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The potential use of a Gadget model to predict stock responses to climate change in combination with Bayesian networks: the case of Bay of Biscay anchovy

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The European anchovy (*Engraulis encrasicolus*) is a short-lived pelagic species distributed in Atlantic European waters, with the Bay of Biscay being one of the main centres of abundance. Because it is a short-lived species, the state of the stock is determined largely by incoming recruitment. Recruitment is highly variable and depends on a variety of factors, such as the size of the spawning stock and environmental conditions in the area. The use of a coupled model that could serve to predict the evolution of the anchovy stock in the short, medium, and long term under several fishing-pressure scenarios and given climate scenarios is demonstrated. This coupled model consists of a Gadget (Globally Applicable Disaggregated General Ecosystem Toolbox) model that was used to analyse the status of the Bay of Biscay anchovy population and to simulate future scenarios based on the estimated recruitment levels, combined with a probabilistic Bayesian network model for recruitment estimation based on machine-learning methods and using climatic indices as potential forecasting factors. The results indicate that certain combinations of medium to high fishing pressure and adverse environmental conditions could force the stock outside its biological reference boundaries.

Keywords: anchovy, Bay of Biscay, Bayesian networks, climate, Gadget, recruitment.

Introduction

Biological characteristics

The European anchovy (*Engraulis encrasicolus*) is distributed in Atlantic European waters, but is now considered to be concentrated mainly in two well-separated areas: the Bay of Biscay and the Gulf of Cadíz (Uriarte *et al.*, 1996; ICES, 2008). Some residual coastal populations also exist off the Iberian coast and in the English Channel, Celtic Sea, and North Sea (Beare *et al.*, 2004; ICES, 2007b).

The European anchovy is one of the most important pelagic species in the Bay of Biscay ecosystem, along with sardine (*Sardina pilchardus*), mackerel (*Scomber scombrus*), and horse mackerel (*Trachurus trachurus*). Anchovy spawn each year in the Bay of Biscay during spring (Furnestin, 1945; Cort *et al.*, 1976; Arbault and Lacroix-Boutin, 1977; Lucio and Uriarte, 1990; Motos *et al.*, 1996), and spawning takes place mainly in areas of increased biological production potentially, such as river plumes, shelf and shelf-break fronts, and oceanic gyres (Motos *et al.*, 1996). Spawning is generally limited to the French and Spanish coasts (south of 46°30′N and east of 5°W). Early juvenile stages start schooling as early as August and are found during summer and autumn in the southeastern part of the Bay of Biscay (Cort *et al.*, 1976; Uriarte and Motos, 1991). Interannual variations of anchovy abundance and distribution are important, but the relationship between their recruitment and stock size is not obvious (Massé, 1996; Uriarte *et al.*, 1996, 2002; ICES, 2001).

The fishery

As for many areas of the world with extensive clupeoid fisheries (Blaxter and Hunter, 1982), anchovy has been one of the most important species for Spanish and French fleets operating in the Bay of Biscay. Both the economy of the fleets and the cultural roots of the surrounding countries have been largely conditioned by its availability. The Spanish fleets targeting anchovy consist only of purse-seiners that operate mainly during spring in ICES Divisions VIIIb and VIIIc (Figure 1). In contrast, French catches are mainly made by pairtrawlers, but some purse-seiners still operate in the area. The pairtrawler fishery starts at the beginning

Figure 1. Map illustrating the ICES Areas: the Western European coast (from www.ices.dk).

of the year, and the major fishing areas are Divisions VIIIa and VIIIb in the first and second halves of the year, respectively (ICES, 2008). Pairtrawlers are not allowed to fish in Division VIIIc [European Union (EU), 1998]. French purse-seiners, conversely, operate mainly in coastal water during spring, but their catches are not regular, because their target species is sardine (ICES, 2008).

Total landings of anchovy have fluctuated over time, peaking during the 1960s (~83 000 t) and at a minimum level in 2004 (<10 000 t), just before the closure of the fishery in July 2005, because of the collapse of the stock. This fluctuation in time, from 1960 to 2010 and disaggregated by country, is displayed in Figure 2.

Historical assessment and management of the stock

The stock is assessed annually in June by ICES, delivering short-term management advice to the European Commission (EC). It is evaluated using a Bayesian two-stage biomass-based model (Ibaibarriaga *et al*., 2008), where the population dynamics are described for biomass with two distinct age groups, recruits or fish aged 1 year and fish that are 2 or more years old. For these purposes, several sources of fisheries-independent information are required; they are obtained from different surveys in the Bay of Biscay. The population is monitored by two annual spring surveys of the spawning stock: the daily egg production method (DEPM) and the French acoustic (PELGAS: Campagne PELagiques GAScogne) surveys have been done regularly since 1989. Both surveys provide spawning biomass and population-at-age estimates. There is an additional acoustic survey (JUVENA: juvenile anchovy acoustic survey), which has been done in autumn since 2003, but it remains under evaluation (ICES, 2008; ICES, 2009b) and has not been used for this study.

Following the advice given by ICES in June 2009, the EC retained the closure of the fishery until the end of 2009. In December 2009, the EC made the same proposal for keeping the fishery closed until June 2010. However, the Council of Fisheries Ministers of the EU that met in December 2009 decided to reopen the fishery for 2010 with a provisional total allowable catch (TAC) of 7000 t. This decision was undertaken after the national governments received indications that a better level of recruitment was entering the population during autumn 2009.

