this pattern was observed for deeper layers. These changes over time also were reflected in time variations in heat and salinity fluxes and in the North Atlantic Oscillation and Artic Oscillation indices (Figure 3).

3.2. Blackspot seabream fishery simulation

A total of 4032 simulations corresponding to seven different biological scenarios were carried out. From these, only 751 simulations (18.6%) provided non-extinct stocks in the period 1983-2016. In these seven scenarios, the number of age classes ranged from 15 to 20, the biomass of class 0+ at time t=0 oscillated between 20 and 45 t, the parameters a_R and b_R of the Ricker stock-recruitment relationship varied between 0.015-0.02 and 0.002-0.0025, respectively, and the percentages of spawn oscillated between 100% and 10% over the months of January, February and March.

To show the behaviour of the simulations, we have selected biological scenario number 5, which was characterized by an average natural mortality that oscillated between 0.223 and 0.233, and average biomass of class 0+ at time t=0 that varied between 28.3 t and 30.3 t for a total of six different age class configurations (from 15 to 20 age class). The simulations obtained in these biological conditions without considering the catches are shown in Figure 4a. In this scenario, although all simulations selected have a similar behaviour independent on the number of age classes, slight differences were detected in the maximum and minimum values. For example, the second maximum for the biomass simulation with 19 age classes was reached in 2007, while for the set with 16 age class this second maximum was observed in 2005.

When catches are considered, all the simulations result in a similar behaviour until the early 2000s (Figure 4b). The change in the total biomass starts from a peak biomass of around 5300 t from which it decreases to a minimum in 1999 (618 t). This period matches with the years in which the landings drop sharply, the total biomass only representing 20% of the potential biomass (Figure 4c and 4d) and a cycle change occurred after the first period of positive anomalies of monthly landings (Figure 4e). The second period of positive landing anomalies (2008-2011) overlapped with a slight increase in the average total biomass simulated from the year 2000 to 2009. From this point onwards, the simulations indicate an increase in the total biomass to a similar level to that observed in 1992 although this corresponded with a high deviation in the percentages with respect to the potential biomass (15 age class: 20%; 17 age class: 72%).

For these two age class sets (15 and 17), the annual fits of ARIMA models provided good fits. In the case of 15 age classes, the average annual variance explained was 63.5% and therefore, 36.5% of the biomass variation could be a consequence of the effects of environmental factors. With this level of explained variance, the corresponding RMSE was 79 t/year. On the other hand, the set of simulations obtained considering 17 age classes explained a level of variance slightly higher than that with 15 age classes (64.5%), although the average RMSE was close to 82 t/year.

3.3. Environmental component. EF and RW indexes

The variation in *EF* index of water temperature as a function of depth between January 1990 and December 2015 is shown in Figure 5a. It is possible to observe periods in which the *EF* index indicates that the temperature has a positive and negative effect. In addition, there are relatively long periods in which this parameter does not seem to have any effect on biomass. These are clearly longer between 2000 and 2009. There are two periods with significant positive and negative effects. The first period is between 1992 and 2000 and the second between 2009 and 2014. Both periods match with strong positive anomalies of temperature in upper surface layers of the sea. Additionally, the second period coincides with strong negative anomalies of temperature in deeper layers (Figure 3). The global relative weight of the sea temperature was slightly higher than 0.1 (RW=0.1023) which indicates that the effect of temperature on the variation in biomass in the period between 1990 and 2015 was not very strong. Nonetheless, the temperature effect was quite high some years, such as 1993 and 2009 when RW reached values close to 0.5 (RW_{1993}=0.4238; RW_{2009}=0.4891).

A similar pattern was detected for salinity. As for temperature, the significant effects lie mostly between 1992 and 2000 and 2009 and 2014. In the first period, the negative effects are matched with strong positive anomalies at the surface. In contrast, in the second period, the negative effects seem to be associated with significant positive-negative anomalies in surface and deeper layers, respectively (Figure 5b). Compared with the temperature effect, the relative weight of salinity was greater (RW=0.1419). As for temperature, globally, the effect of the variation in salinity in the period analysed was clearly low, but 3 years showed relatively high weights (RW_{1993}=0.5090; RW_{2000}=0.6042; RW_{2009}=0.6879).

Globally, for the rest of environmental variables and atmospheric indices except the salinity flux, the *EF* index had a very smooth behaviour (Figures 5c, 5d, 5e, 6a and 6b). The heat flux through the Strait of Gibraltar showed a global RW lower than 0.05 (RW=0.0349). Only two significant values of the *EF* index were detected, these being found in 1998 (EF_{1998}=RW_{1998}=0.2972) and 2001 (EF_{2001}=RW_{2001}=-0.4166). Likewise, for the chlorophyll concentration (RW=0.0006), NAO index (RW=0.0040) and AO index (RW=0.0318), the values of *EF* seem to indicate the absence of a significant effect on the biomass. Only in the case of AO index, there was a notable value of *EF*, in this case in 2001 (EF_{2001}=RW_{2001}=0.5851). Finally, as for salinity, the salinity flux has a significantly higher relative weight than that calculated for the environmental variables previously analysed (Figure 5d). Relatively high values of *EF* were observed in several years (1994, 1999, 2000, 2001 and 2009) and these were associated with *RWs* close to 0.13 (*RW*=0.1255).

