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Impact of Climate Scenarios on Small Pelagic Fisheries Along the Moroccan Part of the Alboran Sea: A Comparative Study Between the European Sardine (*Sardina pilchardus*) and the Atlantic Horse Mackerel (*Trachurus trachurus*)

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ABSTRACT

Ecosystem models provide a better understanding of fish populations and their environmental impacts. In this research, data from the Moroccan main ports landing logbook, along with two climate scenarios (RCP 2.6 and RCP 8.5), were used. Generalized additive models (GAMs) were applied to analyze the relationships between landing per unit effort (LPUE), fishing effort, and environmental factors for both species. The study investigated the influence of climate scenarios on LPUE and fishing effort to project future potential landings for both species. In addition, it compared the proportional changes between 2022 and 2100, relative to the 2010-2022 average in the southern Alboran Sea. Phytoplankton was identified as the main driver of sardine LPUE, while sea level anomaly influenced Horse Mackerel LPUE. By the end of the 21st century, Sardine potential landings are projected to increase by +15% under RCP 8.5 and +80% under RCP 2.6 compared to the 2010-2022 average. In contrast, the Atlantic horse mackerel potential landings are expected to increase by +200% under RCP 2.6, while decreasing by -100% under RCP 8.5 by the end of the century. This research underscores the importance of considering environmental factors in managing small pelagic fisheries to ensure their sustainability in a changing climate.

INTRODUCTION

The escalating frequency of marine heatwaves, driven by climate change, coupled with its extensive effects, is leading to significant alterations in the abundance and distribution of small pelagic fish populations within marine ecosystems **(Doney *et al.*, 2012; Frölicher & Laufkötter, 2018)**. This chronic threat demands the attention of the marine scientific community, which regularly turns to the Intergovernmental Panel on Climate Change (IPCC) projections for guidance **(Hoegh-Guldberg *et al.*, 2023)**. These projections inform nuanced qualitative and quantitative predictions of how marine ecosystems respond to the environmental changes caused by rising greenhouse gas concentrations **(Hollowed *et al.*, 2013)**. However, the impact of climate change is not a one-dimensional force, with different marine ecosystems responding at varying rates, magnitudes, and durations **(Stocker *et al.*, 2014)**. Understanding these diverse responses and their consequences for the fish that sustain us is a crucial challenge for the future of sustainable fisheries and healthy marine environments.

The changes in physico-chemical factors of our oceans directly impact phytoplankton abundance and variability, the engine driving primary production that leads to changes in the food web **(Brander, 2010; Behrenfeld & Boss, 2018)**. Climate change is expected to affect fisheries productivity, the life cycle and distribution of fish species, interactions within the food web, and primary production **(Hussain *et al.*, 2021)**. Despite being a group of relatively few species, small pelagic fish, which dominate the mid-trophic levels of the marine food web, are more numerous and exhibit a wide range of sizes. They are regulated by two key mechanisms: top-down, where predation pressure affects their abundance, and bottom-up, driven by environmental conditions and the availability of prey resources **(Pikitch *et al.*, 2014; Checkley & Rykaczewski, 2017)**. According to **Poloczanska *et al.* (2016)** and **Barange *et al.* (2018)**, small pelagic fish with short generation periods are more susceptible to the impacts of climate change. Multiple studies illustrate how pelagic fish are reacting to climate change.

Small pelagic fish (SPF) populations, such as the European sardine (*Sardina pilchardus*), account for 47.4% of all fish captured in the Mediterranean Sea **(FAO, 2018, 2024)**. Although, the Atlantic horse mackerel (*Trachurus Trachurus*) is one of the most extensively fished species, from 2014 to 2016, it accounted for only 2% of the total catch in the Mediterranean and Black Sea. The biomass and landings of many species in the Mediterranean have decreased after the 1990s **(Vasilakopoulos *et al.*, 2014; FAO, 2018)**. Rising temperatures in the Mediterranean Sea are expected to drive significant ecological changes **(Salat *et al.*, 2019)**, potentially shifting ecosystem states and disrupting the delivery of goods and services that underpin current consumption patterns. This raises concerns regarding the distribution and quantity of SPF in this region in the future, presenting of both ecological and economic concerns **(Pennino *et al.*, 2020; Gordó-Vilaseca *et al.*, 2021)**.

Therefore, we should pay attention to how changes in the marine environment, both now and in the future, may affect fish resources. Species distribution models (SDM) in particular, and ecological modelling techniques overall are frequently applied to support this process **(Gordó-Vilaseca *et al.*, 2021)**. Generalized additive models (GAM) can provide the possibility to examine the interactions between the response and the independent variable. The main focus of this paper was to determine how the European sardine and the Atlantic horse mackerel fishery responded to changes in the relevant environmental factors in the SAS, specifically sea surface temperature (SST), sea surface salinity (SSS), sea level anomaly (SLA), the chlorophyll-α (Chl), phytoplankton (Phy), and zooplankton (Zoo) concentrations. We also synthesized fisheries data and representative concentration pathway (RCP) scenarios to elucidate the future trend of fisheries under two RCP scenarios (RCP 2.6 and 8.5). GAM was applied to the weighted landing per unit effort (LPUE), relative effort, and environmental datasets to study the impacts of environmental factors (used from RCP 8.5 data) on the fisheries for the European sardine and the Atlantic horse mackerel and to predict the fisheries potential pattern under RCP scenarios 2.6 and 8.5.

MATERIALS AND METHODS

1. Study area

The southern Alboran Sea is located in the Mediterranean Geographic sub-area (GSA03) (Fig. 1). It extends from the northern Moroccan coastline to the 36°N latitude and from the strait of Gibraltar (5.6°W) to the Algerian-Moroccan border (2.21°W). The continental margin, between the coastline and the 200m isobath, accounts for 20% of the regional seas, while the remaining 80% consists of deep waters ranging from 200 to 1907m in depth.

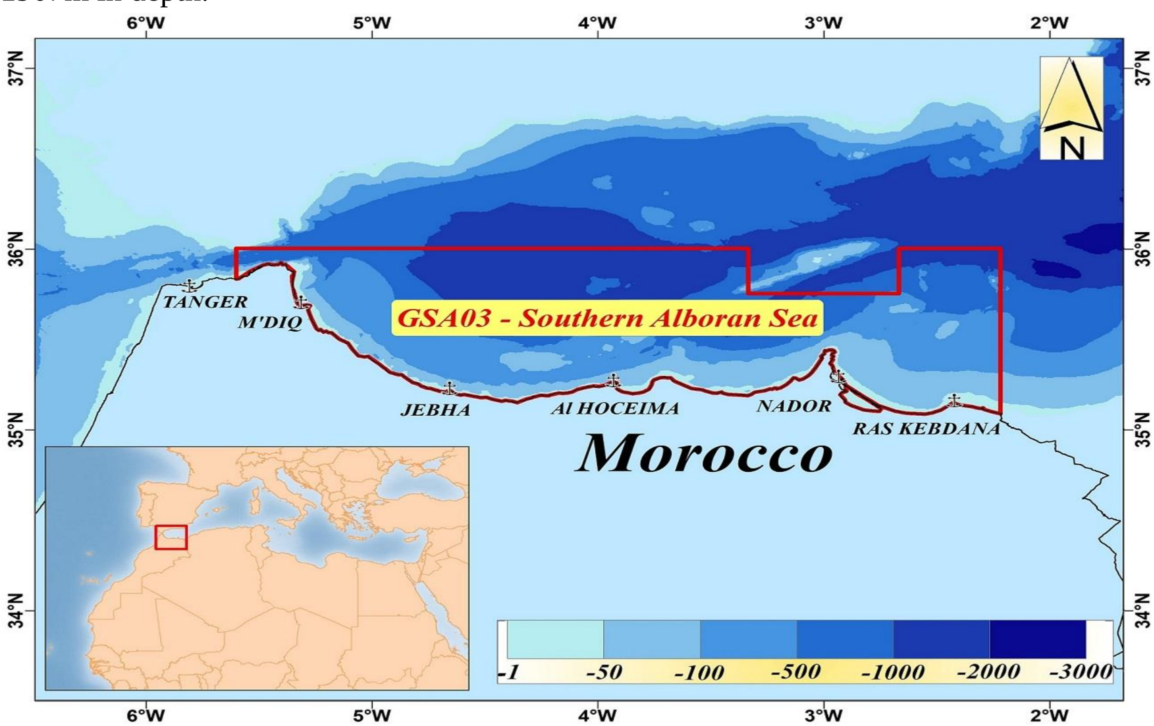

Fig. 1. Bathymetric map of the study area with the locations of major landing ports along the southern Alboran Sea coast (GSA-03)

