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Research Article

Modelling climate change impacts on anchovy and sardine landings in northern Chile using ANNs

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ABSTRACT. Artificial Neural Networks (ANN) are adjusted to predict monthly landings of anchovy (*Engraulis ringens*) and sardine (*Sardinops sagax*) in northern Chile (18°21'-24°00'S). Fishing effort (FE), landings and twelve environmental variables are considered from 1980 to 2012. External validation for the best models using all variables showed an R^2 of 95% for anchovy and 99% for sardine, with an efficiency of 0.94 and 0.96, respectively. The models were simplified by considering only FE and sea surface temperature (SST) from NOAA satellites (SST-NOAA). Using these variables, very similar fits were achieved, comparing with the previous models, maintaining their predictive capacity. Downscaled SST for A2 climate change scenario (2015-2065) obtained by statistical regionalization from the Community Climate System Model (CCSM3) from National Center for Atmospheric Research (NCAR) and three FE scenarios (2010-2012 average, + 50% and -50%), were used as inputs for ANN simplified models. For A2 future climate change scenario (2015-2065) using 2010-2012 average FE as inputs, anchovy and sardine landings would increase 2.8% and 19.2% by 2065 respectively. With FE variations (-50%), sardine landings show the highest increase (22.6%) by 2065 when FE is decreased.

Keywords: forecast, pelagic landings, climate change, artificial neural net works, northern Chile.

INTRODUCTION

Total annual landings in Chile have averaged 5.4 million ton over the last three decades (1983 to 2012), 32% of which is represented by pelagic resources in the northern part of the country (18°21'-24°00'S). Industrial fishing in the area began in the 1950s with landings of Peruvian anchovy (*Engraulis ringens*), which increased, fluctuated and then fell strongly in 1972-1973, remaining low until 1985, when they again began to fluctuate and increase, reaching new historic levels (SAG, 1950-1977; SERNAPESCA, 1978-2012). After the collapse of anchovy in 1972-73, the sardine became a targeted species (*Sardinops sagax*) with catches increasing until 1985, before falling notably and remaining low until the present. These species are affected by fishing effort, El Niño phenomena, fluctuations associated with regime change (Yáñez *et al*., 2001; Chávez *et al*., 2003; Alheit & Ñiquen, 2004) and climate change (Merino *et al*., 2012; Yáñez *et al*., 2014).

The most significant impact of climate change on the ecosystems that support the main fisheries are, among others, increased sea surface temperature (SST), the rise in sea level, increased CO_2 concentrations, habitat compression due to changes in the oxygen concentration and the depth of the mixed layer, as well as effects on ecological interactions (Poloczanska *et al.*, 2007). Climate change can therefore affect regional systems such as the Humboldt Current System (Allison *et al*., 2009; Belkin, 2009; Frèon *et al.*, 2009; Cheung *et al*., 2010; Aiken *et al.*, 2011).

Fishing shows different trends in response to changes that affect larval stages, reproduction, feeding and migration, as well as anthropic pressures. Climate variation has intermediary or phased effects on a regional and local level. Possible environmental changes, such as the increased SST, depth of the mixed layer and the thermocline, surge intensity and nutrient concentration mechanisms, though slight, can affect the food chain and therefore the abundance, distribution and

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and availability of fish populations (Miller & Schneider, 2000). Climate change can also have impacts on the composition of a community and the performance of ecosystems (Hiddink & Hofstede, 2008; Ling *et al*., 2008).

The connection between variations in pelagic resources and environmental changes on different time and/or spatial scales allows predictions of landing characteristics, one of the main objectives of management of fisheries. Marine ecosystems, however, are constantly in a state of imbalance and are characterized by nonlinear relationships (Murdoch, 1994; Stenseth *et al*., 2002). The use of artificial neural networks (ANNs) to model ecosystems began in the 1990s, particularly for situations in which the data cannot be fit to classical statistical assumptions and in which it is precisely nonlinear relationships that predominate. ANNs behave better than linear models and have the capacity to generalize when new data are input (Lek *et al*., 1996; Lek & Guégan, 1999; Özesmi *et al*., 2006). Gutiérrez-Estrada *et al*. (2007) used nonlinear modeling with anchovy fishing in northern Chile, and the ANNs considered only monthly landings with a 6-month time lag. Later, Gutiérrez-Estrada *et al*. (2009) used an ecosystem approach to predict monthly landings of sardine in the same area, and Yáñez *et al*. (2010) used ANNs to predict the ecosystem characteristics of anchovy and sardine in northern Chile. Predictions based on environment/resource relations, including fishing effort in some cases, have been carried out under different climate change scenarios (Hare *et al*., 2000; Lindegren *et al*., 2010; Andonegi *et al*., 2011; Muhling *et al*., 2011; Brochier *et al*., 2013; Yáñez *et al*., 2014).

Given the importance of pelagic fishing in northern Chile, this study analyzes a modelling of anchovy and sardine landing predictions up to 2065 using ANNs models under a climate change scenario. This multivariate approach considers the monthly catches of anchovy and sardine, local and global environmental variables and fishing effort for the period 1980-2012.

MATERIALS AND METHODS

The study zone comprises the area covered by the industrial seine fishing fleet that operates in northern Chile (18°21'-24°00'S) from the coast to 73°W. The analyzed data includes environmental and fishing data for the 1980-2012 period for anchovy and sardine. Table 1 shows a description of each variable considered for analysis.

Artificial neural networks

Originally described by McCulloch & Pitts (1943), ANNs are mathematical models inspired by the neural architecture of the biological nervous systems (Hebb, 1949; Rosenblatt, 1958). There are various applications ranging from identification, optimization or regression, prediction and classification, where they are efficiently able to find patterns through data, in some cases more than conventional models (Lek *et al*., 1996; Lek & Guégan, 1999; Allende *et al*., 2002; Suryanarayana *et al*., 2008).

