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Effects of environmental factors on the historical time serie of blackspot seabream commercial landings (1983 to 2015) in the strait of Gibraltar: A shared marine resource between the Spanish and Moroccan fleets

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ABSTRACT

In the Strait of Gibraltar, the Blackspot Seabream (*Pagellus bogaraveo*, Brünnich 1768) is an economic resource of great commercial importance for the Spanish and Moroccan artisanal and Moroccan longline fleets. Given the great interest of the species for the fleets, it is of vital importance to know the dynamics of landings and how this can be influenced by environmental variability. From this arises the hypothesis of the present study: environmental mechanisms cause forcings in the dynamics of landings. To this end, we analysed the average annual dynamics of the time series of commercial landings of the Blackspot Seabream from 1983 to 2015 from a multivariate perspective. We applied trend, principal component (PCA) and time series clustering analyses to determine patterns and relationships between the fishery series and different oceanographic variables and climatic indices. In addition, we determined the influence of this set of variables on landings from a linear approach based on multiple linear regressions (MLRs) and generalized linear models (GLMs) and non-linear determined by generalized additive models (GAMs). The results obtained indicated the presence of common temporal patterns and the existence of significant influence between landings and ocean temperature with the current velocity modulus in specific layers and heat flux, causing lower fishing yields as we get colder waters with less intense currents. Such studies are of vital importance for the application of an ecosystem approach to the management of this resource by understanding the effect and influence of the environment on the dynamics of landings from the fishery.

1. Introduction

Blackspot Seabream (*Pagellus bogaraveo*, Brünnich 1768) is a widely fished benthopelagic marine sparid species that can be found from along the coast of Norway to the Canary Islands and Senegal, as well as in the Mediterranean basin (Carpenter and Russell, 2014). One of the most important Blackspot Seabream stocks from an ecological, social and economic point of view is located in the Strait of Gibraltar (Cabrera, 2014; CopeMed, 2019; Gil-Herrera et al., 2021).

In this region, the Blackspot Seabream is the target species of the Spanish and Moroccan artisanal "*voracera*" fleets and the Moroccan longline fleet. Although both fleets use a longline system as a catching gear, there are important operational and catch differences as a consequence of the legislative structures of each country (Belcaid et al., 2012; CopeMed, 2018, 2019).

Changes in landings have been observed in recent years, with a general downward trend in landings in the main Spanish ports (Gutiérrez-Estrada et al., 2017; Sanz-Fernández et al., 2019; Sanz-Fernández and Gutiérrez-Estrada, 2021; Gil-Herrera et al., 2021), which has been associated with a variation in climatic and oceanographic conditions (Báez et al., 2014).

In the area of the Strait of Gibraltar, several studies have analysed the effect of environmental variability on the commercial landings of the Spanish fleet's Blackspot Seabream. Castilla Espino et al. (2010) studied the relationship with sea surface temperature (SST) and Báez et al. (2014), analysed the influence of climatic indices (NAO and AO) and oceanographic variables (temperature and salinity). Continuing in the same line of work, but also including information on the commercial landings of the Moroccan fleet's Blackspot Seabream, Sanz-Fernández and Gutiérrez-Estrada (2021) analyse the effect of two environmental variables using a simple correlation analysis. All previous studies suggest, the existence of relationships between environmental factors and

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the evolution of Blackspot Seabream exploited fish stock indicate that negative trends and relationships could reduce fishery yields, but none of them are fully conclusive.

For the analysis and quantification of the effect of environmental variability on fishery production (commercial landings) data a wide variety of statistical techniques can be applied, from traditional regression statistical modelling based on a linear and non-linear approach to advanced time series modelling (Nicola et al., 2018). Multiple linear regression models (MLRs), generalized linear models (GLMs) and generalized additive models (GAMs) are presented as tools to detect and elucidate the relationships between fishery and environmental variables, being able to quantify the effects of environmental variability on the fishery and ecological dynamics of the resource (Borja et al., 1998; Damalas et al., 2007; Silva et al., 2015; Castro-Gutiérrez et al., 2022).

The application of multivariate statistical techniques focused on the classification and reducing the dimensionality of the dataset, such as principal component analysis (PCA) and time series clustering, can be very useful as they can detect common patterns among variables along with their clustering. For this reason, the combined use of traditional regression models and clustering and dimensionality reduction techniques can be presented as an analytical approach to assess common patterns and relationships between the historical series of landings and environmental parameters, trying to identify which of them and what extent influence landings.

Additionally, as for other fish species (Lloret et al., 2001; Erzini, 2005), apart from the effects of environmental-oceanographic variability on fisheries data (commercial landings), we should take into account those of climatic and oceanic variations, which are involved in changes in the status of fish populations. Gutiérrez-Estrada et al. (2017), Sanz-Fernández et al. (2019) and Gutiérrez-Estrada et al. (2020) obtained simulated biomasses of the *P. bogaraveo* population in the Strait of Gibraltar using simulation models that incorporate the biological aspects of the species and the dynamics of landings, concluding that any modification in the environmental parameters of its surroundings is a barrier that prevents its optimal development, with a devastating effect on its population, especially when the population reaches low biomass levels as a result of excess fishing pressure.

The aim of this study was to assess in depth and comprehensively the relative impact of a range of environmental parameters on the *P. bogaraveo* commercial landing of the Spanish and Moroccan fleets operating in the Strait of Gibraltar. According to the European Union (EU)'s Common Fisheries Policy (CFP), one of the objectives of which is to safeguard the sustainably of fishing activity, the consideration of environmental information is essential for proper management of resource from an ecosystem-based approach (Europe, 2022). Hence, our primary objective was to increase our knowledge of the potential relationships between commercial landings of *P. bogaraveo* and a wide set of environmental variables and two climatic indices. Our initial hypothesis was that these variables do influence annual variability in commercial landings, which could explain part of the variability of landings. To explore this hypothesis, a literature review is carried out and an analysis is applied to the historical series of commercial landings of *P. bogaraveo* in the Strait of Gibraltar from 1983 to 2015, grouping and modelling the landings according to a broad framework of environmental parameters and climatic indices, in order to detect and clarify their patterns and relationships, as well as to identify which of them influence the landings and quantify their effects. For this reason, the combined use of MLR, GLM and GAM models together with PCA and time series clustering are applied.

2. Material and methods

2.1. Study area and fishing data

The area of the Strait of Gibraltar is a particular oceanographic environment. It is located to the south of the Iberian Peninsula and north of Morocco and creates an approximately 60-km long natural border between geographical Europe and Africa (Bruno et al., 2013). From a fluid dynamics perspective, it is a two-layer system of inverse exchange flow between water masses of the Atlantic Ocean and the Mediterranean Sea. The lower salinity of Atlantic water and therefore lower density, flows at the surface towards the Mediterranean, while Mediterranean water flows at depth towards the Atlantic, as it is more saline and has a higher density (Echevarría et al., 2002; Vázquez López-Escobar, 2006). This pattern of water currents is strongly influenced by the prevailing winds, topography of the Strait, tidal currents from ocean mixing processes, upwelling and the generation and propagation of internal waves (Echevarría et al., 2002; Bruno et al., 2013). These characteristics provide the key conditions for the Strait's high marine productivity and broad range of fisheries (Echevarría et al., 2002; García Horcajuelo, 2018; Cort and Abaunza, 2019; Gil-Herrera et al., 2021).

We used the historical series of commercial fish landings of *P. bogaraveo* made by the Spanish artisanal fleets in the ports of Algeciras, Ceuta, Conil and Tarifa and the Moroccan fleet in the port of Tangier between 1983 and 2015. These data were provided by the Spanish Oceanographic Institute and the National Institute of Fisheries Research in Tangier. Specifically, we used annual average landings in tonnes. These data are derived from the estimation of the average per year of the total series corresponding to the sum of the monthly landings of the Spanish ports of Algeciras (1995–2015), Ceuta (1987–2001), Conil (2001–2015) and Tarifa (1983–2015) and the Moroccan port of Tangier (2001–2015). The area of the study was limited to the fishing areas of the fleets corresponding to the far southeast of International Council for the Exploration of the Sea (ICES) Division IXa from 6°25′W to 5°15′W and 35°45′N to 36°15′N (Burgos et al., 2013) (Fig. 1 upper panel).

2.2. Oceanic data and climatological indices

We used the historical annual average data from 1983 to 2015 of the following oceanic variables: surface ocean heat flux coming through coupler and mass transfer (W m^{-2}), salinity flux (kg m^{-2} s^{-1}), salinity (PSU), ocean water temperature (°C) and zonal and meridional components of the current velocity (m s^{-1}) (current velocity modulus). These data were retrieved from the Simple Ocean Data Assimilation (SODA) ocean reanalysis data set, version 3.3.1 (SODA3.3.1 files http://www.atmos.umd.edu/~ocean). Version 3 of this dataset uses version 5 of the Modular Ocean Model developed by the Geophysical Fluid Dynamics Laboratory of the US National Oceanic and Atmospheric Administration (NOAA). The variables are mapped in 3D onto a horizontal 1/2° x 1/2° Mercator mesh at 50 vertical levels (z, detph) (Carton et al., 2018). The transformation of the data from positional to temporal scale was carried out by area averaging. The database was filtered to obtain the first 24 layers, corresponding to depths from 5 to 525 in 10 to 80 m intervals. The choice of this depth range is due to the demersal nature of the species, with the vast majority of fishing operations taking place within this depth range (Gil, 2006; CopeMed, 2019).

The climatic indices used were the North Atlantic Oscillation (NAO) and the Arctic Oscillation (AO). The time series of these indices between 1983 and 2015 were downloaded in a monthly format and annual means were calculated. The NAO index was downloaded from the US National Center for Atmospheric Research Climate Analysis Section (Hurrell and National Center for Atmospheric Research Staff, 2020) and the AO index from NOAA's Climate Prediction Center, (http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/monthly.ao.index.b50.current.ascii).