The coupled model

Because it is a short-lived species, the anchovy population depends strongly on annual recruitment, which in turn depends on environmental conditions. It is known that environmental

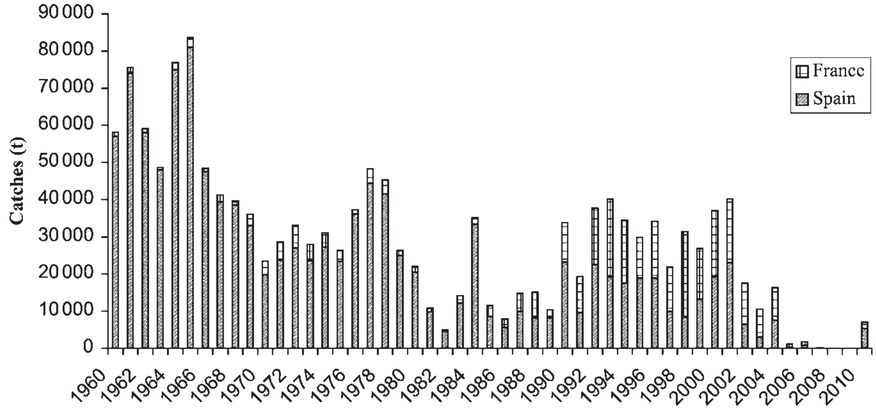

Figure 2. Historical international landings of European anchovy by country and year since 1960.

conditions and climate play an important role in the recruitment of fish, in particular of short-lived fish species (Cushing, 1982; Baumgartner *et al.*, 1992; Alheit and Hagen, 1997; Brunel and Boucher, 2007; Borja *et al.*, 2008). Successive recruitment failures since 2002 related to unfavourable environmental conditions in combination with certain other factors (fishing pressure, changes in the pelagic ecosystem, etc.) are believed to have been possible causes for the depletion of the stock (ICES, 2008). Therefore, the use of environmental and climate information to improve recruitment predictions could contribute considerably to fishery management (Schirripa and Colbert, 2005; Planque and Buffaz, 2008).

Many studies using different techniques have been undertaken to utilize such environmental information to forecast recruitment (Chen and Ware, 1999; Bailey *et al.*, 2005; Dreyfus-León and Chen, 2007; MacKenzie *et al.*, 2008; Ruiz *et al.*, 2009). Changes in global and local environmental indices have also been described for the Bay of Biscay, such as the North Atlantic Oscillation (NAO) index and Polar Eurasia and East Atlantic patterns (ICES, 2007a; Borja *et al.*, 2008), as well as upwelling and stratification indices (Borja *et al.*, 1998; Allain *et al.*, 2001).

Modelling tools need to be robust for management purposes, and that is exactly the purpose of this study. Recruitment forecasting is problematic because of the great uncertainty (Mäntyniemi *et al.*, 2009). Machine-learning techniques have been proposed as an appropriate approach with desirable properties to address uncertainty (Dreyfus-León and Chen, 2007; Uusitalo, 2007; Dreyfus-León and Schweigert, 2008; Fernandes *et al.*, 2010) in combination with expert knowledge. In particular, probabilistic methods provide estimates of the uncertainty associated with predictions, as demonstrated by Fernandes *et al.* (2010). The goal of the current study was to couple the recruitment model proposed in Fernandes *et al.* (2010) with a fisheries population model (implemented with the Globally Applicable Disaggregated General Ecosystem Toolbox: Gadget, http://www.hafro.is/gadget). This coupled model aims to simulate the anchovy population dynamics based on forecast environmental and climate variables. The tool could prove to be valuable in predicting stock status in the long term and therefore meet the EU's obligations to promoting long-term sustainable fishing (EU, 2002; Daw and Gray, 2005) and to supporting international agreements such as the precautionary approach to fishing (FAO, 1995).

Gadget was developed to simulate complicated marine ecosystems, taking into account both the relationships between the ecosystem components and the effect of human activities on them. The toolbox has been applied in many ecosystems, mainly for single-species modelling, but also with some multispecies examples (Taylor and Stefánsson, 2004; Lindstrøm *et al.*, 2009). It has also been adopted recently by the ICES Benchmark Workshop on Roundfish (WKROUND) and the ICES Benchmark Workshop for Deep-Sea Species (WKDEEP) as the assessment model for the evaluation of the southern stock of hake (ICES, 2010b) and the tusk stock in Icelandic waters, respectively (ICES, 2010a). Although Gadget has been used thus far only for single-stock assessments and this study follows that trend, it could nevertheless represent a step towards multispecies modelling in the Bay of Biscay.

Material and methods

The anchovy population analysed is the one concentrated in the Bay of Biscay area (Figure 1). The area extends from 48°N to 44°30′N and from 11°W to the coastlines of France and northwestern Spain, corresponding biogeographically to a subtropical–boreal transition zone, as classified by the OSPAR Commission for the Protection of the Marine Environment of the Northeast Atlantic (OSPAR, 2000).

A probabilistic recruitment model for anchovy

A methodology proposed in Fernandes *et al.* (2010) builds a probabilistic model (Langley *et al.*, 1992) in which three levels of anchovy recruitment (low, medium, and high) could be forecast, based on a subset of climate or environmental indices. The methodology permits identification of the boundaries of those recruitment levels, based on the method of Fayyad and Irani (1993), in addition to a small set of climatological variables with low cross-correlation, which are all highly correlated with recruitment, based on the method of Hall (2000).

A subset of climatological variables was selected by Fernandes *et al.* (2010) from a large set of possible driving or forecasting variables: a composed climate variable from global teleconnection indices (CLI1; Bode *et al.*, 2006; Fernandes *et al.*, 2010) and the local environmental indices in the Bay of Biscay: upwelling (Borja *et al.*, 1998; Allain *et al.*, 2001) and north–south winds (Irigoien *et al.*, 2007; Fernandes *et al.*, 2010). Note that CLI1 is the first component of the principal component analysis of global climate indices: NAO; East Atlantic pattern; East Atlantic–Western Russia pattern; Scandinavia pattern; Tropical–northern hemisphere pattern; Polar/Eurasia pattern. These indices reveal sufficient forecasting power to distinguish between three levels of anchovy recruitment (Fernandes *et al.*, 2010). To produce a possible future scenario for climate change, most of these factor values have been simulated randomly from 2009 to 2020, as is often done with weather generators (Gutiérrez *et al.*, 2004): the value of a year is based on random variation in the value in the previous year within the average and limits of past observed values. However, other climate scenarios could be considered, and it is hoped that further research on climate models will allow the use of more reliable climate scenarios in a few years [Marine Ecosystem Evolution in a Changing Environment (MEECE), EU project contract no. 212085].