4. Discussion

4.1. On the methodology

The methodology implemented in Sfish SubClass 1.1 establishes that the simulation of the variation in the biomass/abundance of a species in which constant environmental conditions are assumed can be modelled as a linear stationary stochastic process. That is, the residual time series generated as consequence of a lack of fit between an autoregressive model and the simulated data could be a consequence of extra-compensatory effects contained in the series of real catches and, therefore, the potential environmental effects on the biomass/abundance could be integrated in the proportion of variance not explained by the lineal stationary stochastic model. To fit the models, we used the ARIMA models proposed by Box and Jenkins (1976). These models, widely used to hindcast and forecast catches or landings of different fisheries from the 1990s (Stergiou et al., 1997; Park, 1998; Lloret et al., 2000; Becerra-Muñoz et al., 2003; Koutroumanidis et al., 2006; Czerwinski et al., 2007; Gutiérrez-Estrada et al., 2007; González-Herraiz et al., 2009), have proven to be a very useful tool for the analysis of trends and seasonal patterns in this type of time series which generally are characterised by a high inter-annual variability.

For all ARIMA models, the forecast is adaptive and any result obtained for a time t+1 with the available information until time t is the same as that obtained for the same period taking data until t-1 as a basis and adding an error term. In this way, it is understandable that the residual time series obtained as the value observed minus the value forecast by the ARIMA model must not contain information potentially linearly correlated with the variable to be forecast. In fact, the residual time series must behave as white noise series if the ARIMA model parameters are accepted. However, this does not mean that the residual time series does not contain relevant information. The nature of this residual information may be structured linearly and related to an external variable or be non-linear whereby it could be related to the variable to be forecast.

These properties have been exploited by several authors to improve the fit capacity of models in various estimation contexts. For example, Zhang (2003) presented a hybrid time series model using ARIMA and artificial neural network (ANN) models. This hybrid approach assumed that every time series y_t is a combination of linear patterns which can be extracted by the ARIMA model, and non-linear patterns that contain information from the part of the time series not fitted by the ARIMA model, that is, the residual time series. This configuration significantly improved the isolated fit of ARIMA and ANN models. A similar approach was used by Gutiérrez-Estrada et al. (2007) to improve the monthly catch forecasting of anchovy (*Engraulis ringens*) in the north area of Chile. These authors report that the information contained in the residual series and modelled by a hybrid approach increased the values of the persistence index at six points with respect to that obtained by powerful recurrent neural networks which implied an explained variance of over 81% in the external validation phase.

4.2. Simulations

Regarless of the parameters used, all the simulations provided initial values of biomass that oscillated around values slightly high than 5000 t. The biomass decreased gradually until the first years of the 2000s independently of the number of age classes considered. This period coincided with the geographical expansion of the blackspot seabream fishery following permissive European legislation in relation to the quotas and minimum catch size (Council Regulation -EEC- No. 3094/869). From this point onwards, the relation between biomass simulated with catches and the potential biomass oscillated between 20% and 72% (at the end of 2016) which is a clear indication that the population structure and the process whereby, year-to-year, individuals are incorporated to higher age classes have a strong influence on the simulated biomass variation. This is a consequence of the number of age classes is a quantitative property for each simulation that is not modulated by the environmental conditions and, therefore, the way in which the catches are subtracted from each age class and how the individuals of the last age class are withdrawn from the population are highly dependent on the deterministic structure established at the start of the simulation. This is a good example of the importance of detailed knowledge of life history characteristics for a proper assessment of fishery resources.

In any case, the biomass simulations support the real catch record in the Strait of Gibraltar. In all cases, the catch peaks (between 1994 and 1997, and 2009) match with ranges of biomass of 20% and 40% of the potential biomass. This indicates a recovery in biomass from 1999. After this year, the quota was reduced to 1000 t (Council Regulation –EEC- No 2340/2002), the Spanish fleet increased the minimum catch size by 32% compared to the previous regulation and the fishing effort was shortened to 140 days per season. The global effect of these actions was a slight recovery in the biomass that is reflected in the simulations and that allowed catch levels in 2009-10 to reach similar levels to those recorded in the 1990s.

4.3. Environmental component

Environmental variation and climate change are sources of disturbance of different aspects of the biology and ecology of species of commercial fisheries. Evidently, this is not a new idea. In the 1980s, Kondo (1980) and Hayasi (1983) reported that the wide fluctuation in sardine populations in the Kuroshio system could be caused by the variation in environmental conditions. Since these studies, a large number of authors have reported evidence of the relationship between abundance and various environmental factors in a wide range of ecosystems and exploitation systems (Lluch-Belda et al., 1989; Pauly et al., 2002; Chávez et al., 2003; Gutiérrez-Estrada et al., 2009; Gamito et al., 2015; Báez, et al., 2014; Gutiérrez-Estrada and Pulido-Calvo, 2015).

