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Modeling Chile Fishing Data Using Environmental Exogenous Variables with GARCH-X Model

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Abstract. Fishing industry has always been an economic motor in many countries around the world, but the fisheries production faces a lot of uncertainty and instability due to the complex factors involved in its operations. In this article, we consider the problem of modeling Chile fishing data using environmental exogenous variables with generalized autoregressive conditional heteroskedasticity (GARCH-X) type models. We carried out this by proposing an ARMA type model for the mean with GARCH-X noise. First, the ARMA, GARCH and GARCH-X models are briefly introduced and the data is described. The exogenous variables are selected from a group of environmental and climatic indicators by correlational analysis. Then, ARMA GARCH and ARMA GARCH-X models with exogenous variables are fitted and compared by information criteria and classical error measures, and stability of its parameters are checked. The statistical tests and comparisons evidenced that a model with inclusion of external variables in mean and variance with the ARMA GARCH-X specification performed better and adjusted the observed values more rigorously. Finally, some conclusions

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and possible refinations of the applied techniques are given.

Keywords. Environmental Modeling, Exogenous Variables, Fishing Data, GARCH-X, Time Series.

MSC: 62P12, 92D40.

1 Introduction

The fishing activity in the northern region of Chile had always been an important source of pelagic resources, based mostly on sardine (*Sardinops sagax*) and anchovy (*Engraulis rigens*). Official data presented by the Chilean National Fisheries and Aquaculture Service (SERNAPESCA, 2021) show a cyclical alternance trend between the total landings of both species, that also is described with information from about 250 years (Valdés et al., 2008). Moreover, the oceanic ecosystem that supports the anchovy-sardine fisheries activity is very complex, due to environmental changes in different spatial and temporal scales (e.g. El Niño events, cold-warm regime shifts, climate change, among others) that could drive behaviour changes in migratory, reproductive and food web patterns, thus affecting the volume of captures of the aforementioned species (Yáñez et al., 2016).

Given the uncertainty, stochastic nature, and delicate relationships that describe the phenomena involved in the marine environment, the modelling of the industrial fishing activity constitutes a challenge that has been faced through different approaches worldwide. Traditionally, the most common approach considers the implementation of the Box-Jenkins methodology and its many variants. In that regard, these models were used in Mediterranean waters (Stergiou, 1989) and showed advantages in both fitting past data and predicting future data, compared to other techniques (Stergiou, 1991). Although methodological developments allow an increase in complexity when dealing with the main problem, autoregressive models keep being the basis for numerous studies on fishery resources modelling (Koutroumanidis et al., 2006; Tsitsika et al., 2007; Park and Yoon, 1996; Lai et al., 2005). Furthermore, if studies in the same country are considered, recent works have been oriented more towards the use of artificial neural networks (Yáñez et al., 2010, 2016) and wavelet-type transfer functions (Vivas et al., 2019), having all confirmed the usefulness of a hollistic approach by including environmental, climatic and oceanographic variables.

The present study applies a model of the ARMA family with conditional heteroskedasticity (ARMA-GARCH) to the landings of sardine off northern Chile (1821'S - 24S) from 1963 to 2007. The model also considers the introduction of exogenous variables in both the mean and variance equations, selected from a set of local and global climatic and environmental variables. The performance of some variants of this approach is evaluated by means of classical error measures. Possible extensions and corrections of the applied techniques are also discussed.

The rest of the manuscript is organized as follows: in Section 2 we introduce the ARMA, GARCH and GARCH-X models, and based on these we propose a specification to adjust the data to be analyzed. Section 3 presents the estimation of the variants of the main model, and the parameters, indicators and tests performed on each model, with a discussion of the results. Finally, Section 4 shows our conclussions and possible new applications and improvements of the model.