Initially, the spawning-stock biomass (SSB) provided by the assessment working group (ICES, 2008) was considered as a predictive variable for the recruitment model. However, the methodology followed here discards that information, which is coherent with the reproductive strategy of a short-life species, based on spawning thousands of eggs per individual (Motos, 1996). It is also coherent with the observed historical data in Figure 3 (SSB and recruitment data for anchovy in the Bay of Biscay), where very different SSB levels have produced a great variety of recruitment levels for different years. Some of these examples have been highlighted with an ellipse in the figure. However, although the SSB has not been introduced as a predictive variable in the model, it has been considered a limiting factor by setting a minimum SSB needed to achieve feasible recruitment for the species (the SSB could not be equal to zero at any point).

The methodology provides probabilistic estimates of a limited number of recruitment levels (low, medium, and high, i.e. discrete recruitment values), which is appropriate for decision-making. However, actual point estimates (recruitment values on a continuous scale) are sometimes needed, such as for integration with Gadget models. In this context, it would be valuable to be able to provide a predictive continuous distribution of recruitment, but maintaining the properties of the model proposed by Fernandes *et al.* (2010). This could be accomplished with the climate factors selected using that methodology, but using original continuous values of recruitment and climate factors, as well as a "naive Bayes for regression" paradigm (Frank *et al.*, 2000) instead of "naive Bayes with discretized variables". The "naive Bayes for regression" paradigm is based on the kernel density estimation paradigm (Silverman, 1986; Wand and Jones, 1995; Pérez *et al.*, 2009).

A single-species anchovy model using Gadget

The internal structure of Gadget and various potential submodels and options available are described in detail in the Gadget User's Guide (Begley, 2004) and in the Overview of Gadget (Begley and Howell, 2004).

As a first step, Gadget simulates the population forward, taking into account both the biological actions in the populations and the interaction between them. Gadget has a number of possible biological functions for each characteristic that can be implemented in the model, as described in the Gadget User's Guide (Begley, 2004). The way the program deals with all these functions is presented in the overview of Gadget (Begley and Howell, 2004), and the functions used in the current model are described below.

As a fisheries model, a submodel in Gadget must also simulate the fleet. A Gadget "fleet" can be treated as a simplified predator, implying that it is a "stock" with a single age group and a single length group, but which does not grow, mature, migrate, recruit, or reproduce. The only process a fleet contributes to within the submodel is the consumption of a portion of the stock biomass, i.e. removing biomass from prey stocks.

The second step in Gadget is to compare the simulated system with the available data ("real" or observed data), making the model statistically testable. These data are deemed "likelihood data" and each dataset used is assigned to a "likelihood component", specifying the statistical relationship to be used when comparing simulation results with the observed data. The data used as likelihood components depend on data availability and the aim of the model. Gadget allows the use of a variety of datasets, from both commercial fisheries and scientific surveys (e.g. length distributions, age–length keys, and survey abundance indices; Taylor *et al.*, 2007). These likelihood components are described in detail in the Gadget User's Guide (Begley, 2004), and information about how they work and the statistical functions used is available in the overview of Gadget (Begley and Howell, 2004). All the components and data used in this study are described in detail below.

The last step in the Gadget approach is the estimation of parameters using one or more algorithms to optimize parameter

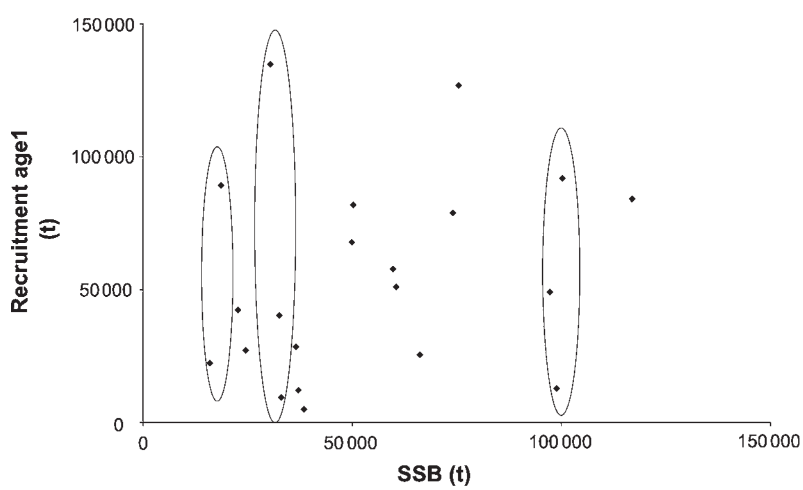

Figure 3. Relationship between SSB and recruitment at age 1 for European anchovy in the Bay of Biscay. The ellipses are the examples of why SSB is not very efficient at predicting recruitment.

values iteratively, i.e. those that give the lowest negative log-likelihood score for the given case study. This overall negative log-likelihood score gives a measure of how well the resulting model fits the data used as likelihood components. Three search algorithms are implemented in Gadget: Hooke and Jeeves (1961), simulated annealing (Corana *et al.*, 1987), and BFGS (Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; Shanno, 1970). These algorithms can be used either on their own or by combining them into a single hybrid algorithm (Begley, 2004).

The anchovy model runs from 1987 to 2008 in quarterly time-steps and covers only a single area: the Bay of Biscay, which corresponds to ICES Divisions VIIIa, b, and c. The main model period starts in 1994, with earlier years acting as a lead-in period to the model. The model simulates the anchovy population from age 1 (recruitment) to age 4, which is considered to be a plus group. The length range considered is 11–21 cm, aggregated in 0.5 cm intervals. Growth is assumed to follow a von Bertalanffy (1938) equation:

$$\frac{\mathrm{d}L}{\mathrm{d}t} = K(L_\infty - L(t)), \quad t \in \mathbf{R}^+, \tag{1}$$

and

$$L(t) = L_\infty(1 - \mathrm{e}^{-Kt}), \quad t \in \mathbf{R}^+, \tag{2}$$

where L is the length at time t, L_∞ the asymptotical maximum length, and K the growth rate. Note that $\mathbf{R}^+$ denotes the real positive numbers. The growth parameters L_∞ and K have not been estimated by Gadget, but have to be calculated outside the Gadget model, using data obtained from real observations (A. Uriarte, unpublished data; $L_\infty = 21.0$ cm and $K = 0.8$). This information was already available for this species in the database and, to avoid over-parametrization of the model, it was introduced directly into the parameters file. Natural mortality is accepted as constant, using the value used by the assessment working group ($M = 1.2$; ICES, 2008). To develop the ecosystem over time, Gadget requires the addition of the youngest modelled age group. One way to do this is to add recruits annually into the youngest age group of the stock. This recruitment is calculated by the Gadget model each year from 1987 to 2008. From 2009 to 2020, recruitment values are simulated using the probabilistic recruitment model. Because this model gives a single number for the recruitment each year, these numbers are then introduced directly as fixed parameters in the Gadget model, to simulate forward the population dynamics until 2020. Note that this forecast recruitment series has been recalculated using the historical series given by the Gadget model, trying to follow the precautionary approach principle (FAO, 1995).