Nonetheless, in spite of the importance of the environmental component, it is rare to take into account its effects in practical situations (Cochrane and Starfield, 1992). Basically, this is a consequence of: i) the uncertainty associated with the forecast of the environmental factors in the medium and long term, and ii) a lack of knowledge about the weight and role played by a given environmental parameter in relation to abundance.

The uncertainty in environmental factor forecasts is an inherent property of each variable and only can be decreased under certain circumstances. On the other hand, the weight of the environmental factor can be calculated by means of various statistical procedures and its interpretability depends on the complexity of the methodology applied. For this purpose, SFish provides the value of an index (*EF*) that oscillates between 1 (favours an increase in biomass) and -1 (favours a decrease of biomass). Therefore, *EF* is a statistical measure that allows us to compare the effects of an environmental factor in relation to different time points and the average value of the absolute *EF* (*RW*) provides the relative weight of the environmental factor.

The analysis of *RW* indicated that the salinity, salinity flux and sea temperature had the highest values (around 0.12). The relative weight of the sea temperature is not surprising and, in fact, their direct and indirect effects on abundance of fish populations are widely documented. For example, Attrill and Power (2004) reported significant correlations between water temperature and the abundance of fish species in the Thames estuary using quadratic functions. In addition, Gutiérrez-Estrada et al. (2008) found similar functional relationships between temperature and Shannon diversity index in the Tagus estuary.

In the Strait of Gibraltar, Báez et al. (2014) reported high significant linear negative correlations (R=-0.68) between normalized sea surface temperature and landings of blackspot seabream in the period between 1986 and 2006, with an explained variance of 46%. Globally, this level of explained variance found by Báez et al. (2014) is higher than the fraction not explained by the ARIMA models in the biomass time series (around 36%) for a longer period (1986-2015). Additionally, our results indicate that from an annual point of view, the correlation oscillates between positive and negative values as was reflected by the *EF* index. This differs from the results found in others studies (Fock et al., 2004; Tian et al., 2012; Gutiérrez-Estrada and Pulido-Calvo, 2015) in which the sea temperature modulates the abundance in a single direction and matches with conclusions of Attrill and Power (2004) and Gutiérrez-Estrada et al. (2008).

In contrast to temperature, the role that salinity could play in abundance is not clear. Even in ecosystems in which the salinity fluctuations are very high (like estuaries), the causality in relation to abundance is not clear. For example, Henderson and Holmes (1991) reported no significant correlation when abundance series of dab, sole and flounder were compared with salinity concentration in the Severn estuary. In contrast, Thorman (1986), Thiel et al. (1995), Maes et al. (1998), Marshall and Elliott (1998) and Pasquaud et al. (2012) indicated that salinity had a strong influence on total biomass and abundance of several fish species in various European estuaries. Further, Ojaveer and

Kalej (2012) reported that a high level of salinity favours reproduction, elevated abundance and wide distribution of cod, flounder *Platichthys flesus trachurus* and sea herring in the Baltic sea. In the Strait of Gibraltar, the salinity average anomalies did not go beyond ±0.2 psu considering the period 1983-2015 and a depth range of 500 m, but surprisingly, it was the variable with the highest relative weight of those considered in this study (*RW*=0.1419). Likewise, our results are in accordance with those obtained by Báez et al. (2014) who, for the same study area, found a strong significant negative linear correlation (*R*=-0.71) between salinity and landings of blackspot seabream.

Just like salinity, the salinity flux had a high relative weight (*RW*=0.1255). Although salt in the ocean is not lost or gained, the salinity flux in this area could have an important effect on biomass as a consequence of the interaction of the current systems in the strait. That is, the salinity flux that may be calculated as the integral of salinity per velocity of water mass over a determined area, could be (more than other parameters) explained in the framework of its interaction with other parameters such as chlorophyll *a* concentration. For example, Moyano and Hernández-León (2011) found a significant negative linear correlation between temporal evolution of average salinity in the mixed layer and average chlorophyll *a* in the coast off Gran Canaria Island. These authors concluded that the fish larval assemblage off Gran Canaria Island exhibited a clear seasonal variation in accordance with the physical properties of the water column. Therefore, the variation in salinity flux could be a proxy for plankton growth which is known to be related to spawning and can strongly influence egg survival, feeding and the growth of recruits (Grauman, 1969; Cushing, 1969; Iles and Sinclair, 1982; Perretti et al., 2017).

Heat flux, chlorophyll *a* concentration and the AO and NAO indices had relatively low weights. In all cases, *RW* was lower than 0.04. Among these variables, heat flux and AO index were the most important. It is notable the low value of *RW* obtained for NAO index because in the last years a large number of studies have reported significant correlations between the behaviour of different fisheries and the variation in this index (Hughes et al., 2015; Leitão et al., 2016; Baptista et al., 2016; Rubio et al., 2016; Teixeira et al., 2016; Muñoz-Expósito et al., 2017). Further, Báez et al. (2014) reported that between 1986 and 2006 the NAO index explained more than 90% of the variance in blackspot seabream landings in the main harbours of the Strait of Gibraltar. This contrasts with the results obtained by Gutiérrez-Estrada et al. (2017) who concluded that the NAO index can modulate the abundance of blackspot seabream some years, particularly those in which the biomass had significantly low levels. These conclusions are coherent with the results obtained in the present study and reveal the difficulty involved in establishing causal relations between atmospheric factors and biological parameters of commercially exploited fish populations.

