Granger-causality analysis of integrated-model outputs, a tool to assess external drivers in fishery

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Abstract

Integrated models are able to combine several sources of data into a single analysis using joint likelihood functions, fostering the consistency of assumptions among analyses and the ability to diagnose goodness of fit and model-misspecification. Owing to their capacity to consistently combine diverse information, integrated models could detect the variability induced by external drivers, such as various environmental drivers, on key components of the stock dynamics (e.g. recruitment) in cases where these external drivers are relevant but not yet identified or incorporated into the modelling exercise. This diagnosing power could then be used to explore causality between fishery dynamics, as estimated by the integrated model, and external drivers. To achieve this aim, a correlation analysis is neither necessary nor sufficient to prove causation. An alternative statistical concept, Granger-causality, provides a framework that uses predictability, rather than correlation, to give more evidence of causation between time-series variables.

A two-step procedure to investigate external forcings in stock dynamics is proposed. First, an integrated model is implemented to detect anomalies that cannot be explained by the internal dynamics of the stock. Then, in a second step, Granger-causality is used to detect the external origin of these anomalies. This two-step procedure is explored using the European anchovy in the Gulf of Cádiz as an example population where the external (environmental) drivers are well documented. The fishery dynamics is first estimated through an age-length model (Gadget). Then Granger-causality is used to assess the predictive power of different environmental drivers on recruitment. The results indicate that this is a powerful procedure, although also with important limitations, to determine predictability and that it can be implemented in a wide variety of stocks and external drivers. Moreover, once Granger-causality has been identified, it is shown that it can be used to forecast by making few modifications of the integrated model used for diagnosis.

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1. Introduction

Population dynamics models aimed at supporting fishery management are increasingly incorporating data of different origin and nature to enhance their diagnosing capacities (Demyanov et al., 2006). Thus, assessing stock dynamics frequently relies on inferences from commercial catches but can also benefit from auxiliary information, such as survey indexes, fishing effort and length-age relationships, that is assimilated into models (Fournier and Archibald, 1982; Deriso et al., 1985; Methot, 1989). Combining this diverse information is beneficial for quantitative assessments but it is also challenging, in particular when all this information is implemented together in the same model. The integrated analysis is able to combine several sources of data into a single analysis using joint likelihood functions, fostering consistency of assumptions among analyses and the ability to diagnose goodness of fit and model-misspecification (Maunder and Punt, 2013). Owing to their capacity to consistently combine diverse information, integrated models could detect the variability induced by external drivers, both environmental and from another source, on key components of the stock dynamics such as recruitment even in cases where these external drivers, despite being relevant, are not yet identified or incorporated into the simulation exercise. This diagnosing capacity could then be used to explore the forecasting power of external drivers on diagnosed fishery dynamics, as estimated by the integrated model.

To achieve this aim, a correlation analysis between the model output and the external driver is not enough to assess predictability. As in other fields of sciences, causality and correlation are too tightly associated in fisheries but correlation is neither necessary nor sufficient to prove causation (Yule, 1926). An alternative statistical concept, Granger-causality (Granger, 1969; Sims, 1972), provides a framework that uses predictability, rather than correlation, to provide more evidence of causation between time-series variables. Granger-causality is considered (Sugihara et al., 2012) as the main advance on the causation problem since Berkeley's treatise on the principles of human knowledge (Berkeley and Krauth, 1874). Granger-causality states that a stationary time-series variable X is said to "Granger-cause" (Granger, 1969) the stationary time-series variable Y , if past values of X help to predict the current value of Y better than just the past values of Y do (Stern and Kaufmann, 2014). This concept has been extensively used in the field of economics (Masih and Masih, 1996; Mookerjee and Yu, 1997; Tedds and Giles, 2002; Foresti, 2006). In fishery science it has been recognized as useful to address the recruitment autocorrelation problem (Ye, 2000), where autocorrelation could potentially increase or decrease our capacity to diagnose a stock-recruitment relationship (Gilbert, 1997; A. Myers and Mertz, 1998; Walters, 1985; Caputi, 1988).

In this paper, we propose a two-step procedure to diagnose external forcings in stock dynamics. First, an integrated model is implemented to detect anomalies that cannot be explained by the internal dynamics of the stock. Then, in a second step, Granger-causality is implemented to detect the external origin of these anomalies. This two-step procedure is explored for the European anchovy in the Gulf of Cádiz where the external environmental drivers are well documented. First, the fishery dynamics are analysed with Gadget (Globally applicable Disaggregated General Ecosystem Toolbox), an age-length-structured modelling environment able to assimilate data on surveys and landings for parameter optimization through weighted likelihood components (Begley and Howell, 2004). Then Granger-causality is used to assess the predictive power of different environmental drivers on recruitment. The results indicate that this is a powerful procedure, although also with important limitations, to assess predictability that can be implemented in a wide variety of stocks and external drivers. Moreover, once Granger-causality has been identified, it is shown that it can be used to forecast by making a few modifications of the integrated model used for diagnosis.

2. Material and Methods

As explained above, the stock of European anchovy in the Gulf of Cádiz was chosen to explore the procedure because environmental forcing of recruitment is well characterized. The modelling framework Gadget is used here owing to its ability to combine large pools of disparate data from diverse sources. Causality between estimated recruitment and environmental forcing was then assessed by using Granger-causality techniques.