As a fisheries model, a submodel in Gadget must also simulate the fleet(s). A Gadget "fleet" could be a commercial fleet or a survey. As mentioned in the previous subsection, this fleet is treated as a simplified predator (it neither grows, matures, migrates, recruits, nor reproduces), consuming a portion of the stock biomass and operating in a single area: the Bay of Biscay. In this case, we considered one international commercial fleet and two surveys.

The results of a simulation are then compared with the available data (observed data), making the model statistically testable. As mentioned before, Gadget allows the use of a variety of datasets, both from commercial fisheries and from scientific surveys. In this case, observed length distributions from the commercial fleet and the surveys were used.

There are two types of likelihood component in the model—note that the names of the likelihood components have been taken directly from the Gadget User's Guide (Begley, 2004).

1. *Catch distribution*: used to compare distribution data sampled from the model and distribution data sampled from landings or survey. These data come from an international commercial fleet and two surveys. The commercial fleet contains all the French and Spanish vessels operating throughout the study area and targets all age groups. The two annual surveys, DEPM and PELGAS, are carried out on the spawning stock, providing estimates of spawning biomass and population-at-age. The preference of the fleet for prey from a specific length group L is implemented in the model with a suitability function (selectivity pattern of the fleet). In this case, the selectivity pattern of the commercial fleet follows an exponential L_{50} suitability function, defined by the following equation:

$$S_{P,p}(L) = \frac{1}{1 + \mathrm{e}^{-4\alpha(L - L_{50})}}, \tag{3}$$

where L_{50} is the length where fish have reached 50% selectivity, and α is a slope constant to be estimated. This selectivity pattern varies between seasons and is estimated by the model.

Although taken as a total international fleet, containing French and Spanish vessels, the selectivity parameters of that fleet are allowed to change quarterly. The modelled selectivity pattern is displayed in Figure 4, where it is evident that for the first time-step (called PSE1 in the figure), the model assumes a constant suitability pattern, although it was forced to use the L_{50} suitability function (selecting parameter values for the L_{50} function that result in an approximation to a flat line). This indicates that all existing length ranges are caught by the fleet operating in the study area from January to March. Moving into April, the situation changes, and only fish larger than a certain length will be caught by the fleet. Note that PSE2 refers to the fleet that operates during the second quarter of the year; PSE3 refers to the fleet that operates during the third quarter, etc.

The selectivity pattern of the surveys was assumed to be constant over all lengths:

$$S_{P,p}(L) = \alpha, \tag{4}$$

where $\alpha = 1$.

The function used to make the comparisons is the sum of squares:

$$\ell = \sum_{\text{time}} \sum_{\text{ages}} \sum_{\text{lengths}} (p_{\text{taL}} - \pi_{\text{taL}})^2, \tag{5}$$

where p is the proportion of the observed data sample, and π is the proportion of the modelled data sample, both for a time–age–length combination [denoted using the subscript taL in the above equation]. Note that, because there is no spatial structure implemented in the model, Equation (5) does not contain a spatial component.

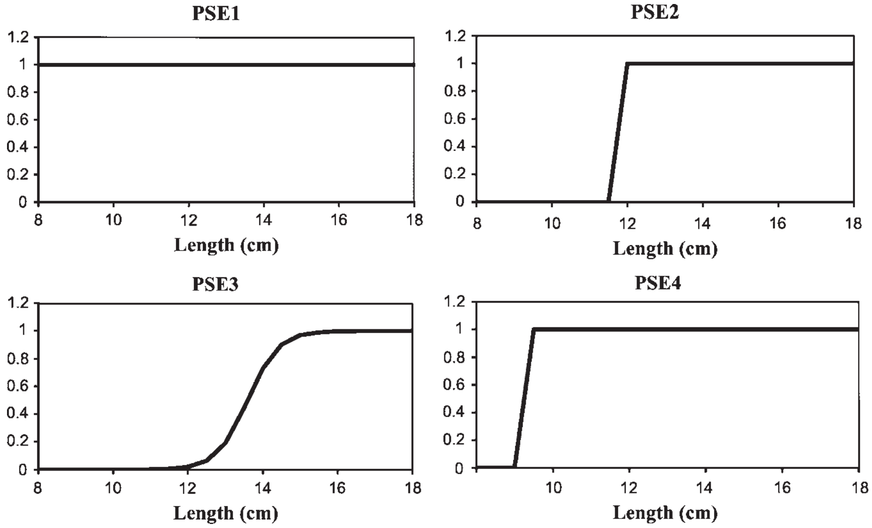

Figure 4. Selectivity pattern of the commercial fleet estimated by the Gadget model. Each panel corresponds to the selectivity pattern of the fleet operating at each time-step of the model, PSE1 being the fleet of the first time-step, PSE2 the one corresponding to the second time-step, PSE3 corresponds to the third time-step, and PSE4 to the fourth one.

2. *Survey indices*: used to compare survey abundance data with the simulation. The likelihood score is then calculated as

$$\ell = \sum_{\text{time}} (I_t - (\alpha + \beta \hat{I}_t))^2, \quad (6)$$

where I is the survey index, $\hat{I}$ the corresponding index calculated in the Gadget model, and α and β the intercept and the slope of the linear regression, respectively. In this study, the slope of this regression is fixed at 1, and the intercept is calculated as a parameter in the model. Here, only a single type of survey index was used (Taylor *et al.*, 2007), namely the survey indices by age for the two survey datasets.

Finally, optimization in the iterative reweighting scheme involves the sequential use of the simulated annealing, BFGS, and Hooke and Jeeves algorithms. Note that both sets of likelihood (catch and survey) have the same weight in the overall likelihood score.