Conclusions

In the short term, one of the objectives of fisheries management should be to ensure the sustainability of the resources exploited. This implies adequate planning of fishing objectives, the design of different management strategies and the capacity to forecast the effects of these strategies in a scenario of environment and climate variability. In this context, models, procedures and methodologies with the capacity to determine the modulating effect of the environmental component should be fundamental tools for fisheries management. In this sense, SFish 1.1 SubClass is specifically designed to extract the weight of the environmental variables on the biomass variation in fish populations exploited commercially.

SFish offers a methodology that is easy to interpret from two indexes (*EF* and *RW*) which it is based on the following assumptions: (i) in a scenario in which the fishery component has been subtracted, the simulated biomass can be described using linear autoregressive models, and (ii) the fraction not explained by the model (residuals) must store information about extra-compensatory effects. We have applied this methodology to the blackspot seabream population in the Strait of Gibraltar. The landings of this species have drastically decreased in recent years which has increased the interest of the regional scientific community in the analysis of environmental mechanisms that underlie this trend at the local level. The results of this study support the idea that although the main factor responsible for the changes in abundance of this species is the fishery component, some environmental factors modulate the biomass variation in blackspot seabream in the Strait of Gibraltar.

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Table 1. Rule set that allow determine the effect type of each environmental variable on biomass.

Rule	Antecendents (if)	Consequent (then)
1	**Residuals>0** (simulated biomass>estimated biomass by ARIMA) and **Anomalies>0** (environmental parameter>mean environmental parameter) and **Correlation>0**	High levels of the environmental parameter favor more biomass (*F*=+1)
2	**Residuals>0** (simulated biomass>estimated biomass by ARIMA) and **Anomalies>0** (environmental parameter>mean environmental parameter) and **Correlation<0**	Low levels of the environmental parameter favor more biomass (*F*=+1)
3	**Residuals>0** (simulated biomass>estimated biomass by ARIMA) and **Anomalies<0** (environmental parameter<mean environmental parameter) and **Correlation>0**	Low levels of the environmental parameter favor more biomass (*F*=+1)
4	**Residuals>0** (simulated biomass>estimated biomass by ARIMA) and **Anomalies<0** (environmental parameter<mean environmental parameter) and **Correlation<0**	High levels of the environmental parameter favor more biomass (*F*=+1)
5	**Residuals<0** (simulated biomass<estimated biomass by ARIMA) and **Anomalies>0** (environmental parameter>mean environmental parameter) and **Correlation>0**	High levels of the environmental parameter favor less biomass (*F*=-1)
6	**Residuals<0** (simulated biomass<estimated biomass by ARIMA) and **Anomalies>0** (environmental parameter>mean environmental parameter) and **Correlation<0**	Low levels of the environmental parameter favor less biomass (*F*=-1)
7	**Residuals<0** (simulated biomass<estimated biomass by ARIMA) and **Anomalies<0** (environmental parameter<mean environmental parameter) and **Correlation>0**	Low levels of the environmental parameter favor less biomass (*F*=-1)
8	**Residuals<0** (simulated biomass<estimated biomass by ARIMA) and **Anomalies<0** (environmental parameter<mean environmental parameter) and **Correlation<0**	High levels of the environmental parameter favor less biomass (*F*=-1)

Table 2. Biological parameters of the *Pagellus bogaraveo* live history experimentally obtained for the strait of Gibraltar population.

Parameter	**Value**
Von Bertalanffy model*	
L_∞, t_0, k	58 cm, -1.1674 years, 0.169
Length-weight relationship (cm-g)	
d, g	0.0140, 3.0140*; 0.001, 3.239**
Length-size standard deviation relationship (cm-cm)†	
a_σ, b_σ	0.8591, 0.3663
Length-fecundity relationship (cm-number of eggs)*	
a_f, b_f	$3\cdot10^{-7}$, 4.26
Month and spawn percentage*	
Spawn proportions (***SP*** vector)	January=10% February=30% March=60% Remaining months=0%