2.3. Identification of common patterns in landings climatic indices and oceanic variables

Two multivariate statistical techniques focused on classification and

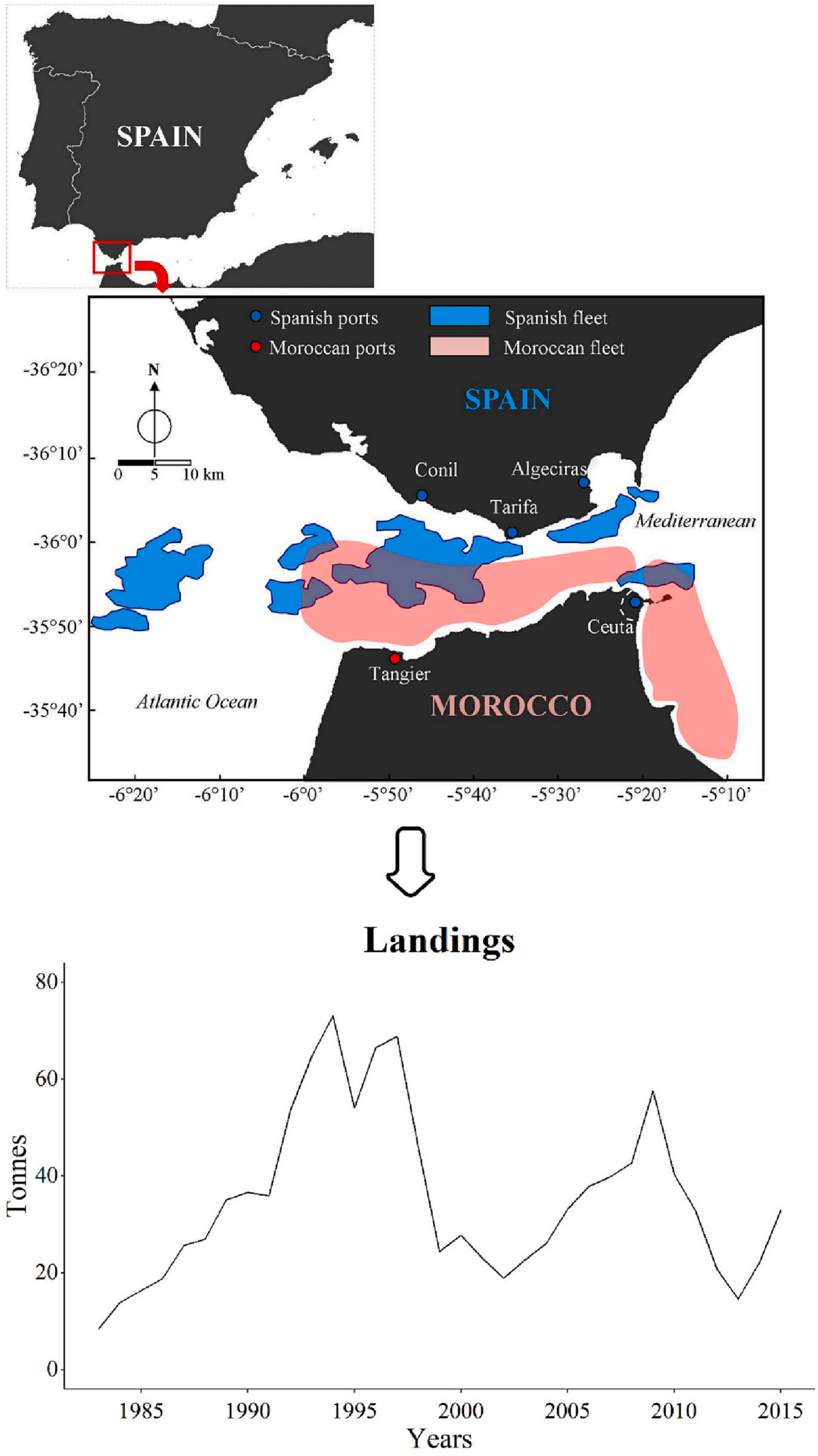

Fig. 1. Operational ground in the Strait of Gibraltar of the Spanish (blue) and Moroccan (pink) "*voracera*" fleet (up) with the annual average landings time series (1983–2015) (below). The points represent the different ports involved in the fishery, blue-Spanish and red-Moroccan. This figure is a modification 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". (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dimension reduction were used: time series clustering and principal component analysis. The combined use of these two techniques was used with the aim of detecting common patterns between the time serie of landings and the time series of climatic indices and oceanographic variables. Based on these two techniques, 1- We corroborate that the landings follow common patterns with the same variables if the two techniques coincide and 2- We identify if the grouping of the landings is the same. To avoid some variables dominating over others due to differences in their units of measurement and orders of magnitude, data were standardised by subtracting their mean and dividing by their standard deviation, making the variables comparable.

2.3.1. *Time series clustering*

We used time series clustering to group the study variables based on their attributes to obtain a set of groups or clusters with the greatest possible homogeneity within them and the greatest possible heterogeneity between them (Supplementary material; Fig. S1). It is considered that the group in which the landings are found indicate that they have similar attributes or maximum homogeneity with the rest of the climatic indices and oceanographic variables found within the same it. For the salinity, temperature and current velocity variables, we performed hierarchical clustering using dynamic time warping with a shape extraction centroid and hierarchical control using an average method (Sardá-Espinosa, 2019). The tsclust() function (Sardá-Espinosa, 2019) was used for this purpose. These new variables were obtained as the mean of values in each cluster. The use of this analysis for the variables salinity, temperature and modulus of current velocity is mainly due to its philosophy of not reassigning individuals once they have been merged, and not separating them at later stages. Given the low variability that occurs between these variables by depth, the use of the hierarchical method allows them to be grouped into 3 ranges by depth: shallow, intermediate and deep.

The clustering of salinity, temperature and modulus of current velocity, once grouped by depth, together with the others (landing, climatic indices and the rest of oceanographic variables) was performed by applying the partitional clustering algorithm with random seed for reproducibility of 200, and Dynamic Time Warping (DTW) distance, with a window size of 10% of the length of the series, function tsclust(). The choice of DTW as the distance is due to its ability to obtain similarity between time series and establish their optimal alignment using a non-linear approach (Gonzáles Castellanos and Soto Valero, 2013).

The optimal number of clusters was identified by an iterative procedure (Sardá-Espinosa, 2019) based on optimising the following parameters: maximising the Silhouette index (Rousseeuw, 1987), Dunn index (Arbelaitz et al., 2013), Calinski-Harabasz index (Arbelaitz et al., 2013) and Score Function (Saitta et al., 2007) and minimising the COP (Arbelaitz et al., 2013), modified Davies-Bouldin (Kim and Ramakrishna, 2005) and Davies-Bouldin (Arbelaitz et al., 2013) indices. During this procedure, the prototypes or centroids Partition Around Medoids (PAM) (a medoid is a time series whose average distance to the other components of the same cluster is minimal) and DTW Barycenter Averaging (DBA) were used (Petitjean et al., 2011; Sardá-Espinosa, 2019). The variation in the initial number of clusters ranged from 2 to 8 cluster, given that we were considering 13 study variables. Further consideration of clustering would give a much disaggregated result, favouring the creation of individual clusters per variable.

Having identified the optimal number of clusters, the best time series centroid adjusted to the optimal number of clusters with 1 repetition was also determined by internal validation, using the above indices, taking into account only the two previous centroids.

Finally, having identified the optimal number of clusters and centroid, the final clusters were obtained. They are obtained using the tsclust() function specifying in their arguments the number of optimal clusters and the centroid detected in the previous steps. Subsequently, stability of the final clusters was evaluated using the dissimilarity function (Hornik, 2021) (Supplementary material; Fig. S1). Dissimilarities using minimal Euclidean membership distance. The cluster stability study was carried out to quantify the degree of agreement of different replicates, which in this case were 20. The results presented are those in which the pairs of replicates had dissimilarity equal to 0.

2.3.2. Principal component analysis (PCA)

PCA was used to explore interannual variability, observe and identify similar patterns and the variables that explain the most variance in the data, reduce the dimensionality of the dataset and construct biplots showing the joint two-dimensional distribution of the variables (Kassambara, 2017). PCA biplot graph allows us to visualise the two-dimensional distribution of the variables that fall within the principal components, observing the common direction of the variables. In this way, it detect common patterns between landings and the rest of the variables, taking years as observations. If two variables point in the same direction, it means that they will have high values in those years. The length of the arrow refers to the correlation of the variables with respect to the dimensions, so the longer the arrow, the higher the correlation between the variables and the dimensions. Variables with positive correlations between them are grouped together while variables with negative correlations are placed on opposite sides of the graph. For selecting the number of principal components, the threshold for minimum total variance explained was set at 70%. The FactoMineR package was used for performing the PCA and plotting the results (Lê et al., 2008).

2.4. Modelling the relationship between commercial landings and environmental variables

The relationship between commercial landings and environmental variables was assessed by using linear and nonlinear analysis, basing the linear approach on two types of models, multiple linear regression (MLR) and generalized linear models (GLMs), and the nonlinear approach on generalized additive models (GAMs). In both approaches, the response variable was commercial landings while the explanatory variables were climatic indices and oceanic variables. The joint use of these techniques allows us to compare results from a linear and non-linear perspective, knowing that linear models will only explain the linear variability of landings and the GAMs models will explain the variability of landings that is due to the non-linear pattern.