The initial values that Gadget needs for both the recruitment each year and the initial population in the first year of the model are chosen arbitrarily, the only constraints being that there should be sufficient fish in the system (Taylor *et al.*, 2007).

Results

Implementing the probabilistic recruitment model for anchovy provided a long recruitment time-series for anchovy (hindcast simulation) that matches reasonably well with the available data, both from the official assessment group and from the new Gadget model. This is clear in Figure 5, where three estimated recruitment time-series have been plotted.

As in Fernandes *et al.* (2010), there is notable periodicity in recruitment that coincides with the trend in some of the forecasting variables, particularly with component CLI1. Based on this evidence and the results displayed in Figure 5, semi-random forecast simulations were carried out to predict recruitment levels in the long term from the Gadget time-series (Figure 6). The definition of "long term" depends on the species lifespan; therefore, for a short-lived species like anchovy, we considered that 10 years (or three generations) constitute "long term", consistent with that used by the group of experts that defined the long-term management plan (LTMP) for anchovy (STECF, 2008) and that used in other related studies (Rademeyer *et al.*, 2007). Figure 7 shows the time-series of climate indices (i.e. the forecasting factors of the new recruitment model) from 1987 to 2020. The forecast simulation of these variables, from 2009 to 2020, was calculated following the methodology of Gutiérrez *et al.* (2004). Two points were highlighted in each of the time-series, corresponding to the large recruitments predicted for 2012 and 2018.

The results of this recruitment model have been introduced into the single-species Gadget model that simulates the anchovy population from 1987 to 2008. Based on those recruitment data, some projections have been plotted from 2009 to 2020 under different fishing pressure scenarios. Figure 8 shows the historical trend in fishing mortality (F) since 1990, as estimated by the Gadget model. The major decrease in fishing pressure is clear in this figure, and it corresponds to the decrease in SSB levels, displayed in Figure 9. Although the fishery officially closed in July 2005, the catch levels of the earlier years were very low, with values very close to zero for 2004 (Figures 10–12). Note that this catch level was estimated by the Gadget model based on the individuals removed from the system by all fleets, i.e. accounting for the total removals caused by all commercial fleets and surveys. Although the total number of vessels has decreased (ICES, 2008), total fishing effort in the past decade (until 2005) was higher than during the 1980s and the first years of the 1990s (STECF, 2008). In addition, there are explicit indications in the literature regarding the effort that the fishers made just before the closure of the fishery (ICES, 2005). This means that fishing effort had been high up to the closure of the fishery and that the reduction in catch before the closure could not be ascribed to any reduction in effort.

Anchovy mature at age 1, so the entire population in this study could be considered mature (age 0 was not included in the model). Figure 9 shows that the anchovy population was below its precautionary limit (B_{pa}) from 2004 and that it declined below B_{lim} in the past year, although the fishery was closed. Note that B_{lim} is the

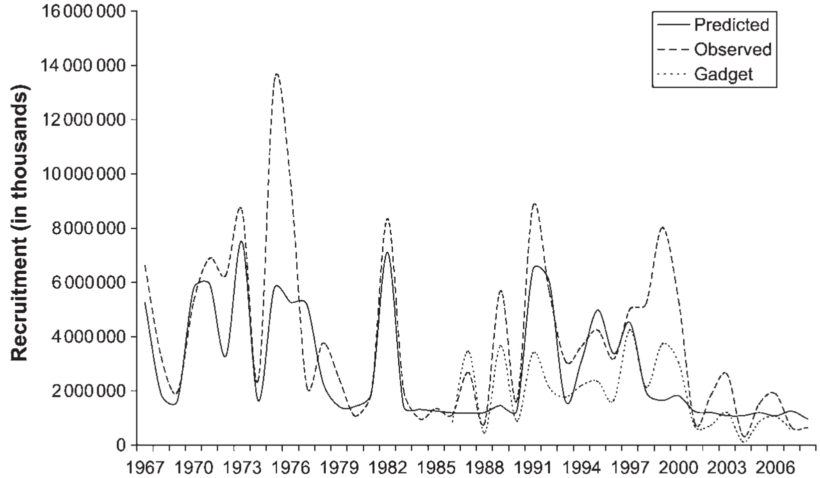

Figure 5. Historically observed recruitment values in biomass (dashed line) compared with the values simulated by the new recruitment model (solid line) and the recruitment time-series estimated by Gadget as the predictive variable (dotted line).

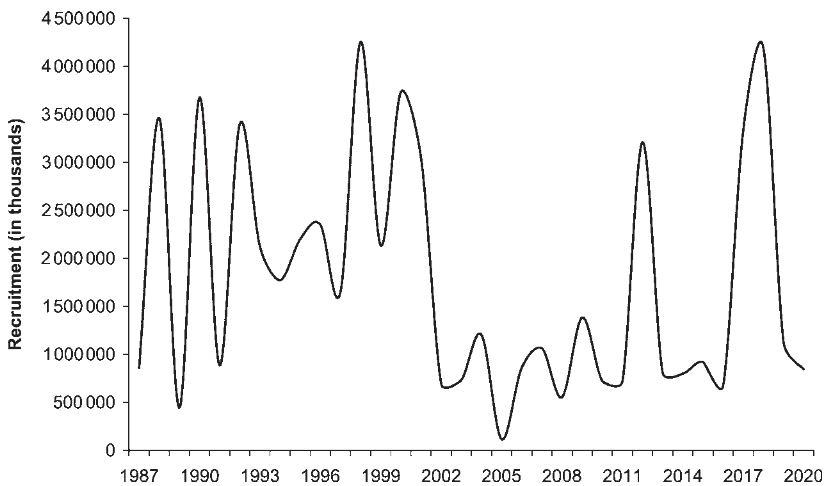

Figure 6. Long-term recruitment predictions from the new recruitment model.

limit reference point for biomass, i.e. the SSB below which there is a substantial increase in the probability of obtaining reduced (or "impaired") recruitment. Below B_{lim}, there is a greater risk that the stock could collapse. Given that anchovy are short-lived, this B_{lim} equals B_{loss}, which is the lowest observed spawning stock size (ICES, 2003) and was estimated as 21 000 t by the assessment working group (ICES, 2004). However, the spawning biomass can only be estimated with uncertainty. Therefore, more conservative reference points are required, and ICES defines B_{pa} as the biomass level where some management action to protect the stock must be taken, the precautionary reference point for biomass (Hauge *et al.*, 2007), which is derived from B_{lim} and is always higher than B_{lim} ($B_{\text{pa}} = B_{\text{lim}} \times 1.645$; ICES, 2004). The value 1.645 corresponds to a probability of 5% of the stock actually being below B_{lim} when a stock is estimated to be at B_{pa}. The B_{pa} for anchovy in the Bay of Biscay is estimated at 33 000 t (ICES, 2004).