2.1. European anchovy in the Gulf of Cádiz

The environmental vulnerability of the stock of European anchovy *Engraulis encrasicolus* at the Gulf of Cádiz is well documented. The stock is exploited under a BotTop pattern (Ruiz et al., 2007) where fishing mortality prevents adults from reaching older age groups and stock survival between years relies on early stages (Ruiz et al., 2006). Eggs and larvae occupy the sea shelf and are vulnerable to easterly winds. In contrast, juveniles occupy nursery zones close to or within the estuary of Guadalquivir River and are, consequently, sensitive to freshwater inputs into that habitat (Ruiz et al., 2009; González-Ortegón et al., 2010; González-Ortegón and Drake, 2012). It is then a neat case where known external drivers are forcing the dynamics of the stock and where the capacity of the procedure to detect Granger-causality can be tested.

Data of these external drivers were obtained from public databases. Daily wind between 1988 and 2009 was extracted from a meteorological database <http://datosclima.es> that stores information provided by the Spanish meteorological agency and then transformed into annual quarters by counting the number of days with easterly winds above 30 Km/h (Relvas and Barton, 2002; Ruiz et al., 2006, 2009; Peliz et al., 2013). Discharges

60 from the Alcalá del Río dam (the main input of freshwater to the estuary) between 1988 and 2016 were obtained
61 from the Confederación Hidrográfica del Guadalquivir (www.chguadalquivir.es).

62 The information incorporated into the integrated model was obtained from ICES reports as well as from
63 different records on this stocks compiled by the Instituto Español de Oceanografía for the last decades. These
64 include:

- 65 • Quarterly catches in numbers (1988-2015).
- 66 • Length distribution of landings (1998-2015).
- 67 • Age distribution of landings (1998-2015).
- 68 • Mean length at age in landings (1988-2015).
- 69 • Biomass indexes from ECOCADIZ scientific acoustic survey (second quarter 2004, 2006; third quarter 2007,
70 2009, 2010, 2013 and 2014).
- 71 • Age and length distribution of scientific acoustic survey ECOCADIZ (second quarter 2004, 2006; third
72 quarter 2007, 2009, 2010, 2013 and 2014).
- 73 • Biomass indexes from PELAGO scientific acoustic survey (first quarter 1999, 2001-2003, second quarter
74 2005-2010, 2014).
- 75 • Age and length distribution of scientific acoustic survey PELAGO (first quarter 1999, 2001-2003, second
76 quarter 2005-2010, 2014).
- 77 • Biomass indexes from SAR scientific acoustic survey (last quarter 1998, 2000, 2001, 2007 and 2012).

78 *2.2. Integrated model*

79 To integrate different sources of information, the modelling framework Gadget was used to produce a synthesis
80 of the stock dynamics. A typical Gadget model is an age-length-structured model that runs forward simulations
81 while minimizing an objective function (negative log-likelihood) that measures the difference between the model
82 and data. Discrepancies between model and data are presented as a likelihood score for each time period and
83 model component. Gadget structure and options are described in detail by Begley and Howell (2004) with
84 example implementations documented in Taylor et al. (2007); Bartolino et al. (2011); Elvarsson et al. (2018).

85 Gadget consists of three parts, simulation of the biological dynamics of the population (simulation model),
86 fitting the model to observed data using a weighted log-likelihood function (observation model) and the opti-
87 mization of the parameters using different minimization algorithms.

88 In the first part, biological processes are simulated for a given set of model parameters in the following order:
 89 Predation by the fleets, natural mortality, growth, recruitment and ageing. This is repeated for all timesteps until
 90 the end of the simulation period. At the end of the simulation, the output of the objective (likelihood) function
 91 score is produced by comparing the model output to observed measurements. Then based on the objective
 92 function model parameters are adjusted, and the model re-run, until an optimum is found, which corresponds to
 93 the model with the lowest objective function (likelihood) score.

94 The model was set up as with quarterly timesteps from 1998 to 2015. Fisheries interactions were implemented
 95 by setting the purse-seine fleet as a predator and consequently catches (in numbers) data were included in the
 96 predation component of the first part. The remaining datasets listed above were used as observed measurements
 97 and combined in the objective function as a weighted sum of squares.

98 The weights of the likelihood components were assigned following the heuristic approach presented in Taylor
 99 et al. (2007) and in the appendix of Elvarsson et al. (2014) based on the iterative reweighting scheme of Stefánsson
 100 (1998) and Stefánsson (2003). This weighting process is implemented in the *gadget.iterative* function in the R
 101 package (Elvarsson and Lentin, 2016). Data processing and input file formatting used the tools from the *mfdb* R
 102 package (Lentin, 2014) Further details on model parameterization, model validation and weighting of likelihood
 103 components are described in the Appendix.

104 2.3. Granger-Causality analysis

105 The typical Granger-causality test can be problematic because of non-stationarity of time series involved
 106 (He and Maekawa, 2001). Consequently, Toda and Yamamoto (1995) approach was followed here to apply the
 107 test when one or both of the time series are non-stationary (Zombe et al., 2017). The method to prove that X
 108 Granger-cause Y fits the following vector autoregressive model (VAR(L+m)):

$$Y_t = a + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \dots + \alpha_L Y_{t-L} + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \dots + \beta_{L+m} X_{t-(L+m)} + \epsilon_t \quad (1)$$

$$X_t = b + \delta_1 X_{t-1} + \delta_2 X_{t-2} + \dots + \delta_L X_{t-L} + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \dots + \theta_{L+m} Y_{t-(L+m)} + \epsilon_t \quad (2)$$

109 Where L is the appropriate maximum lag length for the variables in the VAR, chosen using an usual infor-
 110 mation criteria, such as Akaike information criteria (AIC) (Akaike, 1974, 1998), m is the maximum value chosen
 111 from the order of integration of time series X_t and Y_t , and ϵ_t accounts for the error. Then, it is necessary to
 112 tests two hypothesis, $H_0^1 : \beta_i = 0, i = 1, \dots, L$ and $H_0^2 : \theta_i = 0, i = 1, \dots, L$ using a standard Wald test (*aod* R
 113 package, Lesnoff et al. 2012).