2. Representative concentration pathways (RCP)

The representative concentration pathways (RCPs) are a collection of potential future scenarios that illustrate various radiative forcing and greenhouse gas concentration paths **(Van Vuuren *et al.*, 2011)**. The radiative forcing on Earth at the end of the twentyfirst century would increase by 2.6 (RCP 2.6) or 8.5W/ m^2 (RCP 8.5). These scenarios were chosen for the composition of this research due to their distinct characteristics: RCP 2.6 is regarded as the optimal scenario, depicting a future in the case of a transition towards environmentally sustainable greenhouse gas emission policies with ~490 ppm CO_2-eq **(Van Vuuren *et al.*, 2007, 2018)**. On the other hand, scenario 8.5 represents the worst scenario, illustrating the potential consequences if current greenhouse gas emission policies persist with ~1370 ppm CO_2-eq **(Riahi *et al.*, 2007)**. In terms of greenhouse gas emissions, it approximately reflects the actual situation (~40 $GtCO_2$/yr according to Joint Research Center (JRC) **(Crippa *et al.*, 2022)**.

The southern Alboran Sea (SAS) data variables were gathered from the **Climate4Impact** website which is connected to Earth System Grid Federation (ESGF) infrastructure by the Intergovernmental Panel on Climate Change (IPCC) and averaged monthly. The data source, as well as the period, and resolution, are shown in Table (1).

Table 1. RCP variables used in creating models and subsequent tests, including their units, spatial resolution, time period, and sources for scenarios 2.6 and 8.5.

Variable	*Units*	*Spatial*	*Time period*	*Source*
SST	°C	1°	2006 -2100	Climate4Impact
SSS	PSU			
SLA	m			
Chl	$mg.m^{-3}$			
Phy	$mmol.m^{-3}$			
Zoo				

3. Fisheries data

In this study, we explored and analyzed fisheries data related to two important fish species, the European sardine (*S. pilchardus*) and the Atlantic horse mackerel (*T. trachurus*). The fishing effort associated with LPUE is a critical component of fish stock assessments to determine the state of fish stocks for effective management. It is strongly correlated with fishing mortality **(Hussain *et al.*, 2021)**. Therefore, effort and LPUE constituted the study's response variables. For that, data on capture and effort for European sardines and Atlantic horse mackerel were gathered from the fisheries laboratory of the Moroccan National Institute of Fisheries Research, containing landing information for the most important ports in the SAS (Fig. 1). The fisheries statistics were available from 2009 to 2022, including SPF catches (in kg), landing ports, and fishing effort by each vessel. The monthly landings per unit effort (LPUE) were obtained by dividing monthly landings by fishing efforts. LPUE and effort are both included in the scope of this paper.

4. Model construction

To study the relationship between fish distribution and environmental data, temporal variations of two parameters, LPUE and Effort, were analyzed using a generalized additive model (GAM). Additionally, recursive feature elimination (RFE) was used for feature selection and to train models for predicting both response variables. RFE is a feature selection technique in machine learning that identifies the most important features for building a predictive model by: 1) starting with all features; 2) iteratively eliminating the least important features; 3) rebuilding the model with the remaining features; 4) ranking features based on their impact on model performance; and 5) repeating steps 2-4 until the desired number of features is reached or model performance no longer improves. The number of knots was limited to 5 using the R *mgcv* package **(R Core Team, 2017; Wood, 2017)** to reduce the chance of overfitting the model. The GAM equation was applied in the form described below :

$$G(Y) = \beta_0 + S_1(X_1) + \ldots + S_i(X_i)$$

Where, G is the link function; Y is the response variable (LPUE and Effort) for each species; $X = (X_1, \ldots., X_i)$ are covariables (Sea surface temperature (SST), sea surface salinity (SSS), sea level anomaly (SLA), chlorophyll-α concentration (Chl), phytoplankton concentration (Phy), and zooplankton concentration (Zoo), temporal variation (Years)); S_i is a spline smoothing function for each model predictor X_i; and β_0 is the intercept. Therefore, GAMs provide more flexible models by avoiding assuming a linear relationship between the response variable and the covariables **(Gordó-Vilaseca *et al.*, 2021)**.

The variables of interest are implemented from RCP 8.5 scenario for the period between 2006-2022 are integrated into generalized additive models (GAMs) based on the RFE-selected features, alongside the response variables to be predicted.

5. Validation and prediction

Model performance was assessed using key metrics, such as *P*-value (less than 0.05), R-squared (the higher is the better), deviance explained (0–100%; the greater proportion, the further deviance explained), Generalized cross-validation (GCV) (A lower GCV indicates a model that balances good fit with simplicity), and Akaike information criterion (AIC) (the lower is the better) **(Giannoulaki *et al.*, 2011; McElreath, 2018)**. Plots are generated to visualize the relationships between actual and predicted values for both response variables. This allows for a comprehensive evaluation of models.

Using RCP's environmental data, the model will predict potential landings by multiplying LPUE and effort outputs, and estimate the variability and rate of change compared to the 2010–2022 average.

RESULTS

1. Fisheries changes along the SAS

1.1. For S. pilchardus

The European sardine fishery along the southern Alboran coast has demonstrated notable annual changes since 2009, as shown in Fig. (2). It indicates that the highest recorded catch of the European sardines was 13959 tons in 2009. Afterward, the fishery showed a steep fall and reached low values in 2011 with 6357 tons. Yet, since 2012, the fisheries have gradually increased in subsequent years. After 2014, there was a sharp decrease, reaching 700 tons annually.

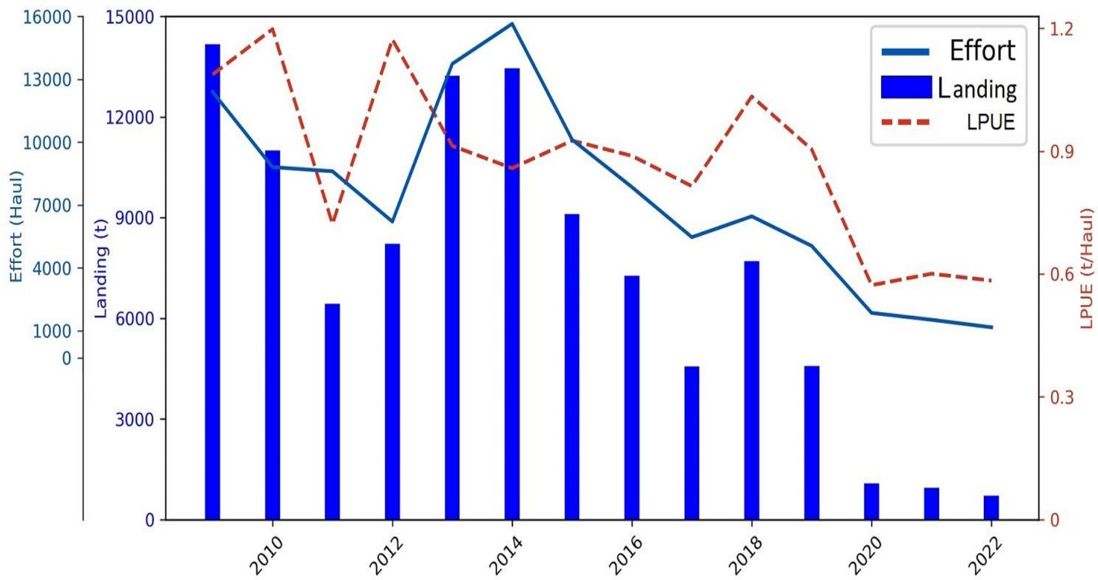

Fig. 2. The annual variability of the European sardine (*S. pilchardus*) fishery along the SAS between 2009 and 2022 for the landing in tons/year (blue bars), the effort in Hauls (blue solid line), and the LPUE in Ton/Haul (red dashed line)