Examination of the recruitment simulations indicates that the decrease in SSB coincided with a period of low recruitment (Figure 5). Based on the predictions for recruitment, Figure 10 shows what the evolution of this population could be under a low–medium fishing pressure scenario ($F = 0.3$), consistent with continuing the exploitation levels experienced in 2010. In the SSB graph of Figure 10, we can see that this catch level would result in a slight recovery of the population, because it coincides with a high-recruitment year. However, if this fishing pressure is kept constant and the catch level increases consequently, the population could decline again in a period of low recruitment.

In a scenario of greater fishing pressure, for example, by increasing the F to 0.5 (which is relatively low, compared with the historical average), it is evident from Figure 11 that the population would decline below the precautionary limit after each low recruitment period. However, this would not be evident by examining only the catch level, which could probably be at the same levels they were just before the closure of the fishery. The evaluation process in use at that time was not examining the environmental conditions, and it was based only on the SSB level of the preceding year. According to some earlier studies (Schirripa and Colbert, 2005; ICES, 2009a), SSB is not a key factor, nor even relevant, for a recruitment forecast. In fact, as explained above, it has

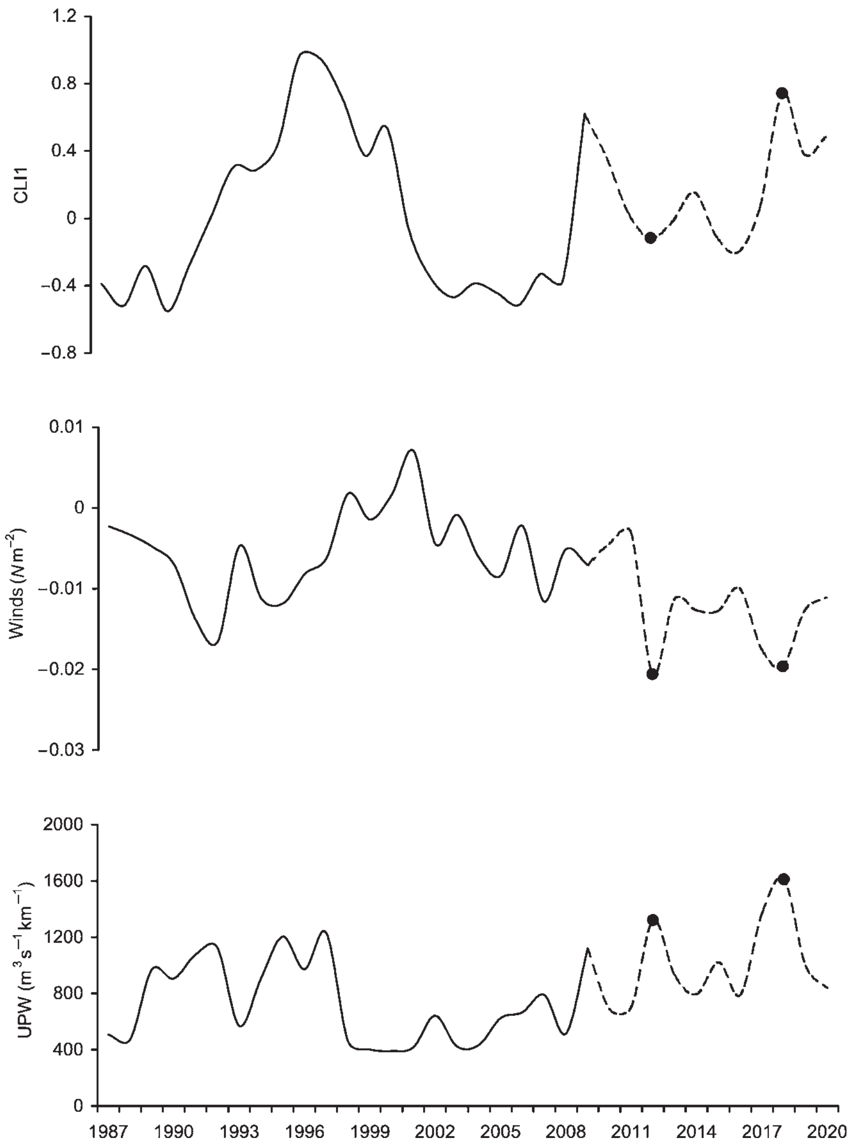

Figure 7. Global and local environmental and climatic components variability from 1987 to 2020: the upper panel illustrates the temporal variability of the CLI1 index; the middle panel illustrates the temporal variability of the winds in the study area; and the lower panel corresponds to the upwelling index. For the first period, from 1987 to 2008, the time-series is derived from the literature; for the second period (from 2009 to 2020), the time-series is from a semi-random simulation, such as usually done in weather generators (Gutiérrez *et al.*, 2004). The points highlighted in all the forecast-simulated time-series correspond to the years 2012 and 2018.

not been included as a predictor in the recruitment model, but as a limiting factor aiming at forcing the model to obtain a zero recruitment value if the SSB is zero.

If the fishing pressure increases to values comparable with the first years of the time-series ($F = 0.9$), where the fishery was at its maximum level, it is evident (Figure 12) that whenever there is a period of low recruitment, the stock declines below its precautionary limits. However, total catch levels, although they also decline considerably, would not indicate poor condition of the stock.

Discussion

Development of an LTMP is one of the main goals of current fishery management science. However, predicting population dynamics of a short-lived species is non-trivial. In addition to the variables traditionally used in assessment, such as details of the fishery and stock biology, a consideration of the environmental and climate conditions is required.

