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Pelagic resources landings in central-southern Chile under the A2 climate change scenarios

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Abstract Artificial neural networks (ANNs) were used to predict landings of anchovy (*Engraulis ringens*), common sardine (*Strangomera bentincki*), and jack mackerel (*Trachurus murphyi*) in central-southern Chile. Twelve environmental variables were considered along with fishing effort (fe) and landing statistics from 1973 to 2012. During external validation, the best models with all of the selected variables gave r^2 values of 90 % for anchovy, 96 % for common sardine, and 88 % for jack mackerel. The models were simplified by considering only fe and sea surface temperature from NCEP/NCAR reanalysis data (SST-NOAA), and very similar fits were achieved (87, 92, and 88 %, respectively). Future SSTs were obtained from the A2 climate change scenario and regionalized using statistical downscaling techniques. The downscaled SSTs were used as input for landings predictions using ANN simplified models. In addition, three scenarios of future fishing efforts (2010–2012 average, average + 50 %, and average − 50 %) were used as the input data for landing simulations. The results of the predictions show a decrease of 9 % in future landings of sardine and an increase of 17 % for jack mackerel when comparing 2015 and 2065 monthly projections. However, no significant differences are shown when comparing the estimated landings for the three fishing effort scenarios. Finally, more integrative and complex conceptual models that consider oceanographic-biophysical, physiological, environmental-resource, and interspecies processes need to be implemented.

Keywords Forecast · Artificial neural networks · Pelagic landings · Central-southern Chile · Climate change

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1 Introduction

The exploitation of pelagic resources in central-southern Chile (32°S–42°S) began in the early 1940s. Landings reached 94,000 t of anchovy (*Engraulis ringens*) in 1969 and 113,000 t of common sardine (*Strangomera bentincki*) in 1974, which later decreased and remained low until 1988; thereafter, they exceeded the previous peaks at 520,000 t for anchovy in 2007 and 886,000 t for common sardine in 2011 (SAG 1950–1977; SERNAPESCA 1978–2012). After 1974, there was also a notable increase in landings of Chilean jack mackerel (*Trachurus murphyi*), which reached 4.4 million tons in 1995. Afterwards, the landings decreased and stabilized at approximately 1 million tons until 2007, when the decrease continued to 200,000 t by 2012. The fluctuations in these fishing activities are related to the intensity of the exploitation and environmental changes associated with El Niño events, interdecadal phenomena, and possibly climate change (Hare et al. 2000; Yáñez et al. 1992, 2001, 2014; Chavez et al. 2003; Alheit and Ñiquen 2004; Cheung et al. 2010; Merino et al. 2012).

In the face of variable and uncertain scenarios, prediction plays a central role in resource management and decision making (Makridakis et al. 1983). In fisheries management, the main objective is to identify the permissible level of catches to ensure resource sustainability. However, in most cases, achieving this objective is challenging due to the need to predict uncontrollable events (Gutiérrez-Estrada et al. 2007, 2008, 2009; Gutiérrez-Estrada and Yáñez 2008). Nonlinear relationships between fishery resources and the environment hinder precise forecasting with traditional statistical methods (Cisneros et al. 1996). One alternative for modeling nonlinear relationships is the use of artificial neural networks (ANNs), which perform better than linear models and have the capacity to generalize new data (Lek et al. 1996; Özesmi et al. 2006). In recent years, the application of ANNs has increased in different fields of science and engineering, including fisheries science (Hardman-Mountford et al. 2003; Gutiérrez-Estrada et al. 2007, 2009; Yáñez et al. 2010; Naranjo et al. 2015).

Given the importance of pelagic resources in central-southern Chile, the present study analyzes the performance of ANNs in the prediction of monthly landings of anchovy, common sardine, and Chilean jack mackerel based on fishing efforts and environmental variables. Forecasted landings of each species are calculated through 2065 and take into account the selected ANN models under the A2 climate change scenario of the Intergovernmental Panel on Climate Change (IPCC) and three fishing effort projections (2010–2012 average, average + 50 %, and average − 50 %).

2 Materials and methods

The study zone consisted of the purse seine fleet operating area off central-southern Chile (32°S–42°S) from the coast to 60 nm offshore for anchovy and common sardine (75°W) and over 200 nm from the exclusive economic zone for jack mackerel (78°W) (Fig. 1). The analyzed data include environmental and fishing data from 1983 to 2012 for anchovy and common sardine and 1973–2012 for jack mackerel.

2.1 Artificial neural network model applications

2.1.1 Data

For anchovy and common sardine, the values for total monthly landings (t) were obtained from the Fishing Statistics Annual Report of the National Fishing Service (SERNAPESCA 1983–2012); the values for jack mackerel landings are from yearly reports by the same association (SERNAPESCA 1978–2008) and from the Agriculture and Livestock Service reports (SAG 1973–1977). The joint statistics on landings and fishing effort of the industrial purse seine fleet and the artisanal fleet were obtained from the Monitoring Program of the Principal National Fisheries gathered annually by the Institute of Fishing Development (IFOP). The environmental data consisted of the monthly averages of 12 variables recorded at weather and oceanographic stations located off the coast of Talcahuano (36°S–73°W) and included in reports by global climate centers (www.cpc.ncep.noaa.gov/data/indices). The environmental variables included the following: sea surface temperature (SST) and mean sea level (MSL) from oceanographic stations; SST from NCEP/NCAR reanalysis data (Kistler et al. 2001) for the common sardine, anchovy, and jack mackerel fishing zones; air temperature (AT); Pacific Decadal Oscillation (PDO); SST in the El Niño 1 + 2 region (SST NIÑO 1 + 2); SST in the El Niño 3.4 regions (SST NIÑO 3.4); Southern Oscillation Index (SOI); Cold Tongue Index (CTI); and Antarctic Oscillation (AAO). The wind speed and direction at Carriel Sur (36°46′S–73°03′W) were used to estimate the Ekman Transport (ET) (Bakun et al. 1974) and the turbulence index (TI) (Elsberry and Garwood 1978). The data for all of these variables are available on the CLIPESCA website (www.clipesca.cl/index.php/productos/info-historica/ambiental-temporal).

The fishing and environmental data were analyzed to determine which variables to include in the ANN models. First, any strongly correlated variables were excluded from the analysis. Then, a principal component analysis was conducted to visualize the level of representation of each variable on the main axes (Yáñez and Barbieri 1983); these are the variables that present an individual value that is higher than the average of the values generated by each factor (Hair et al. 1999). Finally, a linear cross-correlation analysis was performed for the selection of time lags in time series models based on a 95 % confidence level (α = 0.05). To decrease high-frequency noise and thus clearly identify trends, the data were smoothed out through the use of a mobile mean centered around 3 months of data (Freón et al. 2003).

Regionalized projections of SST for central-southern Chile were used to forecast landings with ANN models, considering the fishing zones of anchovy, sardine, and jack mackerel for the period 2015–2065 (Fig. 2).

2.1.2 Artificial neural network models

The ANN models included monthly landings, fishing effort, and environmental variables, with time lags for the period of 1983 to 2012 for anchovy and common sardine and 1973 to 2012 for jack mackerel. Regarding modeling, 60 % of the data was used to calibrate the network (training), 20 % was used for the selection stage (learning verifies the network), and 20 % was used for the test step (validation model); all data were randomly selected (e.g., Makkearsorn et al. 2008; Gutiérrez-Estrada et al. 2009; Yáñez et al. 2010; Naranjo et al. 2015). Monthly landing estimates for anchovy, common sardine, and jack mackerel were the output variables of the models.

The ANNs were tested with a hidden layer and by varying the number of nodes for each model depending on the number of input variables. The ANN that functioned best in the