There is a broad spectrum of ANNs architectures, the most widely studied and used structures are multilayer feed forward networks or multilayer perceptrons (Rumelhart *et al*., 1986; Allende *et al*., 2002). A schematic outline of the structure of an ANN of those characteristics is shown below (Fig. 1).

Figure 1 shows a three-layer ANN, with q, n and s neurons in the input layer, hidden layer and output layer, respectively. There are weight vectors, W_{ji} y W_{kj}, corresponding to the connections between the neurons of the input layer and the hidden layer, and between the hidden layer and the output layer, respectively. Each neuron j receives signals from each of the neurons i of the anterior layer. Associated with each signal x_i, there is a weight W_{ji}. The received effective signal I_j of neuron j is the weighted sum of all signals, that is:

$$I_j = \sum_{i=1}^{g} x_i W_{ji}$$

On the effective signal, a transfer function (or activation function) Ψ is applied to produce the output signal y_i of neuron j:

$$Y = \beta_0 + \sum_{k=1}^{r} \gamma_k \Psi(x^T.\beta_k + v_k) + \varepsilon$$

where x is a p-dimensional vector of explanatory variables, the β_k s are projected vectors and v_k represents changes in the argument of the sigmoidal function Ψ to locate the vectors projected in the indicated place. There are several transfer functions, associated with different objectives and expected results (Gardner & Dorling, 1998; Özesmi *et al*., 2006). In this study the logarithmic sigmoidal function is used as a transfer function:

$$\Psi(x) = \Psi_{v,\beta}(x) = \frac{1}{1+e^{(v+x^T.\beta)}}$$

To determine the value of the weights, a process called training or learning takes place. The training defines the interconnections between neurons (weights), from vectors of known inputs and outputs (data or training patterns). It is an iterative process based on a convergence method of error. There are several methods of training, one of the most used is the backpropagation algorithm (Rumelhart *et al*., 1986). Lek *et al*. (1996), present a scheme for the backpropagation algorithm:

Table 1. Variable description for the study.

Variable	Description
AT	Air Temperature from Antofagasta coastal oceanographic station
SST	Sea Surface Temperature from Antofagasta coastal oceanographic station
SST-NOAA	Sea Surface Temperature measured via NOAA satellite
TI	Turbulence Index from Antofagasta coastal oceanographic station
ET	Ekman Transport from Antofagasta coastal oceanographic station
MSL	Mean Sea Level from Antofagasta coastal oceanographic station
PDO	Pacific Decadal Oscillation index
SSTNIÑO 1+2	Climatic Index in the Niño 12 area
SSTNIÑO 3+4	Climatic Index in the Niño 34 area
SOI	Southern Oscillation Index
CTI	Cold Tongue Index
AAO	Antarctic Oscillation index
FE ANC	Fishing effort for anchovy fishery
FE SAR	Fishing effort for sardine fishery
DESANC	Anchovy landings in northern Chile
DESSAR	Sardine landings in northern Chile

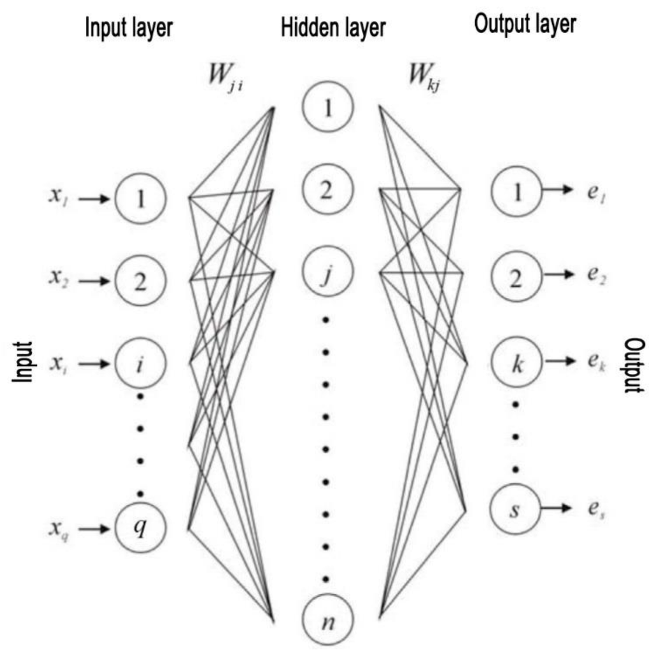

Figure 1. Representative scheme of a feedforward ANN.

1. Initialize the number of hidden neurons.
2. Initialize the maximum number of iterations and the learning rate η. Start all weights and thresholds with small random numbers. Thresholds are weights with corresponding inputs always equal to *1*.
3. For each training vector (input $X_q = (x_1, x_2, \ldots, x_q)$, outputs *Y*) repeat steps 4-7.
4. Present the vector of inputs in the input neurons and the outputs in the output neurons.
5. Compute the inputs to the neurons of the hidden layer: $a_j^h = \sum_{i=1}^{n} W_{ij}^h x_i$. Calculate the output of the hidden layer neurons: $x_j^h = f\left(a_j^h\right) = \frac{1}{1+e^{-a_j^h}}$. Compute the inputs to the neurons of the output layer: $a_k = \sum_{j=1}^{s} W_{jk} x_j^h$ and the corresponding outputs: $\hat{Y} = f(a_k) = \frac{1}{1+e^{-a_k}}$. Note that $k = 1$ and $\hat{Y}_k = \hat{Y}$, s is the number of neurons in the hidden layer.