The current study demonstrates a coupled model that could be used to reach this goal, trying to link the population dynamics of European anchovy with global and local environmental and climate variables that have been associated with the recruitment of European anchovy in the Bay of Biscay. The robustness of the methodology for selection of environmental factors for forecasting anchovy recruitment proposed in the first study of Fernandes *et al.* (2010) was verified in a second study developed for the ICES Benchmark Workshop on Short-lived species (WKSHORT) in 2009 (ICES, 2009a). In the latter, several modifications were made to the database: the anchovy recruitment time-series was recalculated, more candidate factors were added, and some of

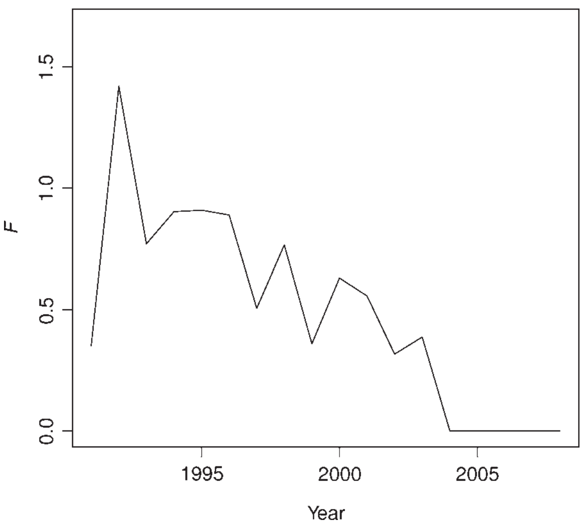

Figure 8. Fishing mortality values simulated by the anchovy single-species Gadget model.

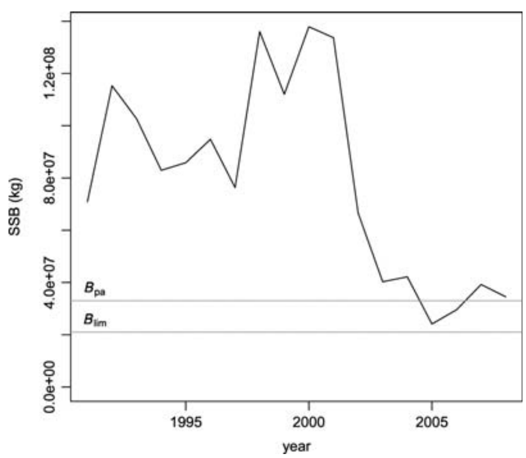

Figure 9. SSB time-series simulated by the Gadget model. Biological reference points are also indicated.

the factors earlier used in the estimation procedure were removed, because they were no longer available. However, some of the same factors have been selected (upwelling and CLI1), or they have been replaced by one similar to that eliminated from the analysis. This was the case for the ICOADS N–S wind annual mean (45°N 3°W) that was replaced by the FNMOC N–S windstress annual mean (45°N 2°W), which was not considered earlier. The results in both studies are similar, even after incorporating new data, indicative of the robustness and stability of the methods used.

To validate the new recruitment model better, a leave-one-out cross-validation (LOOCV) scheme was used (Monsteller and Tukey, 1968). This technique involves using a single observation from the original sample as the validation data, and the remaining observations as the training data: each observation is predicted using a model computed using the rest of the data. The result of this LOOCV analysis demonstrates that the performance of this model is quite good (Figure 5).

In earlier sections, it was noted that the recruitment time-series chosen as an observed variable in the recruitment model was the one estimated by Gadget, instead of the one estimated by the assessment model. The Gadget time-series and the one modelled with the current assessment model display similar trends; both time-series seem to be correlated, but the absolute values are different: the absolute values estimated by Gadget are lower than those estimated using the current assessment model (Figure 5). In fact, the calculated correlation factor is quite high ($r^2 = 0.88$). Based on that, it may be concluded that under the precautionary approach (FAO, 1995), the recruitment estimated by Gadget could be more suitable than the official one; therefore, this one was selected for the current study. The combination of using this time-series with the inclusion of new predicting factors (i.e. the global and local environmental and climatic variables in this case) will result in a more conservative assessment and consequently in a more sustainable management of this natural resource. Furthermore, it is noticeable that using the recruitment time-series predicted with the recruitment data estimated by Gadget as the observed variable allows avoidance of the big differences in the large-recruitment estimations provided by the official assessment model and the recruitment model for the final years of this period (Figure 5). This difference might be caused by the way recruitment is estimated in each approach: recruitment is calculated depending on the biomass level for each year and without taking into account any climatological variables, whereas in the recruitment model the approach is totally different, as mentioned in the earlier sections.

The final recruitment dataset introduced in the Gadget model as the initial point to simulate the population dynamics is displayed in Figure 6. As mentioned before, during the estimation of this dataset (in the recruitment model), the SSB of the preceding year was only considered a limiting factor, not allowing the model to calculate any recruitment if this SSB value equalled zero. This value could be changed for each case study; because of the uncertainty in the determination of a stock–recruitment relationship for this study, this was chosen as the best option here (there was very high recruitment after very low SSB levels and *vice versa* in the historical time-series; Figure 3).

Focusing on the recruitment time-series (Figure 6), it is noticeable that in the forecast simulated period (from 2009 to 2020), there are two points where recruitment levels are very high, and they condition and determine the dynamics of the stock under any fishing scenarios (Figures 10–12). These two points correspond to 2012 and 2018, which have also been highlighted in Figure 7, where the climate index time-series have been plotted. Careful examination of Figures 6 and 7 makes it clear that these periods of high recruitment match a combination of very high values of the upwelling index and very low values for the north–south wind index, which in fact correspond to the local environmental indices. In contrast, the relation with the CLI1 component (the global environmental variable included in this study) is not clear: for 2012, the value of this index is close to zero, whereas for 2018 it is high, but not the highest. This suggests that the local environmental variables are those that affect the recruitment levels of this species in the Bay of Biscay, whereas the global variables apparently control the general trend in recruitment, as suggested by earlier studies (Fernandes *et al.*, 2010).