2 Materials and Methods

2.1 Model

2.1.1 ARMA Model

ARMA (Autoregressive Moving Average) models (Box and Jenkins, 1976) are a special case of a general class, called ARIMA (Autoregressive Integrated Moving Average) models. These models imply that a time series can be adjusted as a linear combination of its past values and past and present values of a random error term. Let $Y_1, \ldots, Y_T$ be a time series, and ϵ_t be a white noise with mean 0 and variance σ^2. The model ARMA(p, q) is defined as follows:

$$Y_t - \sum_{i=1}^{p} \phi_i Y_{t-i} = \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}, \tag{2.1}$$

for $1 \leq t \leq T$. If we define the backward operator B by

$$B^n (X_t) = X_{t-n}, \; n \geq 1,$$

then (2.1) can be written as

$$\left(1 - \sum_{i=1}^{p} \phi_i B^i\right) Y_t = \left(1 + \sum_{j=1}^{q} \theta_j B^j\right) \epsilon_t, \tag{2.2}$$

and $\Phi(B) = 1 - \sum_{i=1}^{p} \phi_i B^i$ and $\Theta(B) = 1 + \sum_{j=1}^{q} \theta_j B^j$ are known as the AR and MA polinomials, respectively.

It is important to state that ARMA models are applied to stationary series, and if it is not the case, techniques like seasonal and non seasonal differencing, and logarithmic and power transformations can handle non stationarity on most occasions. Determining the adequate values for p and q is also essential. And it comes from the careful inspection of the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the time series.

2.1.2 GARCH and GARCH-X Model

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models (Bollerslev, 1986) were developed to deal with volatility in time series. This behavior is common in financial and economic series, where values with high or low volatility are usually clustered. GARCH models assume that dynamic changes in the conditional variance of a time series are influenced by its past values and also the past values of its variance. Further developments of this model were theorized, and among them, the GARCH-X model (Brenner et al., 1996), introduces the possibility of using external convenient variables to explain the heteroskedasticity of a time series.

The GARCH-X model is defined by the following equations, for $1 \leq t \leq T$:

$$\epsilon_t | \mathcal{F}_{t-1} \sim N(0, \sigma_t^2), \tag{2.3}$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 + \sum_{k=1}^{p} \beta_k \sigma_{t-k}^2 + \sum_{l=1}^{s} \gamma_l X_{lt}, \tag{2.4}$$

where $\mathcal{F}_{t-1}$ is the information at time $t-1$, ϵ_t is the error term and $X_1, \cdots, X_s$ are the external variables. This equations represent also the GARCH model by discarding the last summation in (2.4).

In order to preserve the positiveness of the variance at all times, it is necessary to define certain restrictions on the coefficients, i.e., $\omega > 0, \alpha_j \geq 0, \beta_k \geq 0, \forall j, k$ and $\sum_{j=1}^{q} \alpha_j + \sum_{k=1}^{p} \beta_k < 1$. Regarding the external variables, they must comply that $\omega + \sum_{l=1}^{s} \gamma_l X_{lt} > 0$.

2.1.3 Model Definition

The model that we propose in this paper can be described by the following equations:

$$\Phi(B)(Y_t - \mu_t) = \Theta(B)\epsilon_t, \tag{2.5}$$

$$\mu_t = \mu + \sum_{i=1}^{r} \delta_i X_{it} + \lambda\sigma_t^2, \tag{2.6}$$

$$\epsilon_t|\mathcal{F}_{t-1} \sim N(0, \sigma_t^2), \tag{2.7}$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 + \sum_{k=1}^{p} \beta_k \sigma_{t-k}^2 + \sum_{l=1}^{s} \gamma_l Z_{lt}, \tag{2.8}$$

where $Y_1, \ldots, Y_T$ are the observations of the time series, B is the backward operator previously defined, Φ and Θ are the AR and MA polinomials respectively, X and Z are sets of exogenous variables that are used to explain the mean and the variance. As before, regarding the external variables, they must comply that $\omega + \sum_{l=1}^{s} \gamma_l Z_{lt} > 0$.

It is easy to notice that (2.5) defines an ARMA model for the main time series, where (2.6) describes the use of exogenous variables in the conditional mean of the observations and also the inclusion of an ARCH effect in the mean. Equations (2.7) and (2.8) define a GARCH model that also allows external factors (GARCH-X) which may not be necessarily the same as the ones used in the mean model. A particularly useful specification is using lagged exogenous variables in the mean and variance equations. In this study, we use one time lag for the exogenous variables in both parts of the model, and discard the estimation of the ARCH-in-mean effect ($\lambda = 0$). Our objective is to compare four diferent models that are particular cases of the main definition:

- without exogenous variables ($\delta_i = \gamma_l = 0, \forall i, l$),
- with exogenous variables in the mean ($\gamma_l = 0, \forall l$),
- with exogenous variables in the variance ($\delta_i = 0, \forall i$),
- with exogenous variables both in mean and variance.