1.2. For T. trachurus

The Atlantic horse mackerel fishery has exhibited fluctuations, as depicted in Fig. (3). Notably, between 2009 and 2013, the catch ratios were high compared to the subsequent years. The highest recorded catch of the Atlantic horse mackerel was 3559 tons in 2009 and 3482 tons in 2012. After 2013, the fishery dropped steeply and reached lower values with a minimal value of 277 tons in 2021.

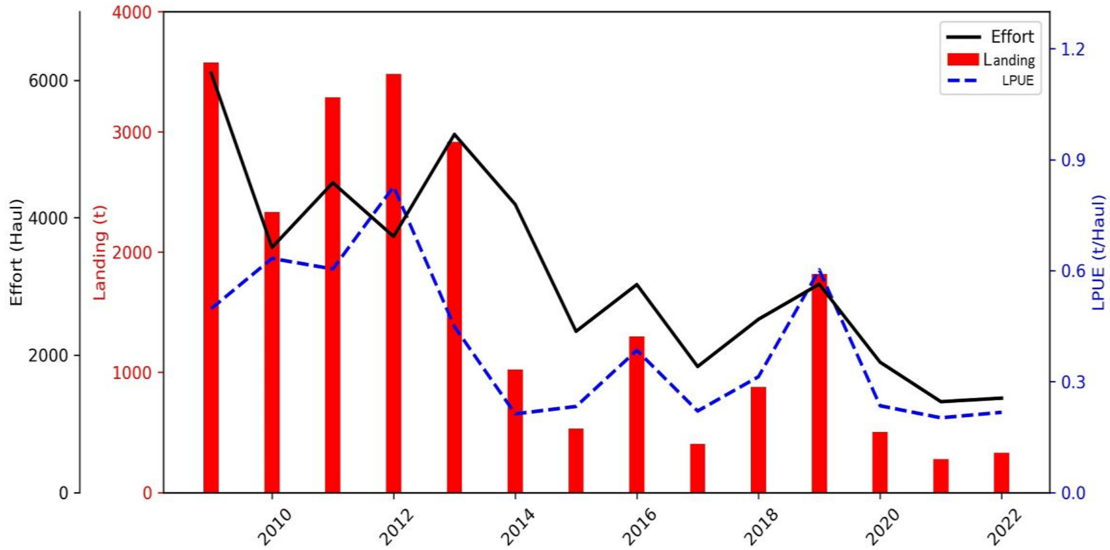

Fig. 3. The inter-annual variability of the Atlantic horse mackerel (*T. trachurus*) fishery along the SAS between 2009 and 2022 for the landing in tons/year (red bars), the effort in Hauls (black solid line), and the LPUE in Ton/Haul (blue dashed line)

2. Environmental variables Projection along the SAS

2.1. Physico-chemical variables

The trends of the physico-chemical variables along the SAS from 2006 to 2100 are illustrated in Fig. (4a, b). It is evident that the SST and SLA average of the region has increased since the beginning of the 21st century and will keep rising till the end of this century under both scenarios, with 0.5°C and 0.12m under RCP 2.6 and 2°C and 0.39m under RCP 8.5, respectively. On the contrary, the SSS average rises by 0.6psu under RCP 2.6, then under RCP 8.5 the SSS maintains a mean value of 37.75psu until 2045, when it declines by 1.5psu till the end of the 21st century.

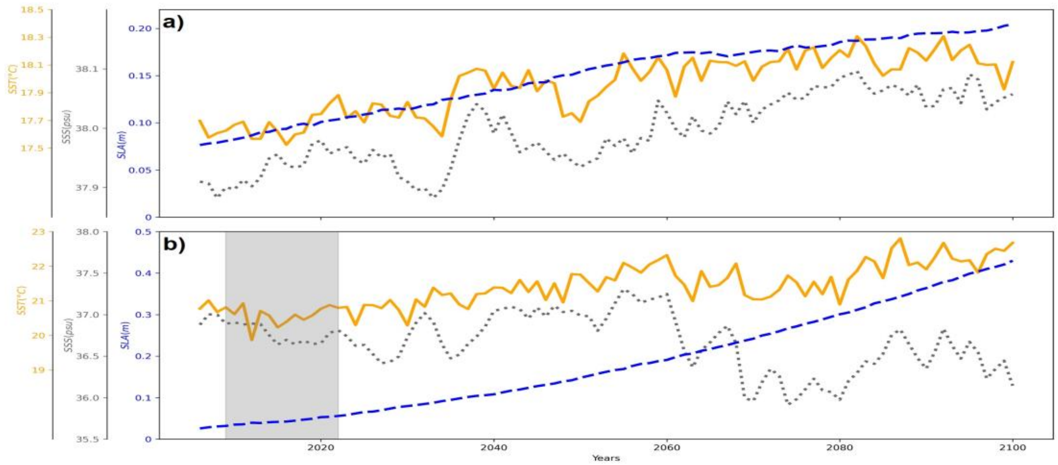

Fig. 4. The physico-chemical components variation for **(a)** RCP 2.6 and **(b)** RCP 8.5 climate change scenario between 2006 and 2100; Sea surface temperature (yellow), Sea surface salinity (grey); and Sea level anomaly (blue)

2.2. Bio-geochemical variables

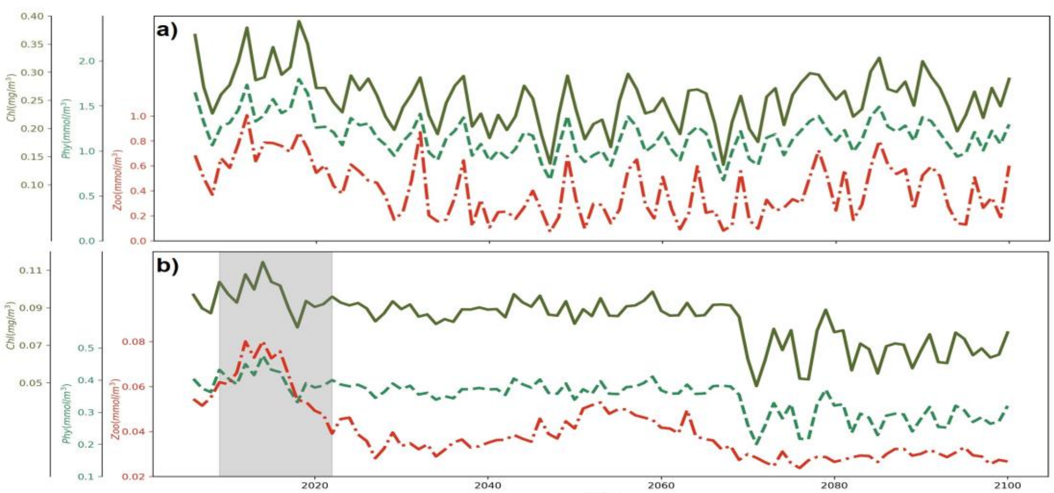

Fig. 5. The bio-geochemical components variation for **(a)** RCP 2.6 and **(b)** RCP 8.5 climate change scenario between 2006 and 2100; chlorophyll-α concentration (olive), phytoplankton concentration (green), and zooplankton concentration (red)