*Gil (2006, 2010)
**Czerwinski (2008)
†Gutiérrez-Estrada et al., 2017

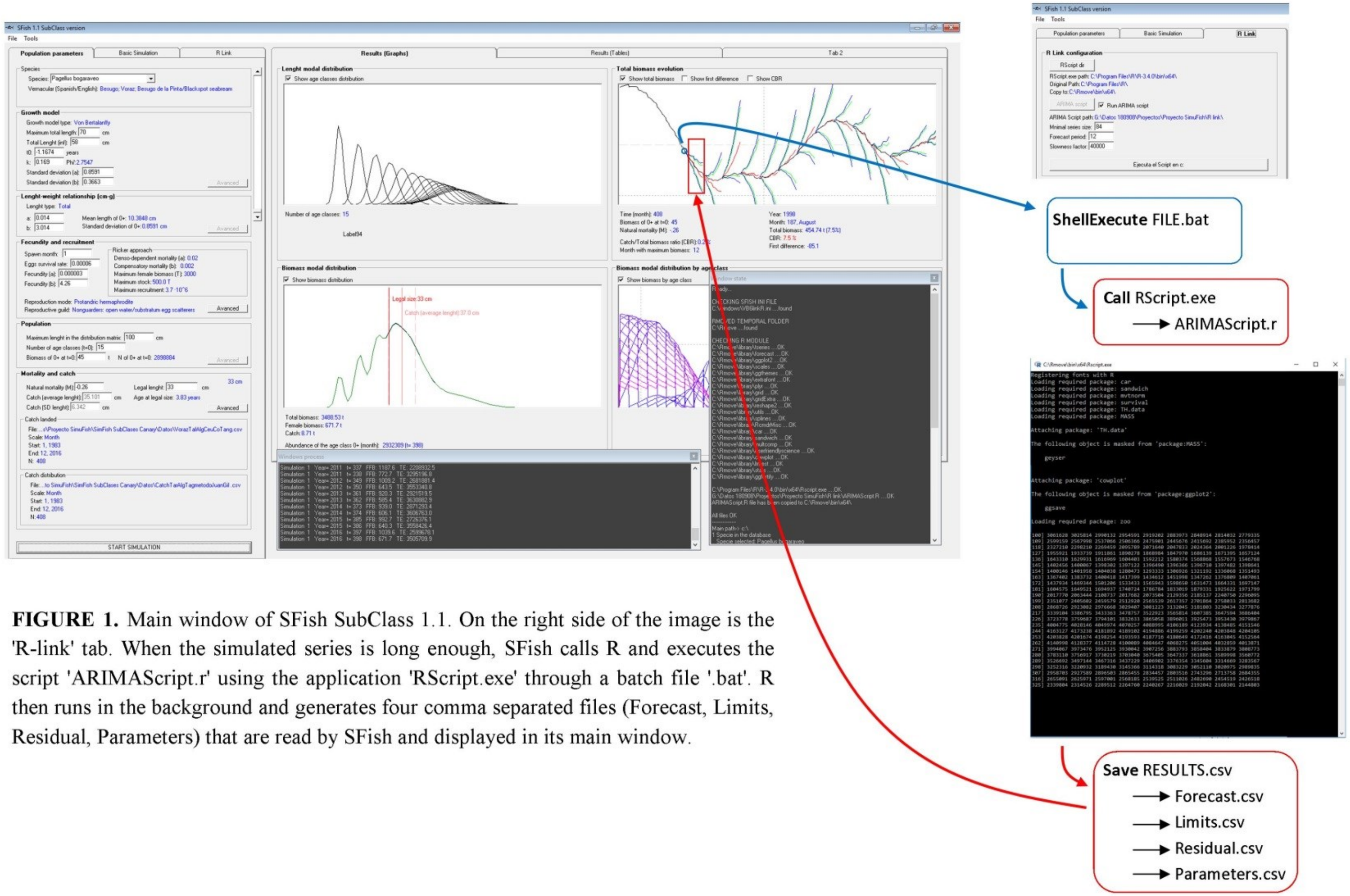


FIGURE 1. Main window of SFish SubClass 1.1. On the right side of the image is the 'R-link' tab. When the simulated series is long enough, SFish calls R and executes the script 'ARIMAScript.r' using the application 'RScript.exe' through a batch file '.bat'. R then runs in the background and generates four comma separated files (Forecast, Limits, Residual, Parameters) that are read by SFish and displayed in its main window.