6. Compute the error terms of the output neurons: $\delta_k = (Y - \hat{Y}) f'(a_k)$ and for the neurons of the output layer: $\delta_j^h = f'(a_j^h) \sum_k \delta_k W_{jk}$.
7. Update the weights in the output layer: $W_{jk}(t+1) = W_{jk}(t) + \eta \delta_k x_j^h$ and in the hidden layer: $W_{ij}(t+1) = W_{ij}(t) + \eta \delta_j^h x_i$.

As long as the estimated errors are greater than the predetermined threshold or the number of iterations is less than the number of predetermined iterations, repeat steps 4-7.

A detailed description of multilayer perceptrons ANNs performance can be found in Tsoukalas & Uhrig (1996), Allende *et al*. (2002) and Gutiérrez-Estrada *et al*. (2008). Moreover, one of the most common problems when training neural networks is over training or memorization. It is normal for the learning error to decrease as the training is performed. However, the network may be adjusting noise to the weights estimate. In order to avoid this problem, in this work, an internal validation was used that iteratively monitors and evaluates the error, when it begins to increase, the training is stopped and the weights are saved and used in the external validation phase (Tsoukalas & Uhrig, 1996).

Data sources

The monthly landings statistics (in ton) and the fishing effort (m^3 of fleet capacity, FC) of the industrial seine fishing fleet for the period 1980-2012 are obtained from the State Monitoring Program of the Principal National Fisheries, which is conducted annually by the Instituto de Fomento Pesquero (IFOP). The environmental data are in the form of monthly averages of five local variables (air temperature, sea surface temperature, mean sea level, turbulence index and Ekman transport) recorded at weather and oceanographic stations located on the coast of Antofagasta (23°26'S). SST in the study zone were measured by NOAA satellites (SST-NOAA) and six global variables (Pacific decadal oscillation, southern oscillation index, SST in area Niño 1+2, SST in area Niño 3+4, cold tongue index and Antarctic oscillation index) were obtained from freely available reports written by global climate centers (www.cpc.ncep.noaa.gov/data/indices). The Ekman transport (Bakun *et al*., 1974) and turbulence index (Elsberry & Garwood, 1978) were estimated using wind speed and direction data from the coastal weather station at Antofagasta. The data of these variables are available on the CLIPESCA website (http://www. clipesca.cl/).

The fishing and environmental data were analyzed to determine which variables to include in the ANNs models. First, any strongly correlated variables were excluded from the analysis in order to avoid multicollinearity between predictor variables, which in the case of ANNs can be less parsimonious and can result in a non optimal input variables configuration that could lead into bad training performance, therefore, poor validation results. Then, a principal component analysis was then conducted to visualize the level of representation of each variable on the main axes (Yáñez & Barbieri, 1988); 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*., 2010). 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 moving average centred around three months of data (Freón *et al*., 2003).

Down scaled projections for northern Chile and the period of 2015-2065 (Fig. 2) were used to predict climate change; they were obtained from the Community Climate System Model (CCSM) of the National Center for Atmospheric Research (NCAR) (https://gisclima-techange.ucar.edu/gis-data). The CCSM bases its projections on climate scenarios from the Intergovern-mental Panel on Climate Change (IPCC). The present study uses the A2 scenario, which has the highest temperature increase of all those proposed.

Artificial neural networks modelling

The ANN models included monthly landings, fishing effort and environmental variables with time lags for the period of 1980 to 2012 for anchovy and sardine. The monthly anchovy and sardine landings, fishing effort and environmental data were divided into three groups and selected at random; 60% was used to calibrate the network parameters, 20% for internal validation and 20% for external validation. This random selection procedure has been used by several researchers (Makkearsorn *et al*., 2008; Gutiérrez-Estrada *et al*., 2009; Yáñez *et al*., 2010, Naranjo *et al*., 2015). Monthly landing estimates for anchovy and sardine were the models output variables.

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 validation stage was then chosen, and 30 repetitions of the calibration process were performed for each ANN structure (Anctil & 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 & Rhinehart, 1999). The learning algorithm for calibration purposes and subsequent validation of the

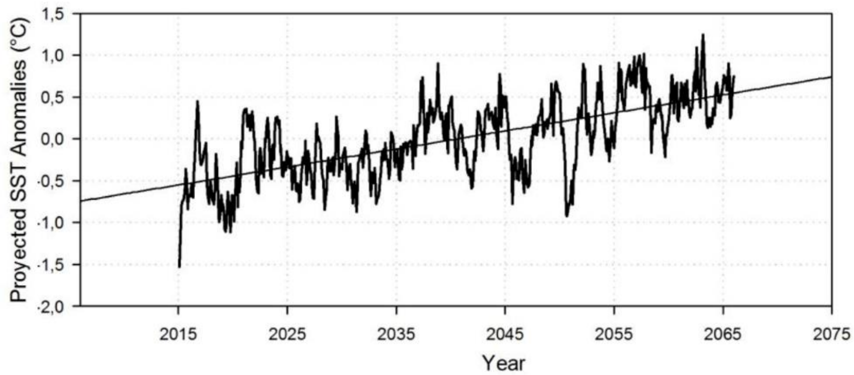

Figure 2. Scaled SST projections for northern Chile and the period of 2015-2065.

models was the supervised second-order Levenberg-Marquardt algorithm (Shepherd, 1997), which is a variation on the backpropagation algorithm (Rumelhart *et al.*, 1986) and is highly recommended (*e.g.*, Tan & Van Cauwenberghe, 1999; Anctil & Rat, 2005; Özesmi *et al.*, 2006; Suryanarayana *et al.*, 2008). The software Statistica 7.0 was used to run the ANNs models.