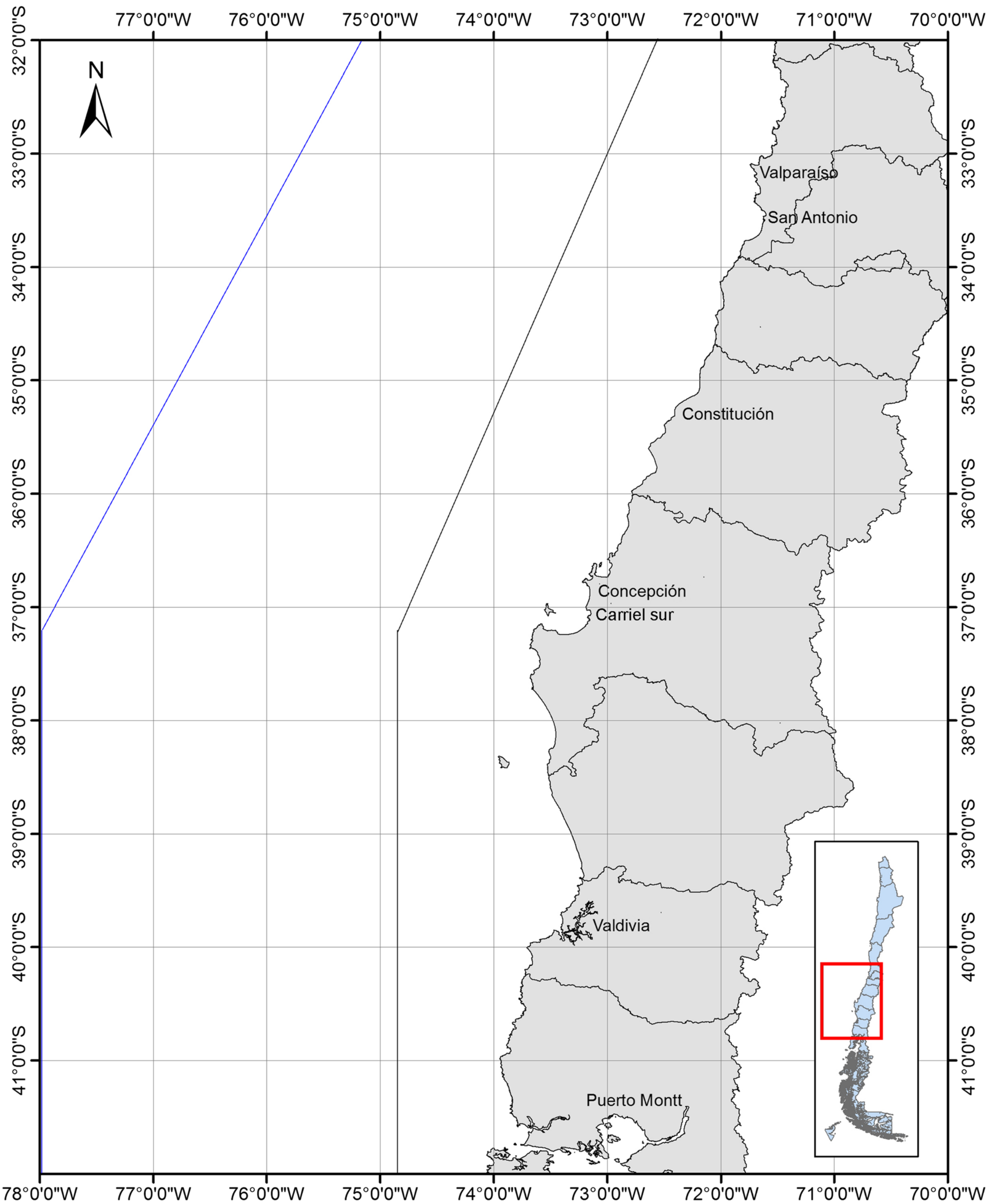


Fig. 1 Location of the study area comprises the purse seine fleet operating area off central-southern Chile (32°S–42°S). *Black line* indicates the anchovy and common sardine fishing areas (until 60 n mi offshore) and *blue line* indicates the jack mackerel fishing area (until 200 n mi offshore)

validation stage was then chosen, and 30 repetitions of the calibration process were performed for each ANN structure (Anctil and Rat 2005; Pérez-Marín et al. 2006). Based on this number of repetitions, the chosen model was within the best 14 % of all possible models with a 99 % confidence level (Iyer and Rhinehart 1999). The learning algorithm for calibration purposes and subsequent validation of the models was the supervised second-order Levenberg-Marquardt algorithm (Shepherd 1997), which is a variation of the backpropagation algorithm (Rumelhart et al. 1986) and is highly recommended (e.g., Tan and Van Cauwenberghe 1999; Martín del Brío and Sanz 2001; Anctil and Rat 2005, Özesmi et al. 2006; Suryanarayana et al. 2008). The software STATISTICA 7.0 was used to run the ANN models.

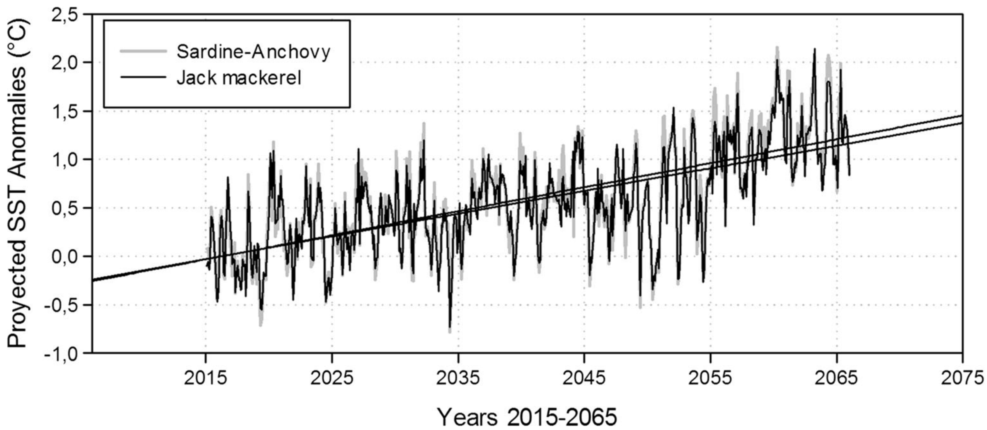


Fig. 2 National Centre for Atmospheric Research (NCAR) model projections of regionalized sea surface temperature (SST) anomaly (°C) for the high emission CO_2 scenario (A2) of the Intergovernmental Panel on Climate Change (IPCC) for anchovy-common sardine and jack mackerel fishing areas

2.1.3 Model evaluation

With a randomly selected dataset (20 %), the functioning of the ANNs was evaluated during the validation stage using the coefficient of determination (r^2), the percentage standard error of prediction (%SEP) (Ventura et al. 1995), the coefficient of efficiency (E) (Nash and Sutcliffe 1970; Kitanidis and Bras 1980), and the average relative variance (ARV) (Griñó 1992). These indices are not influenced by the range of variation of their elements and are used to identify the extent to which the model is able to explain the total variation of the data. Similarly, the error can be quantified in terms of the units of the variable being estimated. These absolute error measurements included the root mean square (RMS). To accept the fit, the values of r^2 and E must be close to one, and the values of %SEP and AVR must be near zero. The persistence index (PI) was also used to assess the models (Kitanidis and Bras 1980). A PI value of one indicated a perfect fit between the estimated and observed values, whereas a zero value indicated that the model was no better than a "naïve" model, which always gives the previous observation as the next prediction. A negative PI value indicated that the model was altering the original information to give a level of function that was worse than a naïve model (Anctil and Rat 2005).

2.1.4 Sensitivity analysis

A sensitivity analysis was conducted to identify the most significant input variables. This analysis treats each input variable on the neural network as if it were unavailable in the model (Hunter et al. 2000). To evaluate the sensitivity of variable X, the sums of squares residuals for the model when the respective predictor was eliminated from the neural net were calculated; ratios (of the reduced model versus the full model) were also calculated, and the predictors were sorted by their importance or relevance for the particular neural network. If the value was less than or equal to one, adding or removing the variable had no significant effect on the model.

2.2 Statistical SST downscaling

SST simulations from the AR4 of the IPCC (IPCC 2007) were used for prediction. The AR4-IPCC included simulations from 23 different global climate models run with standardized CO_2 emission scenarios. In this study, we used the National Centre for Atmospheric Research (NCAR) Community Climate System Model 3.0 (CCSM3) and considered the high future CO_2 emission scenario known as A2 (IPCC 2007). The simulations extend from 2000 to 2100 under the hypothetical A2 emissions scenario (Nakicenovic et al. 2000). The NCAR CCSM3 is a global, coupled ocean–atmosphere–sea ice–land climate model (Collins et al. 2006) used to drive marine ecosystem models to investigate the responses of fishery resources to global warming (Di Lorenzo et al. 2008; Hare et al. 2010). The model used in this study is the same model used at higher resolution for the IPCC AR4 projections of future climate, with an ocean horizontal resolution corresponding to a nominal grid spacing of approximately 1° latitude × 1° longitude. However, the resolution of the NCAR CCSM3 model is coarse, potentially limiting the use of this model to assess regional changes in marine ecosystems, particularly in coastal and shelf waters. For this reason, there is a need to use climate and oceanographic projections with better spatial resolution (e.g., using statistical downscaling) in regional assessments (Stock et al. 2011). In this study, the change factor (CF), or Delta method, was applied because it is a relatively straightforward and popular downscaling method for the rapid impact assessment of climate change (Wilby and Wigley 2000; Silva et al. 2015). The CF method involves adjusting the observed monthly SST ($SST_{obs,\ m}$) obtained from MODIS climatology (2003–2013) by adding the interpolated anomaly (delta) or difference in

Table 1 Correlation matrix between environmental variables with highly correlated in bold

	AT	SST	SST-NOAA	MSL	TI	ET	PDO	SST NIÑO 1 + 2	SST NIÑO 3.4	SOI	CTI	AAO
AT	1											
SST	0.68	1										
SST-NOAA	**0.93**	**0.69**	1									
MSL	−0.12	−0.01	−0.02	1								
TI	0.59	0.34	0.56	−0.45	1							
ET	0.34	0.13	0.32	0.15	−0.12	1						
PDO	0.01	0.18	0.13	0.26	−0.03	0.09	1					
SST NIÑO 1 + 2	0.52	0.59	**0.67**	0.24	0.18	0.02	0.28	1				
SST NIÑO 3.4	−0.23	0.06	−0.14	0.33	−0.21	−0.13	0.45	0.38	1			
SOI	0.02	−0.12	−0.01	−0.29	0.04	−0.09	−0.41	−0.18	**−0.66**	1		
CTI	−0.01	0.15	0.01	0.22	0.01	0.02	0.44	0.29	**0.83**	−0.72	1	
AAO	0.03	0	0.05	−0.08	0.08	−0.14	−0.12	−0.02	−0.18	0.14	−0.19	1

Environmental variables correspond to anchovies and common sardines fishing areas. Values are Pearson correlation coefficients with $P < 0.01$

monthly SST predicted by the global climate model (GCM) NCAR CCSM3 between the 2065 horizon and the reference period ($SST_{GCM,2065,m} - SST_{GCM,ref,\ m}$). A monthly adjusted SST at the 2065 horizon ($SST_{adj,2065,m}$) is then obtained:

$$SST_{adj,2065,m} = SST_{obs,m} + \left(SST_{GCM,2065,m} - SST_{GCM,ref,m}\right)$$

Before adding $SST_{obs,m}$, the anomalies ($SST_{GCM,2065,m} - SST_{GCM,ref,m}$) were interpolated by the Kriging algorithm over a grid with the same spatial resolution (4 km) and extent as $SST_{obs,m}$ to downscale the coarse grid resolution (1° = 111.1 km) of the NCAR CCSM3 model. Using GIS tools, the future mean SST from the predicted SST maps were extracted for anchovy, sardine, and jack mackerel fishing areas.