2.1.4 Model Identification

Similar to the ARMA model, the problem of model identification is the optimal election of the values of p and q in the GARCH model. (Tsay, 1987) suggests that GARCH(1,1) performs better than higher specifications of the GARCH model considering goodness of fit of the volatility of a time series; thus, we will use that specification in our work.

2.1.5 Model Estimation

The parameters of our model are estimated by Quasi-Maximum Likelihood techniques. We define the parameter vector $\vartheta = (\phi, \psi)$ where $\phi = (\mu, \phi, \theta, \delta)$ are the parameters for the ARMA model and $\psi = (\omega, \alpha, \beta, \gamma)$ are the parameters for the GARCH-X model, which belong to the parameter space (Φ, Ψ). With some convenient initial values that allows us to define

$$\tilde{\epsilon_t} = \Phi(B)(Y_t - \mu_t) - \sum_{j=1}^{q} \theta_j \epsilon_{t-j},$$

$$\tilde{\sigma_t}^2 = \omega + \sum_{j=1}^{q} \alpha_j \tilde{\epsilon}^2_{t-j} + \sum_{k=1}^{p} \beta_k \tilde{\sigma}^2_{t-k} + \sum_{l=1}^{s} \gamma_l Z_{lt},$$

the QML estimators are the solution to

$$\hat{\vartheta} = \underset{\vartheta \in (\Phi, \Psi)}{\arg\max}\, \tilde{L}_T(\vartheta) = \frac{1}{T} \sum_{t=1}^{T} \left(-\log \tilde{\sigma_t}^2(\psi) - \frac{\tilde{\epsilon}^2_t(\phi)}{\tilde{\sigma_t}^2(\psi)} \right).$$

Under mild conditions, QML estimators are consistent and asymptotically normal (Ling and McAleer, 2003).

2.2 Data

The total monthly landings of sardine of northern Chile are available in the Statistical Fishery Yearbooks in the webpage[1] of SERNAPESCA to public access. In order to get a better performance, we run a logarithmic transformation of the landings (LSAR) to get the time series to be adjusted. The external environmental variables were registered at the Antofagasta station (2326'S) and its monthly averages were calculated. The variables analyzed were sea surface temperature (SST) of the station, the turbulence index (TI), Pacific decenal oscillation index (PDO), the Southern Oscillation index (SOI), the Cold Tongue index (CTI), and the sea surface temperature in El Niño region 1 and 2 (N12) and in El Niño region 3 and 4 (N34). These regions are respectively located in 0S - 10S and 90W - 80W, and in 5N - 5S and 170W - 120W. Every analysis performed on this data is computed using the open source R software (Ghalanos, 2020).

[1] http://www.sernapesca.cl/informes/estadisticas.

3 Results and Discussion

3.1 Variables Selection

In order to select the variables better suited as exogenous for the model, the Pearson correlation coefficients between the variables and LSAR were calculated and analyzed, as well as Granger causality tests with 1 temporal lag. Based on the results shown in Table 1, we select two exogenous variables: SST and TI, which are the ones that are statistically significant base on both tests. Table 2 shows descriptive statistics of the three variables in the model.

Table 1: Results of Pearson correlation and Granger causality tests between the captures of sardine and the environmental variables.

Variable	Correlation with LSAR	p-value (t distribution)	Granger test statistic	p-value (F distribution)
SST	0.12	0.0052	12.62	< 0.001
TI	0.40	< 0.001	8.04	0.0048
PDO	0.32	< 0.001	2.27	0.1326
SOI	-0.07	0.0883	0.26	0.6083
CTI	0.06	0.1887	0.41	0.5242
N12	0.07	0.1196	3.98	0.0466
N34	0.02	0.7105	0.67	0.4137

Table 2: Descriptive statistics of the variables.