ANN model evaluation

With a randomly selected data set (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 & Sutcliffe, 1970; Kitanidis & 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 to what extent 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). In order 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 & 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 and giving a level of function that was worse than a naïve model (Anctil & Rat, 2005).

Model 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 network was executed with a set of test cases, and the resulting error was saved. The same network was then used again replacing the observed values of X with the estimated values by substituting the missing values, and the resulting error was again saved. Because information used by the network had been removed (*i.e.*, one of the input variables), the level of error was greater. The basic measurement of sensitivity was the quotient between the network error without the input variable and the original error. If the value was less than or equal to one, adding or removing the variable did not have any significant effect.

Future SST downscaling

The SST future simulations come from the National Center for Atmospheric Research (NCAR) Community Climate System Model 3.0 (CCSM3), considering the high future CO_2 emission scenario known as A2 (IPCC, 2007). The change factor (CF) was applied because it is a relatively straightforward and popular statistical downscaling method for rapid impact assessment of climate change (Wilby & Wigley, 2000; Silva *et al.*, 2015). The CF method involves adjusting the observed monthly SST (SSTobs, m) obtained from MODIS climatology (2003-2013) by adding the interpolated anomaly (delta) or difference in monthly SST predicted by the global climate model (GCM) NCAR CCSM3 (A2 scenario) until the 2065 horizon and the reference period.

Landings forecasts

The reduced ANNs models calibrated for the three fishing activity types were used to forecast landings. The averages of fishing effort, considering the last three years of each fishing activity (2010-2012 for anchovy and 2003-2005 for sardine), were used as input values. In addition, downscaled SST predictions based on the A2 scenario on climate change (CC) from the IPCC were also used; these predictions were scaled to the area of northern Chile for the period of 2015-2065 (Fig. 2).

In order to predict and identify the net climate change effect on the anchovy and sardine fisheries in northern Chile, SST predictions based on the A2 (2015-2065) and the monthly fishing effort averages as constant with three fishing effort scenarios, higher, lower and normal fishing effort (averages + or - 50%) to 2065.

RESULTS

Correlations between variables and principal component analysis (PCA)

Table 2 shows the results of the correlation matrix between the environmental variables for anchovy and sardine, in which it can be seen that the SST-NOAA is strongly correlated with Air Temperature (AT), SST and SSTNIÑO 1+2 (0.93, 0.91 and 0.74, respectively). The same occurs between Turbulence Index (TI) and Ekman Transport (ET) (0.92) and between SSTNIÑO 3+4 and Southern Oscillation Index (SOI) (-0.66) and Cold Tongue Index (CTI) (0.83).

PCA generates 12 factors that together contain 100% of the total variance. The criterion used states that the chosen factors are those that have an individual value above the average of all values generated by all the factors. According to this criterion, factors 1, 2 and 3 were chosen, accounting for 36%, 23% and 15% of the variance, respectively, and therefore totaling 74% of the total variance.

The correlation matrix of each variable is then estimated using each factor, giving the highest values (Table 3). Finally, taking into account the results of the correlation matrix between the variables and the PCA for anchovy and sardine, the variables SST-NOAA, SSTNIÑO 3+4 and TI were preselected.

Crossed correlations

In accordance with the criteria in question, in order to ensure confidence in the anchovy figures, Figures 3 and 4 give maximum values of 0, -12 and -26 months of lag (though the latter are quite low) and maximums of 0 and -12 months to ensure confidence in the sardine figures. For the TI, maximums of -9, -16 and -28 months of lag are considered for anchovy and 0, -12, -24, -36 and -49 months for sardine. For the SSTNIÑO 3+4 for anchovy, maximum lags of -3, -24, and -35 months are considered, whereas for sardine the maximums are -8 and -38 months. For the SST-NOAA for anchovy, the maximum lags are -2, -14 and -26 months and for sardine, -5, -17, -28 and -40 months.

ANN modelling

For anchovy the model with all variables selected shows the best architecture with 12:12:1; *i.e.*, 12 nodes on the input layer, 12 nodes on the hidden layer and 1 node on the output layer. This model explains 95% of the variance and has an IP of 0.95, indicating a very good degree of fit. A slight level of dispersion between the observed and estimated series is seen in the SEP value of 16.05% and the RMS of 12,742 ton, though both are the lowest of the estimated values (Table 3). For sardine the best model has an architecture of 132:17:1 and an explained variance of 99% with an IP of 98%; the SEP is 12.2% and the RMS is 10,158 ton (Table 4). Table 4 shows the configuration of both models, in terms of input variables and variables ranked with their respective lags.

Despite the above, the simplified models consider only FE and SST-NOAA as the input variables, both of which are of particular importance in the aforementioned models (Table 5). The SST-NOAA can be forecast be considering the global warming predictions in different IPCC scenarios. Table 6 shows the results of the best simplified model for anchovy with an architecture of 12 nodes on the input layer, 12 to 12 nodes on the hidden layer and 1 node on the output layer. This configuration explains 81% of the variance, with an IP of 0.89, indicating a good fit between the observed and estimated values. There is slight dispersion between the observed and estimated values, which is seen in the SEP of 36.62% and RMS of 21,18 ton, where both of these values are the lowest. For sardine the best configuration of the simplified model is 13:17:1, with R^2 = 99%, SEP = 19.41, IP = 96 and a RMS of 13.11 ton (Table 6).

Table 7 shows the sensitivity analysis of the simplified models, in which the most notable result is the FE (t-0) for both fishing activities, though the FE is relatively more important for the sardine, which is likely due to the greater influence of the environment on anchovy. These simplified models are not greatly different from the model that was fit with all the chosen variables, as they lose practically no predictive capacity, particularly for sardine (Fig. 5).