2.3 Landings forecasts

The reduced ANN models calibrated for the three fishing activity types were used to forecast landings. The averages of fishing effort over the last 3 years of each fishing activity (2010–2012) were used as input values. SST output predictions based on the A2 climate change scenarios were also used. To force the ANN models, SST time series predictions were extracted according to the three fisheries (anchovy, sardine, and jack mackerel) areas in central-southern Chile and for the period 2015–2065 (Fig. 2).

To simulate and identify the effects of climate change in the aforementioned fisheries, downscaled SST (A2 scenario) predictions (2015–2065) and three scenarios of future fishing effort (2010–2012 average, average + 50 %, and average − 50 %) were used as input for landing simulations.

Table 2 Correlation matrix between environmental variables with highly correlated in bold

	AT	SST	SST-NOAA	MSL	TI	ET	PDO	SST NIÑO 1 + 2	SST NIÑO 3.4	SOI	CTI	AAO
AT	1											
SST	0.71	1										
SST-NOAA	**0.89**	**0.72**	1									
MSL	−0.08	0.00	0.03	1								
TI	0.19	0.10	0.16	0.12	1							
ET	0.52	0.40	0.47	−0.42	−0.36	1						
PDO	0.04	0.15	0.12	0.30	−0.02	−0.04	1					
SST NIÑO 1 + 2	0.53	0.53	**0.75**	0.29	−0.02	0.16	0.29	1				
SST NIÑO 3.4	−0.15	0.09	−0.01	0.44	−0.11	−0.20	0.46	0.43	1			
SOI	−0.03	−0.15	−0.05	−0.35	−0.02	0.02	−0.41	−0.21	**−0.67**	1		
CTI	0.03	0.19	0.03	0.31	0.05	0.00	0.45	0.33	**0.81**	−0.71	1	
AAO	0.00	−0.04	0.02	−0.04	−0.16	0.05	−0.11	0.01	−0.15	0.17	−0.20	1

Environmental variables correspond to jack mackerel fishing area. Values are Pearson correlation coefficients with $P < 0.01$

3 Results

3.1 Artificial neural network models

3.1.1 Correlations between variables and principal component analysis (PCA)

Table 1 indicates that the SST-NOAA for the common sardine and anchovy fishing zone is strongly correlated with AT, SST, and NIÑO 1 + 2 (0.93, 0.69, and 0.67, respectively); similar correlations were found between SST NIÑO 3.4 and the variables CTI (0.83) and SOI (0.66). According to Table 2, the correlation matrix for jack mackerel has similar values among the environmental variables, although the SST-NOAA is for a more oceanic fishing zone.

PCA leads to 12 factors that together explain 100 % of the variance. However, for anchovy and common sardine, factors 1, 2, 3, and 4 were selected. When combined, these factors account for 29.4, 26.2, 11.2, and 8.8 % of the variance, respectively; therefore, they explain 75.6 % of the total variance. For jack mackerel, factors 1, 2, 3, and 4 account for 30.4, 25.2, 11.8, and 9.2 % of the variance, respectively, which results in a combined total variance of 76.6 %.

For anchovy and common sardine, the correlation matrix of environmental variables with each principal factor shows the highest values for SST-NOAA, AT, and SST with factor 1; SST NIÑO 3.4, CTI, and SOI with factor 2; MSL and TI with factor 3; and ET with factor 4 (Table 3). For jack mackerel, these correlations are similar for factors 1 and 2, but ET has the highest value for factor 3 and AAO for factor 4 (Table 4).

Table 3 Rotated loading (correlation coefficient) matrix provided by the multivariate analysis of environmental variables in order to define principal components or factors (factor 1, factor 2, factor 3, and factor 4)

	Factor 1	Factor 2	Factor 3	Factor 4
AT	**0.91**	−0.12	−0.20	0.19
SST	**0.81**	0.14	−0.06	−0.02
SST-NOAA	**0.96**	−0.05	−0.09	0.11
MSL	0.05	0.27	**−0.83**	0.04
TI	0.51	−0.03	**−0.74**	−0.08
ET	0.28	−0.12	0.30	**0.76**
PDO	0.17	0.59	0.19	0.08
SST NIÑO 1 + 2	0.75	−0.35	0.21	−0.20
SST NIÑO 3.4	−0.07	**0.91**	0.18	−0.11
SOI	−0.03	**−0.81**	−0.06	−0.14
CTI	0.05	**0.90**	−0.03	0.06
AAO	0.13	−0.28	0.12	−0.69

Environmental variables correspond to anchovy and common sardine fishing areas

Absolute correlation values higher than 0.7 in bold

Table 4 Rotated loading (correlation coefficient) matrix provided by the multivariate analysis of environmental variables in order to define principal components or factors (factor 1, factor 2, factor 3, and factor 4)

	Factor 1	Factor 2	Factor 3	Factor 4
AT	**0.93**	−0.09	−0.10	−0.10
SST	**0.83**	0.13	−0.11	−0.09
SST-NOAA	**0.97**	0.00	−0.02	0.04
MSL	0.03	0.48	0.63	0.25
TI	0.21	−0.17	0.69	−0.50
ET	0.47	−0.07	**−0.79**	−0.01
PDO	0.11	0.64	0.06	0.01
SST NIÑO 1 + 2	0.73	−0.40	0.13	0.26
SST NIÑO 3.4	−0.03	**0.92**	0.10	0.06
SOI	−0.04	**−0.82**	0.00	0.16
CTI	0.07	**0.88**	−0.01	−0.18
AAO	0 03	−0.21	0.00	**0.82**

Environmental variables correspond to jack mackerel fishing area

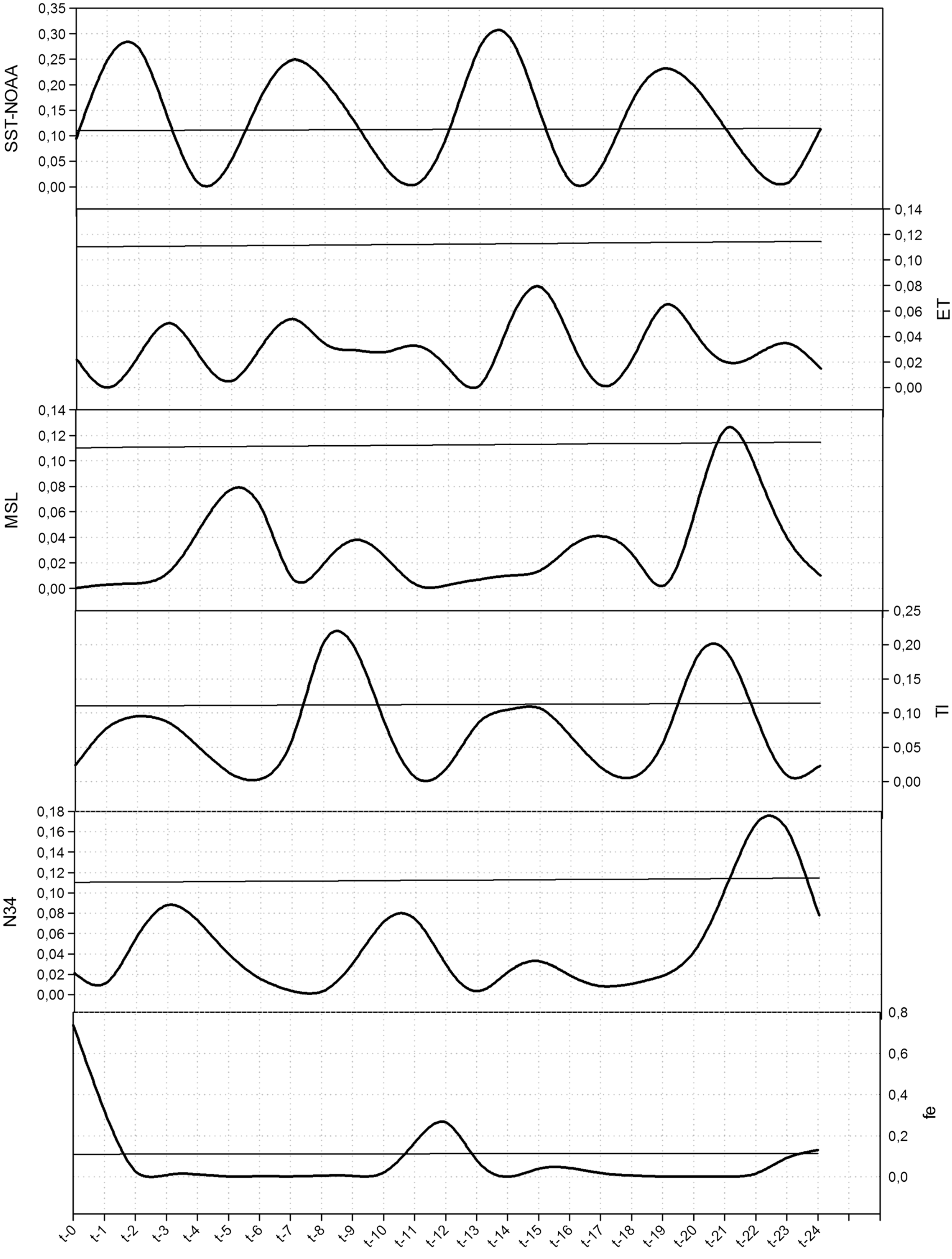
Absolute correlation values higher than 0.7 in bold

Considering the correlation matrix results between the environmental variables and the PCA, the pre-selected variables for anchovy and common sardine are SST-NOAA, SST NIÑO 3.4, ET, TI, and MSL, and the variables for jack mackerel are SST-NOAA, SST NIÑO 3.4, ET, and AAO.