The annual variability averaged for bio-geochemical parameters in the SAS for the period between 2006 and 2100 are presented in Fig. (5). The concentrations of chlorophyll-α, phytoplankton, and zooplankton slightly declined between 2006 and 2050; in contrast, they slightly rised between 2050 and the end of the 21st century under RCP 2.6 (Fig. 5a). In this scenario, it is evident that there is a fluctuation between 0.15 - 0.4 mg.m^{-3}, 0.6 - 1.8 mmol.m^{-3}, and 0 - 1 mmol.m^{-3}, respectively, for Chl, Phy, and Zoo. Additionally, concentrations reveal stability under RCP 8.5 (Fig. 5b) until nearly 2070, with values between 0.08 - 0.11 mg.m^{-3}, 0.3 - 0.5 mmol.m^{-3}, and 0.03 - 0.08 mmol.m^{-3} for Chl, Phy, and Zoo, respectively, then a slight decrease until the end of the century, the values of Chl, Phy, and Zoo falling into the range of 0.05 - 0.09 mg.m^{-3}, 0.2 - 0.35 mmol.m^{-3}, and 0.02 - 0.03 mmol.m^{-}3, respectively.

3. The preferred environmental conditions

The variables included in the LPUE and Effort models for *S. pilchardus* and *T. trachurus*, along with their significance, explained variances (DE%), and Akaike information criterion (AIC) values, are detailed in Tables (2, 4). The predictor factors that exhibited significance (IP-value < 0.05) for both LPUE and Effort models were retained in the models. Model selection was automatically performed using recursive feature elimination (RFE), which integrates variables based on their significance, explained variances (DE%), and AIC values. The process then eliminates the least important variables that reduce model performance from the final selected model.

3.1. For S. pilchardus

The annual interaction in the univariate LPUE GAM analysis (Table 2) accounted for 22.1% of the variance, with an AIC of 61.3, making it the most influential component in the model. Following that, Phy (12.0% and AIC = 81.6), Chl-α (12.0% and AIC = 81.8), SST (11.6%), and SLA (11.4%) were the next most significant variables. In addition, the univariate effort GAM analysis showed an association with annual variance (DE = 36% and AIC = 2456), followed by SLA (11.6%), SSS (5.4%), SST (5.1%), Phy (2% and AIC = 2533), and Chl-α (1.8%). All factors were significant, except for SSS in the LPUE model and Zoo concentration in both the LPUE and effort analyses.

During the construction of the optimal model (Table 3), we examined the correlation between the actual and predicted values. The results indicated a significant correlation between the predicted and actual values (R^2 = 0.606 for the LPUE model and R^2 = 0.709 for the effort model). Additionally, a significant correlation was observed in the residuals of both the LPUE and effort models (Fig. S1 in supplementary material) for sardine. The QQ plot and histogram of the residuals showed a normal distribution, indicating that the deviations were symmetrically distributed.

Table 2. Significance (*P*-value), deviance (DE%), and AIC of each environmental variable for LPUE and effort models of the European sardine (*S. pilchardus*)

	LPUE model			*Effort model*		
	P-value	***DE%***	***AIC***	***P-value***	***DE%***	***AIC***
S(Years)	1.2e^{-10} ***	22.1	61.3	<2e^{-16} ***	36	2456
S(SST)	6.5e^{-06} ***	11.6	72.6	0.003 **	5.1	2523
S(SSS)	**0.30**	-----	-----	0.002 **	5.4	2522
S(SLA)	7.6e^{-06} ***	11.4	82.9	6.0e^{-06} ***	11.6	2510
S(Chl)	4.1e^{-06} ***	12.0	81.8	0.02 *	2	2526
S(Phy)	4.2e^{-06} ***	12.0	81.6	0.02 *	2	2526
S(Zoo)	**0.38**	-----	-----	**0.66**	-----	-----

Table 3. Deviance, GCV, R-squared, and AIC values for selected GAM models for LPUE and Effort of *S. pilchardus* and *T. trachurus*

Model	*%DE*	*GCV*	*R-sq*	*AIC*
S. pilchardus				
LPUE ~ Years+s(Phy)+s(Chl)+s(SST)+s(SLA)	63.8	0.045	0.60	-42.0
Effort ~ Years+s(SLA)+s(SSS)+s(SST)+s(Phy)+ s(Chl)	72	68634	0.69	2347
T. trachurus				
LPUE ~ Years+s(SLA)+s(SST)+s(Zoo)+s(Chl)	46.9	0.07	0.38	33.2
Effort ~ Years+s(SLA)+s(Phy)+s(Chl)	69.8	14484	0.67	2086

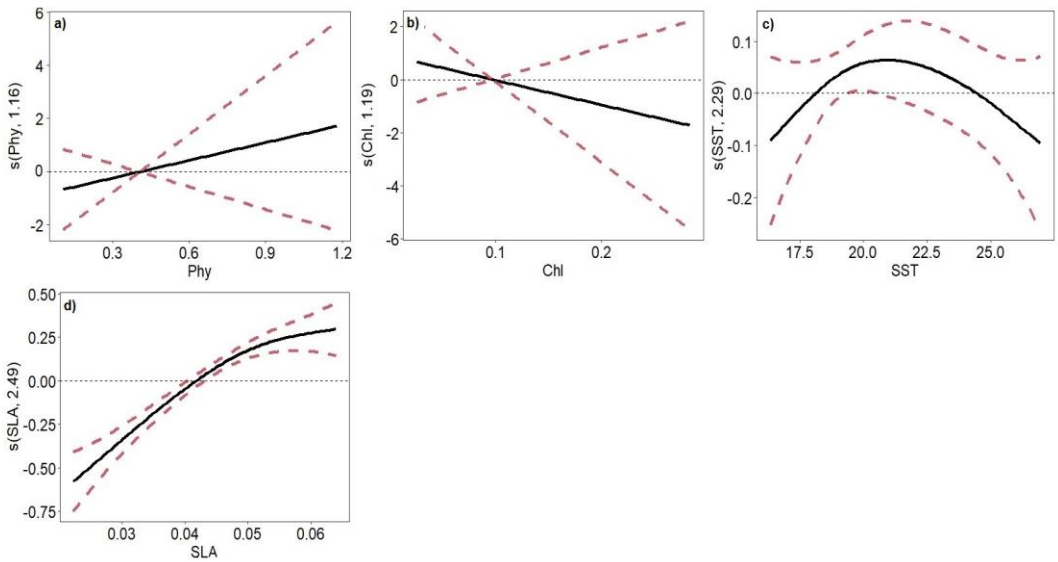

Fig. 6. The functional correlations between the LPUE model and environmental variables of the European sardine: **(a)** Phy, **(b)** Chl, **(c)** SST, and **(d)** SLA. The solid line showed the fitted GAM functions, while the red dashed shading showed the 95% confidence intervals