114 If there is enough evidence to reject H_0^1 , i.e. to say that $\beta_i, i = 1, \dots, L$ coefficients are different from zero,

and at the same time that there is not enough evidence to reject H_0^2 , i.e. is highly probable that $\theta_i, i = 1, \dots, L$ coefficients are zero, we can say that X Granger-cause Y.

It is necessary to check also that the VAR(L) model is well-defined: stable and with non-serially correlated errors. Stable to guarantee that the variance is finite and that the matrix system has a solution, and non correlating, to avoid bias on the estimated coefficients (Lütkepohl, 2013). Stability was tested by calculating the eigenvalues of the matrix associated to the equivalent first-order vector autoregressive form and checking that they were less than one. Serial correlation for errors was tested with the multivariate Portmanteau and Breusch-Godfrey test (Lütkepohl, 2013; Breusch, 1978; Godfrey, 1978). Both tests are implemented in the *VAR*S R package (Pfaff, 2008) which were used here.

2.4. Forecast

If the environmental variable, E , Granger-cause the recruitment, R , the first equation of the well defined VAR(L) model is selected (equation (1) with $m = 0$), restricted to significant coefficients and tested for non-serial correlation (Portmanteau test). Then, the population model is used to project stochastically based on a restricted version of this equation to provide a prediction of catches 3 years into the future (2016-2018). In each projection the recruitment was sampled from a normal distribution with mean derived from the restricted equation and standard deviation equal to the standard deviation of the fitted model residuals ϵ_t . The values of the environmental variable in this equation are fixed to illustrate two different environmental scenarios: A base scenario assuming that environmental conditions remain constant and, an adverse scenario based on calculations to have a recruitment worse than the previous year. Resulting values are used as initial values for recruitment parameters in a Gadget simulation assuming a constant effort. The implementation details are listed in the Appendix.

2.5. Reproducibility

The manuscript was generated using a combination of L^AT_EX and R codes with the R package *knitr* (Xie, 2014). "The knitr package was designed to be a transparent engine for dynamic report generation with R", where transparency means that the user has full access to every piece of the input and output (see <https://yihui.name/knitr/>). The file to assure reproducibility is included as Supplementary Material and the instructions and requirements to reproduce this document entirely are in the Appendix.

3. Results

Figure 1, illustrates the sum of squares of the differences between available and estimated data (likelihood scores). Together with Figures A.2 and A.3 (in the Appendix) show that there is a reasonable match between

modelled and observed age and length frequency distributions. This suggests that the model adequately explains the population dynamics as observed in the data. However, there is a notable poor fit in 1996 for age and length distribution of landings (Figures 1A and 1B), just before the implementation of the minimum landing size regulation. The estimated parameter values are shown in Table A in the Appendix.

Figure 1: Likelihood scores for A. Landings age distribution, B. Landings length distribution , C. ECOCADIZ survey length distribution and D. PELAGO survey length distribution. Dots represent the score for each quarter.

Figure 2 shows the population estimates of Gadget for the time series of stock size, fishing mortality, recruitment and catch in numbers. The estimates also point to 1996 as a singular year with a remarkable change in the trend after a minimum in abundance, recruitment and catches in the year 1995. These minima coincide with the smallest signal in the time series of discharges, where years of very low discharges are followed (in 1996) by a sudden jump to high values (Figure 3.A), while the time series of wind does not show such a distinctive and abrupt event (Figure 3.B). It is worth to mention here that neither discharges nor wind information were used by the Gadget model, therefore the diagnosis achieved in Figure 2 is based on fishery and survey information alone. These extreme discharge events between 1994 and 1996 could hinder the effect of other environmental variables on recruitment. Particularly for this fishery, easterly winds and discharges have been identified as the main sources of mortality before recruitment (Ruiz et al., 2006). To understand how this abrupt fluctuation of discharges could hinder the detection of wind effects, appropriate time windows were selected for Granger-causality analysis between wind and Gadget recruitment output time series: the whole time series available (1988-2009),

161 and a time window where discharge signal is not so extreme (1996-2009).

Figure 2: Gadget diagnostics: Yearly time series for A. stock size, B. recruitment, C. annual fishing mortality and D. catches.

162 A VAR(4) model was fitted for both time windows ($L = 4$ according to AIC criterion) and the Granger-
 163 causality test was implemented after model stability and non-serial correlation tests were passed: All eigenvalues
 164 lie inside the unit circle and there wasn't enough evidence to reject the null hypothesis of non-serial correla-
 165 tion. (H_0 : No serial correlation, for time window (1988-2009): $p = 0.34$ and $p = 0.64$, in Portmanteau and
 166 Breusch–Godfrey test, respectively. For time window (1996-2009): $p = 0.84$ and $p = 0.24$, in Portmanteau and
 167 Breusch–Godfrey test, respectively).

168 The Wald test revealed that wind does not Granger-cause recruitment for the first time window selected
 169 ($m = 1$, Wald test for a fitted VAR(5): $H_0^1, p = 0.68$ and $H_0^2, p = 0.65$) but it does for the period between 1996
 170 and 2009 ($m = 1$, Wald test for a fitted VAR(5): $H_0^1, p = 0.045$ and $H_0^2, p = 0.99$).