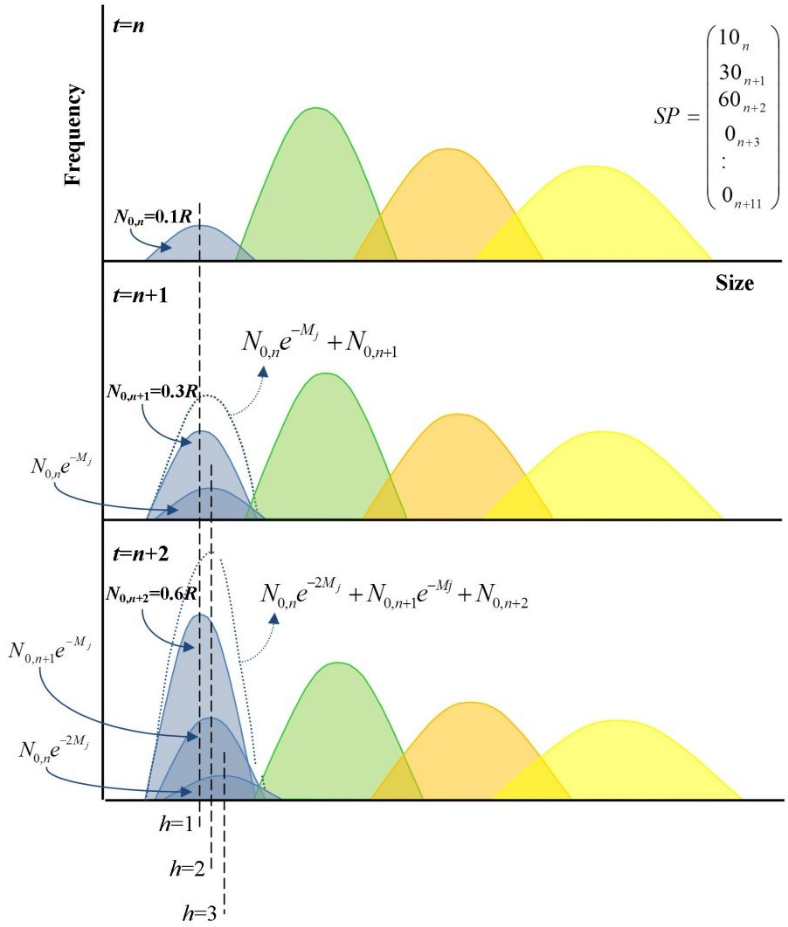


FIGURE 2. Example showing how SFish incorporates recruits in age class 0+ born in three different consecutive periods (January, February and March) and three different proportions (10%, 30% and 60%).

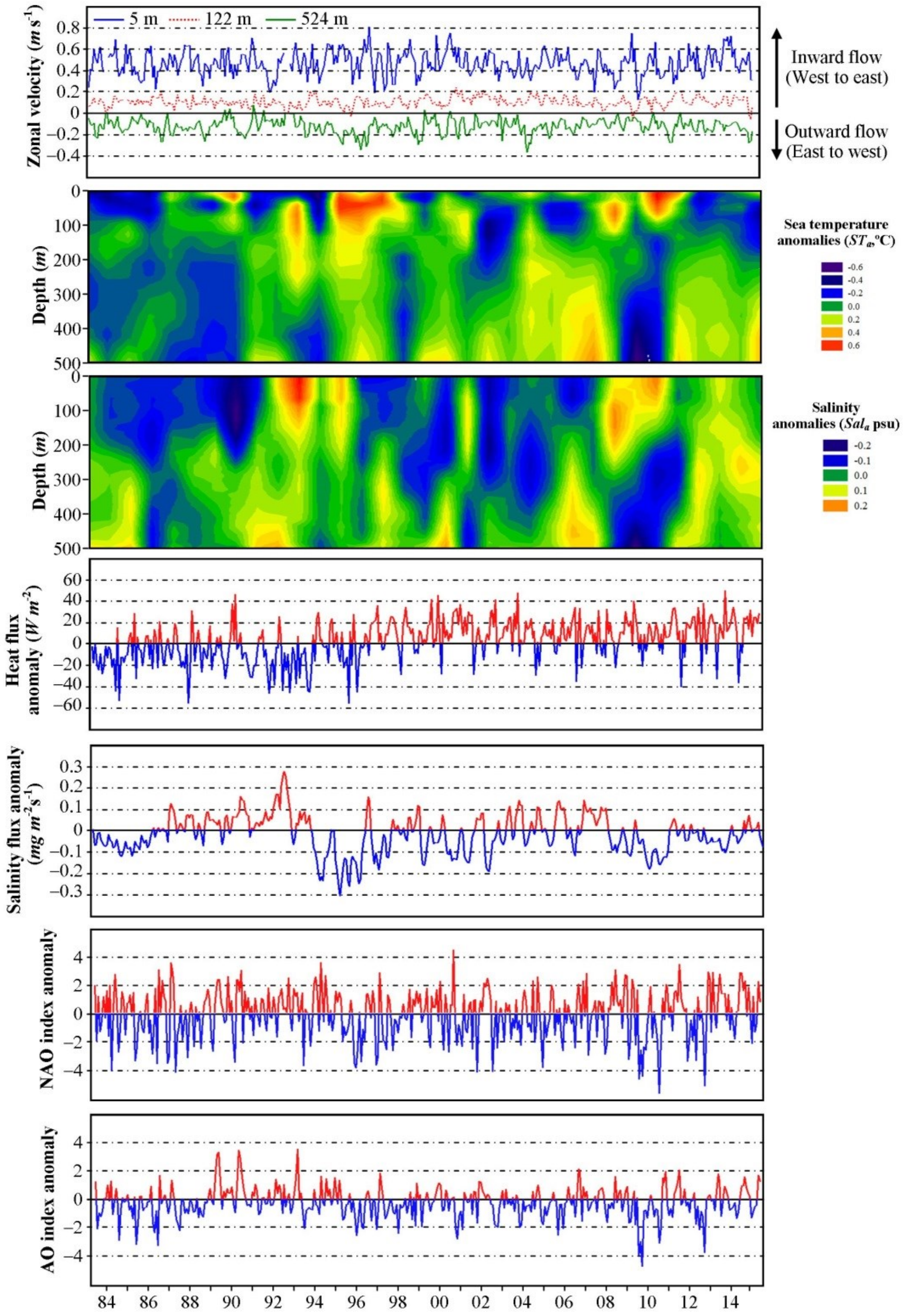


FIGURE 3. Zonal avegare speed at 5, 122 and 524 m and anomalies of sea temperatura, salinity, heat flux, salinity flux, North Atlantic Oscillation index (NAO) and Artic Oscillation index (AO) between 1983 and 2016