The MLR and GLM models were built using the lm() and glm() functions of the stats package (R Core Team, 2020), respectively. Prior to running the GLMs and GAMs, it was assessed whether the response variable was best described by normal or gamma distributions. The best distribution was selected graphically and by considering the lowest Second-order Akaike Information Criterion for small samples (AICc). AICc should be used when the ratio between the number of observations and the number of estimated parameters is than 40 (Burnham and Anderson, 2004). In our case the number of observations per variable is 33. The mlnorm(), mlgamma() and AICc()functions were used for this purpose. (Moss, 2019; Barton et al., 2020). In this case, the gamma distribution was selected (gamma distribution AICc = 279.44, normal distribution AICc = 284.69 and Supplementary material; Fig. S13). Subsequently, link functions (identity, inverse and log) were assessed by building block models (one for each link function) using all the variables resulting from the exploratory analysis and the best function was selected based on the lowest AICc for the GLMs.

The implementation of the GAM models was performed with the gam() (Wood, 2017). To avoid over-fitting in the non-parametric part, the maximum number of degrees of freedom allowed was 3 (k = 4) and we used the thin plate regression spline ("tp") basis. The method of estimating the number of degrees of freedom of the smoothing parameter was generalized cross validation for unknown scale parameter (GCV.Cp) coupled with a double penalty incorporated by the arguments select (= true) and gamma (Marra and Wood, 2011). The value of gamma was set to 1.4 to avoid the known overfitting tendency in GCV. Using this value corrects for this to a large extent without compromising model fit and without greatly degrading prediction error performance (Kim and Gu, 2004; Wood, 2017). The link function was selected on a case-by-case basis. Once the best model per function was obtained, the selection of the best of the 3 models was made on the basis of the validation of its residuals.Only the model that met all the conditions for validation of the residuals is presented. In our case 2 of the best GAM models presented temporal correlation in the residuals.

For selecting the explanatory variables in each of the types of models (MLRs, GLMs and GAMs), an algorithm was developed with the main goals of obtaining a model that was significant (all its components being significant, $p < 0.05$) and parsimonious but explained as much variability as possible in the response variable (R^2 in MLRs and pseudo R^2 in GLMs and GAMs). In this way, an attempt is made to cover all possible possibilities in order to find the model with the least loss of information, the greatest significance in its variables and the greatest variability explained.

The model selection algorithm is based on the forward direction approximation using the AICc as the selection criterion. The algorithm will advance in each of its iterations, selecting as best those models with the lowest AICc at the beginning of the iteration. The algorithm will terminate when the AICc is not improved. In each iteration, new branches are opened with each of the selected models, and the branch will end when the AICc is not improved. Once at the end, if the final model with the lowest AICc has all its variables significant and a higher explained variability, the algorithm stops, otherwise it goes backwards checking the significance of the variables of the previous models until it finds the model with the highest significance in its variables and the highest explained variability. It is possible to converge to the same model from different branches.

The models selected were validated by calculating the residuals and a set of external errors obtained by comparing observed values and those predicted by the models. The residuals were assessed for homogeneity, normality (except in the case of GLMs and GAMs using a gamma distribution), independence (due to model misspecification or inherent in the time correlation) and most influential variables (Zuur et al., 2009; Zuur and Ieno, 2016). In the MLRs, GLMs and GAMs, the ordinary residuals (observed value minus model fitted value) obtained through the resid() function were used (R Core Team, 2020). The collinearity of the predictors was assessed by calculating the Variance Inflation Factor (VIF) (vif() function) in the case of MLRs and GLMs (Fox and Weisberg, 2019) and concurvity (the GAM equivalent of collinearity) (Lee et al., 2021) (concurvity() function) in the case of GAMs (Wood, 2017). The output of the latter function presents 3 indices of concurvity, worst, observed and estimate, all bounded between 0 and 1, where 0 indicates no concurvity and 1 indicates total lack of identifiability (Wood, 2017). Although there is no universal criterion for concurvity, estimated concurrence values of <0.5 and at worst <0.8 are generally considered acceptable (Barton et al., 2020; Goldshtein et al., 2021; Ross, 2023).

In the VIF, the reference value was taken to be equal or close to 5 to indicate that each explanatory variable is independent of the others (Zuur et al., 2009), for the estimated concurvity it was <0.5 and in the worst case 0.8. The likelihood ratio test of nested models was used to assess the significance of each model (lrtest() function) (Zeileis and Hothorn, 2002). For the GLM and GAMs, the pseudo R^2 is calculated (Zuur et al., 2009).

Finally, we perform an external validation of the model results obtained. For this we use the model-adjusted landings values and the actual landings values. The type error measures were calculated: the determination coefficient (R^2), the root-mean-square deviation (RMSE), mean absolute error (MAE), standard error of prediction, as a percentage (%SEP) (Ventura et al., 1995), coefficient of efficiency (E_2) (Nash and Sutcliffe, 1970; Kitanidis and Bras, 1980), average relative variance (ARV) (Griñó, 1992), the persistence index (PI) with a 1-year lag (Kitanidis and Bras, 1980) and modified Kling-Gupta Efficiency (KGE′) (Kling et al., 2012). To be considered the best model, a model was required to explain a high level of variance (ARV and E_2) and show good agreement between observed and predicted values (KGE′), with no time lag (PI) and a low level of absolute (RMSE, MAE) and relative (%SEP) errors. All analyses in this study were carried out in R (R Core Team, 2020).

3. Results

The application of the hierarchical cluster analysis with DTW distance with centroid shape extraction and hierarchical control according to the average method on the oceanographic variables salinity, temperature and current velocity modulus generated the following variables as a function of depth: surface salinity (5–75 m) or S5–75, intermediate salinity (85–125 m) or S85–125, deep salinity (135–525 m) or S135–525, surface temperature (5–85 m) or T5–85, intermediate temperature (95–225 m) or T95–225, deep temperature (255–525 m) T255–525, modulus of surface current velocity (5 m) or UV5, modulus of intermediate current velocity (15–335 m) or UV15–335, modulus of deep current velocity (385–525 m) or UV385–525. All of them obtained as the average of the depth-identified cluster. Thus, the dataset on which the analyses were made was the following: fishery variable: commercial landings, climatic indices: NAO and AO and oceanographic variables: heat flux, salinity flux and the rest of the variables mentioned at the beginning of the paragraph. This makes a total of 14 initial variables.

The supplementary material shows the results obtained after the application of the exploratory analysis and the trend analysis (Supplementary material; Fig. S2; Fig. S3; Fig. S4; Fig. S5; Fig. S6; Fig. S7; Fig. S8; Table S1, Table S2; Table S3). By way of summary, the variable S5–75 was eliminated from the initial set of variables for the time series clustering, PCA, linear and non-linear models because its vif value was higher than 5 (Supplementary material; Table S1). A total of 13 variables were used for the latter analyses. Finally, NAO, salinity flux, S85.125, S135.525 and UV385.525 had no significant trends. The landings showed a significant trend of order 3 in all terms ($p < 0.001$) which is upward from 1991 to 1993 and downward from 2003 to 2013 (Supplementary material; Fig. S8; Table S3).

3.1. *Time series clustering*

Fig. 1 (lower panel) and Fig. 2 show the time series of the different variables analysed. Time series clustering analysis indicated that the optimal numbers of clusters for both centroids (PAM and DBA) were 3, 7 and 8 because in most cases they presented a higher number of optimal results per index (Supplementary material; Table S4; Table S5; Table S6: Table S7: Table S8; Table S9; Table S10; Table S11). For each of the clusters selected, the best centroid was obtained with PAM, except for 3 where a draw (3/3) was achieved between DBA and PAM. (Supplementary material; Table S12). The stability analysis of the 3-cluster with DBA centroid solution indicated a convergence of landings with flux salinity, T5–85, T95–225, UV5 ($|UV|$ (5 m)), UV15–335 and UV385–525. For the 3-cluster with PAM centroid solution indicanted a convergence of landings with T5.85, T95.225, $|UV|5$, $|UV|15.335$ and $|UV|385.525$. In the case of the 7-cluster solution, a link was observed with T5–85 and T95–225. Finally, in the 8-cluster solution, landings were grouped with T95–225 and UV15–335. In the results established by the optimal numbers of clusters, we observed a common pattern characterised by the grouping of landings by water temperature and current speed (Fig. 3). In the results established by the optimal number of clusters in which the landings were located, a common pattern was clear, namely, with higher values between 1990 and 1999 and 2003–2013, showing the existence of a non-linear pattern among the variables (Fig. 4).

3.2. *Annual PCA*

All the assumptions for PCA were met (Supplementary material; section anual PCA). The first component explained 23.94% of the observed variance, while the second, third, fourth and fifth components explained 16.99%, 13.59%, 10.52% and 9.26%, respectively. The overall variance explained was 74.28%. The variables contributing the most to the two first components were (in descending order): T95–225, UV15–335, landings, T5–85 and salinity flux (PC1) and AO, NAO, UV385–525 and UV15–335 (PC2). The first and fourth components had the highest contribution of landings, 14.18% and 10.43% respectively (Supplementary material; Fig. S10).