3.1.2 Cross-correlations

For anchovy, SST-NOAA has significant values for cross-correlation with the rectangular hyperbolic II function and time lags of −2, −7, −14, and −19 months (Fig. 3). For common sardine, significant values are achieved with the Cauchy function with time lags of −1, −6, −16, and −18 months (Fig. 4). The Cauchy function also produces significant values for jack mackerel but with time lags of −2, −14, −26, −38, −50, and −62 months (Fig. 5). SST NIÑO 3.4 reaches its maximum correlation value at −22 months with the rectangular hyperbolic II function for anchovy, at −3 months with the reciprocal rectangular hyperbolic I function for common sardine, and at −46 months with the rectangular hyperbolic II function for jack mackerel. The TI attains significant correlations with the rectangular hyperbolic II function at −8 and −21 months for anchovy and with the parabolic function at −8 and −20 months for common sardine. The MSL attains its maximum significant correlation value with the parabolic function at −21 months for anchovy and with the Cauchy function at −5 and −17 months for common sardine. The ET does not give significant correlation values for any of the

Fig. 3 Linear and nonlinear cross-correlation for anchovy landings and sea surface temperature from NCEP/NCAR reanalysis data (SST-NOAA), Ekman transport (ET), mean sea level (MSL), turbulence index (TI), SST in El Niño 3.4 regions (SST NIÑO 3.4), and anchovy fishing effort (fe). Significance level also included ($P = 0.05$)


SST-NOAA
0,35
0,30
0,25
0,20
0,15
0,10
0,05
0,00
ET
0,14
0,12
0,10
0,08
0,06
0,04
0,02
0,00
MSL
0,14
0,12
0,10
0,08
0,06
0,04
0,02
0,00
TI
0,25
0,20
0,15
0,10
0,05
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N34
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species, and no significant values are obtained with AAO for jack mackerel. The standard fishing effort (fe) shows significant cross-correlation values with the reciprocal rectangular hyperbolic I function at 0 and −12 months for anchovy and at 0, −12, −24, and −36 months for jack mackerel and with the parabolic function at 0, −11, and −22 months for common sardine.

Although the nonlinear and linear cross-correlations are very similar, the nonlinear cross-correlations generally account for more variance, particularly in terms of fishing effort. In addition to the previously mentioned significant values, there are other significant values, but these were disregarded to avoid redundancy, which can negatively affect the modeling.

3.1.3 ANN modeling

After initial data treatment, phase 1 defined the ANN models with their respective input variables and corresponding time lags: SST-NOAA, fe, MSL, TI, and SST NIÑO 3.4 for anchovy and common sardine and SST-NOAA, SST NIÑO 3.4, and fe for jack mackerel. Therefore, the best architecture for anchovy was 10:9:1 (10 nodes on the input layer, 9 nodes on the hidden layer, and 1 node on the output layer), which gave an r^2 of 90 % and PI of 0.92, indicating a good degree of fit (Table 5). However, a slight degree of dispersion between the observed and estimated series is evident in the %SEP and RMS values of 28 % and 7275 t, respectively. For common sardine, the best model has a 12:12:1 architecture with an r^2 of 96 %, a coefficient of efficiency of 96 %, and a PI close to 1. The %SEP and RMS values are 22 % and 10,039 t, respectively. For jack mackerel, the best model has an 11:13:1 architecture with an r^2 of 88 % and E of 89 %. The standard error is 34.75 %, indicating that there is dispersion between the observed and estimated series, whereas the RMS is 39,790 t.

Table 6 shows the sensitivity analysis that evaluates the importance of each variable in the best ANN models identified in phase 1 for each fish species.

To simplify the models, phase 2 involved decreasing the number of input variables in the models without losing an important degree of fit. The variables selected to reduce the models were fe and SST-NOAA, whose ratios in the phase 1 models were above the median (Table 6). Therefore, the anchovy model considers variables with ratios above 1.36: $fe_{(t-0)}$, $SST\text{-}NOAA_{(t-14)}$, $SST\text{-}NOAA_{(t-7)}$, and $SST\text{-}NOAA_{(t-2)}$. The median value for common sardine is 1.57; therefore, the input variables are $fe_{(t-0)}$, $SST\text{-}NOAA_{(t-13)}$, $SST\text{-}NOAA_{(t-1)}$, $SST\text{-}NOAA_{(t-2)}$, $SST\text{-}NOAA_{(t-18)}$, and $SST\text{-}NOAA_{(t-6)}$. The median value for jack mackerel is 1.76, and the included variables are $fe_{(t-0)}$, $SST\text{-}NOAA_{(t-50)}$, $SST\text{-}NOAA_{(t-14)}$, $SST\text{-}NOAA_{(t-38)}$, $fe_{(t-12)}$, and $fe_{(t-36)}$. SST-NOAA and fe are of particular importance in the models (Table 6); SST-NOAA is included in the models to allow the use of future temperature scenarios of climate change as inputs for the fisheries landings simulation. However, MSL was discarded for anchovy and common sardine despite giving a ratio above the median value.

Fig. 4 Linear and nonlinear cross-correlation for common sardine landings and sea surface temperature from NCEP/NCAR reanalysis data (SST-NOAA), Ekman transport (ET), mean sea level (MSL), SST in El Niño 3.4 regions (SST NIÑO 3.4), turbulence index (TI), and common sardine fishing effort (fe). Significance level also included (P = 0.05)

Table 7 shows the best models selected in phase 2 for the three fish species. Compared with the phase 1 models, anchovy and common sardine show r^2 and RMS values with minimal differences, although increases in %SEP are more notable, as they suggest slightly more dispersion between the observed and estimated data; by contrast, the PI values indicate a similar quality of fit (Figs. 6 and 7). For jack mackerel, the indices of error show practically no variation except for a lower index of persistence; therefore, the models were simplified without losing any predictive capacity (Fig. 8).

3.2 Temperature downscaling

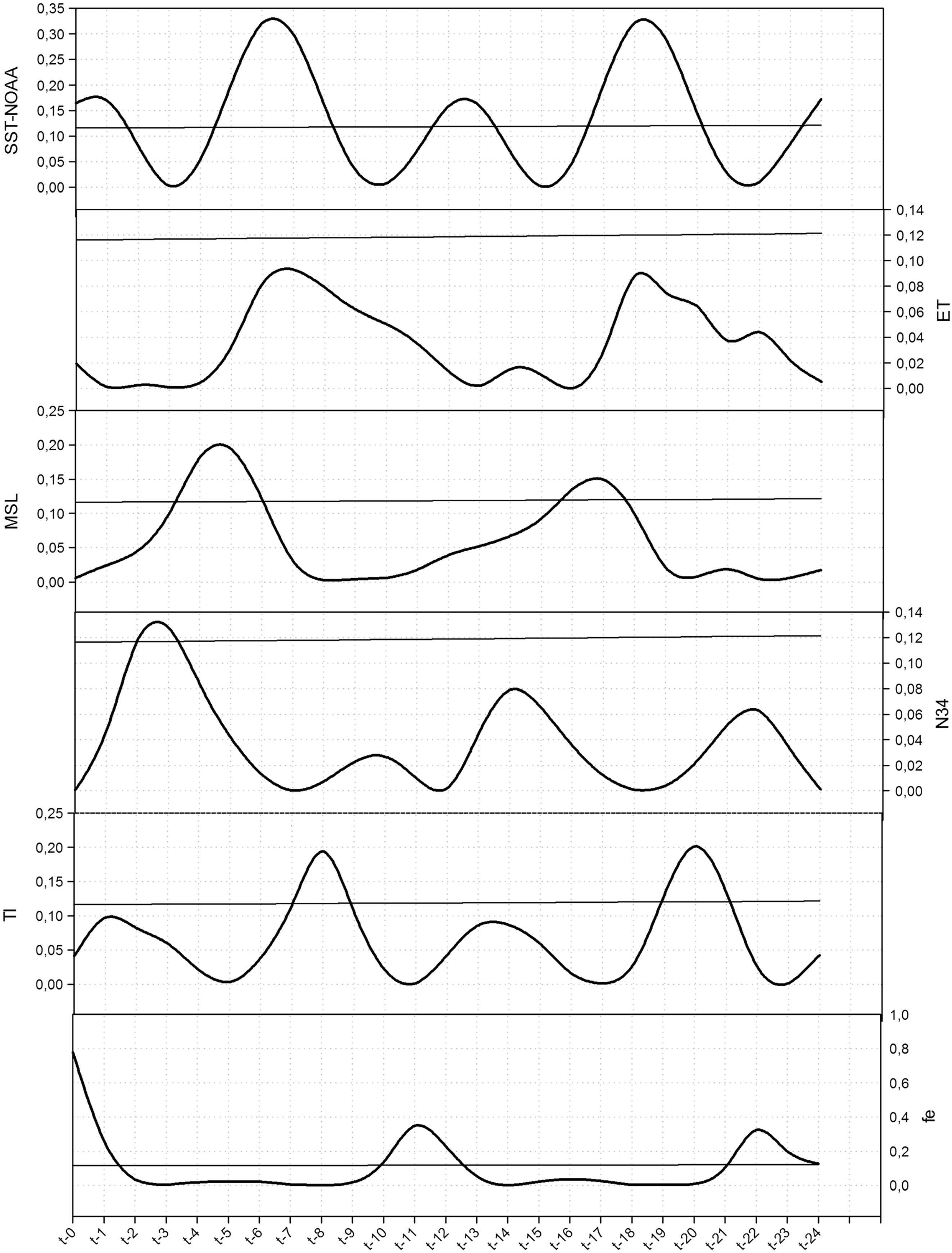
For NCAR-corrected SST anomalies forecast under the A2 scenario, the linear regressions were fitted, showing positive trends for anchovy-sardine and jack mackerel fishing areas (Fig. 2). Considering changes in the sea surface temperature (SST) from 2015 to 2016 with a fitted linear regression (Fig. 2), Table 8 show increases (change) in the projected SST from 2015 to 2065 for anchovy, common sardine, and jack mackerel fishing areas.