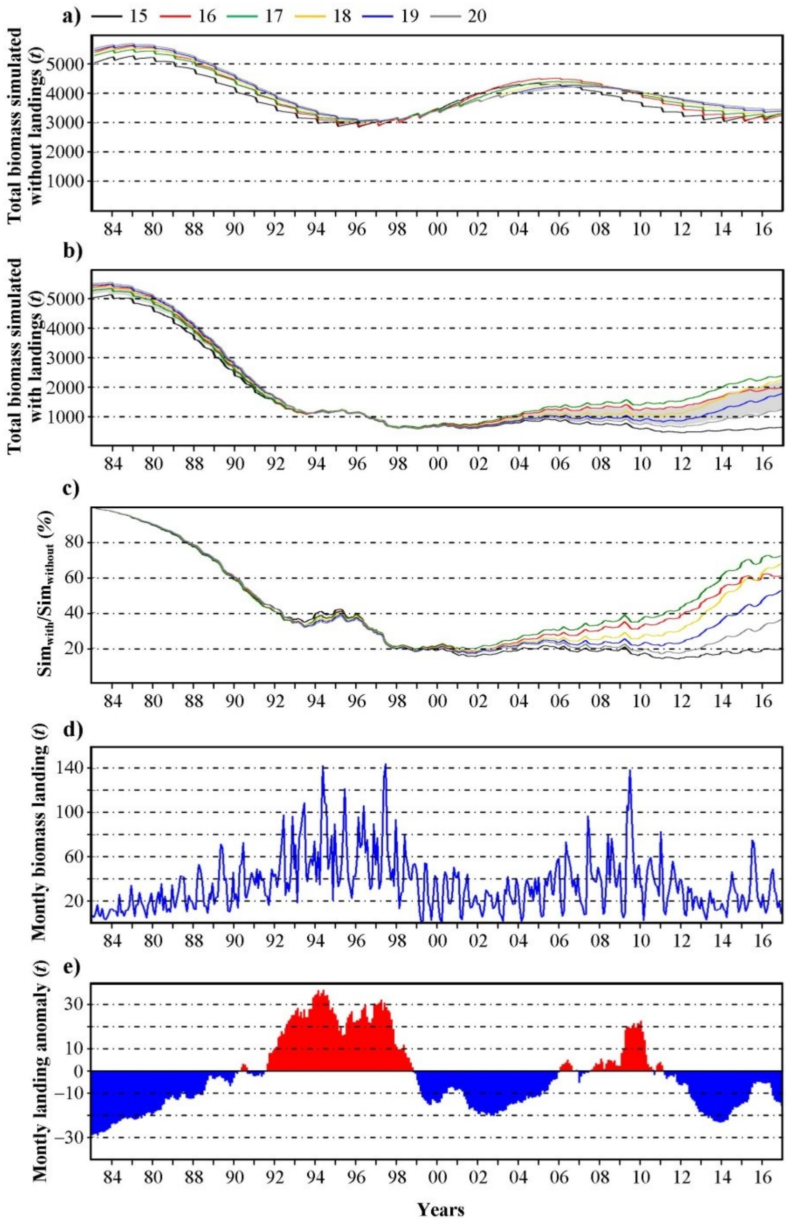
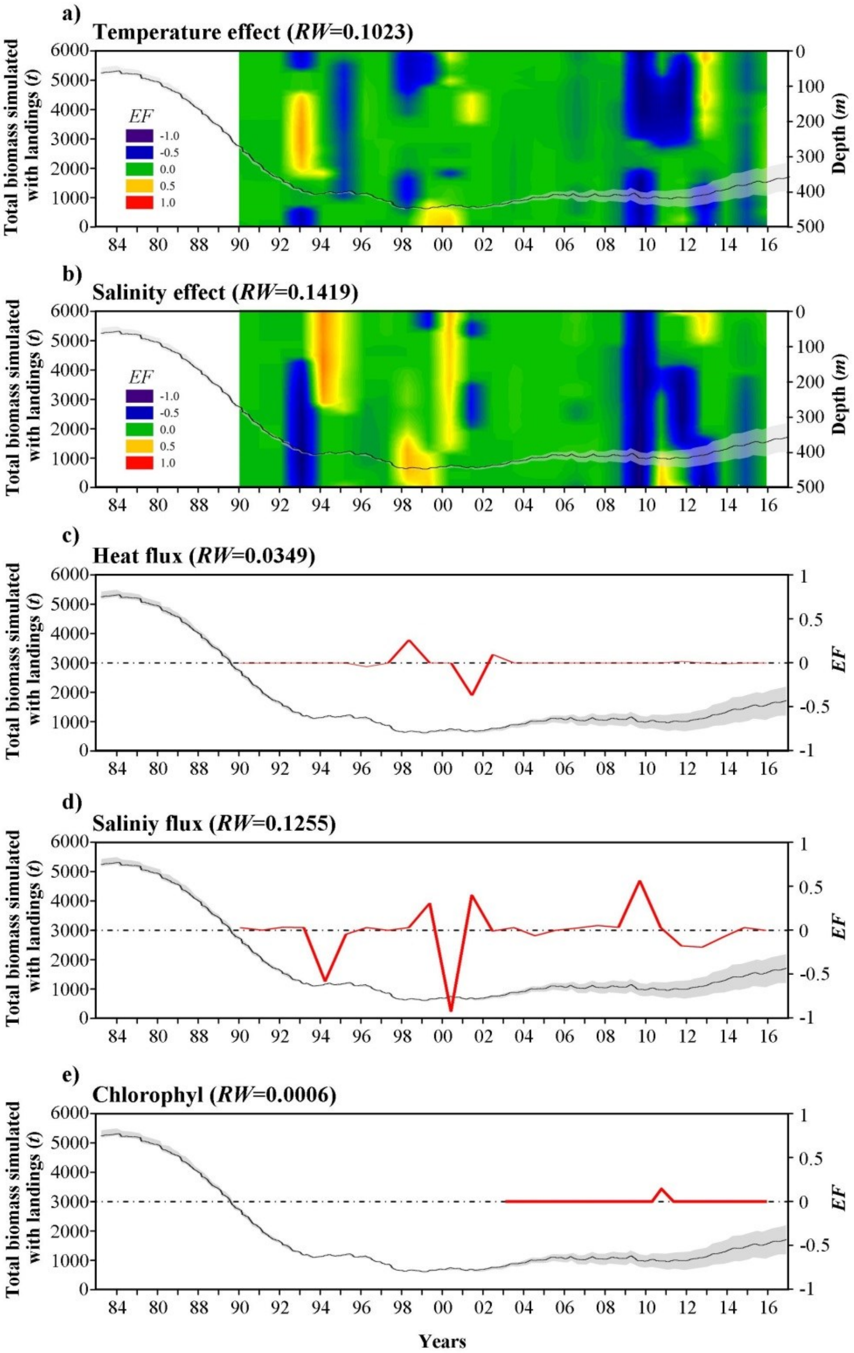