Downscaling of temperature

Third-grade polynomial regressions were fitted to the SST-NOAA data for anchovy-sardine fishing areas showing a cooling trend in the last years. The latter could be related with interdecadal-scale variability

Table 2. Environmental variables correlation matrix. AT: Air Temperature, SST: Sea Surface Temperature, SST-NOAA: Satellite NOAA SST, MSL: Mean Sea Level, TI: Turbulence Index, ET: Ekman Transport, PDO: Pacific Decadal Oscillation, SSTNIÑO 1+2: SST in area Niño 1+2, SSTNIÑO 3+4: SST in area Niño 3+4, SOI: Southern Oscillation Index, CTI: Cold Tongue Index, AAO: Antarctic Oscillation Index.

Enviromental variable	AT	SST	SST-NOAA	MSL	TI	ET	PDO	SSTNIÑO 1+2	SSTNIÑO 3+4	SOI	CTI	AAO
AT	1											
SST	0.96	1										
SST-NOAA	0.93	0.91	1									
MSL	0.37	0.38	0.38	1								
TI	0.38	0.39	0.36	0.04	1							
ET	0.37	0.38	0.35	0.03	0.92	1						
PDO	0.11	0.18	0.21	0.24	0.16	0.12	1					
SSTNIÑO 1+2	0.68	0.69	0.74	0.43	-0.09	-0.1	0.31	1				
SSTNIÑO 3+4	-0.03	-0.01	0.04	0.3	-0.22	-0.25	0.43	0.42	1			
SOI	-0.13	-0.14	-0.13	-0.28	-0.13	-0.1	-0.38	-0.22	-0.66	1		
CTI	0.15	0.16	0.15	0.35	0.12	0.09	0.43	0.33	0.83	-0.73	1	
AAO	-0.04	-0.03	-0.02	-0.08	-0.12	-0.1	-0.13	-0.02	-0.19	0.18	-0.21	1

Table 3. ACP factor *versus* variable correlation. In bold, absolute correlations higher than 0.7.

Enviromental variable	Factor 1	Factor 2	Factor 3
AT	0.85	0.4	0.22
SST	0.86	0.39	0.2
SST-NOAA	**0.86**	0.36	0.24
MSL	0.57	-0.21	0.17
TI	0.42	0.5	**-0.71**
ET	0.4	0.52	-0.7
PDO	0.45	-0.38	-0.22
SSTNIÑO 1+2	0.76	-0.13	0.52
SSTNIÑO 3+4	0.39	**-0.86**	-0.02
SOI	-0.48	0.6	0.34
CTI	0.55	-0.68	-0.29
AAO	-0.17	0.19	0.33

(Yáñez *et al*., 2001; Chávez *et al*., 2003; Alheit & Ñiquen, 2004). This SST cooling trend would have started by early 80s and show a decrease of 0.2°C by decade (Falvey & Garreaud, 2009).

Landing forecasts

Figures 6 and 7 show anchovy and sardine landings projections, from 2015 to 2065, considering scaled SST for the A2 climate change scenario and average fishing effort with both increase and decrease in -50% and +50%, respectively. Anchovy showed less steep trends than sardine, while sardine show more variability. Table 8 show anchovy and sardine increases of 2.8% and 19.2%, respectively. With +50% FE, anchovy landings decrease by 1.2%. For -50% FE both anchovy and sardine landings increase.

DISCUSSION

This study was conducted in two stages. The first involved the calibration and validation of the models using an approach similar to that used in Yáñez *et al*. (2010), who modeled the abundance of anchovy and sardine in northern Chile using a multivariate method with ANNs. The second stage applies the work of Yáñez *et al*. (2014), who used a modelling approach to predict anchovy landings in northern Chile based on a linear increase in SSTs at Antofagasta, considering different climate change scenarios.

The lags in SST-NOAA in the selected models are mainly in reference to two effects. The first effect is related to aspects of reproduction that particularly affect anchovy recruitment, which occurs at 5-6 months (Gil, 1975; Braun *et al*., 1995; Castillo *et al*., 2002) and therefore the age groups involved in the catch at 6 to 36 months (Serra *et al*., 1979; Braun *et al*., 2005). This implies a lag of 14 and 26 months. The second effect, which is related to the availability of the species, is connected to the lag of 2 months (Plaza *et al*., 2008; Yáñez *et al*., 2010). The lags in SST-NOAA in the selected models for sardine suggest an effect on recruitment, in the case of lags, of 38-40 months, and on availability when considering lags of fewer months. This is in agreement with the conclusions of Yáñez *et al*. (2010), who associate an effect on availability with lags of less than 36 months, whereas lags above 36 months are linked to environmental conditions for reproduction and recruitment, considering that after hatching, it takes 2 to 3 years for the species to be recruited (Serra & Tsukayama, 1988; Alheit & Ñiquen,