	LSAR	TI	SST (C)
Mean	8.54	423.5	17.48
Median	8.59	385.0	17.30
Variance	7.08	31908.67	4.19
Std. Deviation	2.66	178.63	2.04

3.2 ARCH Effect Test

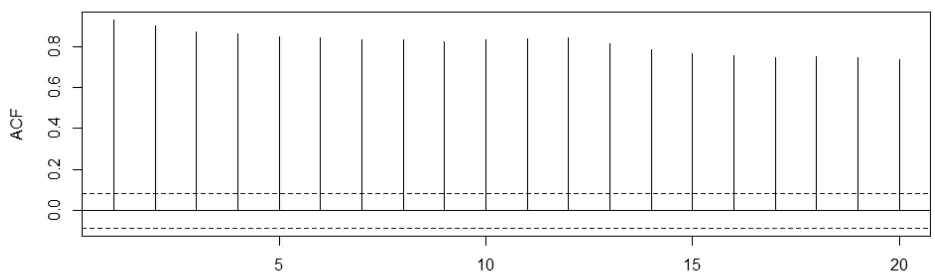
Before starting parameter estimation, we run an ARCH-LM test to statistically assure the presence of volatility in the series. Table 3 shows the results of the test with lags from 1 to 4, which proves the relevance of a GARCH model to fit the observations of LSAR.

Table 3: ARCH-LM test results (lags 1 to 4).

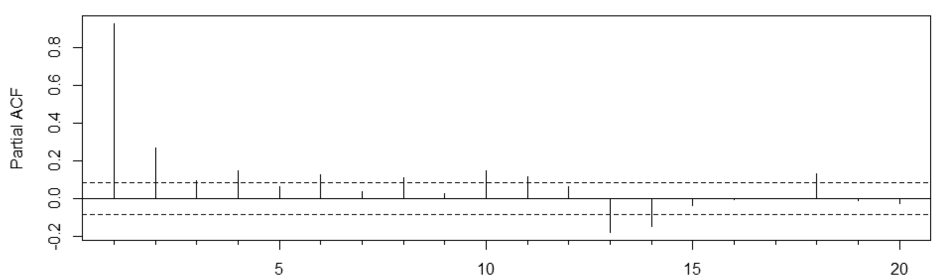
Lag	Test statistic	p-value
1	459.98	< 0.001
2	464.53	< 0.001
3	464.01	< 0.001
4	466.65	< 0.001

3.3 Model Fitting

Once we have completed the preliminary steps, we proceed with the estimation of the parameters of the models.Figure 1 presents the ACF and PACF of LSAR in order to define the ARMA part of the model. It shows that a good specification to this part comes from an AR(2) model, and the exogenous variables will handle the evident seasonality of the series shown in the ACF since they share the same behavior.



(a) ACF



(b) PACF

Figure 1: ACF and PACF of the variable LSAR.

In the GARCH section, first we fit the classic GARCH model with no exogenous variables, and then compare it with the GARCH-X variant with exogenous variables in the mean, variance, as well as in both components. From now on, we call this four possible variations Model 1 to 4, respectively. By comparing the coefficients, shown in Table 4, we find some interesting results. First, ARMA coefficients are significant and almost constant across all models, proving that a GARCH model is not enough to explain the time series and the inclusion of the autorregressive equation is useful. Also, in Table 4, we report the robust standard errors of the estimators. According to Bollerslev and Wooldridge (1992), the QML estimators are consistent even when the conditional distribution of the residuals is not normal.

Table 4: Estimated parameters of the ARMA GARCH models.

Model	AR1	AR2	μ	TI (mean)	SST (mean)	ω	α	β	TI (var)	SST (var)
Model 1: ARMA GARCH	0.6749 ***	0.2728 ***	6.6155 ***	···	···	0.3003	0.1343 ***	0.8440 ***	···	···
(no variables)	(0.0625)	(0.0468)	(0.7324)	···	···	(0.0259)	(0.0376)	(0.0568)	···	···
Model 2: ARMA GARCH-X	0.6473 ***	0.3003 ***	4.7537 ***	0.0002	0.0928 ***	0.0183	0.1502 ***	0.8488 ***	···	···
(variables in mean)	(0.0621)	(0.0497)	(0.8880)	(0.0002)	(0.0177)	(0.0178)	(0.0493)	(0.0578)	···	···
Model 3: ARMA GARCH-X	0.7057 ***	0.2796 ***	5.9643 ***	···	···	0.0000	0.4998 ***	0.2903 *	0.0006 **	0.0000
(variables in variance)	(0.0529)	(0.0508)	(0.2363)	···	···	(0.0000)	(0.1753)	(0.1708)	(0.0003)	(0.0068)
Model 4: ARMA GARCH-X	0.6819 ***	0.3153 ***	4.2437 ***	-0.0001	0.0811 ***	0.0000	0.6433 ***	0.2908 *	0.0004 **	0.0000
(variables in both)	(0.0599)	(0.0574)	(0.4610)	(0.0002)	(0.0217)	(0.0000)	(0.2088)	(0.1587)	(0.0002)	(0.0059)
Model 5: ARMA GARCH-X	0.6883 ***	0.3086 ***	4.2503 ***	···	0.0775 ***	0.0000	0.6373 ***	0.2883 *	0.0005 **	···
(variables in both)	(0.0551)	(0.0540)	(0.4711)	···	(0.0208)	(0.0000)	(0.1681)	(0.1099)	(0.0005)	···