3.3 Landings forecasts

Figures 9, 10, and 11 show the respective anchovy, common sardine, and jack mackerel landing projections from 2015 to 2065 periods based on the A2 climate change scenario and three fishing effort projections considering a 2010–2012 average, a 50 % average increase, and a 50 % average decrease. Anchovy and sardine projections have less pronounced trends than jack mackerel; the latter shows higher variability. In Table 9, based on the A2 climate change scenario, anchovy and sardine landings would decrease by 1 and 4 %, respectively, whereas jack mackerel landings would increase by 13 %.

4 Discussion

In recent years, artificial intelligence has been used to manage large databases and algorithms through a complex structure to produce easily interpreted results (Bravo-Oviedo and Kimdermann 2004). The aim of using predictive models with fishing activities is to provide those responsible for resource


SST-NOAA
ET
MSL
N34
TI
fe
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0,30
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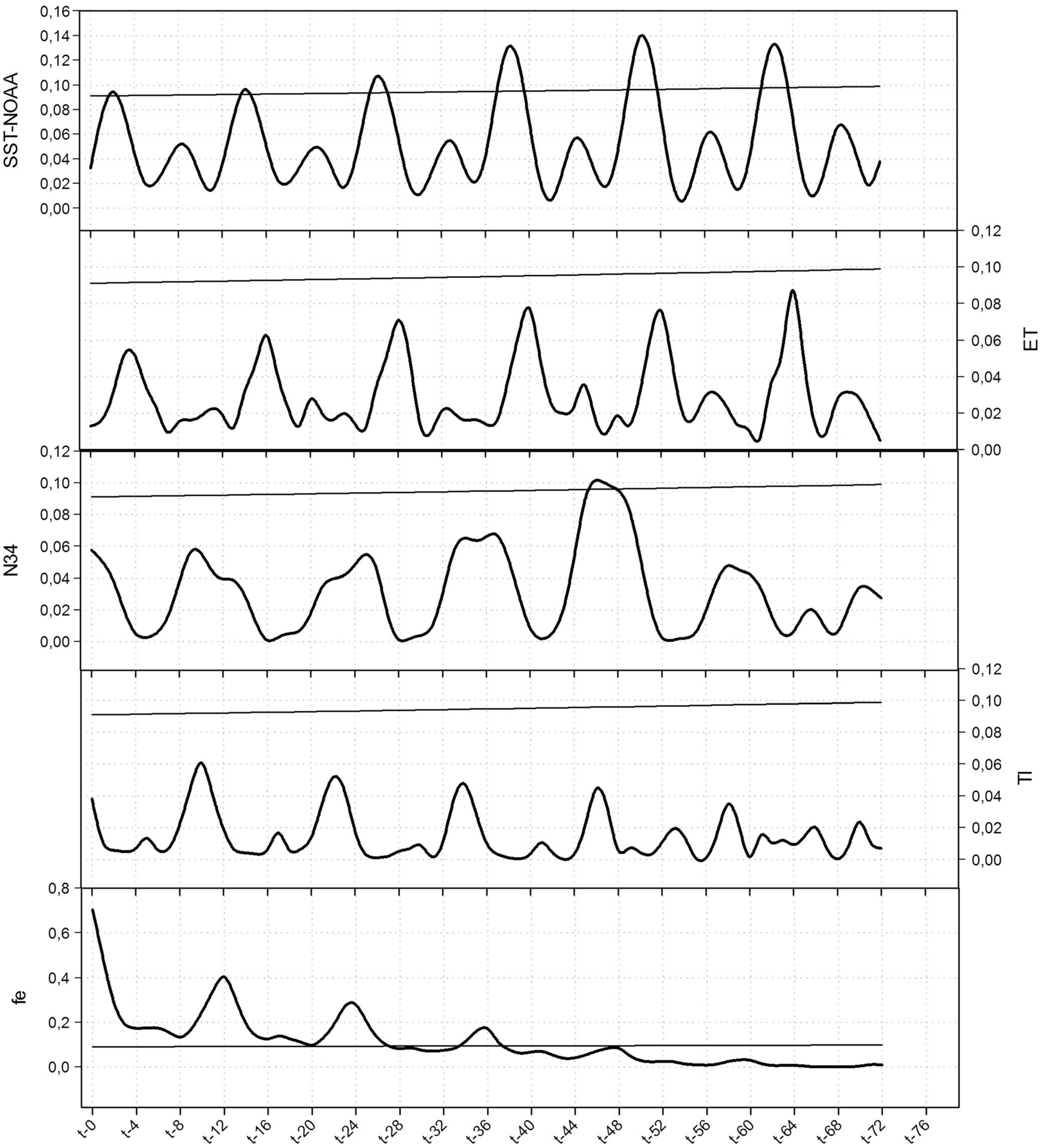

Fig. 5 Linear and nonlinear cross-correlation for jack mackerel landings and sea surface temperature from NCEP/NCAR reanalysis data (SST-NOAA), Ekman transport (ET), SST in El Niño 3.4 regions (SST NIÑO 3.4), turbulence index (TI), and jack mackerel fishing effort (fe). Significance level also included ($P = 0.05$)

management and other users with information on the biological and/or environmental effects of fishing on available stocks. However, conventional production models are not always adequate, as variations in fishing effort account for only a portion of the changes in landings; there is often a residual variation caused by environmental phenomena that affect abundance and/or catchability of stocks from one year to the next (Freón et al. 1993).

Based on the time series analyses in the present study, strong correlations were identified between the variables, such as SST

Table 5 Anchovy, common sardine, and jack mackerel artificial neural networks (ANN) models (phase 1) architecture and accuracy measures (error index)

Error index								
Species	Architecture	N	Parameters	r^2	RMS	%SEP	E	PI
Anchovy	10:9:1	9	99	0.90	7275	28.06	0.89	0.92
Common sardine	12:12:1	12	156	0.96	10,039	22.20	0.96	0.96
Jack mackerel	11:13:1	13	156	0.88	39,790	34.75	0.88	0.89

Presented are the values of the best model for each hidden neuronal architecture following the external validation (EV)

and AT. These two variables were measured at coastal stations but were also correlated with SST-NOAA, a variable that represents an average of the SST values in the fishing zone that was slightly better represented in the first component of the PCA (Table 3). Therefore, SST-NOAA was selected as an input variable in the models. The CTI and the SOI were discarded because they were strongly correlated with SST NIÑO 3.4, which was chosen as an input variable because it represents the dynamics transmitted by trapped waves on the south-eastern Pacific coast. Plaza et al. (2008) and Yáñez et al. (2010) obtained similar correlations when conducting the same analyses to reduce the input variables in their ANN models to predict the abundance of anchovy and common sardine in northern Chile. Yáñez et al. (1992) included AT and other variables to account for inter-annual variations in abundance and catches of jack mackerel in central-southern Chile.

Strong correlations between observed and estimated landings using ANN models were estimated (Figs. 6, 7, and 8). However, it could be clearly seen that the models tended to overestimate the low landing levels (close to zero). This overvalue is important, as it occurs when the population is close to collapse, a condition under which a model should work fine. In spite of this, the models captured the general trends of the anchovy, sardine, and jack mackerel landings data series.

The three fishing operations were modeled using the same methods and considering the input variables fe, SST-NOAA, MSL, TI, and SST NIÑO 3.4, which, along with their respective time lags, attained the necessary level of significance in cross-correlation analyses (Table 6). These variables have been considered in previous studies. Gutiérrez-Estrada et al. (2009) and Yáñez et al. (2010) include SST NIÑO 3.4 in predictive ANN models for common sardine and anchovy landings in northern Chile, respectively; Yáñez et al. (1992) included TI, fishing effort, MSL, and AT to explain inter-annual fluctuations in abundance and catches of jack mackerel in central-southern Chile; and Yáñez et al. (2014) considered fe and SST to explain the inter-annual abundance and catches of jack mackerel using a CLIMPROD production model (Freón et al. 1993) and obtained a significant correlation ($r^2 = 0.89$).

The exclusion of ET because it was not significant in the cross-correlations implied that wind acts preferentially through TI, which affects the vertical structure of the water

Table 6 Sensitivity analysis for the anchovy, common sardine, and jack mackerel artificial neural networks (ANN) models (phase 1)

Ranking	Anchovy model		Common sardine model		Jack mackerel model	
	Variable	Ratio	Variable	Ratio	Variable	Ratio
1	**$fe_{(t-0)}$**	**3.72**	**$fe_{(t-0)}$**	**4.24**	**$fe_{(t-0)}$**	**3.07**
2	**$SST\text{-}NOAA_{(t-14)}$**	**2.95**	**$SST\text{-}NOAA_{(t-13)}$**	**3.11**	**$SST\text{-}NOAA_{(t-50)}$**	**2.97**
3	**$SST\text{-}NOAA_{(t-7)}$**	**1.96**	**$SST\text{-}NOAA_{(t-1)}$**	**2.52**	**$SST\text{-}NOAA_{(t-14)}$**	**2.61**
4	**$SST\text{-}NOAA_{(t-2)}$**	**1.47**	$MSL_{(t-5)}$	2.25	**$SST\text{-}NOAA_{(t-38)}$**	**2.11**
5	$MSL_{(t-21)}$	1.44	**$SST\text{-}NOAA_{(t-18)}$**	**1.99**	**$fe_{(t-12)}$**	**2.06**
6	$TI_{(t-8)}$	1.27	**$SST\text{-}NOAA_{(t-6)}$**	**1.75**	**$fe_{(t-36)}$**	**1.76**
7	$SST\text{-}NOAA_{(t-19)}$	1.24	$fe_{(t-22)}$	1.39	$SST\text{-}NOAA_{(t-2)}$	1.75
8	SST NIÑO $3.4_{(t-22)}$	1.15	$TI_{(t-8)}$	1.33	$SST\text{-}NOAA_{(t-26)}$	1.53
9	$TI_{(t-21)}$	1.05	$TI_{(t-20)}$	1.17	$SST\text{-}NOAA_{(t-62)}$	1.46
10	$fe_{(t-12)}$	1.02	$MSL_{(t-17)}$	1.16	$fe_{(t-24)}$	1.31
11			$fe_{(t-11)}$	1.12	SST NIÑO $3.4_{(t-46)}$	0.95
12			NIÑO $3.4_{(t-3)}$	1.02		
Median		**1.36**		**1.57**		**1.76**