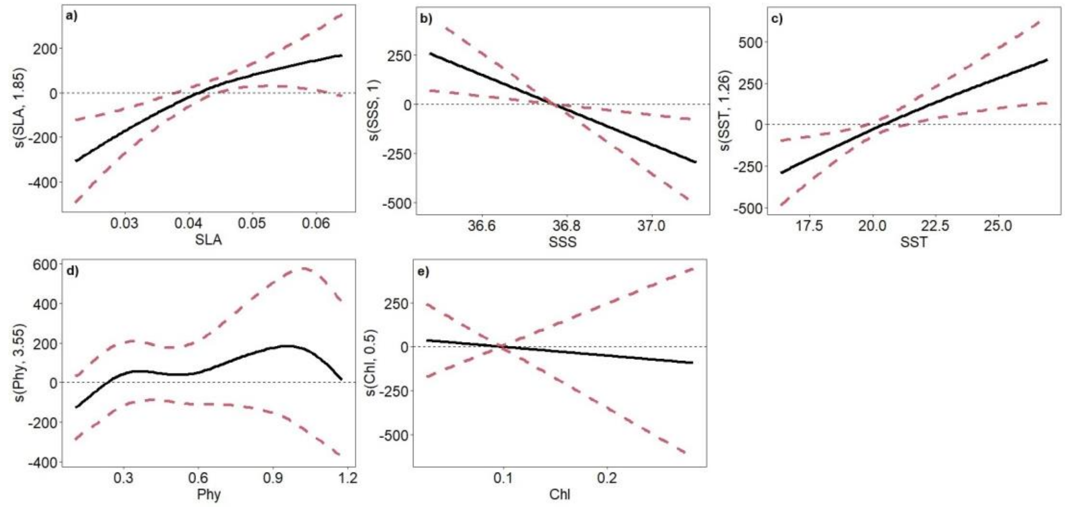

Fig. 2. The functional correlations between the effort model and environmental variables of the European sardine: **(a)** SLA, **(b)** SSS, **(c)** SST, **(d)** Phy, and **(e)** Chl. The solid line showed the fitted GAM functions, while the red dashed shading showed the 95%'s confidence intervals

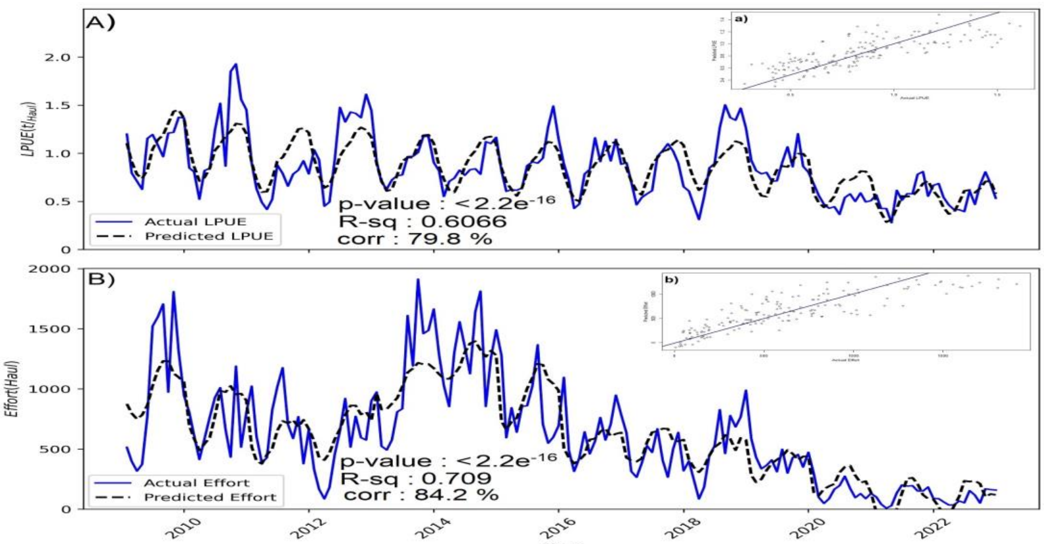

Fig. 3. The actual versus predicted LPUE (**(A)** as line-plot and **(a)** as scatterplot) and Effort (**(B)** as line-plot and **(b)** as scatterplot) of the European sardine (*S. pilchardus*) in the SAS zone

Compared to the LPUE model (Table 3), the effort model performs better, accounting for more than 72% of the total deviance explained, whereas the LPUE model only accounts for 63.8%. The functional correlations between the LPUE and effort model and environmental variables are presented in Figs. (6, 7). For the LPUE model, the Phy has a positive impact above 0.4 mmol.m^{-3}, and a negative effect at a Chl concentration above 0.1mg.m^{-3}. Nevertheless, The SST effect on the LPUE model also revealed a positive impact at 18°C, followed by a decreasing trend. Finally, the positive LPUE trend for SLA was observed below 0.04m. The effort model was linked to changes in SLA, SST, and Phy, with a positive effect above 0.045m, 20°C, and 0.3mmol.m^{-3}, respectively. Additionally, the impact of SSS and Chl concentration show a negative effect on the effort above 36.8psu and 0.1 mg.m^{-3}. The correlation between predicted and actual values was significant, with 79.8% for the LPUE model (Fig. 8a), and 84.2% for the effort model (Fig. 8b).

3.2. For T. trachurus

Under the univariate LPUE GAM analysis (Table 4), the SLA was the variable that generated a significant change in DE, which contributed 17% of the variation, followed by annual variations (14.9%), SST (4%), Zoo (3%), and Chl-α (2%). The Phy and the SSS are non-significant variables for the LPUE models. Furthermore, the effort GAM analysis reveals a strong association with SLA by 36.7% of the variation, followed by annual variations (24.7%), Phy (5.3%, AIC = 2250), Chl-α (5.3%, AIC = 2253), SSS (3.7%). The SST and the Zoo are the non-significant variables for the effort models.

Table 4. Significance (*P*-value), deviance (DE%), and AIC of each environmental variable for LPUE and effort models of the Atlantic horse mackerel (*T. trachurus*)

	LPUE model			*Effort model*		
	P-value	***DE%***	***AIC***	***P-value***	***DE%***	***AIC***
S(Years)	2.3e^{-07} ***	14.9	68.87	<2e^{-16} ***	24.7	2205
S(SST)	0.009 **	4	89.14	**0.10**	**-----**	**-----**
S(SSS)	**0.25**	**-----**	**-----**	0.01 *	3.7	2255
S(SLA)	2.8e^{-08} ***	17	64.69	<2e^{-16} ***	36.7	2185
S(Chl)	0.02 *	2	97.5	0.003 **	5.1	2253
S(Phy)	**0.20**	**-----**	**-----**	0.003 *	5.3	2250
S(Zoo)	0.01 *	3	92.65	**0.44**	**-----**	**-----**

The residual associations were examined after generating the best model. The results indicated that there was a significant correlation in the effort model residuals for the horse mackerel with a normal distribution of QQ plot, histogram of the residuals showing that the deviation is distributed skewed (symmetry of the histogram), and the residuals vs linear predictions are distributed uniformly. In contrast, the LPUE model residuals showed a medium correlation and a residuals histogram showed that the deviation was not normally distributed (the histogram was asymmetric). The skewed distribution of the QQ plot (light-tailed) and the residuals vs linear predictions aren't distributed uniformly. The SLA, SST, and Zoo concentration show a negative impact on the LPUE model (Fig. 9) over 0.04m, 21°C, and 0.07 mmol.m^{-3}, respectively. While, the Chl concentration show a positive effect below 0.5mg.m^{-3} and between 0.08 and 0.13mg.m^{-3}. For the effort model, as shown in Fig. (10), the SLA, Phy, and Chl-α concentrations have a positive effect on the effort below 0.04m, 0.4mmol.m^{-3}, and 0.1mg.m^{-3}. In contrast, they show negative effects above these values. The correlation between predicted and actual values (Fig. 11) was 65.4% for the LPUE model, and 82.9% for the effort model.