The biplots of PC1 had the same pattern as that detected for the landings and their relationships with oceanic and climatic variables (Fig. 5). The landings were associated with UV15–335, T95–225 and T5–85, having in common the same direction and location. Climatic indices showed the opposite pattern to landings in all cases (Fig. 6). The

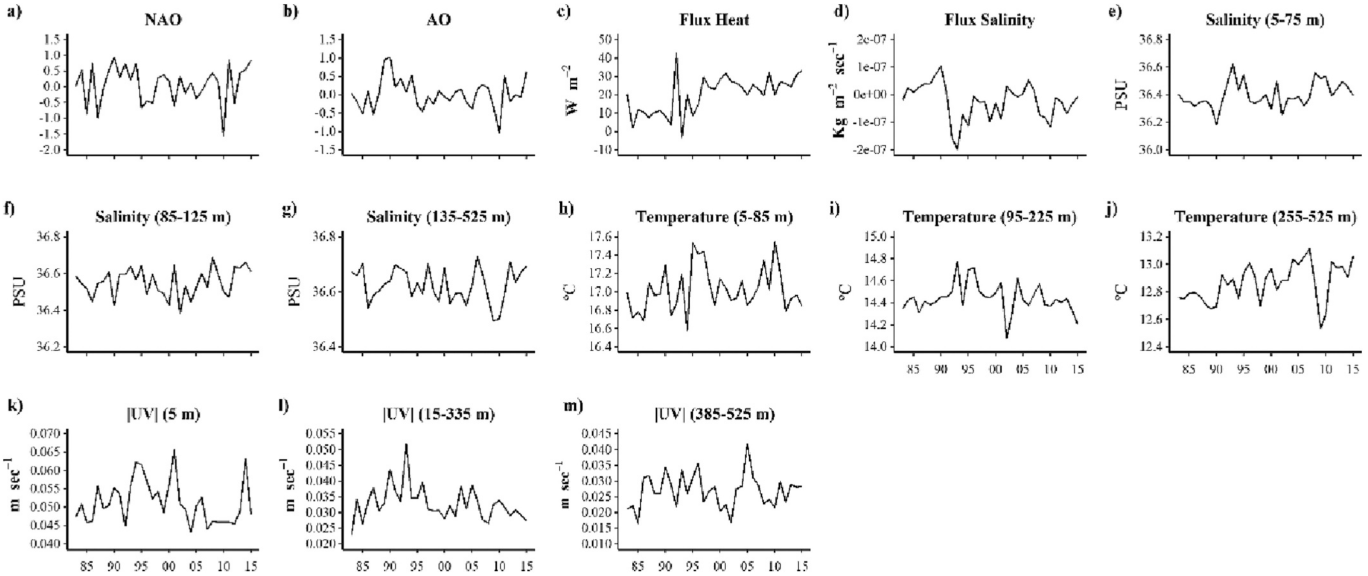

Fig. 2. Anual time series of the different variables from 1983 to 2015. The intervals in metres (m) refer to the clustering by depth obtained after the application of the hierarchical cluster analysis with Dynamic Time Warping (DTW) distance with shape extraction centroid and hierarchical control according to the average method.

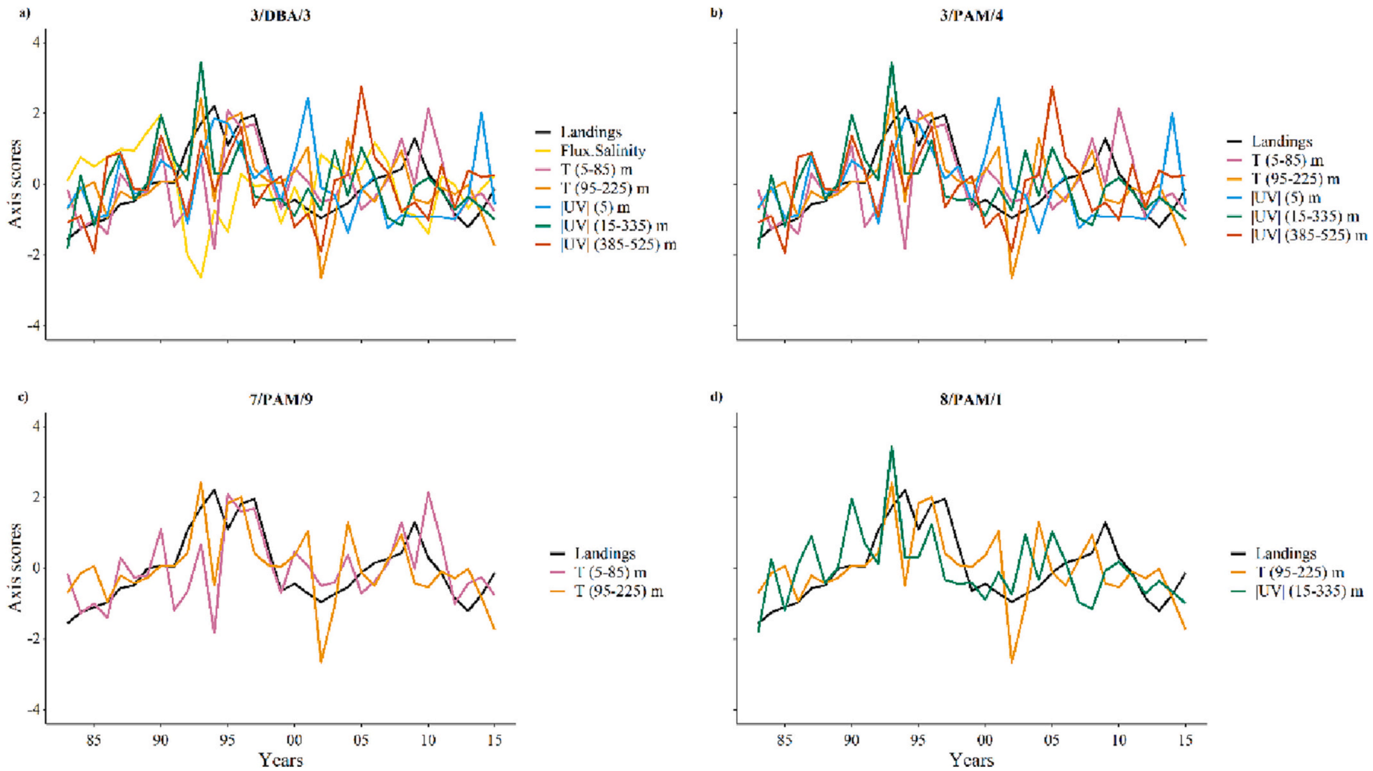

Fig. 3. Time series of the clusters in which the landings are located from 1983 to 2015. a) Optimal cluster number 3, centroid DBA and repetition 3, b) optimal cluster number 3, centroid PAM and repetition 4, c) optimal cluster number 7, centroid PAM and repetition 9, d) optimal cluster number 8, centroid PAM y repetition 1. All the repetitions represented obtained dissimilarity values equal to 0. And in the case of b), the repetition 4 was the one with the highest dissimilarities equal to 0.

PCA biplots clarified the existence of similar patterns between landings and the 3 explanatory variables: UV15–335, T95–225 and T5–85 for the rest of the components (Supplementary material; Fig. S11; Fig. S12). In general terms, the trajectories of the scores of principal components 1, 2, 3, 4 and 5 showed a non-linear pattern with higher values between 1990 and 2000 and 2004–2011, although components 2, 3 and 4 had minimum behaviours during 2009 and 2010 (Fig. 6).

3.3. Modelling the relationship between commercial landings and environmental variables

3.3.1. Multiple linear regression models (MLRs)

The final model obtained included T95–225, UV15–335 and heat flux as explanatory variables. These variables explained 38% of the variance in the landings. They were all significant ($p < 0.05$) and independent of each other (VIF values of around 1) (Supplementary

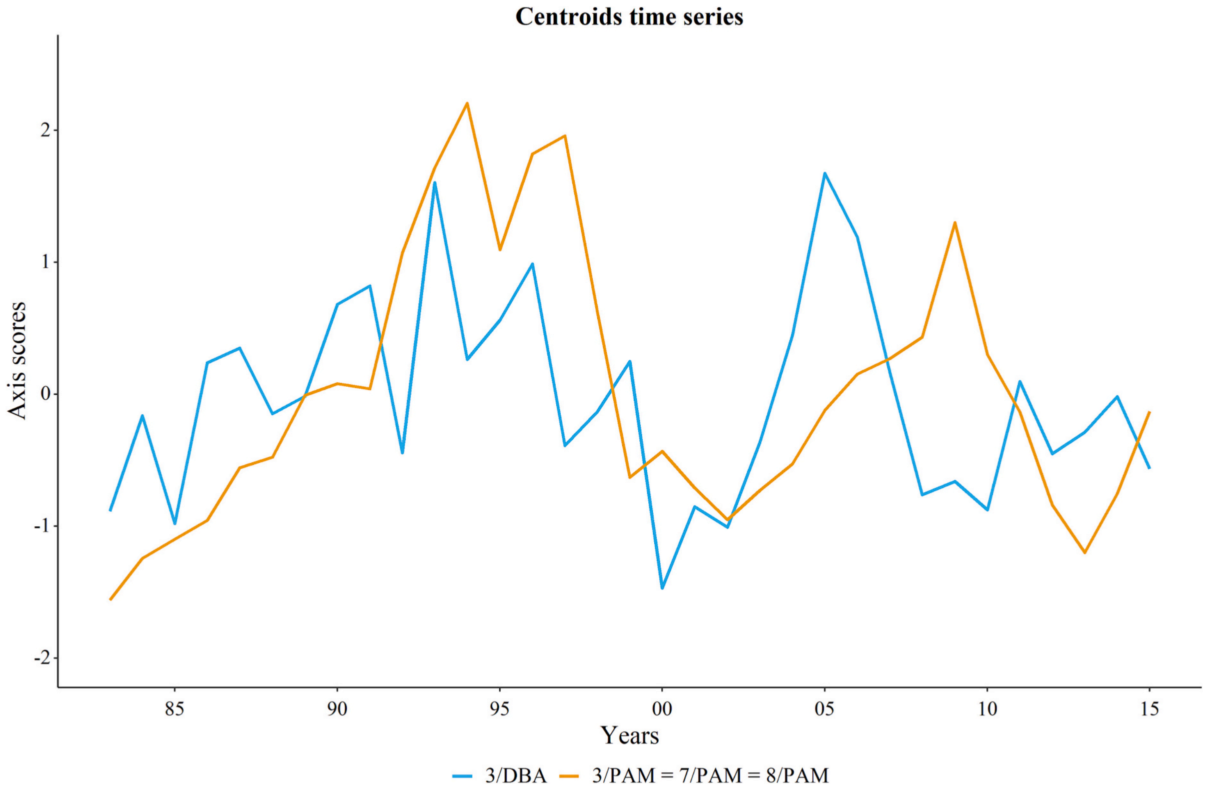

Fig. 4. Time series of the centroids obtained by the clusters represented in Fig. 2 from 1983 to 2015. In this case, the centroid with PAM prototype of 3, 7 and 8 was the same.

material; Table S13). The model was highly significant (likelihood ratio test $p = 0.0012$). The residuals of this model were homogeneous and normally distributed, showing no strong patterns. The variables T5–85 and UV385–525 had a weak nonlinear effect. Additionally, we did not find any influential values, although we observed a slight time dependence (Supplementary material; Fig. S14; Fig. S15). The direction of the effect of the variables was negative between 14.10 and 14.45 °C, 0.025 and 0.033 m s^{-1} and 0 and 20 W m^{-2} (Fig. 7).