Average of the ratios between the network error without the input variable and the original error (see text) for the best models. Ranking and mean ratio are shown. Bold indicates higher-than-median ratio

Table 7 Anchovy, common sardine, and jack mackerel artificial neural networks (ANN) models (phase 2) architecture and accuracy measures (error index)

Error index								
Species	Architecture	*N*	Parameters	r^2	RMS	%SEP	*E*	PI
Anchovy	4:10:1	10	50	0.87	10,187	42.78	0.88	0.89
Common sardine	5:3:1	3	18	0.92	12,716	32.80	0.88	0.
Mackerel	6:10:1	10	70	0.88	40,373	33.20	0.88	0.83

Presented are the values of the best model for each hidden neuronal architecture following the external validation (EV)

column, the distribution of nutrients, and the food, diet, and consumption of small pelagic species (Cubillos et al. 2001). However, according to Cubillos and Arcos (2002), sea surface temperatures and upwelling indexes (such as ET and TI) have high negative relationships with common sardine recruitment, while common sardine recruitment has a negative relationship with anchovy recruitment. Gomez et al. (2012) also showed that coastal chlorophyll, upwelling intensity, and SST anomalies from the NIÑO 3.4 region could potentially help to predict common sardine recruitment. The latter could be considered to be an improvement for future analysis.

The MSL was above the median ratio (Table 6) and therefore should have been included in the anchovy and sardine reduced ANN models. However, this variable was discarded because future simulations were not available, climate change forecasts are mainly associated with variations in temperature, and MSL is mainly associated with the third component (or factor) in the PCA, which, according to the eigenvalues, represents a lower percentage of the total variance (Table 3).

Yáñez et al. (2010) fit ANN models to predict the monthly abundance of anchovy and common sardine in northern Chile using the input variables fe and SST as well as ET and SOI, which were not selected in the present study. The jack mackerel landing models, which included AAO, considered the possible forcing effects from the south and the extreme south, but the inclusion of this variable was not significant.

Variables with close-to-one ratios in the sensitivity analysis did not have an important effect on the ANN models. The variables selected in phase 2, including fe and SST-NOAA, whose ratios were above the median (Table 6), were sufficient to fit the models (Table 7) and achieved a similar predictive capacity compared with the models generated in phase 1 (Table 5). These simplified models were carried out for the 2015–2065 landings projection based on the A2 climate change scenarios from the IPCC. With these scenarios, the estimated SST changes for anchovy and sardine fishing areas and jack mackerel fishing areas showed increases of 0.58 and 2.36 °C, respectively. According to the IPCC (2013), central-southern Chile temperatures will show an increase of 0.7–3.5 °C by 2100.

Gutiérrez-Estrada et al. (2007, 2009) and Yáñez et al. (2010) related the biological processes of anchovy and common sardine to landings with time-lagged environmental variables. Similar results were obtained for anchovy in this paper. For SST-NOAA, the time lags of −2, −7, −14, and −19 months for anchovy and −1, −6, −13, and −18 months for common sardine could possibly imply two different effects, one of which is associated with recruitment and the other is associated with distribution. Braun et al. (1995) and Castillo et al. (2002) indicated that anchovy recruitment occurs at 5–7 months, whereas temperatures at 2–3 months before hatching affect fertility of clupeiform species (Winters et al. 1993;

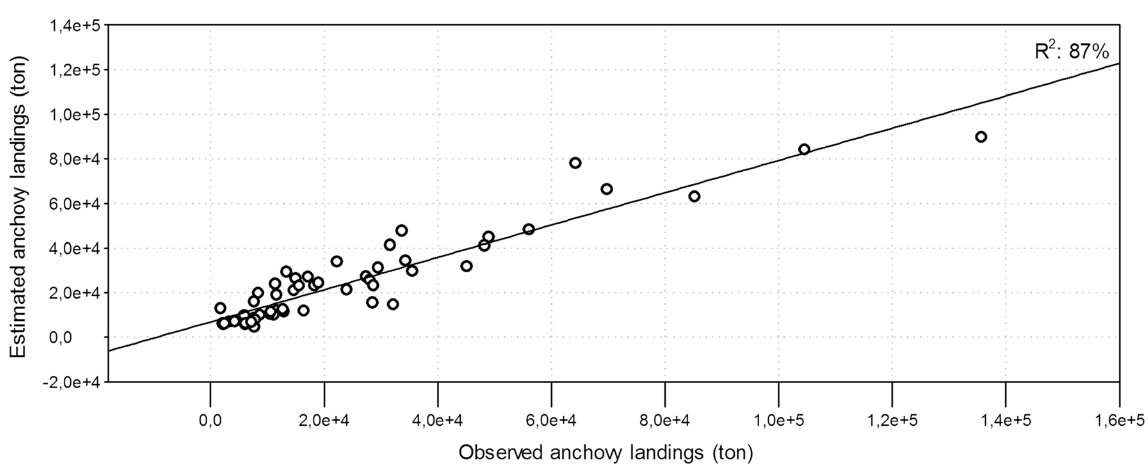

Fig. 6 Best anchovy artificial neural network (ANN) prediction model (phase 2). Scatter plot between observed and estimated jack mackerel landings for external validation (EV)

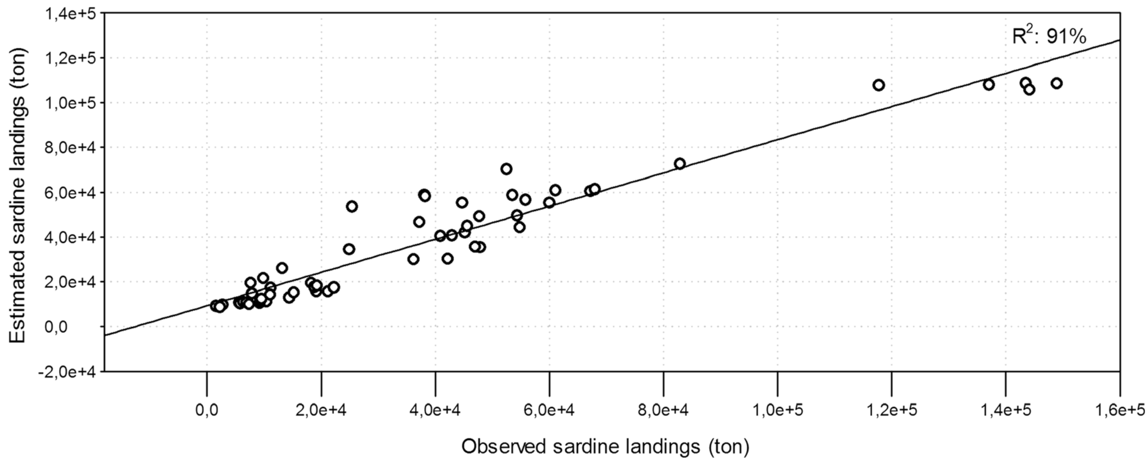

Fig. 7 Best common sardine artificial neural network (ANN) prediction model (phase 2). Scatter plot between observed and estimated jack mackerel landings for external validation (EV)

Tanasichuk and Ware 1987). For common sardine, the recruitment occurs at 11–12 months (Castillo et al. 2000).

Pelagic fish depend on physiological thermoregulation processes. Anchovy and common sardine are stenothermic species (i.e., capable of living or surviving only within a narrow temperature range) and have been reported to spawn in a wide range of upwelling conditions, particularly in weaker and stronger ones. Jack mackerel presents a high plasticity in terms of hydrological conditions such as temperature and can adapt to most of the water masses inside its limitations and preferences; however, this species is usually encountered in subtropical waters (Bertrand et al. 2006). SST is considered a proxy of ecosystem variability (Yáñez et al. 2008), which indicates changes in primary productivity, food, fertility, egg and larval survival due to upwelling turbulence, and, consequently, in recruitment and landings. Furthermore, the probability of catching certain species is affected by trapped waves on the coast, which increase MSL and deepen the thermocline when passing through fishing zones, leading to a lower availability of small pelagic species (Yáñez et al. 2008; Parada et al. 2013). For anchovy, recruitment-related effects could affect the landings in lags greater than 6 months and for common sardine in lags greater than 12 months; similarly, lags of less than 6 months for anchovy and less than 12 months for common sardine are associated with distribution changes (Yáñez et al. 2010).