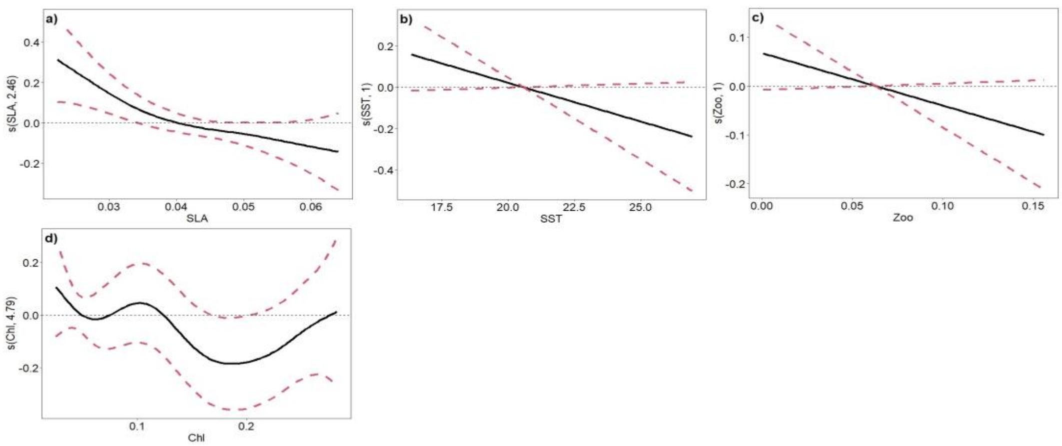

Fig. 4. The functional correlations between the LPUE model and environmental variables of the Atlantic horse mackerel: **(a)** SLA, **(b)** SST, **(c)** Zoo, and **(d)** Chl. The solid line showed the fitted GAM functions, while the red dashed shading showed the 95%'s confidence intervals

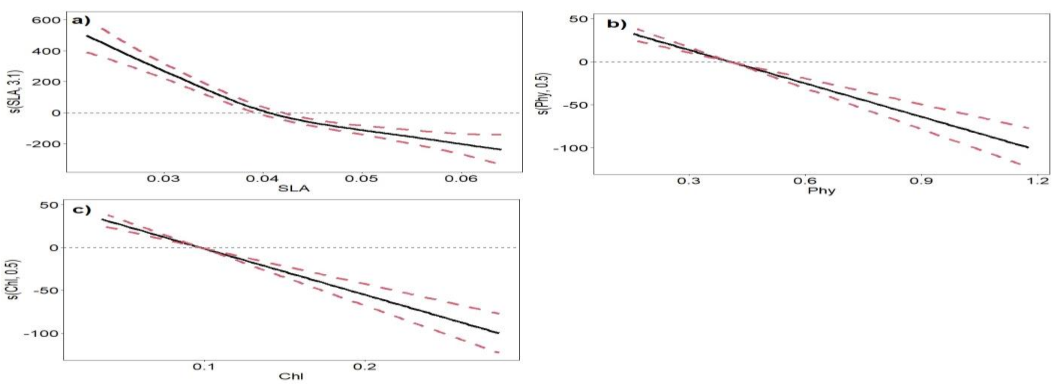

Fig. 5. The functional correlations between the effort model and environmental variables of the Atlantic horse mackerel: **(a)** SLA, **(b)** Phy, and **(c)** Chl. The solid line showed the fitted GAM functions, while the red dashed shading showed the 95%'s confidence intervals

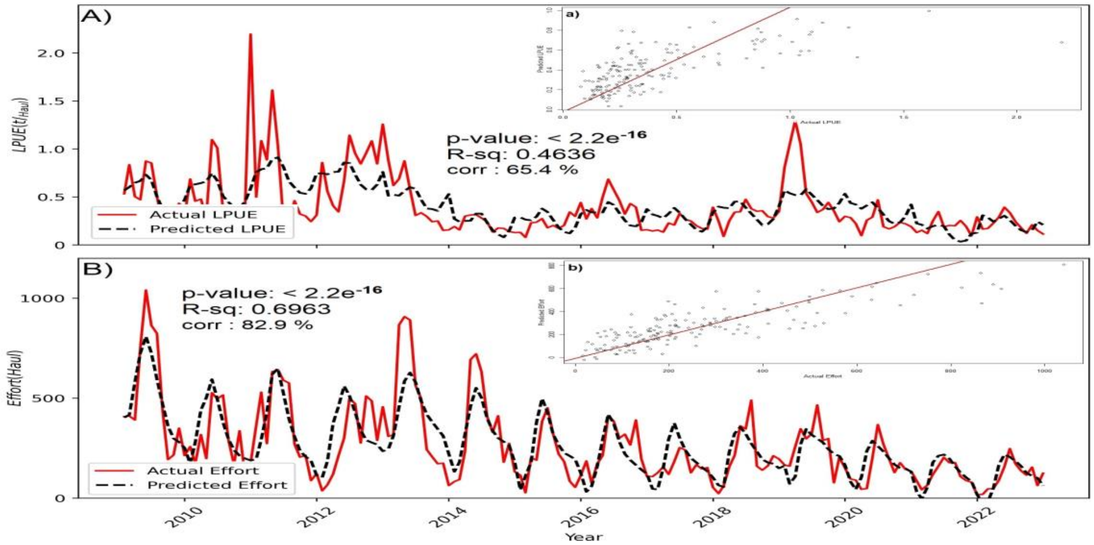

Fig. 6. The actual versus predicted LPUE (**(A)** as line-plot and **(a)** as scatterplot) and effort (**(B)** as line-plot and **(b)** as scatterplot) of the Atlantic horse mackerel (*T. trachurus*) in the SAS zone

4. Predictions

The landing potential along the SAS for the period 2023-2100 was calculated by multiplying the predicted LPUE by the effort values obtained from models. Moreover, the change proportion in the predicted landing from 2023-2100 was compared to the landing average from 2009 to 2022.

4.1. The European sardine predicted LPUE, Effort, and Landing potential

The European sardine's predicted LPUE and Effort obtained shows an increase for both scenarios (with 1.4 t/haul as LPUE for RCP 2.6 and 0.2 t/haul for RCP 8.5, and 4000 haul as Effort for RCP 2.6 and 3000 haul for RCP 8.5). The predicted LPUE between 2050 and 2100 in RCP 2.6 outperforms RCP 8.5 values (Fig. 12a). Furthermore, the predicted Effort in RCP 2.6 exceeds the effort in RCP 8.5 over all the time (Fig. 12b). The observation of the landing potential trends (Fig. 13) shows rises under both scenarios by 80% for RCP 2.6 and 10% for RCP 8.5.

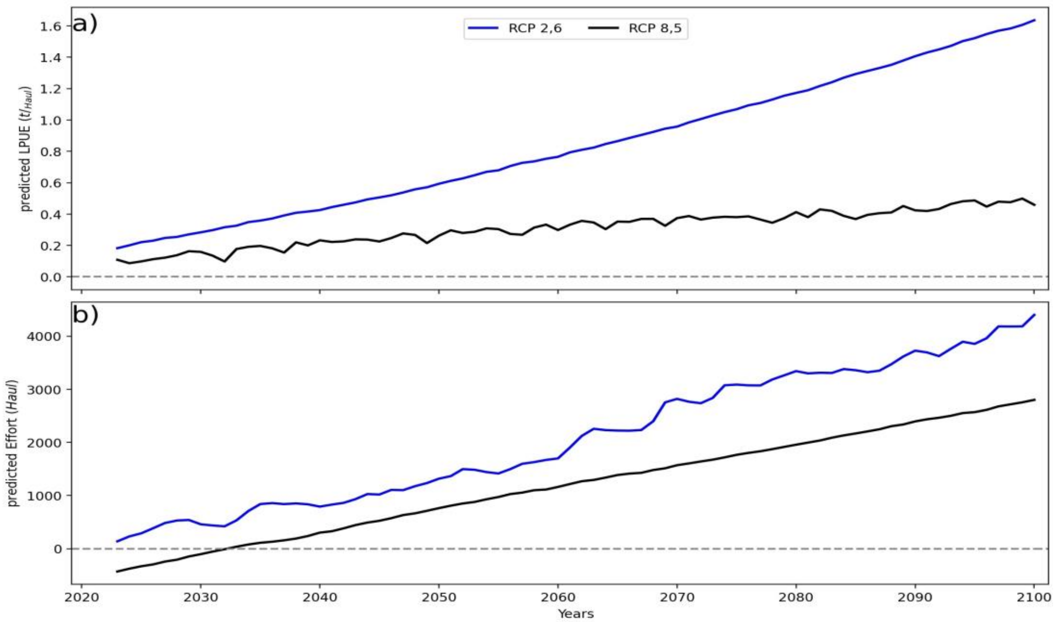

Fig. 7. The predicted **(a)** LPUE and **(b)** effort of the *S. pilchardus* in the SAS zone for RCP 2.6 (blue line) and RCP 8.5 (black line) between 2023 - 2100