3.3.2. Generalized linear models (GLMs)

The explanatory variables T95–225, UV15–335 and heat flux were included in the final model which explained 43.12% of the variance in landings. This model used the identity link function and gamma distribution with dispersion and shape parameters of 0.15 and 6.66, respectively. It was highly significant ($p < 0.001$) and all the variables were highly significant ($p < 0.001$) and clearly independent (VIF values of around 1) (Supplementary material; Table S14). The residuals of this model were homogeneous and there were no influential values. In general, they did not show marked patterns, although we detected nonlinear effects in T5–85 and UV385–525 (Supplementary material; Fig. S16; Fig. S17). As with the MLR, the negative effects on landings appeared around 14.10 and 14.45 °C, 0.025 and 0.033 m s^{-1} and 0 and 21 W m^{-2} (Fig. 8).

3.3.3. Generalized additive models (GAMs)

The final GAM used a gamma distribution together with the identity link function and included the explanatory variables T5–85, UV15–335 and heat flux. The dispersion and shape parameters of the gamma distribution were 0.13 and 7.69, respectively. The model was highly significant ($p < 0.001$) and all the explanatory variables were significant ($p < 0.01$) and independent of each other (Supplementary material; Table S15; Table S16). This model explained 51.50% of the variance in the landings. The residuals of this model were homogeneous, with no influential values, and randomly distributed, with no time dependence, although showing slight patterns in AO, T5–85, S85–125 and UV385–525 (Supplementary material; Fig. S18; Fig. S19). Finally, both UV15–335 and heat flux had linear effects, while T5–85 had a slightly oscillating behaviour. This indicated the presence of negative effects on the landings between approximately 16.70 and 17.10 °C while for UV15–335 and heat flux, negative effects were observed between 0.025 and 0.033 m s^{-1} and between 0 and 20 W m^{-2}, respectively (Fig. 9).

3.3.4. Goodness of fit of the best models constructed

Table 1 lists the error terms of the different models selected. The mean variance in landings explained by the models was 41%, the GAM yielding the best result (49%), followed by the MLR and GLM (which explained 38% and 37% of the variance, respectively). This high level of explained variance was reflected in strong agreement between observed values and those predicted by the models (KGE'), with an average of 51%, the best models being the GAM followed by the GLM and MLR. Given these results, there was agreement with lower percentages of prediction standard errors, with an average of 37%, the highest being found for GLM (38.44%) and the lowest for GAM (34.40%). Overall, we observed that, in terms of absolute and mean quadratic errors, the best model was the GAM and the worst the GLM. Finally, in terms of temporal persistence, there were significant lags in all three models, with an average of −0.70.

4. Discussion

In this study, we applied a wide range of statistical techniques based on trend analysis, classification and dimensionality reduction techniques together with several linear and nonlinear models, to detect and analyse patterns and relationships of the time series of commercial landings of *P. bogaraveo* and various climate indices and oceanic variables recorded from its fishing area, Strait of Gibraltar. PCA and time series clustering have enabled us to identify common patterns while MLRs, GLMs and GAMs have allowed us to examine and quantify the

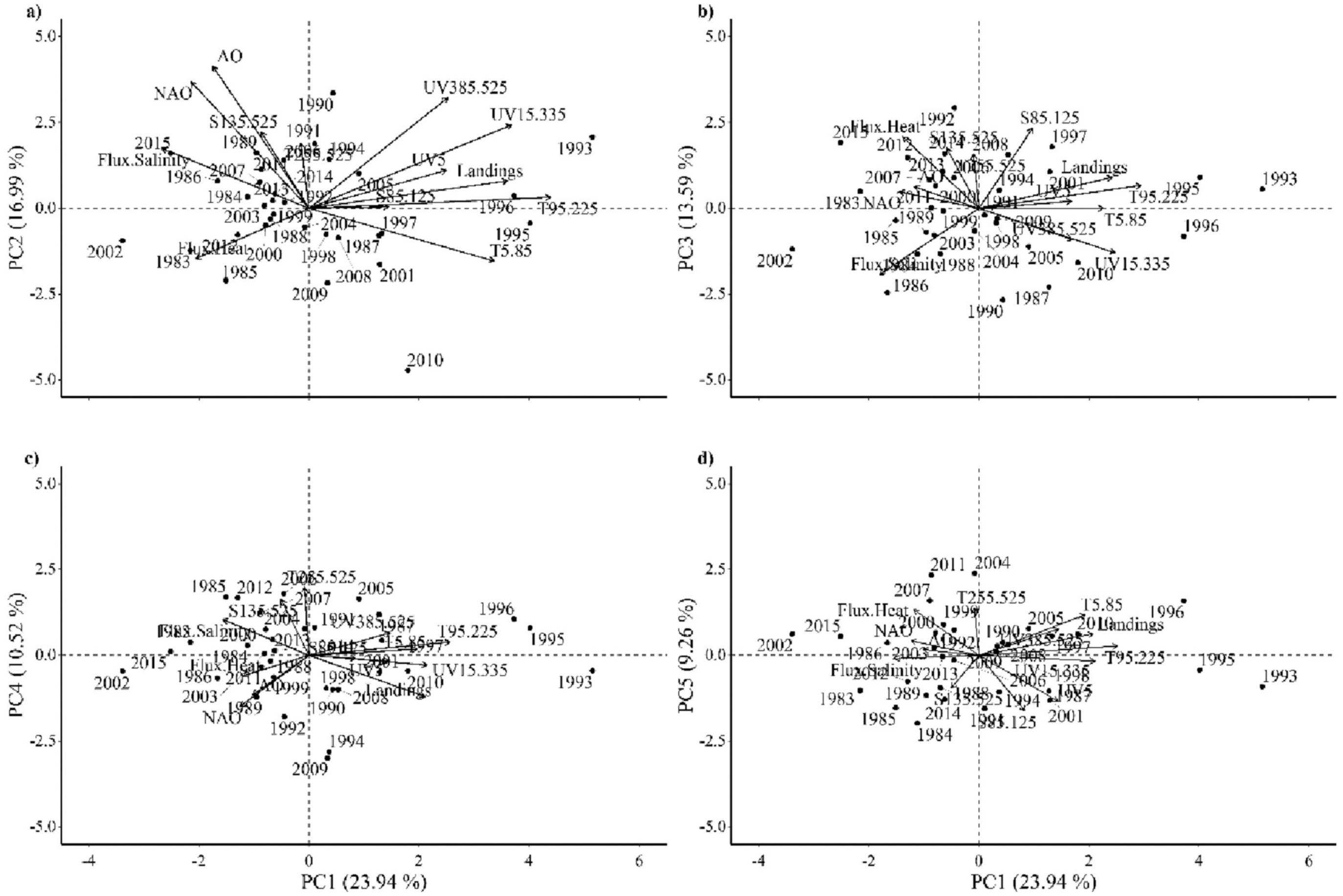

Fig. 5. PCA biplots of component 1 (X-axis) as a function of the rest of the components 2 to 5 (Y-axis). The orientation and distribution of the variables and the individuals (years) grouped according to the change points are shown. Variables and individuals are projected in the space of principal components. a) PC1 vs PC2, b) PC1 vs PC3, c) PC1 vs PC4 and d) PC1 vs PC5.