171 For discharges and recruitment time series, the AIC suggested that the appropriate maximum lag length (L)
 172 should be 5 but the resulting VAR(5) model was not stable (some eigenvalues lie outside the unit circle). VAR
 173 model orders of 6, 7, 8, and 9 were also tested but stability wasn't achieved. As a consequence Granger-causality
 174 test could not be implemented in those time series.

Granger-causality test for wind in the second time window provides information that is useful to forecast
 recruitment using the following equation from the well specified VAR(4) model:

$$R_t = a + \alpha_1 R_{t-1} + \alpha_2 R_{t-2} + \dots + \alpha_4 R_{t-4} + \beta_1 W_{t-1} + \beta_2 W_{t-2} + \dots + \beta_L W_{t-4} + \epsilon_t,$$

175 where R_t and W_t represents recruitment and wind at quarter t , respectively, and a is a constant.

Figure 3: A. Quarterly accumulated cubic hectometers that are discharged from Alcalá del Río dam in logarithmic scale. B. Quarterly number of days with easterly winds above 30 Km/h

Restricting the model to significant coefficients results in the following equation:

$$R_t = a + \alpha_4 R_{t-4} + \beta_2 W_{t-2} + \beta_3 W_{t-3} + \epsilon_t, \quad (3)$$

with $a = 81$, $\alpha_4 = 0.54$, $\beta_2 = 6.3$ and $\beta_3 = -6.5$ and $t = 1, \dots, 48$ corresponding to the number of quarters for 12 years.

Null hypothesis of no correlation for residuals was tested and it couldn't be rejected ($p = 0.48$). The comparison between the recruitment time series and fitted values is presented in Figure 4.

The population status was projected forward to provide a prediction of catches for 3 years into the future

Figure 4: Comparison between Gadget recruitment output time series (solid line) and fitted values (dashed line).

(2016-2018). It was based on recruitment sampled from a normal distribution with mean

$$R_{t'} = a + \alpha_4 R_{t'-4} + \beta_2 W_{t'-2} + \beta_3 W_{t'-3}, t' = 1, \dots, 12,$$

and standard deviation equal to the standard deviation of the fitted model residuals $\epsilon_t, t = 1, \dots, 48$, where t' represent the quarters in years 2016 to 2018, and t the quarters in 1997 to 2009. Note that $R_{t'}, t' = 1, \dots, 4$, were calculated using the model estimated recruitment in 2015. The values $W_{t'}$ were assumed to illustrate two different wind scenarios. Figure 5 shows real catches (1988-2015) as well as the prediction range of 20 trajectories of projected catches (2016-2018) under a favorable (white boxes) and an adverse (grey boxes) wind scenarios. The favorable wind scenario corresponds to 10 windy days (above 30 Km/h) in each quarter while the adverse wind scenario was designed to produce a recruitment worse than the previous year for the 3 projected years. This adverse scenario corresponds to 37 windy days in the first three quarters and in the fifth quarter (the highest quaterly wind of the historical time series), and 10 windy days in the remaining quarters. The highest differences between the good and adverse wind scenarios are found in the last two years while in the first one catches values are similar.

4. Discussion

Integrated models have emerged as tools suitable to assimilate in the same robust statistical framework both data on catch age-length structure and information from scientific surveys. This capacity to assimilate information of diverse nature is helpful to assess stocks through integrated models such as Gadget, which has been formally adopted as the basis for assessment of least 6 European stocks (ICES, 2017, 2016, 2014, 2013, 2012),

Figure 5: Real catches data (1988-2015) together with a summary of 20 trajectories of projected catches (2016-2018) under a favorable (black boxes) and an adverse (grey boxes) wind scenario using a stochastic version of the restricted model (equation 3) to forecast recruitment. Upper and lower limits of the lines outside the box account for maximum and minimum values, while the box accounts for mean and standard deviation

or SS3, which is used when assessing sixty-one stocks worldwide (Methot and Wetzel, 2013). Despite this success to coherently incorporate different types of data in the same model, integrated models do not have a standard way to include environmental effects which are known to potentially have an important role in recruitment (Lehodey et al., 2006). The understanding of key processes controlling the ecosystem is a basic requirement for the implementation of the ecosystem-based approach for fisheries management (EBFM) (Pikitch et al., 2004). Although EBFM has been formally adopted widely and a considerable amount of scientific knowledge has been established, very little of this has been utilized to support decision-making. Ecosystem drivers are actually implemented in only few fisheries management since only when there is a good understanding of ecosystem processes it might be successful to include external drivers in EBFM (Skern-Mauritzen et al., 2016).

This paper illustrates a possible path to the embedding of environmental effects through the implementation of an integrated model, Gadget, to a fishery, European anchovy in the Gulf of Cádiz, whose recruitment is known to be heavily influenced by physical forcings. The procedure starts with the first implementation of a Gadget model to the anchovy in the Gulf of Cádiz. This is achieved through the incorporation in Gadget of a large amount of length-age fishery-data since 1988 as well as numerous scientific surveys conducted in this period (Table A.2). The incorporation of such a volume of information results in an overall good estimation of age and length distributions in the diagnosed time series (Figures A.2 and A.3).

Abundance time series estimated by the Gadget model (Figure 2) are akin to previous (Bayesian) models developed for the fishery (Rincón et al., 2017) although the high volume and the diversity of information assimilated by Gadget allows narrowing the estimated range from 0-2500 millions in Rincón et al. (2017) to 0-750 millions of individuals here. In addition, Figure 2 shows high values of F during the years when recruitment is

lower (1994, 2004, 2007, 2010) and the opposite, i.e. low F when recruitment is high (1996, 2011); in a trend that has already been identified as a consequence of the fixed quota management that puts the biology and the economy of the fishery at risk (Ruiz et al., 2017).