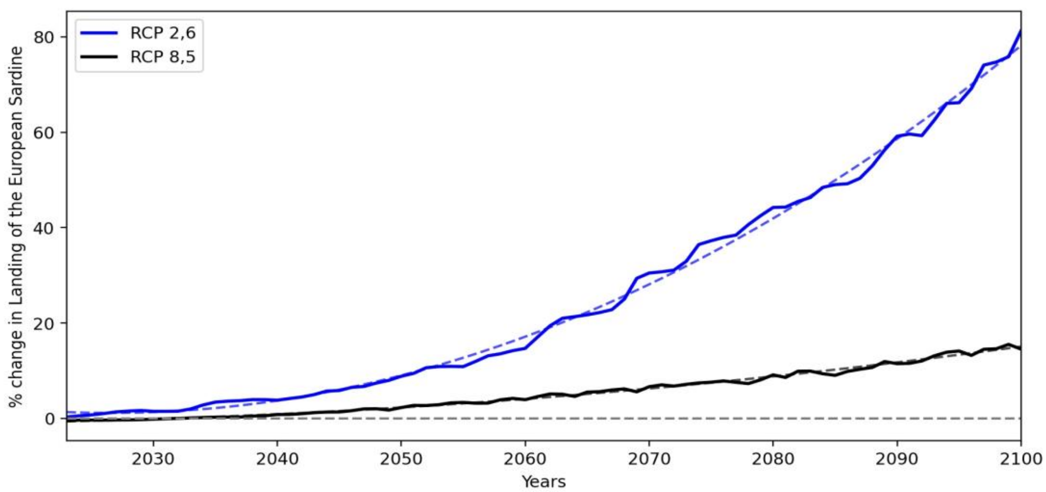

Fig. 8. Change proportion of the European sardine's (*S. pilchardus*) predicted landing compared to 2010–2022 landing average for scenarios RCP 2.6 (blue) and RCP 8.5 (Black) in the SAS zone

4.2. The Atlantic horse mackerel predicted LPUE, effort, and landing potential

The obtained predicted LPUE for the Atlantic horse mackerel shows an increase for both scenarios (Fig. 14a) with 1.4t/ haul for both RCP 2.6 and RCP 8.5. Likewise, the predicted effort for RCP 2.6 (Fig. 14b) increases with 3500 hauls; whereas, in RCP 8.5, it stabilizes below 500 hauls until 2050, where it drastically declines. The observation of the landing potential trends (Fig. 15) shows rises under RCP 2.6 scenarios by 200%. In contrast, it collapses under RCP 8.5 with -100%.

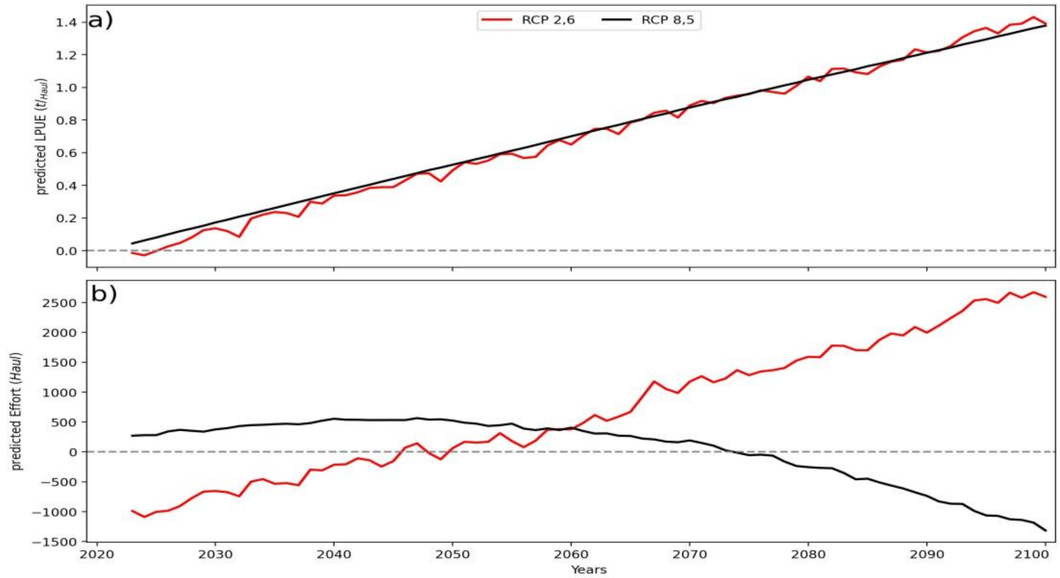

Fig. 9. The predicted **(a)** LPUE and **(b)** effort of the *T. trachurus* in the SAS zone for RCP 2.6 (red line) and RCP 8.5 (black line) between 2023 - 2100

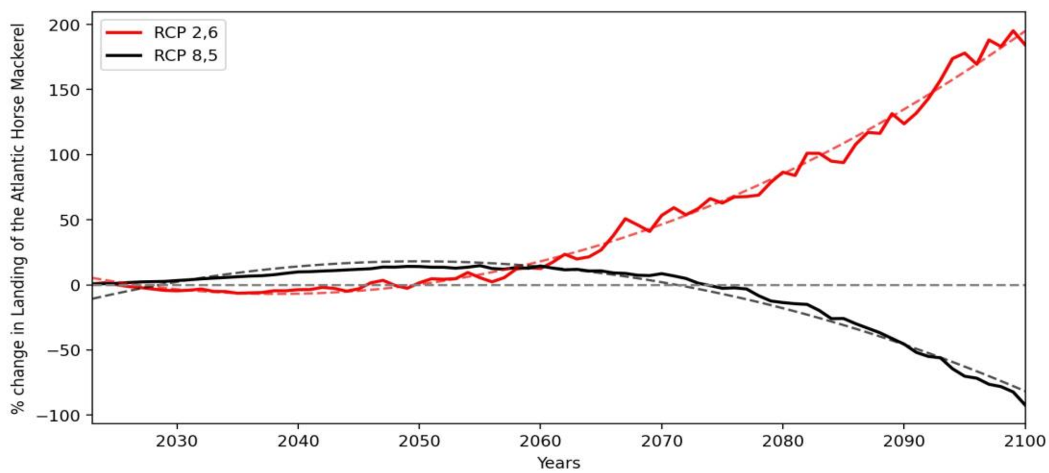

Fig. 10. Change proportion of the Atlantic horse mackerel's (*T. trachurus*) predicted landing compared to 2010–2022 landing average for scenarios RCP 2.6 (Red) and RCP 8.5 (Black) in the SAS zone

DISCUSSION

In marine environments, data-driven GAM models have proven to be useful tools to forecast species richness, diversity, and spatiotemporal abundance patterns **(Smoliński & Radtke, 2017)**. Additionally, models based on CPUE and effort may be used to examine how environmental factors relate to fisheries distribution and abundance **(Yen *et al.*,**

2016). Based on information gathered from assimilated and remotely sensed data, our work provided many marine statistical models to explain the temporal distribution of the European sardine and the Atlantic horse mackerel. Since RCP 8.5 is the climatic scenario that most closely reflects the current situation based on gas emissions, it has been used as environmental data for modeling in this study.