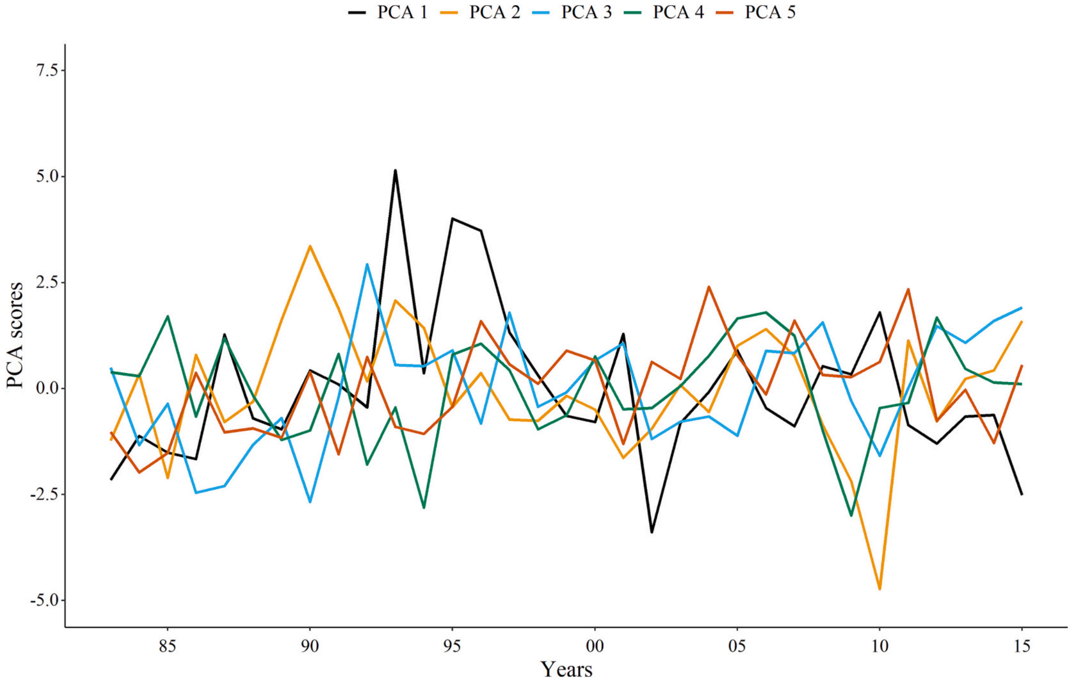

Fig. 6. Trajectories time series from 1983 to 2015 of the scores of the 5 principal components obtained.

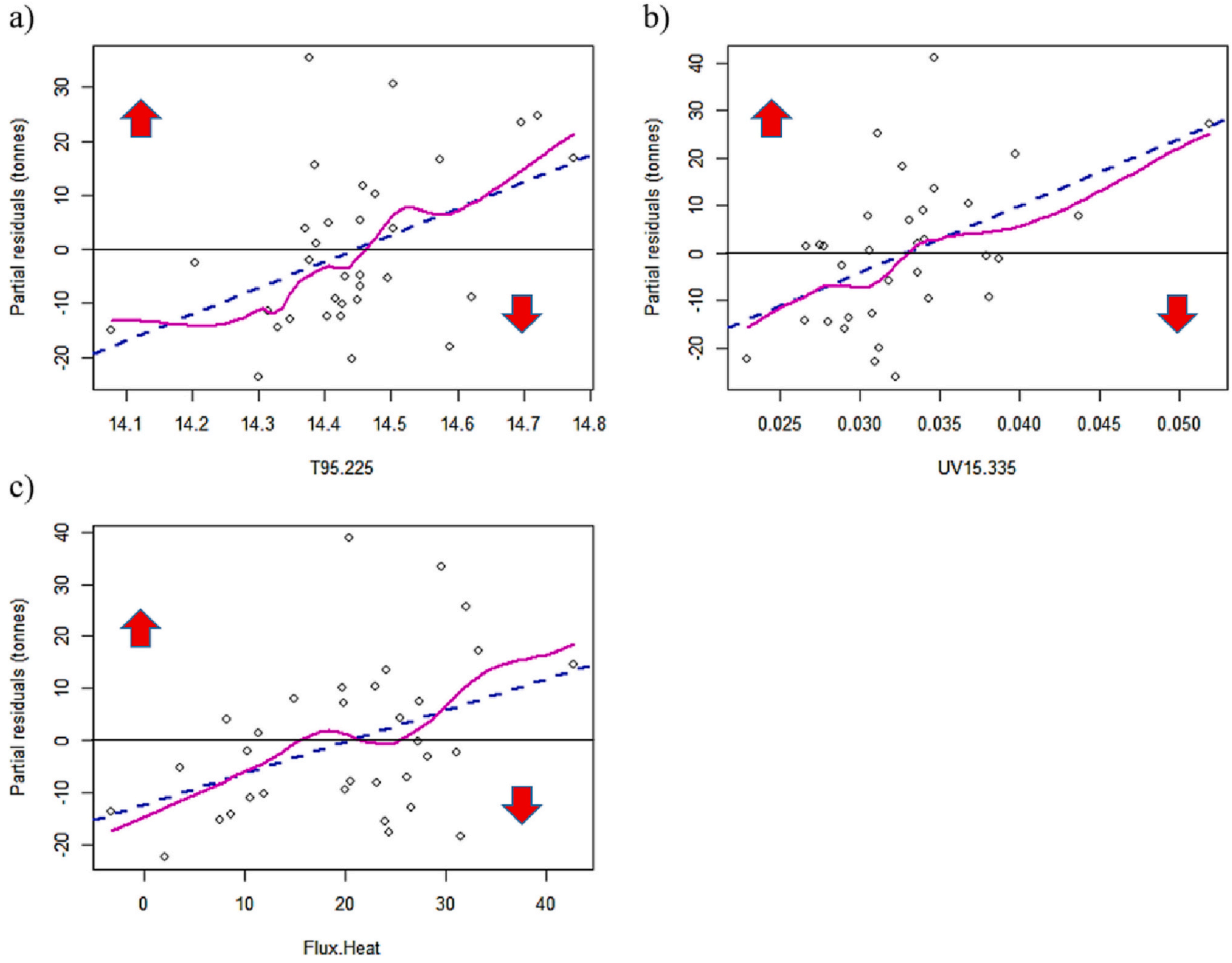

Fig. 7. Effects of the 3 predictor variables of the multiple regression (MLR) on landings from 1983 to 2015. Partial residuals are plotted on the Y-axis and the different predictor variables on the X-axis. a) T95.225 = Temperature °C (95–255) m, b) UV15.335 = $|UV|$ m s^{-1} (15–335) m y c) Flux.Heat = Flux Heat W m^{-2}. The up arrow indicates positive residuals, and thus a positive effect on landings, while the down arrow indicates the opposite. The solid line is a least-squares line and the dashed line is a Loess smoother, span = 0.69.

effect of the environmental variability on the landings.

The landings or catches together with their associated parameters related to fishing effort (LPUE-landings and CPUE-catches per unit effort) have been used as indicators of the status of the population, this information being used as a proxy for the abundance (Mugo et al., 2010). In small pelagic fisheries, such as anchovies or sardines, could be considered as true since localisation methods based on electronic systems and ultrasonic waves allow (Aoki and Inagaki, 1993; Massé, 1996; Gerlotto et al., 2004) accurate estimation of the real abundance. Nonetheless, for the fishery of Blackspot Seabream, no clear association has been found between LPUE or CPUE and real abundance. Although this species tends to assemble in shoals (Gil, 2006), it is very difficult for fishing gear to reach and catch this fish species given the depths at which it is commonly found (up to 525 m). A lack of catches, and therefore landings at port, may be attributable to various factors, including the captain of a vessel lacking sufficient skills to deploy the fishing gear effectively, the random movement of the shoals or non-ideal climatic and oceanic conditions. For this reason, we do not consider landings to be a proxy for abundance although we do understand that greater landings may be favoured by better climatic and oceanic conditions which could increase the probability of finding and catching the fish with the fishing gear.

We used commercial landings to provide data on fishing activity. This type of information has been recognised by various authors to be of great value for understanding the dynamics of resources (Teixeira et al., 2014). Commercial landings at port relate to the amount of the population that meets the criteria to be caught legally and is sold in ports always within the framework for legal sale and distribution. In this Spanish fishery, one of the management and control measures consists of the introduction of a minimum conservation reference size. From 12 cm (total length) to 35 cm (total length), up to the current 33 cm (total length) (Council Regulation [EEC] No 3782 85; Council Regulation [EEC] No 3094/86; Council Regulation [EC] No 1359/2008; Council Regulation [EC] No 1225/2010; and Council Regulation [EC] No 2017/787).

In the case of Morocco, the regulation sets the minimum size at 25 cm fork length (about 28 cm total length) (Gil-Herrera et al., 2021). In relation to this, taking both countries together, the mean fish size landed between 2005 and 2015 was close to or >36 cm (CopeMed, 2019). The changes in legislation have undoubtedly had a strong impact on the population, which may be reflected in the third-order trend observed in this study. This trend indicates a cyclical pattern in mean annual landings, with a first cycle between 1991 and 1993 and a second one between 2003 and 2013. This trend seems to indicate that the effects of fishing activity on the population were stronger in the first cycle than in the second due to the less restrictive legislation that allowed the capture of young and immature fish, reducing population recruitment success the following year. These results are consistent with those of Sanz-