High F and recruitment failures are concomitant features between years 1992 and 1995. Owing to the fixed TAC and the BotTop (Ruiz et al., 2007) nature of this fishery, high F can be considered as the consequence of a recruitment failure rather than the other way around. As mentioned above, the environment is known to have an important impact on the recruitment of this stock. This environmental effect can be integrated into the estimation routine of Gadget by reformulating the spawning stock biomass and recruitment relationship. However, in the present exercise, this was not done since our aim is to prove the capacity of an integrated model to estimate the existence of external forcings even before its nature is known. Therefore, our population model does not explicitly formulate the impact of environment on recruitment. Instead, key impacts of the environment, or other external drivers not explicitly formulated within the population model, force a modulation of recruitment estimates so that the integrated model keeps coherence of internal biological processes with observed fishery and survey data. In such a way, strong signals in recruitment estimates can be used to detect the presence of these external drivers that might be unknown to the modeller.

For anchovy in the Gulf of Cádiz, it is well known that these drivers are easterly winds and discharges which had conditions adverse for recruitment between 1992 and 1995 (Ruiz et al. (2006); Figure 3); these are the years when Gadget estimated recruitment failures (Figure 2). Despite this evidence, Granger-causality was unable to resolve cause-effect connections for freshwater discharges. The resulting VAR model for the estimated recruitment output and freshwater discharges, is not stable, which means that it does not generate stationary time series with time-invariant means, variances, and covariance structure; thus affecting the structural analysis and the reliability of forecasting. The nature of this signal, with a very abrupt fall in 1994-1995 (Figure 3), also seems to affect the Granger-causality analysis carried out between wind and recruitment. Causality between wind and recruitment does not appear in the whole time series, thus suggesting that the sharp signal of 1994-1995 discharges could hinder the effect of the wind at the Granger-causality analysis. This interpretation is supported by previous analysis where wind results as the main source of variability for population size (Rincón et al., 2016) and the very good agreement between the mathematical formulation for recruitment (Equation 3) and Gadget estimations in a time period that does not include those years (Figure 4).

Although the positive output of the Granger-causality test between wind and recruitment does not exclude the existence of other external drivers of recruitment, the concordance shown by Figure 4 indicates that wind could be used for fishery management when discharge signal is not dominant, i. e. in years when a severe drought results in very low river discharges. Thus, despite the significant limitations that these sharp signals seem to bring to Granger-causality analyses, the implementation of this technique for the period between 1997

and 2009 confirms the importance of wind to predict recruitment. Granger-causality analysis in this time slice provides a simple mathematical structure (Equation 3) to predict recruitment and, therefore, to support in management. This structure was used here, to assess different wind scenarios in Figure 5 as an example of how these simple expressions can help decision-makers to assess the consequences of their decisions under different climatic conditions. For example, one of the possible bad scenarios presented here suggests that three successive quarters in a year plus the first quarter in the next year with a high frequency of strong winds could gradually reduce recruitment. Some additional exploration in this direction could be interesting to determine all possible combinations that could increase the collapse probability.

In summary, this paper presents a procedure to predict external forcings on a fishery through the implementation of an integrated model and the analysis of its output recruitment. Gadget has successfully been set up to detect the recruitment failure whose origin is known to be in environmental forcing. The subsequent analysis of causality by Granger techniques has only partially been successful since it did not work for the sharp signal associated with the effect of discharges on recruitment. However, Granger-causality has clearly identified the important role of wind in conditioning recruitment for non-drought years and has provided simple formulations that are transparent and easy to implement in a decision-making frame.

Although it is difficult to find in nature that the variation in one variable is totally caused by another, and this Granger-causality test between wind and recruitment does not exclude the effect of other unknown environmental variables on recruitment, for the last years, Granger-Causality goes beyond correlation confirming the importance of wind to predict recruitment. It suggests that wind data is useful in the management of anchovy and gives a simple mathematical structure to implement when testing management strategies.

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454 A. Appendix: Model description

455 The general Gadget model description and all the options available can be found in Gadget manual (Begley,
 456 2004) and some specific examples can be found in Taylor et al. (2007) and Elvarsson et al. (2014). The Gadget
 457 model implementation consists in three parts, a simulation of biological dynamics of the population (simulation
 458 model), a fitting of the model to observed data using a weighted log-likelihood function (observation model) and
 459 the optimization of the parameters using different iterative algorithms.

460 A list of symbols used, a summary of the real data included and a graph with the Gadget model structure
 461 are presented in Tables A, A.2 and Figure A.1, respectively.

Figure A.1: Graph Gadget model

462 A.1. Simulation model

463 The model consists of one stock component of anchovy (*Engraulis encrasicolus*) in the ICES subdivision 9a
 464 South, South-Atlantic Iberian waters, Gulf of Cádiz. Gadget works by keeping track of the number of individuals,