For jack mackerel, the models considered the yearly fishing efforts and the fishing efforts delayed by 12, 24, and 36 months, as these variables affect both resources and future catches. Significant time delays in SST-NOAA show a strong environment/resource correlation (Table 6), which is mainly associated with recruitment because the most significant classes in the jack mackerel landings are those of 4–9 years with variations over time (Naranjo et al. 2015; SUBPESCA 2012). Since the mid-1970s, jack mackerel landings have increased considerably in the coastal zone due to higher availability and a notable increase in fishing effort. This increase in fishing effort is related to the technological development of the fleet,

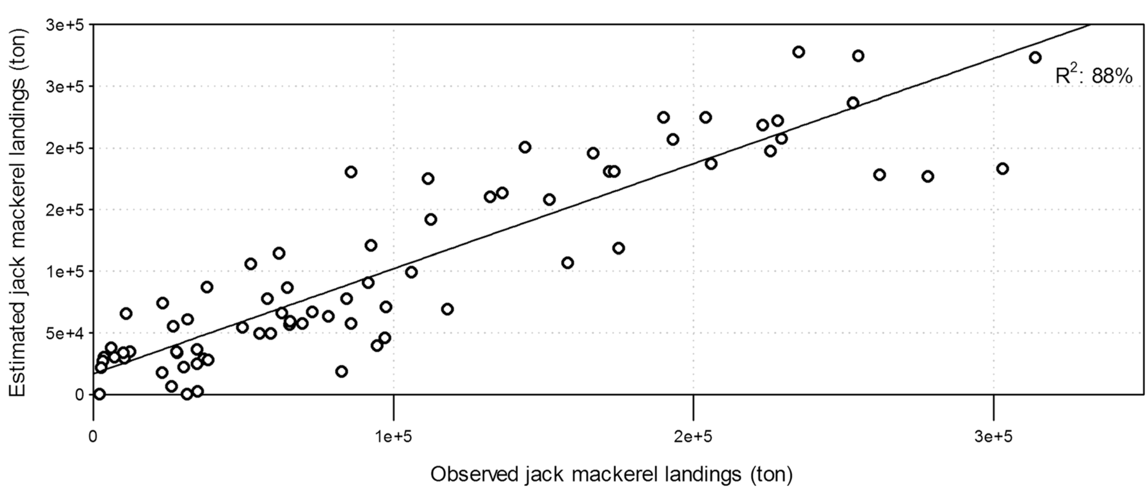

Fig. 8 Best jack mackerel artificial neural network (ANN) prediction model (phase 2). Scatter plot between observed and estimated jack mackerel landings for external validation (EV)

Table 8 Change in sea surface temperature (SST) from 2015 to 2065 in the anchovy, common sardine, and jack mackerel fishing areas

Scenario	Method	Anchovy-common sardine	Jack mackerel
A2	Start and end of lineal adjustment	+1.26 °C	+1.2 °C

Future SSTs were obtained from the A2 climate change scenario of high future CO_2 emission

which added boats with storage capacities up to 2200 m^3 in 2000, and a level of autonomy that allows them to go farther offshore beyond the exclusive economic zone (Aranís et al. 2012). The displacement of jack mackerel towards more oceanic zones increases the duration of fishing journeys (6–7 days) and the number of casts per trip (six or more), thus leading to higher fishing effort to maintain performance.

There is evidence that increases in fishing effort are associated with interdecadal environmental changes with a warmer regime change from 1976 to the 1990s (Yáñez et al. 1992; Yañez 1998). These temporal correlations are also shown in a spatial scale, particularly between the distribution of pelagic resources and SST (Barbieri et al. 1995; Maravelias and Reid 1995; Yáñez et al. 1996), which is consistent with the variables selected in the present ANN modeling. Using data from 1973 to 2008, Yáñez et al. (2014) evaluated jack mackerel fishery variability through global production models that account for the abundance index of catch per unit effort (CPUE) and for the level of catches using variations in SST and fishing effort. One of these models, which considered only fishing effort, achieved a correlation of only 32 % but would have achieved a stronger correlation ($r^2 = 0.89$) by incorporating SST.

According to the sensitivity analysis of the best validated models, the most influential variables were fe and SST-NOAA, implying a dependence on anthropogenic and environmental effects. A great effort was carried out to reduce-select the best combination of input variables. The most important variable for the three models (anchovy, common sardine, and jack mackerel) corresponded to fe(t-0), which seems obvious because the fishing effort is significantly and linearly correlated with landings; however, because these models are used for simulation under different fishing efforts and climate change scenarios, the predictive capacity of the ANN models is not needed, as they work as stimulus-response types of models with no time lags between fishing effort (stimulus) and landings (response). When the variables were reduced to include only fe and SST-NOAA in the models, the fit lost nearly all predictive capacity, especially for the jack mackerel.

The sensitivity analysis clearly showed the importance of fe in explaining the landings of the fish species (Table 6).

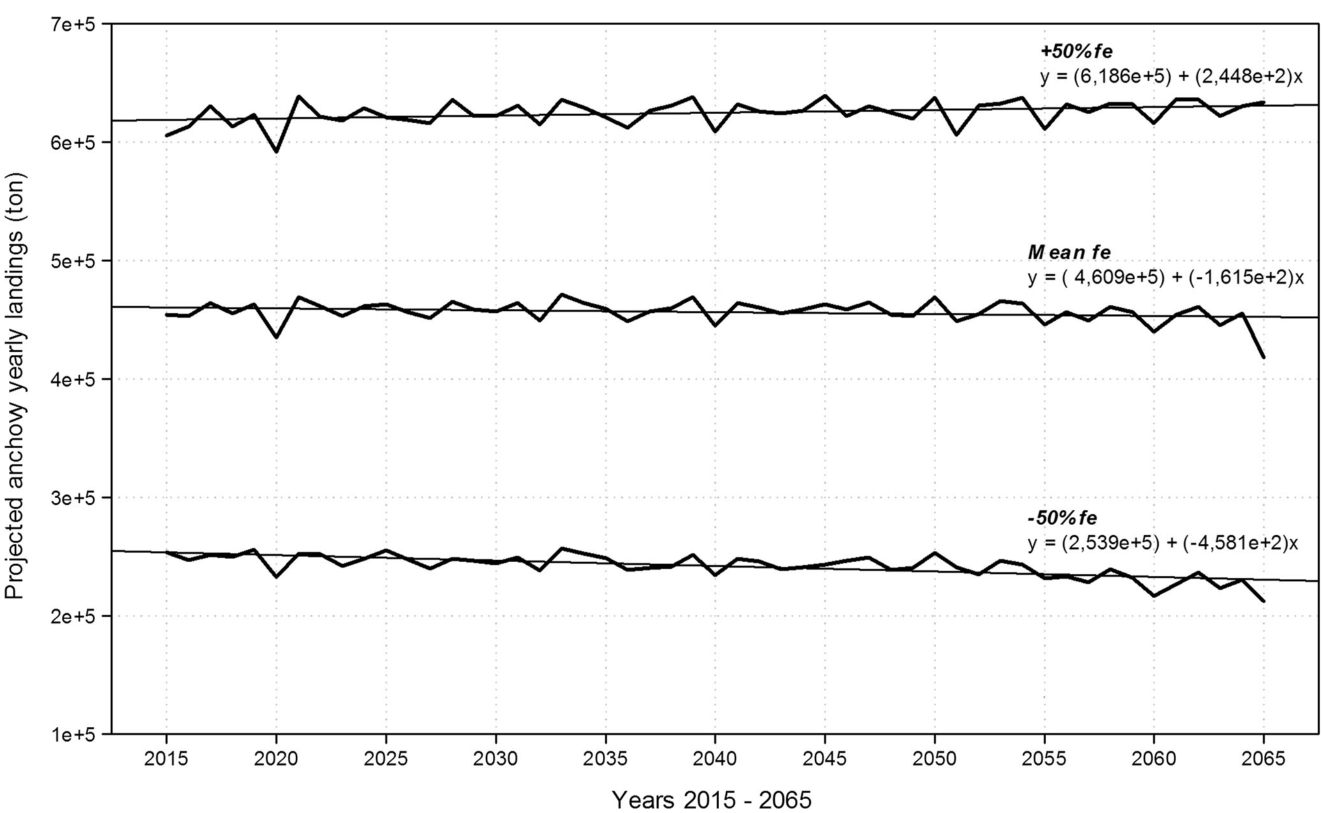

Fig. 9 Anchovy landings projections from 2015 to 2065 and for each fishing effort scenarios: 2010–2012 average, average + 50 %, and average − 50 %

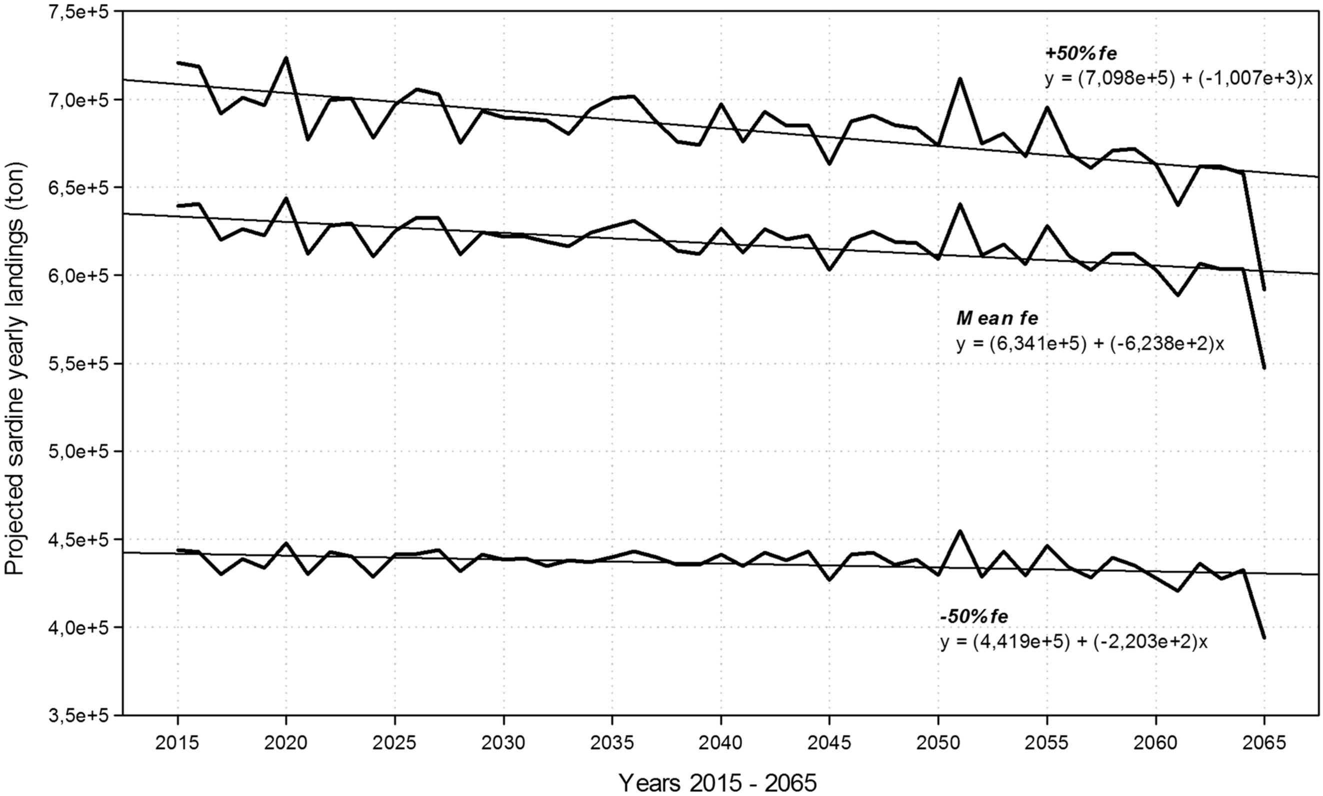

Fig. 10 Common sardine landings projections from 2015 to 2065 and for each fishing effort scenarios: 2010–2012 average, average + 50 %, and average − 50 %