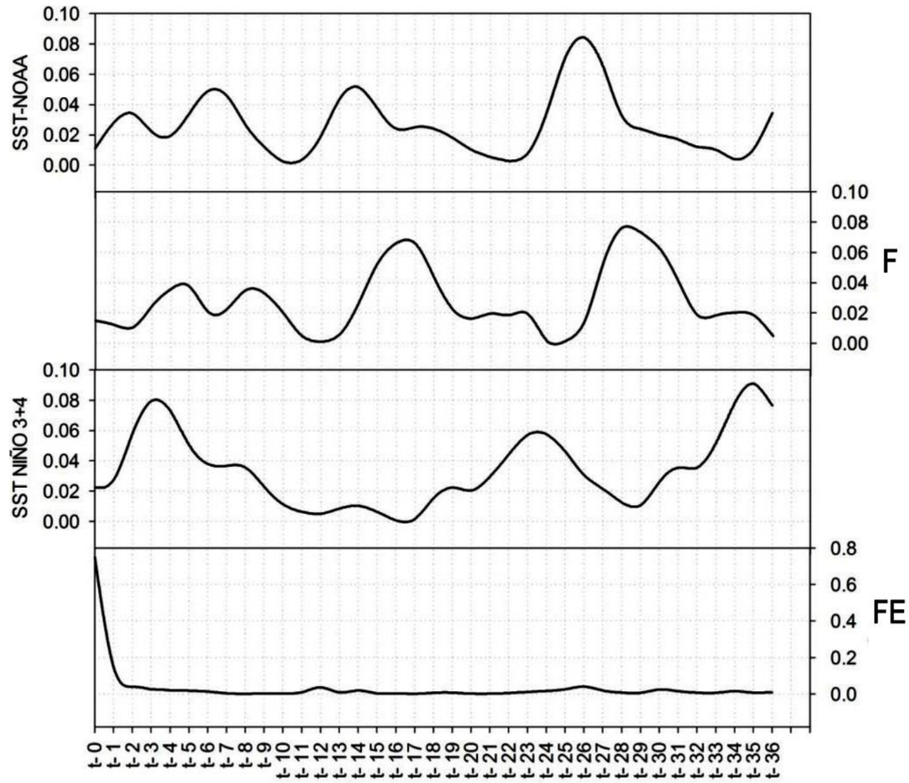

Figure 3. Non-linear cross correlation results for anchovy.

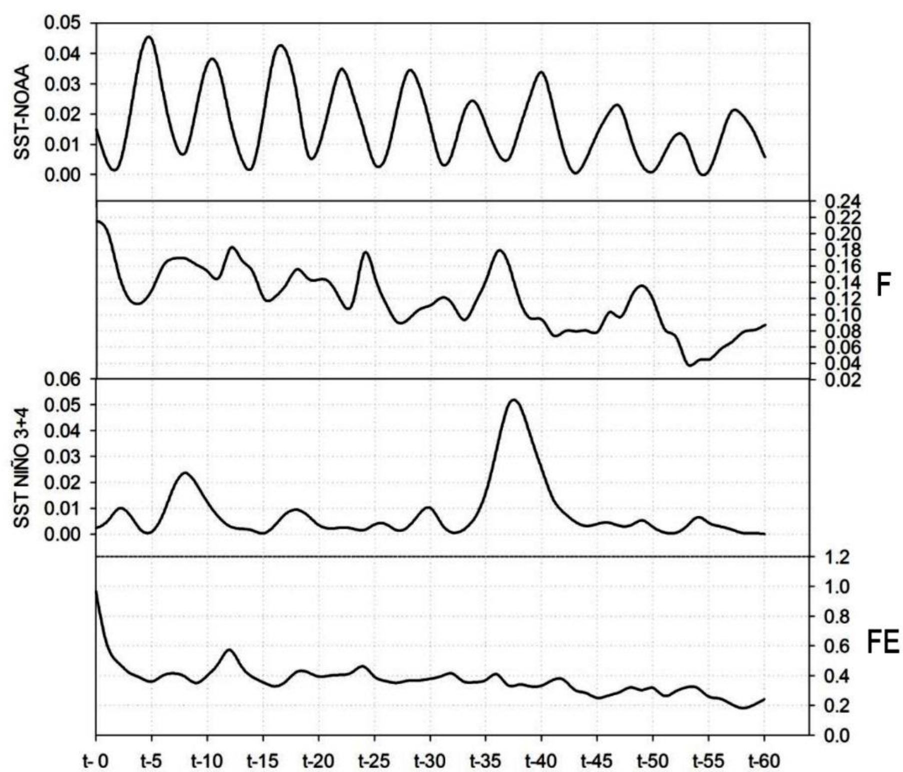

Figure 4. Non-linear cross correlation results for sardine.

Table 4 Anchovy and sardine ANN models configuration (architecture) and accuracy measures with full set of the twelve variables.

Species	Architecture	**n**	Parameters	Index of error				
				R^2	RMS	%SEP	E	PI
Anchovy	12:12:1	12	156	0.95	12,742	16.05	0.94	0.95
Sardine	13:17:1	12	238	0.99	10,158	12.23	0.99	0.98

Table 5. Full anchovy and sardine models variable ratios for sensitivity analysis. In bold, variables considered for reduced models.

Ranking	Anchoveta full model		Sardine full model	
	Variable	Ratio	Variable	Ratio
1	**FE (t-0)**	4.191	**FE (t-0)**	9.490
2	**SST-NOAA (t-26)**	1.857	**FE (t-12)**	2.032
3	**SST-NOAA (t-2)**	1.670	**SST-NOAA (t-40)**	1.987
4	TI(t-28)	1.616	**SST-NOAA (t-28)**	1.772
5	TI(t-16)	1.597	TI (t-49)	1.733
6	TI(t-9)	1.388	TI (t-24)	1.537
7	**FE (t-12)**	1.387	SSTNIÑO 3+4 (t-8)	1.447
8	**SST-NOAA(t-14)**	1.360	TI (t-0)	1.412
9	**FE(t-26)**	1.353	TI (t-12)	1.369
10	SSTNIÑO 3+4(t-3)	1.326	TI (t-36)	1.365
11	SSTNIÑO 3+4(t-24)	1.321	**SST-NOAA (t-5)**	1.288
12	SSTNIÑO 3+4(t-35)	1.297	**SST-NOAA (t-17)**	1.236
13			SSTNIÑO 3+4 (t-38)	1.200

Table 6. Error indexes for anchovy and sardine ANN models with reduced set of variables (fishing effort and SST-NOAA).