The European sardine (*Sardina pilchardus*) and Atlantic horse mackerel (*Trachurus trachurus*) exhibit unique responses to environmental conditions, which significantly impact their abundance. For the European sardine (*Sardina pilchardus*), variations in SST can shift the timing of spawning events, which has been observed in the central Mediterranean, where sardine spawning aligns with optimal thermal conditions **(Ganias, 2014)**. High SSTs during spawning seasons can accelerate developmental rates and improve larval growth, but temperature extremes may lead to increased metabolic costs and lower reproductive output **(Alvarez & Chifflet, 2012)**. **Checkley Jr. *et al.* (2017**) highlighted that elevated chlorophyll-a concentrations can support sardine populations during early life stages through better feeding opportunities. Thus, higher chlorophyll levels, reflecting increased primary productivity, provide necessary food resources for larvae, supporting survival rates during early life stages potentially increasing catch and effort when sardine aggregations are formed in nutrient-rich areas **(Bonanno *et al.*, 2016; Lima *et al.*, 2022**). Additionally, in regions with high productivity linked to upwelling, such as the Mediterranean, seasonal SST and Chl fluctuations play a critical role in supporting sardine biomass and overall reproductive output **(Bonanno *et al.*, 2014; Barra *et al.*, 2015)**. This dynamic underscores how tightly sardine populations are tied to specific environmental parameters, making them particularly sensitive to climate-driven oceanographic changes.

For the Atlantic horse mackerel, factors like sea level anomaly (SLA) and SST play a central role in shaping distribution and feeding opportunities, directly affecting catchability. The horse mackerel populations, particularly during juvenile stages, rely on SST stability and food availability, as SST influences growth rates and spawning success **(Geist *et al.*, 2015; Kamimura *et al.*, 2015)**. Recent studies have shown that fluctuations in SLA and SST can also intensify upwelling processes, and modify habitat suitability **(Thiaw *et al.*, 2017; Lavender *et al.*, 2021)**, causing shifts in population aggregations that lead to seasonal LPUE variations. Together, these variables impact LPUE differently for each species, as sardine and the horse mackerel have distinct life histories and environmental sensitivities, highlighting the need for species-specific management strategies that consider these environmental influences.

The predicted LPUE of the European sardine during 2022-2100 for both scenarios (Fig. 12a), with RCP 2.6 representing a more severe rise than RCP 8.5. The RCP 2.6 indicates favorable phytoplankton (between 0.67 - 1.79 mmol m^{-3}), sea surface emtperature (between 17.52 - 18.3°C), and sea level anomaly (between 0.07 - 0.204m) values to the development of the species, as can be seen by referring to Figs. (6, 7, 8). Alongside this abundance growth, the predicted effort has increased for both RCP scenarios as seen in Fig. (12b). Therefore, the predicted potential landing of the European sardine under both scenarios (Fig. 13) indicates an increase through the end of the 21st century by 15% under RCP 8.5 and 80% under RCP 2.6 compared to 2010-2022 average.

For both scenarios, the predicted LPUE for the Atlantic horse mackerel displays an increase (Fig. 14a). Furthermore, the predicted effort for the RCP 2.6 indicates an increase, as shown in Fig. (14b). In contrast, the effort for the RCP 8.5 remains stable until 2045, at which point it falls. This retention may be attributed to the large number of fishermen who land sardines, and consequently, the fishermen's focus on following sardine fish due to its market value (the price of sardines has averaged 11.66 Dh/kg over the last three years, compared to 18.62 Dh/kg for the horse mackerel) and social value in the Moroccan culture. Furthermore, there is an increase in cpue, it cannot be considered as an indication of abundance of the species, as studies have proved that cpue alone cannot be taken as a measure of fish abundance. Despite an increase in CPUE, studies have shown that CPUE by itself is not a reliable indicator of fish quantities, therefore this rise should not be interpreted as a sign of species abundance **(Maunder *et al.*, 2006; Beverton & Holt, 2012)**. One of the most common types of non-proportionality, known as "hyperstability," is when abundance decreases yet CPUE values increase that can lead to overestimation of biomass **(Maunder & Punt, 2013; Thorson & Minto, 2015; Hussain *et al.*, 2021)**. In addition, **Thorson *et al.* (2017)** noted that the meaning of CPUE is conditional on a knowledge of the total local catch and effort in the strata. Therefore, according to them and other report, it is expected that fish biomass would be low in locations with higher CPUE, low effort, and low catches. Additionally, it has been proven that a lower effort often is considered the strongest indicator of low biomass; otherwise, because of the communication between the mobile fleets, the effort in the strata would have been greater **(Campbell, 2015; Thorson & Somers, 2017)**. Moreover, compared to the 2010–2022 average, the expected potential landing of the Atlantic horse mackerel under RCP 2.6 scenario (Fig. 15) shows a rise of 200%; however, it shows a decrease of 100% in RCP 8.5 to the end of the 21st century. This indicates that the species may disappear from the area.

To address the impact of RCP scenarios on species abundance, our results demonstrate how climate-driven variations in Sea Level Anomaly (SLA) and related oceanographic changes lead to contrasting outcomes in species catch under different RCP scenarios. Under RCP 2.6, which represents a lower greenhouse gas emission pathway **(Van Vuuren *et al.*, 2007)**, conditions appear to favor nutrient-rich upwelling and improved food availability. This scenario likely promotes favorable conditions for primary and secondary production, leading to an increase in prey availability and supporting higher catch levels. Enhanced productivity in this scenario might support stable or even growing populations, as juvenile survival and growth rates improve under more favorable feeding conditions.

Conversely, RCP 8.5, which predicts higher emissions and greater ocean warming **(Van Vuuren *et al.*, 2011)**, may intensify SLA variability, increasing stratification and disrupting upwelling in some regions. This would reduce nutrient availability, impacting primary productivity and leading to lower zooplankton abundance, which is crucial for the early life stages of many species such as the Atlantic horse mackerel. As a result, decreased food availability under this scenario could lower juvenile survival rates and reproductive success, contributing to the declines observed in species catch. This scenario underscores the importance of monitoring SLA and other indicators of ocean productivity, as these changes can have significant effects on fish stock health, ultimately guiding more adaptive and regionally tailored management strategies in fisheries **(Boyd *et al.*, 2020)**.

CONCLUSION

This paper investigates the influence of environmental variables on the landing per unit effort (LPUE) and potential landings of the European sardine and the Atlantic horse mackerel under two climate scenarios: optimistic (RCP 2.6) and pessimistic (RCP 8.5). GAM models revealed that environmental factors significantly affected both species, with phytoplankton, sea surface temperature (SST), and sea level anomaly being the primary drivers for European sardine. The predicted LPUE and potential landings for the European sardine showed an increase under both scenarios, with a more significant rise under RCP 2.6 compared to RCP 8.5.

The LPUE of Atlantic horse mackerel is influenced by factors including sea level anomaly, SST, zooplankton, and chlorophyll-α, while effort is influenced by sea level anomaly, phytoplankton, chlorophyll-α, and sea surface salinity. The predicted LPUE for the Atlantic horse mackerel exhibited an increase under both scenarios, while the predicted effort increased under RCP 2.6 and remained stable until 2045 before declining under RCP 8.5. However, due to potential hyperstability effects, the increase in LPUE should not be interpreted as an indicator of abundance.

The potential landings for the Atlantic horse mackerel are projected to increase under the optimistic scenario but decrease significantly under the pessimistic scenario by the end of the century. This research underscores the importance of considering environmental factors in managing the European sardine and the Atlantic horse mackerel fisheries in the southern Alboran Sea. It highlights the need for careful management to ensure sustainable fishing practices under RCP 2.6 and stricter regulations and potential intervention measures to conserve the Atlantic horse mackerel population under RCP 8.5.

Further research is needed to address the data gap regarding the early life cycle of Atlantic horse mackerel and investigate the hyperstability effect and its implications for LPUE interpretation. Management implications include implementing adaptive strategies based on predicted changes in LPUE and potential landings, establishing quotas and fishing regulations to ensure sustainable catch levels, and protecting critical habitats while implementing conservation measures for vulnerable populations.

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