Note: Standard robust errors of the respective coefficients in parentheses. Symbol * (**,***) represents significance at 10% (5%, 1%) level.

Incorporation of the external variables in the equations proves the influence of the exogenous regressors in the series to some extent. Models 2 and 4 show that just SST is significant in the mean model, and Models 3 and 4 imply the same effect with TI in the variance equation, but with less statistical significance. Therefore, we extend the estimation to a new model (Model 5) with SST in mean and TI in variance, that shows better properties for the significance of coefficients.

Next, we study the models by information criteria. Table 5 presents the value of these criteria for each model, and according to this information Model 5 has the best performance since it has the smallest value in all criteria. Overall, it is clear that the GARCH-X models are better suited in basis of information criteria to explain the time series evolution than a GARCH model.

Table 5: Information criteria of Models 1 to 5.

Information criteria	Model 1	Model 2	Model 3	Model 4	Model 5
Akaike	1356.278	1341.547	1320.935	1309.702	1306.125
Bayes	1382.028	1375.880	1355.267	1352.618	1340.458
Shibata	1356.147	1341.315	1320.702	1309.340	1305.893
Hannan-Quinn	1366.349	1354.975	1334.362	1326.486	1319.552

To ensure the advantages of one specification over another, and taking advantage of the fact that the defined models are nested, we develop some likelihood ratio tests. In all cases, the first model will be considered as the restricted model. Table 6 presents the results of these tests for some important comparisons of Models 1 to 5. This information further supports the evidence in favor of the use of exogenous variables and the GARCH-X model, even though there are some specifications with better results than others. In summary, it seems that Model 5 provides a better fit according to the likelihood ratio test.

Table 6: Likelihood ratio tests of Model 2 to 5.

Comparison	LRT statistic	d.f	p-value (χ^2 distribution)
Model 1 - Model 2	18.73	2	< 0.0001
Model 1 - Model 3	39.34	2	< 0.0001
Model 1 - Model 4	54.57	4	< 0.0001
Model 1 - Model 5	54.15	2	< 0.0001
Model 2 - Model 4	35.84	2	< 0.0001
Model 3 - Model 4	15.23	2	0.0005
Model 5 - Model 4	0.42	2	0.8093

Our next step is the revision of stability in the models using the Hansen-Nyblom test (Hansen, 1992; Nyblom, 1989). This test is an extension of the Chow test that allows the verification of model general stability as well as individual parameter stability in more general situations. Table 7 presents the information from the Hansen-Nyblom tests performed both individually to each coefficient and to the complete model. The null hypothesis is that all the coefficients are constant and the alternative is that some of them are variable. Due to the difficulty of calculating the theoretical distribution of the test statistics, the two last rows of the table showcritical values for the statistic of the complete model and the statistic of each variable separately. If the respective value exceeds the critical value, the null hypothesis of stability is rejected.

Table 7: Hansen-Nyblom test of Models 1 to 5.

	Model 1	Model 2	Model 3	Model 4	Model 5
Joint	1.2902	2.2798	8.2684	8.7559	8.2516
Individual statistics					
AR1	0.0518	0.0518	0.3317	0.1839	0.1932
AR2	0.0337	0.0419	0.2520	0.1461	0.1531
μ	0.3013	0.3266	0.4745	0.2926	0.3200
TI (mean)	$\cdots$	0.0589	$\cdots$	0.0858	$\cdots$
SST (mean)	$\cdots$	0.1630	$\cdots$	0.1578	0.1708
ω	0.2686	0.2595	3.1107	4.1117	4.0816
α	0.1631	0.1088	0.7681	0.4784	0.4964
β	0.1918	0.1620	1.2917	1.5284	1.5379
TI (var)	$\cdots$	$\cdots$	1.0435	1.5439	1.5656
SST (var)	$\cdots$	$\cdots$	2.6254	3.6680	$\cdots$
Critical values (significance level 1%)					
Joint	2.12	2.59	2.59	3.05	2.59
Individual	0.75	0.75	0.75	0.75	0.75

From the results of the Hansen-Nyblom tests, we conclude that Model 1 and 2 as a whole are stable and Model 3 to 5 are not. A closer verification of the individual stability shows that the unstable parameters belong to the variance model. Besides, since the parameters that are considered unstable do not have a numerically high or statistically significant value, we can affirm that instability is not an extremely serious problem in models with exogenous variables.