FIGURE 4. a) Average biomass simulated for six age classes configurations without catches in the period between 1983 and 2016 (scenario 5); b) Average biomass simulated in the scenario 5 considering the catches; c) Relationship between the stock when the catches are considered and the potential biomass; d) Real total landings of blackspot seabream in the main harvours of the strait of Gibraltar; e) Monthly anomalies of landings in the period between 1983 and 2016.



a) **Temperature effect (*RW*=0.1023)**

b) **Salinity effect (*RW*=0.1419)**

c) **Heat flux (*RW*=0.0349)**

d) **Saliniy flux (*RW*=0.1255)**

e) **Chlorophyl (*RW*=0.0006)**

FIGURE 5. Potential effect of the environmental parameters on total biomass simulated: a) sea temperautre; b) salinity; c) heat flux; d) salinity flux; e) chlorophyl a concentration. In all cases, the average biomass corresponding with the six age classes configuration in the scenario 5 and its confidence band at 95% (grey) are shown.

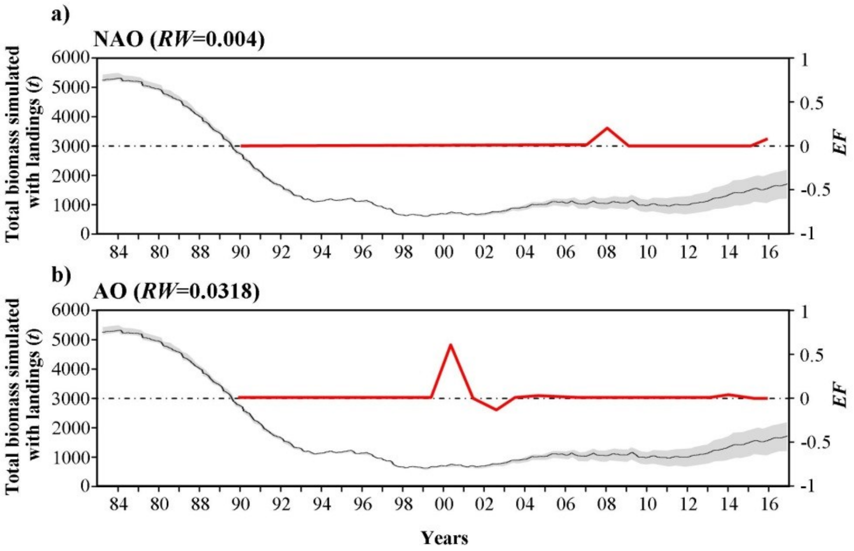


FIGURE 6. Potential effect of the environmental parameters on total biomass simulated: a) NAO index; b) AO index. In all cases, the average biomass corresponding with the six age classes configuration in the scenario 5 and its confidence band at 95% (grey) are shown.