Index	
a	Age, $a = 0, \dots, 3$
l	Length, $l = 3, 3.5, 4, 4.5, \dots, 22$
y	Years, $y = 1988, \dots, 2015$
t	Quarterly timestep, $t = 1, \dots, 4$
T	$T = 1$ for period 1988-2000 $T = 2$ for period 2001-2015
Parameters	
<i>Fixed</i>	
a	Upper asymptote, $a = 2.9 \times 10^{-5}$
b	Growth range, $b = 3.3438$
l_{∞}	Terminal length, $l_{\infty} = 19$
<i>Estimated</i>	
k	Annual growth rate, $k = 0.077272023$
β	Beta-binomial parameter, $\beta = 0.94735941$
ν_a	Age factor, $\nu_0 = 1.0000211 \times 10^{-6}$, $\nu_1 = 1.0000153 \times 10^{-6}$, $\nu_2 = 1.0000101 \times 10^{-6}$, $\nu_3 = 0.026851203$
μ	Mean, $\mu = 10.587297$
σ_t	Standard deviation, $\sigma_1 = 2.1231715$, $\sigma_2 = 0.8514417$, $\sigma_3 = 1.6764533$, $\sigma_4 = 1.546367$
$l_{50,T}$	Length with a 50% probability of predation during period T , $l_{50,1} = 5.201724$, $l_{50,2} = 6$
α_T	Shape of function, $\alpha_1 = 0.8$, $\alpha_2 = 0.8$
Observed Data	
$E_{y,t}$	Number or biomass landed at year y and quarter t
W_l	Weight at length
$I_{y,t}$	Observed survey index at year y and quarter t
$P_{a,l,y,t}$	Proportion of the data sample over all ages and lengths for timestep/age/length combination
$O_{a,l,y,t}$	Observed data sample for time/age/length combination
$x_{a,y,t}$	Sample mean weight from the data for the timestep/age combination
Others	
Δl	Length increase
Δw	Weight increase
Δt	Length of timestep
$N_{a,l,y,t}$	Number of individuals of age a , length l in the stock at year and quarter y and t , respectively.
$q_{a,l}$	Proportion in lengthgroup l for each age group
$R_{y,t}$	Recruitment at year y and quarter t
$p_{l,t}$	Proportion in lengthgroup l that is recruited at quarter t
$C_{l,y,t}$	Total amount in biomass landed by surveys and in number landed by commercial fleet
$S_{l,T}$	Proportion of prey of length l that the fleet/predator is willing to consume during period T
$\pi_{a,l,y,t}$	Proportion of the model sample over all ages and lengths for that timestep/age/length combination
$\mu_{a,y,t}$	Mean length at age for the timestep/age combination
U_t	Understocking for timestep t
lw_i and uw_i	Weights applied when the parameter exceeds the lower or upper bound
lb_i and ub_i	Lower and upper bound defined for the parameter
val_i	Value of the parameter

Table A.1: List of Symbols used in model specification

$N_{a,l,y,t}$, at age $a = 0, \dots, 3$, at length $l = 3, 3.5, 4, 4.5, \dots, 22$, at year $y = 1988, \dots, 2015$, and each year divided into quarters $t = 1, \dots, 4$. The last time step of a year involves increasing the age by one year, except for the last age group, which its age remains unchanged and the age group next to is added to it, like a 'plus group' including all ages from the oldest age onwards (Taylor et al., 2007).

Growth

The growth function is a simplified version of the Von Bertalanffy growth equation, defined in Begley (2004) as the LengthVBSimple Growth Function (*lengthvbsimple*). Length increase for each length group of the stock is given by the equation below:

$$\Delta l = (l_{\infty} - l)(1 - e^{k\Delta t}), \quad (\text{A.1})$$

where Δt is the length of the timestep, $l_\infty = 19cm$ is the terminal length and k is the growth rate parameter.

The corresponding increase in weight of the stock is given by:

$$\Delta w = a((l + \Delta l)^b - l^b), \quad (\text{A.2})$$

with $a = 2.9e^{-5}$ and $b = 3.3438$ set as fixed and extracted from Millán (1999). The growth functions described above calculate the mean growth for the stock within the model. In a second step the growth is translated into a beta-binomial distribution of actual growths around that mean with a parameter β to be fitted by the model as described in Taylor et al. (2007).

Initial abundance and recruitment

Stock population in numbers at the starting point of the simulation is defined as:

$$N_{a,l,1,1} = 10000\nu_a q_{a,l}, \quad a = 0, \dots, 3, l = 3, \dots, 20$$

Where ν_a is an age factor to be calculated by the model and $q_{a,l}$ is the proportion at lengthgroup l that is determined by a normal density with a specified mean length and standard deviation for each age group. Mean length at age and standard deviation was extracted from the age-length key calculated with Powell-Weterall methods in Bellido et al. (2000), the standard deviation was chosen as the same for all age groups and equal to the maximum standard deviation (1.5). The mean weight at age for this initial population is calculated by multiplying the reference weight corresponding to the length by a relative condition factor assumed as 1. Reference weight at length $l = 3, 3.5, \dots, 20$ was approximated with an exponential fit ($w = 6.74e^{-4}e^{0.23 \cdot l}$) using data from length at age (Seasonal Von Bertalanffy growth Bellido et al. (2000)) and transforming them to weight with the formula $w = al^b$, $a = 0.0038$ and $b = 3.19$ for individuals from 1-10 months old and $a = 2.9e^{-5}$, $b = 3.3438$, for individuals older than 10 months (Millán, 1999). In Gadget files this was specified as a normal condition distribution (*Normalcondfile*).

Similarly to the process to calculate the initial abundance described above, the recruitment specifies how the stock will be renewed. Recruits for $t = 3, 4$ and $t = 1, 2$ enter to the age 0 and age 1 population, respectively, as follows:

$$N_{0,l,y,t} = p_{l,t} R_{y,t}, \quad t = 3, 4, l = 3, \dots, 15,$$

and

$$N_{1,l,y,t} = p_{l,t} R_{y,t}, \quad t = 1, 2, l = 3, \dots, 15,$$

where $R_{y,t}$ represents recruitment at year y and quarter t , and $p_{l,t}$ the proportion in lengthgroup l that is recruited

at quarter t which is sampled from a normal density with mean (μ) and standard deviation (σ_t) calculated by the model. The mean weight for these recruits is calculated by multiplying the reference weight corresponding to the length by a relative condition factor assumed as 1. Reference weight at age was the same used to calculate the initial population mean weight at age explained above. In gadget files this was specified also as a normal condition distribution (*Normalcondfile*).