Finally, we compare the models to check the accuracy of their adjusted values. Table 8 presents the mean absolute error (MAE), the root of the mean squared error (RMSE) and the mean absolute percentage error (MAPE) calculated for the models. MAE and RMSE are common indicators in many studies to check the performance of forecasting models, and MAPE is recommended in series with positive values much greater than zero (Hyndman and Koehler, 2006).

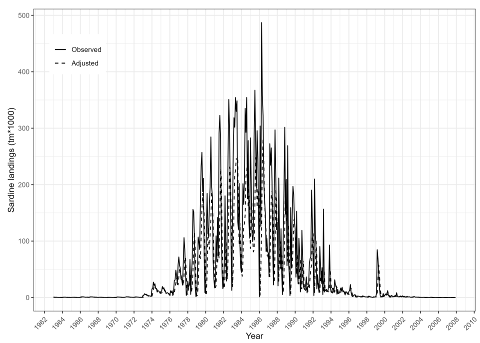
Table 8: Error measurements of Models 1 to 5.

	Model 1	Model 2	Model 3	Model 4	Model 5
MAE	0.6351	0.6422	0.6253	0.6303	0.6293
RMSE	0.9233	0.9221	0.9211	0.9199	0.9196
MAPE	9.09%	9.14%	8.93%	8.97%	8.95%

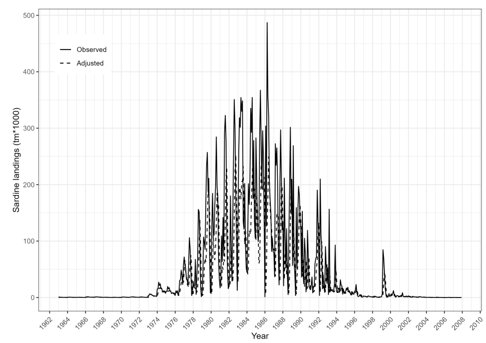
Although the differences are not very high, Models 3 and 5 present the minimum values in MAE, RMSE and MAPE. Therefore, these models perform better at fitting the values of LSAR. Despite this, the remaining models are very close in error measures so their forecasting performance is fairly good. Finally, Figures 2 and 3 present the comparison between the actual values of monthly sardine landings and the values predicted by all models and the empirical distribution of the standardized residuals, respectively. This information confirms that the ARMA GARCH-X specification is useful and the series behavior is well adjusted.

4 Conclusions

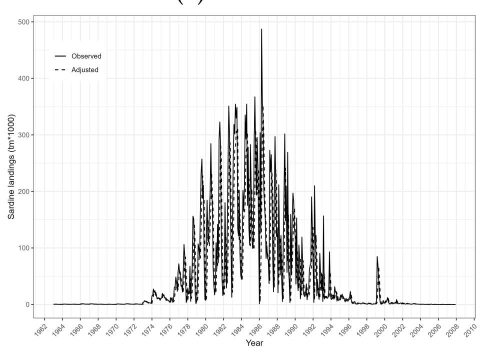
In this paper we proposed an ARMA GARCH-X model to adjust the monthly sardine landings off northern Chile and tested the possible advantages of using environmental variables in the model to improve the results. Based on the results of the analysis, we conclude that an ARMA GARCH-X model with certain external variables in mean and variance surpassed the other possible specifications of ARMA GARCH-X and ARMA GARCH models. Despite not having a clear winner in all the tests that were carried out, the model with variables in the mean (Model 3) as well as the model with different variables in mean and variance (Model 5) performed better in adjustment of observations, information criteria and model selection tests, despite the fact that they could be suffering from instability in some of their parameters. However, our work proved that the inclusion of external variables in the equations is useful and could improve the understanding of the dynamics of pelagic resources in Chile to manage them in a reasonable way, a challenge that is faced by many countries in the region that also have strong fishing industries (de la Puente and López de la Lama, 2019).