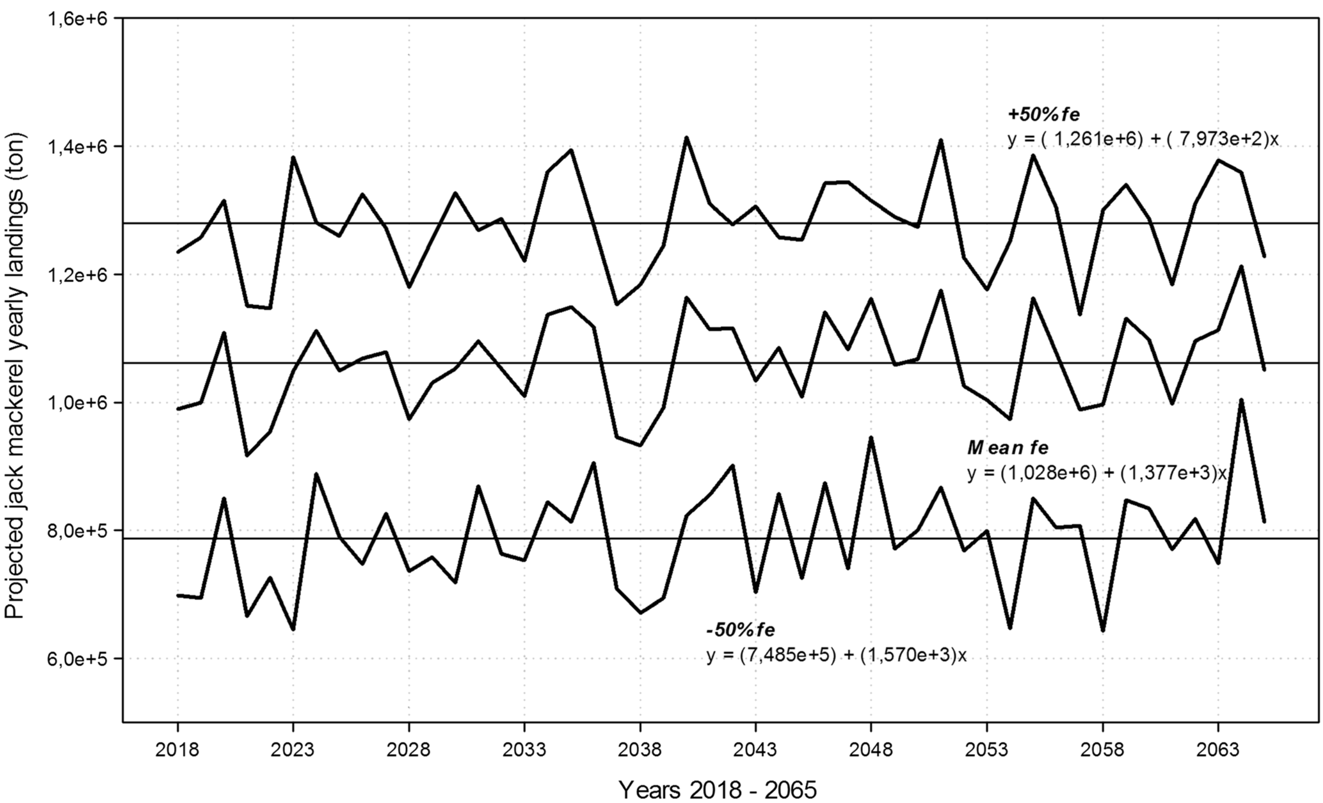

Fig. 11 Jack mackerel landings projections from 2015 to 2065 and for each fishing effort scenarios: 2010–2012 average, average + 50 %, and average − 50 %

Table 9 Change in anchovy, common sardine, and jack mackerel landings projections from 2015 to 2065 and for each fishing effort scenarios (+50 %, mean, −50 %)

	Fishing effort scenarios		
	+50 %	Mean	−50 %
Anchovy	+3 %	−1 %	−8 %
Common sardine	−6 %	−4 %	−2 %
Jack mackerel	+9 %	+13 %	+17 %

However, the fe averages over the last 3 years were maintained as constants in the predictions to estimate the net effect of CC on future landings of the resources. Thus, by 2065, anchovy and sardine show less pronounced trends than jack mackerel, though the latter shows higher variability. Under the A2 scenario and using average fe, anchovy and sardine landings will decrease by 4 and 1 %, respectively; jack mackerel landings will increase by 13 %. Considering average fe, the three species will vary by no more than 7 %. It should be noted that the temperature range in which pelagic species in central-southern Chile develop is wider (14 to 23 °C) than that shown in this study as an effect of CC on SST (Yáñez 1998; Bertrand et al. 2008, 2011; Brochier et al. 2013). Based on predictions using temperature and scaled primary productivity in biochemical and ecological models for different exclusive economic zones, including the Humboldt Current System (HCS), Merino et al. (2012) estimated a decrease of 3 % in pelagic fish catches in Chile by 2050. However, Falvey and Garreaud (2009) forecast a decrease in SST, which may imply increases in anchovy landings in northern Chile (Yáñez et al. 2014).

Based on SST (A2) and fishing effort scenarios, anchovy and common sardine landings will decrease, and jack mackerel landings will slightly increase (Table 9). However, no significant differences are shown when comparing estimated landings for the three fishing effort scenarios. Moreover, the starting values for landing projections (2010 to 2012 averages) were maintained as constants, while the SST projections varied according to the estimated trend.

The results of these simulations provide important information about the possible changes in pelagic fishing operation landings in central-southern Chile in the face of climate change. Yáñez et al. (2008) suggested that anchovy and common sardine landings in northern Chile are indicators of the species abundance given that they show fluctuations that may be directly related to the abundance of the resource. Moreover, the positive projections of landings to 2065, particularly for jack mackerel, could be related to changes in distribution, which favors availability and catchability. Silva et al. (2015) found the same relationship in which a climate change projection favors availability and catchability for swordfish (*Xiphias gladius*) distributed to the south and near the coast.

The influence of climate change on resource abundance (before spawning, in early life stages, in pre-recruitment and post-recruitment) cannot be ruled out. In this regard, the key environmental variables, biological mechanisms involved, time period of the effects, production lags, and types and signs (positive + or negative −) of effects on abundance and/or availability should be identified. Moreover, possible changes in biodiversity due to climate change and its effects on the biological interactions (e.g., food, predation, and competition) that influence these fisheries resources should also be dimensioned. Also to be considered are possibilities of adapting the different resources depending on whether the changes are tolerable or intolerable.

The approach used by this study consisted of modeling the temporal data (time series), which are restricted to a specific area. To improve the quality of living marine resource assessments and forecasts, spatial–temporal models formalizing variation over time and across space and adapted for climate change applications can be used. The main spatial–temporal models used to make predictions about living marine resources under climate change include ecosystem-based approaches, such as habitat suitability or bioclimate envelope models (Cheung et al. 2009; Silva et al. 2015), ecotrophic models (Howard et al. 2008), individual-based models (IBM) (Brochier et al. 2013), end-to-end models that combine climate, planktonic, fishery, and socioeconomic models (Barange et al. 2010), and species distribution models such as MAXENT (Jones et al. 2012). Spatial–temporal models use various statistical and mathematical methods to predict the effects of climate change on living marine resources. These methods include predictive GAMs (Willis-Norton et al. 2015), GAM-GLM (Silva et al. 2015), fuzzy logic (Cheung et al. 2008), and a machine learning, maximum entropy approach to species distribution modeling (Gormley et al. 2015).

The results of the present study open the door for further discussion regarding the need for comparing modeling techniques besides ANN (e.g., GAM, ARIMA, ARMAX, fuzzy logic, etc.) and the limitations of ANN models, especially since it is still unclear whether a network trained with data from the present climate is still applicable in a different climate scenario due to overtraining of the network. There also exists a need for improved scaling of the variables incorporated into the simulations as well as the incorporation of new variables, such as chlorophyll and salinity. Thus, considerations of regional oceanographic models and the incorporation of a spatial component are fundamental to the development of this type of research (Cheung et al. 2010; Merino et al. 2012; Silva et al. 2015). However, a finer resolution of global climate models such as the NCAR-CCSM3 are expected to improve climate-based projections and enhance their applicability to marine resources and related activities. Finally, more integrative and complex conceptual models that consider oceanographic-biophysical, physiological, environmental-resource, and interspecies processes must be implemented.

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