Natural mortality

In the simulation, natural mortality is simply modelled as the proportion of the stock that is removed due to these additional causes from each age group, on each timestep, as follows:

$$N_a = e^{-M_a \Delta t}, \quad (\text{A.3})$$

where M_a represents natural mortality at age. In the model it was assumed as constant with $M_0 = 1.17$ and $M_1 = 0.43$. These values were derived from anchovy mortality in the Alboran Sea (Giráldez et al., 2009) while the values for M_2 and M_3 were chosen high enough to be consistent with catches at age data, where individuals older than two years are rarely found.

Fleet operations

In the model the fleets act as predators. There are three fleets inside the model: two for acoustic surveys (ECOCADIZ and PELAGO) and one for commercial landings (purse-seine fleet). Acoustic surveys fleets are assumed to remove 1 *Kg* in each of the quarters when the surveys take place. Commercial fleet is assumed to remove a number of individuals each quarter based on reported total landings (extracted from ICES reports). Catches are simulated based on these data available for the fleets and a length based suitability function that splits the total amount landed by surveys (in biomass, totalfleet) and the commercial fleet (in numbers, numberfleet) between the length groups, according to equations A.4 and A.5 respectively, as follows:

$$C_{l,y,t} = \frac{E_{y,t} S_{l,T} N_{l,y,t} W_l}{\sum_l S_{l,T} N_{l,y,t} W_l}, \quad (\text{A.4})$$

and

$$C_{l,y,t} = \frac{E_{y,t} S_{l,T} N_{l,y,t}}{\sum_l S_{l,T} N_{l,y,t}}, \quad (\text{A.5})$$

where $E_{y,t}$ represents biomass landed (in *Kg*) at year y and quarter t in equation A.4 and numbers landed in equation A.5, W_l corresponds to weight at length and $S_{l,T}$ represents the suitability function that determines the proportion of prey of length l that the fleet is willing to consume during period $T, T = 1, 2$, where $T = 1$

corresponds to the period 1988-2000 and $T = 2$ to 2001-2015. Splitting the suitability into these two periods corresponds to minimum landing size restrictions effectively applied to the fishery from 2001.

For this model the suitability function is specified in Gadget manual as an ExponentialL50 function (*expsuit-funcl50*), and it is defined as follows:

$$S_{l,T} = \frac{1}{1 + e^{-4\alpha_T(l-l_{50,T})}} \quad (\text{A.6})$$

where $l_{50,T}$ is the length of the prey with a 50% probability of predation during period T and α_T a parameter related to the shape of the function, both parameters are estimated from the data within the Gadget model. The whole model time period (1988-2015) has been split into two different periods for suitability parameters because of changes in minimum landing size regulation for the fishery around 1995 that become effective around 2001.

A.2. Observation model

Data are assimilated by Gadget using a weighted log-likelihood function. The model uses as likelihood components three biomass survey indices (ECOCADIZ, PELAGO and SAR), age - length distributions from two surveys (ECOCADIZ and PELAGO) and one commercial fleet (purse-seine) and mean length at age distribution from that commercial fleet (see Table A.2 for an overview of the likelihood data used in the model).

Data source	type	Timespan	Likelihood function
Commercial landings	Length distribution	All quarters, 1988-2015	See eq. A.8
	Age distribution	All quarters, 1988-2015	See eq. A.8
	Mean length at age of landings	All quarters, 1988-2015	See eq. A.11
ECOCADIZ survey	Biomass survey indexes	Second quarter 2004, 2006	see eq. A.7
	Age-length distribution	third quarter 2007, 2009, 2010, 2013 and 2014	see eq. A.8
		Second quarter 2004, 2006	
PELAGO survey	Biomass survey indexes	third quarter 2007, 2009, 2010, 2013 and 2014	see eq. A.7
		First quarter 1999, 2001-2003	
	Age-length distribution	second quarter 2005-2010 and 2014	see eq. A.8
SAR survey	Biomass survey indexes	First quarter 1999, 2001-2003	see eq. A.7
		second quarter 2005-2010, 2013 and 2014	
		Last quarter 1998, 2000, 2001, 2007 and 2012	see eq. A.7

Table A.2: Overview of the likelihood data used in the model

Biomass Survey indices

The survey indices are defined as the total biomass of fish caught in a survey. The survey index is compared to the modelled abundance using a log linear regression with slope equal to 1 (*fixedslope loglinearfit*), as follows:

$$\ell = \sum_t (\log(I_{y,t}) - (\alpha + \log(N_{y,t})))^2 \quad (\text{A.7})$$

where $I_{y,t}$ is the observed survey index at year y and quarter t and $N_{y,t}$ is the corresponding population abundance calculated within the model. Note that the intercept of the log-linear regression, $\alpha = \log(q)$, with q as the catchability of the fleet (i.e $I_{y,t} = qN_{y,t}$).