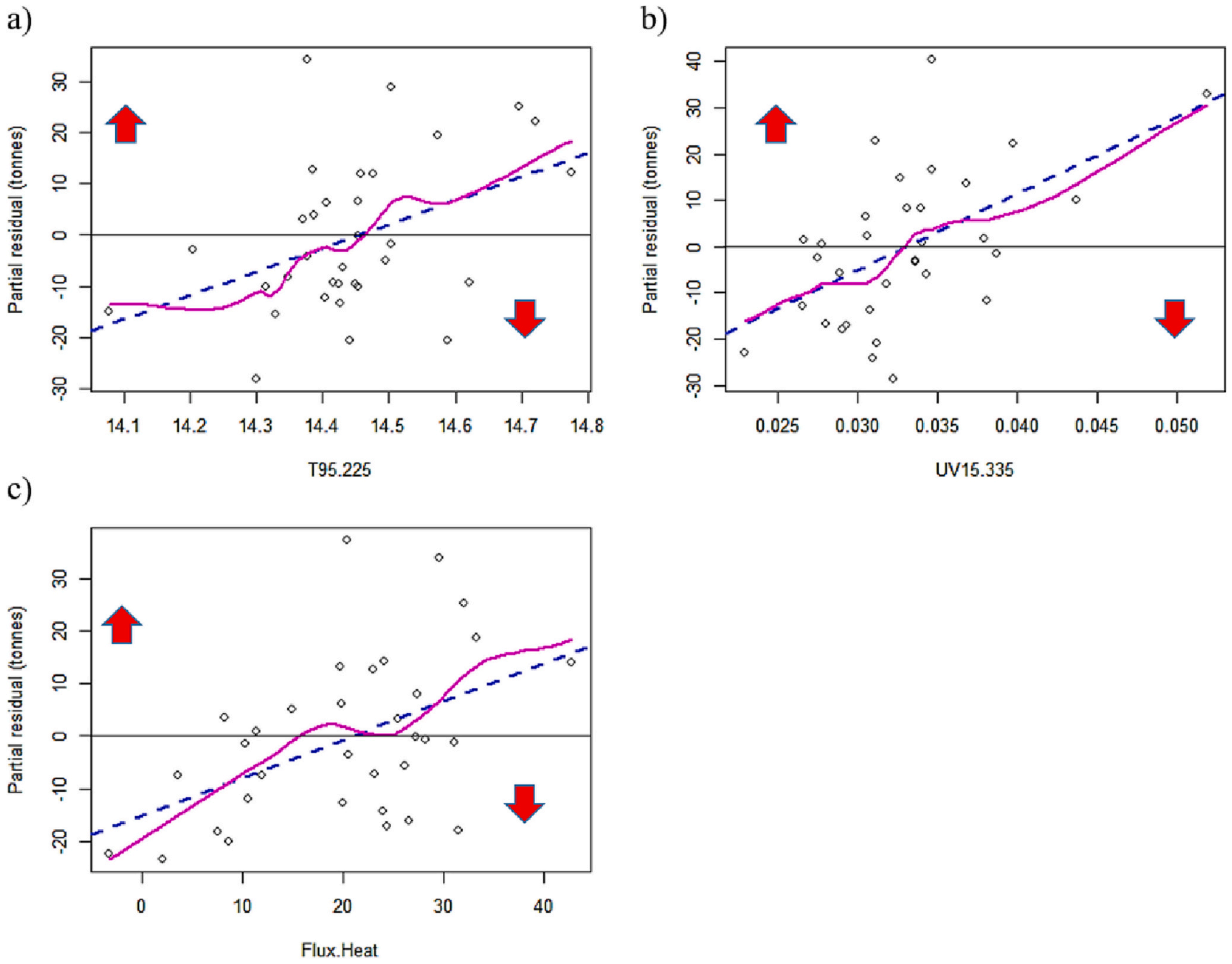

Fig. 8. Effects of the 3 predictor variables of the generalized linear model (GLM) on landings from 1983 to 2015. Partial residuals are plotted on the Y-axis and the different predictor variables on the X-axis. a) T95.225 = Temperature °C (95–255) m, b) UV15.335 = |UV| m s^{-1} (15–335) m y c) Flux.Heat = Flux Heat W m^{-2}. The up arrow indicates positive residuals, and thus a positive effect on landings, while the down arrow indicates the opposite. The solid line is a least-squares line and the dashed line is a Loess smoother, span = 0.69.

Fernández and Gutiérrez-Estrada (2021), who indicated that changes in legislation on landings play a crucial role in understanding the evolution of the fishery over time.

The results of time series clustering and PCA pointed in the same direction. Both types of analysis indicated that the landings had a similar pattern and grouping to those seen for T5–85, T95–225, salinity flux, UV15–335 and UV385–525. Similarly, the centroids from the time series clustering and the PCA scores both indicated two cyclical components with higher values between 1990 and 2000 and 2003–2013. These periods match those described by Sanz-Fernández et al. (2019), Gutiérrez-Estrada et al. (2020) and Gil-Herrera et al. (2021) who identify them as blocks of time with the largest temperature and salinity anomalies. These authors also established that during the years with the greatest variability in temperatures and salinity (1990 to 1998), the abundance of Blackspot Seabream tended to be lowest, it growing again during the first decade of the 20st century. This finding partially differs from that of our study, in the fact that the trend in landings was upward during the first period while in the second period it was downward and then recovered, which may be due to a slight mismatch between landings and abundances between 2001 and 2015. Previous authors, using different approaches to assess the abundance of the Blackspot Seabream in the Strait of Gibraltar, indicate that at the start of the fishery in 1983 the biomass was at or above the 1983 landings, which resulted in a progressive increase in landings. At the same time as the biomass decreased, landings increased to their historical maximum coinciding with the historical minimums of biomass. It is during the second period that this relationship appears to be uncoupled or out of phase as an increase in biomass resulted in a second historical maximum in landings years after the biomass maximum. This could indicate a response effect of landings coupled with abundance from 1983 to 1999–2000 and slightly decoupled from 2001 to 2015. Abundance-biomass data correspond to simulated abundances obtained through simulation models that incorporate the biological aspects of the species and the dynamics of landings.

The periods identified in the present study characterised by significant variations in landings dynamics (1990–2000 and 2003–2013, approximately) have also been detected in fisheries in other parts of the world (Almodóvar et al., 2019; Piroddi et al., 2017; Zhang et al., 2004). During these periods, changes in the dynamics of fish production and ecosystems were detected, helping to support the hypothesis that changes in the environmental conditions affected the dynamics of the marine ecosystem and the fish resources in the area (Zhang et al., 2000; Zhang et al., 2004). In the ecosystem of the Gulf of Cadiz, an area adjacent and connected to the Strait of Gibraltar, Torres et al. (2013) analysed the food-web structure and impacts of fisheries on the Gulf of Cadiz ecosystem, indicating that the ecosystem is highly stressed, with a

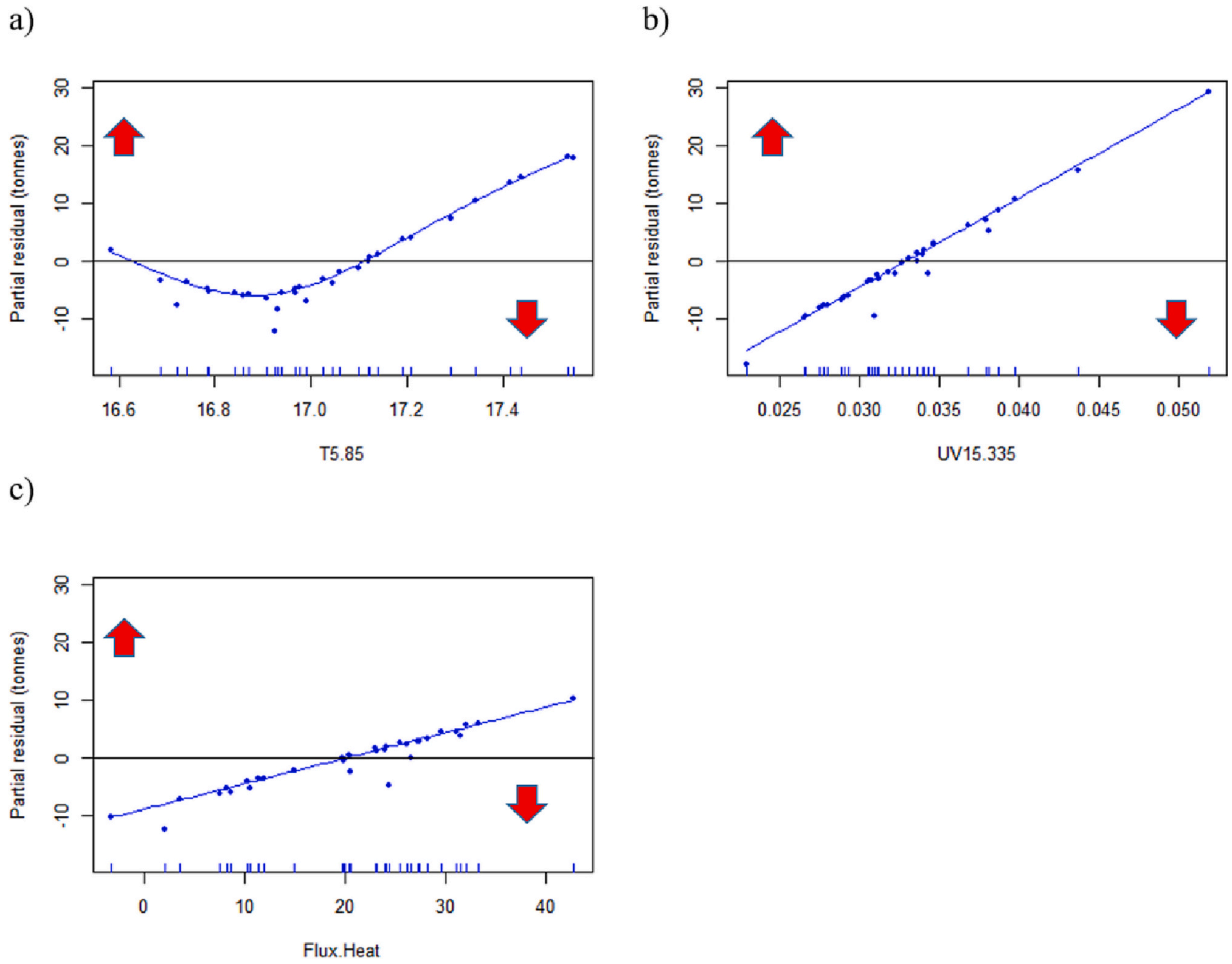

Fig. 9. Effects as solid lines/curves of the 3 predictor variables of the generalized additive model (GAM) on landings from 1983 to 2015. Partial residuals are plotted on the Y-axis and the different predictor variables on the X-axis. a) T5.85 = Temperature °C (5–85) m, b) UV15.335 = |UV| m s^{-1} (15–335) m y c) Flux.Heat = Flux Heat W m^{-2}. The up arrow indicates positive residuals, and thus a positive effect on landings, while the down arrow indicates the opposite.

Table 1
Goodness-of-fit measures of the best models obtained.