Species	Architecture	n	Parameters	Index of error				
				R^2	RMS	%SEP	E	PI
Anchovy	12:12:1	3	21	0.81	21.18	36.62	0.78	0.89
Sardine	13:17:1	7	49	0.99	13.11	19.41	0.98	0.96

Table 7. Reduced anchovy and sardine model variable ratios for sensitivity analysis.

Ranking	Anchovy reduced model		Sardine reduced model	
	Variable	Ratio	Variable	Ratio
1	FE (t-0)	1.954	FE (t-0)	7.740
2	SST-NOAA-N (t-14)	1.618	SST-NOAA (t-28)	1.705
3	SST-NOAA-N (t-26)	1.222	SST-NOAA (t-40)	1.536
4	FE (t-26)	1.128	SST-NOAA (t-17)	1.265
5	SST-NOAA-N (t-2)	1.089	FE (t-12)	1.156
6	FE (t-12)	1.063	SST-NOAA (t-5)	1.065

2004). It is important to also note that environmental conditions may be influenced by pre-recruits, favoring (or decreasing) landings with a lag of more than 36 months.

In addition, the sensitivity analysis clearly shows the importance of fishing effort as an explanatory variable for landings of the species in question, particularly in the case of sardine. For the sardine landings forecasts, the values of fishing effort used in the prediction are very low, due to the negative situation of the species during the latter years of analisys for sardine (2003-2005; SERNAPESCA, 1978-2012), whereas more intermediate values are used for anchovy. These values remain constant in the predictions in order to estimate the net effect of climate change on future landings of these resources.

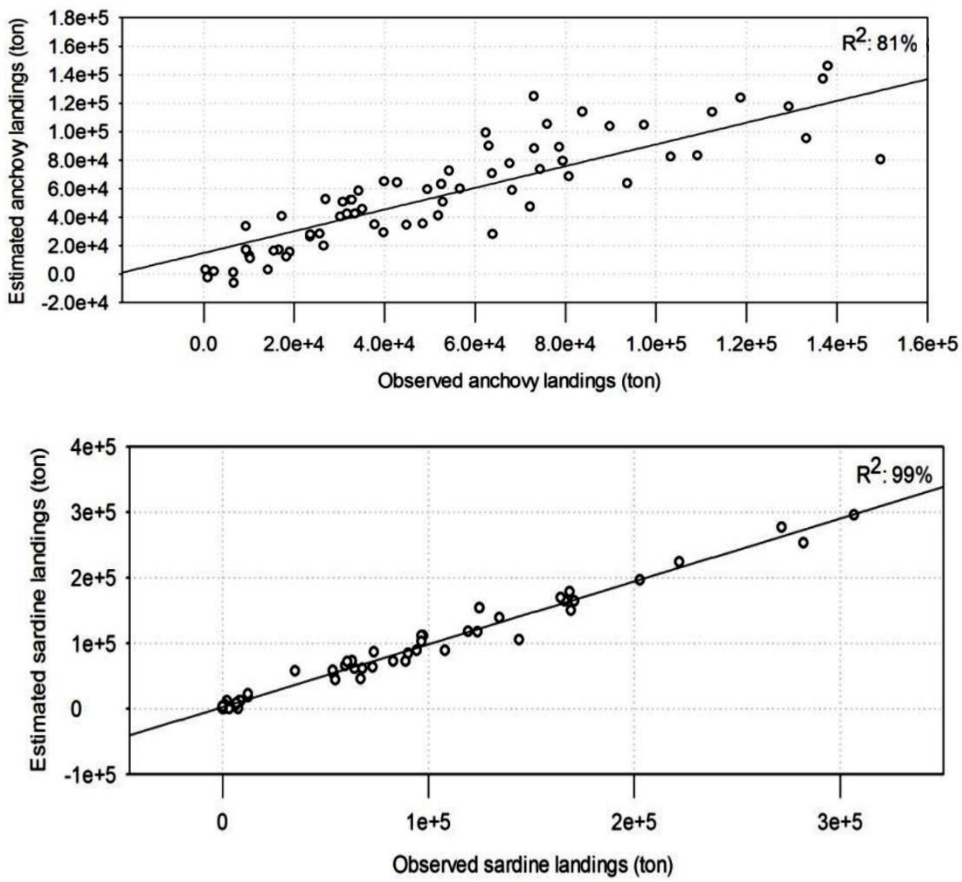

Figure 5. ANN model validation process for a) anchovy, and b) sardine.

Table 8. Anchovy and sardine landings projection results under three fishing effort scenarios (+50%, mean and -50%).

Species	Fishing effort scenarios		
	+50%	Mean	-50%
Anchovy	-1.2%	2.8%	12.2%
Sardine	16.9%	19.2%	22.6%

According to the results for the climate change predictions, the decrease in landings, of approximately 6% for anchovy and less for sardine, may be because climate change will not be that significant on the Chilean coastline (Fig. 3). In effect, the spectrum of temperatures the pelagic species inhabit is wider than shown in this study as an effect of climate change when scaling the SST in northern Chile (Bertrand *et al*., 2008, 2011; Brochier *et al*., 2013). The anchovy is found at temperatures between 16 and 23°C in summer and 10 to 18°C in winter (Yáñez, 1998), whereas the sardine is found below a depth of 30 m and between 16 and 20°C in summer, and in winter at depths of 20-70 m and between 14 and 17°C (Castillo & Guzmán, 1985).

The results are also in agreement with those obtained by Merino *et al*. (2012), who estimated a decrease of 3% in pelagic fish catches in Chile for 2050, with a prediction based on temperature and scaled primary productivity in biochemical and ecological models in different Exclusive Economic Zones (EEZ), including the Humboldt Current System (HCS). However, Falvey & Garreaud (2009) forecast a decrease in SSTs, which may imply increases in anchovy landings in northern Chile (Yáñez *et al*., 2014).