Catch distribution

Age-length distributions are compared using l lengthgroup at age a and time-step y, t for both, commercial and survey fleets with a sum of squares likelihood function (*sumofsquares*):

$$\ell = \sum_y \sum_t \sum_l (P_{a,l,y,t} - \pi_{a,l,y,t})^2 \quad (\text{A.8})$$

where $P_{a,l,y,t}$ is the proportion of the data sample for that time/age/length combination, while $\pi_{a,l,y,t}$ is the proportion of the model sample for the same combination, as follows:

$$P_{a,l,y,t} = \frac{O_{a,l,y,t}}{\sum_a \sum_l O_{a,l,y,t}} \quad (\text{A.9})$$

and

$$\pi_{a,l,y,t} = \frac{N_{a,l,y,t}}{\sum_a \sum_l N_{a,l,y,t}}, \quad (\text{A.10})$$

where $O_{a,l,y,t}$ corresponds to observed data.

When only length or age distribution is available. It is compared using equation A.8 described above but considering all ages or all lengths, respectively.

Catch statistic

Mean length at age for commercial fleets are compared using an unweighted sum of squares of mean length likelihood function (*lengthnostddev*):

$$\ell = \sum_y \sum_t \sum_a ((x_{a,y,t} - \mu_{a,y,t})^2 N_{a,y,t}) \quad (\text{A.11})$$

where $x_{a,y,t}$ is the sample mean weight from the data for the timestep/age combination, $\mu_{a,y,t}$ is the mean length at age calculated from the model for the same combination and $N_{a,y,t}$ is the number of individuals for the same combination.

Understocking

If the total consumption of fish by all the predators (fleets in this case) amounts to more than the biomass of prey available, then the model runs into "understocking". In this case, the consumption by the predators

550 is adjusted so that no more than 95% of the available prey biomass is consumed, and a penalty, given by the
 551 equation A.12 below, is applied to the likelihood score obtained from the simulation (Stefansson, 2005).

$$\ell = \sum_t U_t^2 \quad (\text{A.12})$$

552 where U_t is the understocking that has occurred in the model for that timestep.

553 *Penalties*

554 The BoundLikelihood likelihood component is used to give a penalty weight to parameters that have moved
 555 beyond the bounds in the optimisation process. This component does specify the penalty that is to be applied
 556 when these bounds are exceeded.

$$\ell_i = \begin{cases} lw_i(val_i - lb_i)^2 & \text{if } val_i < lb_i \\ uw_i(val_i - ub_i)^2 & \text{if } val_i > ub_i \\ 0 & \text{otherwise} \end{cases}$$

557 Where $lw_i = 10000$ and $uw_i = 10000$ are the weights applied when the parameter exceeds the lower and
 558 upper bounds, respectively, val_i is the value of the parameter and, lb_i and ub_i are the lower and upper bounds
 559 defined for the parameter.

560 *Iterative re-weighting*

561 The total objective function is a weighted sum of all likelihoods components. The weight for each component is
 562 determined with an iterative process following the approach presented in Taylor et al. (2007) and in the appendix
 563 of Elvarsson et al. (2014) based on the iterative reweighting scheme of Stefánsson (1998) and Stefansson (2003),
 564 which is summarized as follows:

Let $\mathbf{w}_r$ be a vector of length L with the weights of the likelihood components (excluding understocking and penalties) for the run r , and $SS_{i,r}, i = 1, \dots, L$, the likelihood score of component i after run r . First, a Gadget optimization run is performed to get a likelihood score ($SS_{i,1}$) for each likelihood component assuming that all components have a weight equal to one, i.e., $\mathbf{w}_1 = (1, 1, \dots, 1)$. Then, a separated optimization run for each of the components (L optimization runs) is performed using the following weight vectors:

$$\mathbf{w}_{i+1} = (1/SS_{1,1}, \dots, (1/SS_{i,1}) * 10000, 1/SS_{i+1,1}, \dots, 1/SS_{L,1}), i = 1, \dots, L.$$

Resulting likelihood scores $SS_{i,i+1}$ are then used to calculate the residual variance, $\hat{\sigma}_i^2 = SS_{i,i+1}/df^*$ for each

component, that is used to define the final weight vector as

$$\mathbf{w} = (1/\hat{\sigma}_1^2, \dots, 1/\hat{\sigma}_L^2).$$

Degrees of freedom df^* is approximated by the number of non-zero data points in the observed data for each component.

A.3. Fit to data

How well the model fits to age and length data were used as a validation procedure. Model outputs for length and age distributions are presented in Figures A.2 and A.3.

Please note that a complete model validation would require to setting up a larger experiment for simulations of input data or bootstrapping.

A.4. Forecasting

It was necessary to modify the internal structure of `gadget.forward` function to include different recruitment assumptions. The modified function can be found at https://github.com/mmrinconh/gadgetanchovy/blob/master/Anchovy79/gadget_forward_mod_scenarios.r.

B. Reproducibility

Here we summarize the procedure to follow in order to reproduce this document. We assume that the reader have already installed R and Rstudio.

1. Install the package *knitr* in R following the instructions given in <https://cran.r-project.org/web/packages/knitr/index.html>
2. Follow the L^AT_EX installation guide available at <https://www.latex-tutorial.com/installation/> according to your operating system.
3. Unzip the 'Reproducible.zip' file available as Supplementary Material and open the Rnw file ('Rincon_et_al_MS_rep.Rnw') with Rstudio.
4. Click on the 'Compile PDF' button which is located on the top left of the screen. This step will produce a set of files, among them a pdf file (.pdf) which is an exact copy of this document.

Figure A.2: Comparison between observed and estimated catches age distribution. Grey lines represent observed data while black lines represent estimated data.

Figure A.3: Comparison between observed and estimated catches length distribution. Grey lines represent observed data while black lines represent estimated data