Model	Formula in R*	Distribution response variable	Link function	R^2	RMSE (tonnes)	MAE (tonnes)	%SEP	E_2	ARV	PI	KGE'
MLR	T95.225+ UV15.335+ Flux.Heat	Gaussian	Identity	0.38	13.30	10.62	37.78	0.38	0.62	−0.76	0.46
GLM	T95.225+ UV15.335+ Flux.Heat	Gamma	Identity	0.37	13.54	10.95	38.44	0.36	0.64	−0.84	0.51
GAM	s(T5.85, k = 4, bs = “tp”) + s(UV15.335, k = 4, bs = “tp”) + s(Flux.Heat, k = 4, bs = “tp”)	Gamma	Identity	0.49	12.11	10.18	34.40	0.49	0.51	−0.47	0.55

[*] Formulas shown in the R programming language.

high impact of fisheries from 1993 to 2009 causing variations on trophic levels and that therefore to ensure the sustainability of marine resources, management based on ecosystem approaches is necessary. de Carvalho-Souza et al. (2021) carried out the first holistic assessment of the Gulf of Cadiz ecosystem from 1993 to 2015, identifying two main periods of change before 2005 and after 2006. They established that during the first stage the ecosystem was characterised by a progressive degradation caused by permissive fisheries regulation, climate sensitivity and collateral effects of international policy, while in the second stage the imposition of appropriate and integrative regulation was able to reverse the situation, bringing the ecosystem to a more stable configuration. Therefore, our results are in line with the pattern observed for other fisheries, which may be indicating global connectivity of the impact on fisheries through variations in the catch and landing trends caused by changes in the environmental conditions as well as human stressors. Furthermore, the conclusions obtained in neighbouring areas are along the same lines as for this fishery, where greater lateral efforts in international policies would undoubtedly help to improve the resource, as occurred in the Gulf of Cadiz.

The use of models with linear and nonlinear approaches has enabled us to detect significant associations of landings with oceanic variables and climate indices, as well as determine the types of effect and quantifying them. The three techniques used in this study mainly pointed towards the same variables. Multiple linear regression and the GLM indicated that the T95–225, UV15–335 and heat flux were clearly significant, explaining as much as 38% and 43.12% of the total variance in landings. On the other hand, while the GAM also identified UV15–335 and heat flux as significant, unlike the other two models, T5–85 was included instead of T95–225. This latter model explained >50% of the variance in landings. Similar results have been obtained by other authors for *P. bogaraveo* in the Strait of Gibraltar. Báez et al. (2014) detected negative associations between ocean temperature and landings between 1986 and 2006. Similarly, Sanz-Fernández and Gutiérrez-Estrada (2021) reported significant correlations between temperature anomalies and landings with varying time lags of up to 3 years. We have observed that both variables had a direct positive increasing effect on landings, in certain ranges. Water temperature is a key variable in understanding fish population dynamics because of its impact on recruitment and mortality of the stock and consequently on abundance. It is therefore a key factor in understanding the variability of fish stocks (Hare and Mantua, 2000; Frank et al., 2005; Morrongiello et al., 2014; Perretti et al., 2017; Le Bris et al., 2018; Free et al., 2019; Pershing et al., 2015). Several studies have highlighted the influence of temperature and heat flux on *P. bogaraveo* biomass in the Strait of Gibraltar from 1983 to 2015, concluding that both variables play an important role in the dynamics of population abundance and that unusually low temperatures with low heat flux values could favour recruitment in following years and thus explain the increase in landings (Gutiérrez-Estrada et al., 2017; Sanz-Fernández et al., 2019). Additionally and taking into account a short-medium term effect, temperature is of great importance in keeping fish habitats healthy, which in any case will favour good fishery performance (Damalas et al., 2007; Mugo et al., 2010; Giannoulaki et al., 2011). Through otolith analyses of *P. bogaraveo* populations in the Azores, Neves et al. (2021) established that water temperature is a factor affecting the growth of individuals. Warmer deep waters are associated with slower growth, probably reflecting physiological conditions and food availability, which could consequently affect the production of the fishery. We can hypothesize that an inverse effect of temperature on the growth of *P. bogaraveo* in the Strait of Gibraltar will affect the long-term fishing yield, causing maximum landings to take longer to occur as a consequence of slower growth, thus explaining the lower landings when temperature rises in a certain range, as indicated by the models.

Regarding the movements of adult fish in the areas of the Strait of Gibraltar, these are mainly associated with feeding and breeding (Gil, 2006). The diet of Blackspot Seabream is mostly composed of fish and invertebrates. In the Strait of Gibraltar, the main prey is *Sergia robusta* (mesopelagic crustacean), although it also feeds on fishes mainly Myctophidae and Stomiiformes (Polonio et al., 2008). In the Strait of Gibraltar, this crustacean and these fish are preyed upon by other species such as the Atlantic Bluefin Tuna (*Thunnus thynnus*) (Sorell et al., 2017; Varela et al., 2020) that could interact with the Blackspot Seabream for the same resources. Mesopelagic myctophids are targets of Blackspot Seabream. Although the mesopelagic zone is strictly defined at depths of 200 to 1000 m (Sutton, 2013), myctophids are characterised by carrying out vertical migrations (Giménez et al., 2018) which would favour the availability of them in the water column for Blackspot Seabream. In this way, landings would be favoured by high availability of food for Blackspot Seabream.It is suggested that the largest landings are occurring in areas where there is a higher concentration of food for the *P. bogaraveo*, where oceanographic factors combine favourably within an environmental window of optimal range, favouring a greater predator-prey encounter.

All the models included ocean current speed as a significant variable. Previous studies, based on the use of hydrodynamic models coupled with Lagrangian particle tracking, have indicated that Atlantic Jet exiting the Strait of Gibraltar influences in the dispersion process and semidiurnal tidal currents and spring-neap tidal cycle are the main factor determining the horizontal dispersion and the course and pathway of eggs and larvae (Nadal-Arizo, 2019; Sammartino et al., 2019; Nadal et al., 2022). As described by Gil (2006), currents have an impact on fish from birth, given that the larval phase of Blackspot Seabream is pelagic, and the areas of growth are the coastal waters of the Gulf of Cadiz and the Alboran Sea. Therefore, whether fish reach the coast from hatcheries strongly depends on current speed.

In summary, landings could be favoured by hydrodynamic conditions that would facilitate the development of the first stages of the life cycle (eggs and larvae) thanks to their movement towards areas of protection and the predator-prey encounter, resulting in the incorporation of new individuals into the fishery biomass.

Therefore, we could hypothesize that the effect of water temperature, heat flux and current velocity modulus on the landings creates favourable habitat conditions for the continuance of the species, which would lead to a greater probability of encounters between the resource and the fishing gear. This together with the knowledge of fishermen would be translated into a greater landing success. Furthermore, the fact that these variables may have a direct impact on population dynamics may indicate a better status of the food web and larger number of recruits, and consequently, greater landings in the subsequent years.

Finally, although our best model explained approximately 50% of the variability of landings, which is statistically satisfactory, the incorporation of other variables such as wind speed and direction, chlorophyll and the tidal cycle could substantially improve the results obtained. In this sense, wind speed and direction affect water exchange in the Strait of Gibraltar. Wind-induced upwelling on the north coast of the Strait of Gibraltar is the phenomenon responsible for the higher biological production as the nutrient-rich Mediterranean water is shallower, increasing the availability of energy resources for the early life stages of *P. bogaraveo* which, coupled with temporary fishing windows during their reproductive period, would result in strong recruitment and higher landings in subsequent years.

On the other hand, the inference of the results obtained in the present study on the existence of relationships between fisheries production and the environment in which they take place must be interpreted according to the limitations given by the statistical techniques employed and the quality of the data. In general, the models fit the data well and are consistent with other statistical techniques in relation to the relationships obtained and with other studies. However, the statistical modelling techniques employed are based on correlations and therefore causality inference is not possible. Furthermore, a very important fact that must be taken into account is that the final model obtained is conditioned by ecological, statistical and data processing assumptions, and these are responsible for steering the final model in one direction or another (Austin, 2002; Gordó-Vilaseca et al., 2021).

To conclude, a comprehensive understanding of how environmental variability influences the historical dynamics of commercial landings of *P. bogaraveo* in the area of the Strait of Gibraltar has been carried out. For this purpose, a wide range of statistical tools have been used, in addition to a substantial oceanographic-climatic database. The Blackspot Seabream being a shared transboundary resource, the incorporation of this fact through the information on landings of the Spanish and Moroccan fleets has allowed an objective analysis of the real situation of landings of the resource in the area. The results of this study suggest that the historical series of commercial landings of Blackspot Seabream in the Strait of Gibraltar between 1983 and 2015 follow similar patterns to and have significant relationships with temperature, heat flux and current speed in specific layers. A decrease in their values, colder waters with lower current intensity, would be related to lower fishing yields and vice versa. Finally, the fishery of Blackspot Seabream is of great importance for the local economy and relies on it being a renewable resource. This implies that it is necessary to implement policies that favour management of the resource based on legality, transparency and sustainability considering the effects of both fishing and environmental processes.

Author contributions

The two authors contributed extensively to the research and development of the concepts presented in this paper. V. Sanz-Fernández:

Formal analysis, Data curation, Methodology, Investigation, Writing - original draft, Writing - review & editing. J.C Gutiérrez-Estrada: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision.

CRediT authorship contribution statement

V. Sanz-Fernández: Formal analysis, Data curation, Methodology, Investigation, Writing – original draft, Writing – review & editing. **J.C. Gutiérrez-Estrada:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Supervision.

Declaration of Competing Interest

There is no conflict of interests to declare.

Data availability

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jmarsys.2023.103883.

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