The results of these predictions provide relevant information on the possible impact on landings of both fish species in the face of climate change. Yáñez *et al*. (2008) suggest that anchovy landings in northern Chile are an indicator of the abundance of this species, as they show inter-decadal, inter-annual and inter-seasonal fluctuations which may be directly related to the level of abundance of the species. For sardine, the same

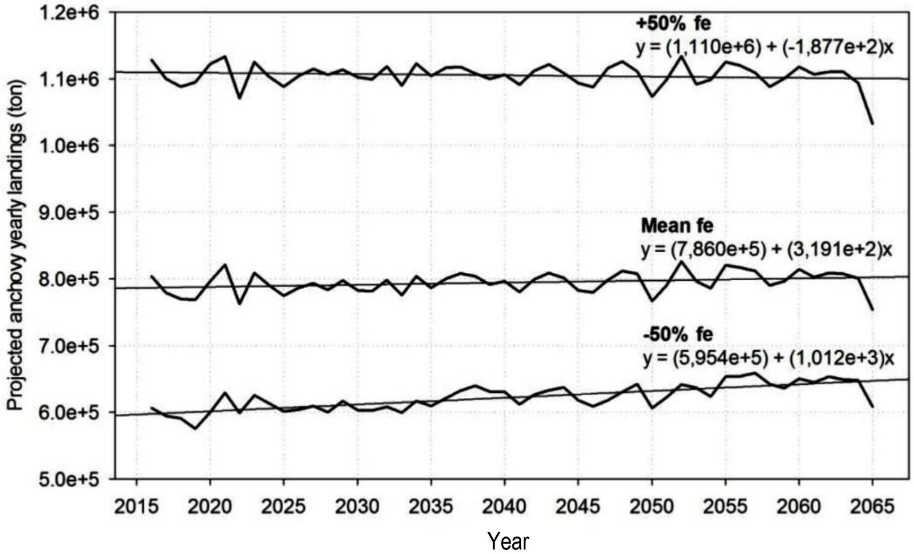

Figure 6. A2 SST and FE scenarios landings projections for anchovy.

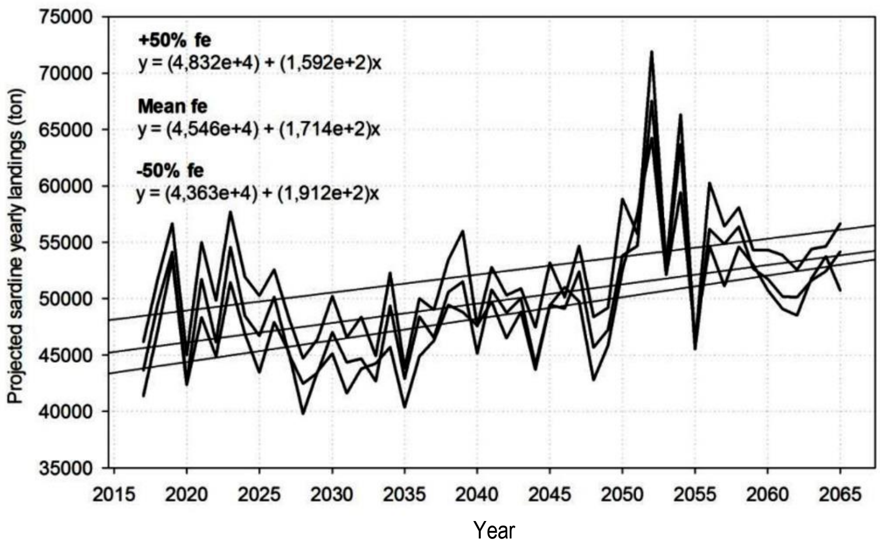

Figure 7. A2 SST and FE scenarios landings projections for sardine.

authors suggest the Catch Per Unit Effort (CPUE) as an abundance index, whereas, according to Yáñez (1998), there is strong correlation between landings, CPUE and the abundance of this resource.

The approach implemented in this work, considers a monthly temporal-based ANN modelling process, working as input-output black box approaches, with similar results as a global production model, which consider fishing effort and an environmental variable as inputs, thus, the northern zone of Chile is considered as one pixel. However, as stated by several authors, there is evidence of impacts on distribution, species composition and seasonality in the Humboldt Current System (Cury *et al*., 2000; Chavez *et al*., 2003; Brander, 2010). Cheung *et al*. (2010), indicate that climate change would impact in a redistribution of total catch by Economic Exclusive Zones (EEZ), in the case of Chile's EEZ, there would be an estimated 6%-13% decline in total fisheries catches possibly due to a shift in the lower-latitude range boundary of many Antarctic species, resulting in a loss of catch potential and, as species move offshore to colder refuges as the ocean warms up, catch potential also shifts to offshore regions from coastal areas, which is the case of anchovy and sardine fisheries in northern Chile. Additionally, since climate change is more complex than a SST increase, it acknowledges the need for including a more integrated analisys, while anchovy and sardine show changes associated with environmental variability, indicators such as abundance, trophodynamics are also affected by predators, competitors and parasites. Furthermore, anchovy and sardine abundance variations, linked to environmental changes in different spatial and temporal scales, open the possibility to study ecosystemic relationships, considering short, medium and long term changes (Zhou *et al*., 2009; Silva *et al*., 2015). In particular, the seasonal local component and the remote response from other variables, such as TI and SSTNIÑO 3+4, respectively, two variables which appear to be influential, according to the previous multivariate analisys should be considered for short-term future work.

Finally, there is a need to improve the scaling of the variables included in the prediction approach. We therefore recommend consideration of regional oceanographic models (ROMs) and the incorporation of a spatial component.

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