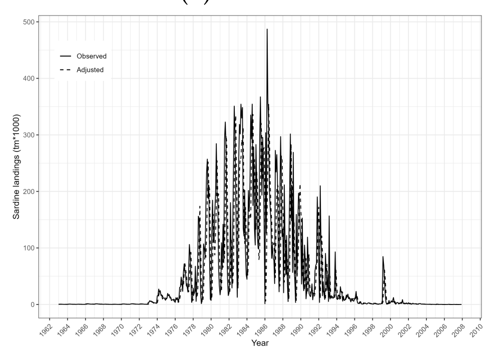
(a) Model 1



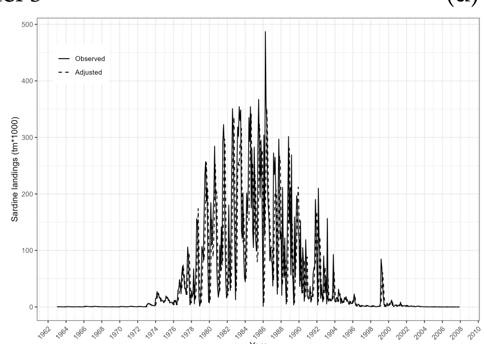
(b) Model 2



(c) Model 3



(d) Model 4



(e) Model 5

Figure 2: Observed against adjusted plot of the monthly sardine landings.

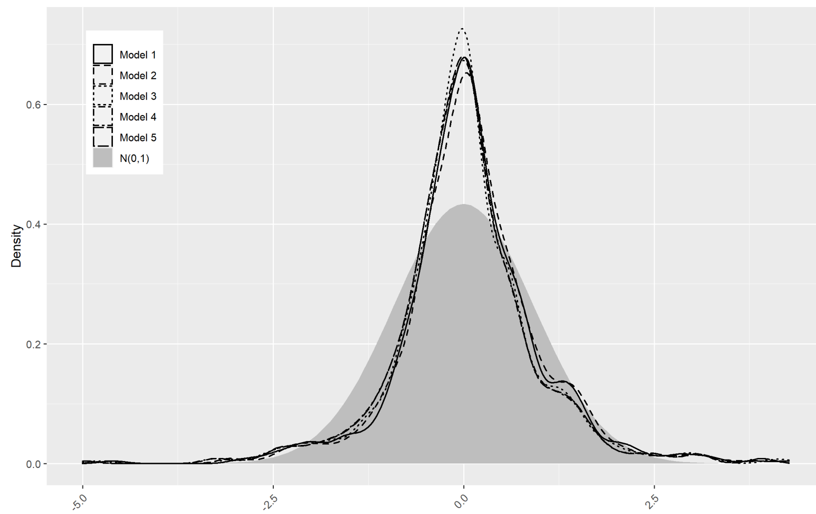


Figure 3: Empirical distribution of the standardized residuals of Models 1 to 5.

As mentioned in the introduction, sardine and anchovy are closely related due to geographic proximity and similar environmental behaviors. Then, it is quite certain that an ARMA GARCH-X model is also a good alternative to forecast the anchovy landings in the same Chilean region. Even more, we expect to extend the application of this model to other regions and species, choosing the possible exogenous variables according to the different natural circumstances well as the human made ones, like fishing effort or capture quotas. However, these are generally difficult to be accurately measured, and their effect may be strongly imprecise.

Finally, as possible additional developments, there is the extension of the methodology to incorporate seasonal components that allow modeling and forecasting short-term dynamics, advancing from the use of an ARMA structure to the more general SARIMA (Seasonal Autoregressive Integrated Moving Average) case. This also entails updating the main definition of our model to include exogenous variables in a compatible way with the new SARIMA structure, given that this inclusion is the main advantage of our proposal to improve the results of a single series model. On a long-term scale, much more sophisticated techniques could also be applied in the modeling of the mean equation, such as TAR (Threshold Autoregressive) or STAR (Smooth Transition Autoregressive) models with their corresponding extensions to admit external variables. These techniques have generally been considered in the analysis of series in the financial field, so there are not many examples of their application to the biological or ecological field, which are the ones we have dealt with in this work.

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