The conclusions all emphasize the sensitivity of this short-lived species to the environment and climate of the study area. In fact, after examining the changes in the stock dynamics under the

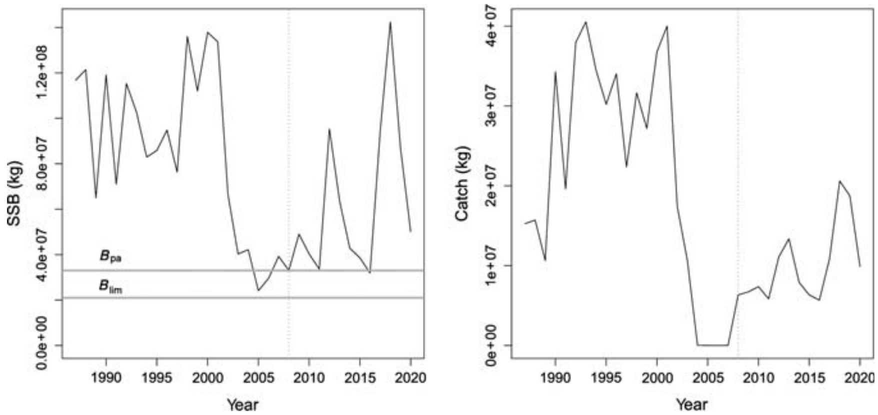

Figure 10. Simulated stock dynamic parameters in a low-medium fishing pressure scenario ($F = 0.3$). The left panel displays the SSB, whereas the right panel illustrates the variability in the catches.

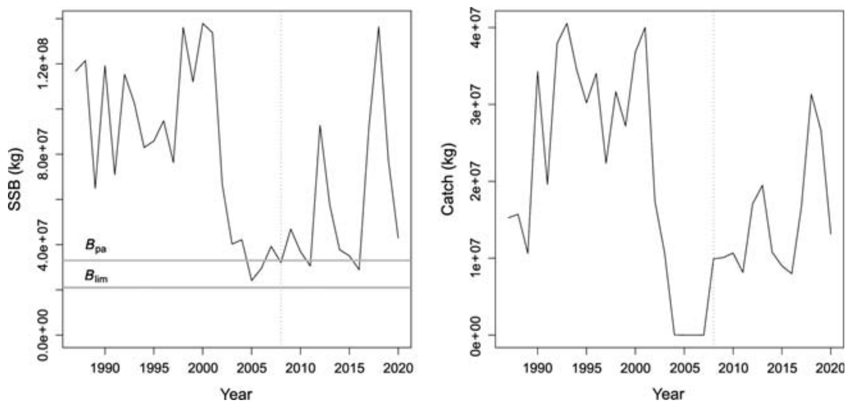

Figure 11. Simulated stock dynamic parameters in a medium fishing pressure scenario ($F = 0.5$). The left panel displays the SSB, whereas the right panel illustrates the variability in the catches simulated.

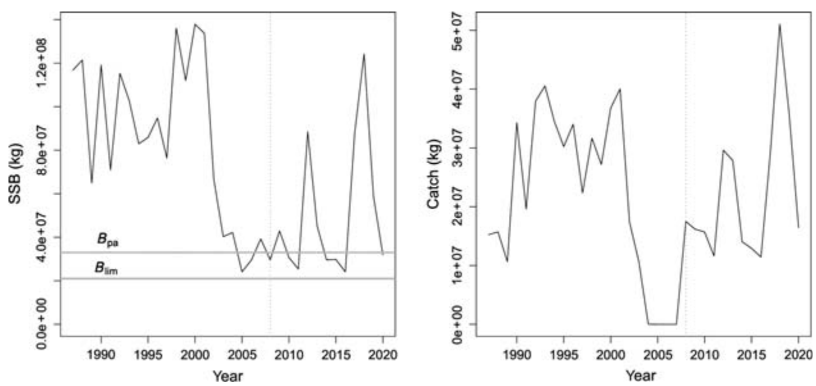

Figure 12. Simulated stock dynamic parameters in a high fishing pressure scenario ($F = 1.0$). The left panel displays the SSB, whereas the right panel illustrates the variability in the catches simulated.

different scenarios, it seems that fishing pressure is no longer a conditioning factor, even if it might be crucial under unfavourable environmental and climate conditions. However, because of the impossibility of controlling environmental and climate variables, management of fishing effort becomes essential to avoid depletion of the stock. Hence, it will be necessary to bear this in mind during the assessment of this stock, avoiding, for instance, any increases in TAC based only on the improvement in the observed status of the stock.

The results of this study also highlight the need for more accurate data to improve the models used in the study, especially data related to the prediction of real climate scenarios in the Bay of

Biscay. This issue is currently being addressed within the framework of several national and international projects, such as the MEECE European project. In fact, and because of the high dependence of the status of this anchovy stock on climate and environmental conditions, the generation of more realistic climate scenarios will be key outcomes in obtaining sensible and reasonable predictions for the dynamics of this stock.

In addition to the uncertainty about future climate and environmental conditions, the use of a fisheries population dynamics model also implies the assumption of several uncertainties, which might arise not only from random sampling errors in the data, but also from model formulation, bias in data collection, misreporting of catches, and deviations from the agreed harvest control rules. One way to measure and assess these uncertainties might be a tool developed by Howell and Bogstad (2010), where the Gadget model has been linked to assessment models available from Fisheries Libraries in R (Kell *et al.*, 2007) and management rules, to allow a full forward simulation of the interacting stocks in the Barents Sea.

Conclusions

This study demonstrates how a coupled model such as the one presented here allows for forecasting the evolution of the stock in the long term, based on the combination of the variables most commonly used in assessment and the climate and environmental conditions of the study area. The study is based on semi-random variation in these conditions, and it could be extended to use the real variation in the environmental and climatic variables, downscaled from the projections already available for global climate parameters. All these results demonstrate that the coupled model used herein could be useful in evaluating the anchovy population in a more realistic way. They also indicate that this approach might be a good tool for short-lived species generally, i.e. those that depend largely on the environmental conditions of the surrounding areas. Moreover, it could also be used for species such as hake, although not linked to environmental conditions to a similar extent as anchovy; hake recruitment has been demonstrated to be highly dependent on such conditions (Fernandes *et al.*, 2010).

This study should be considered as a first step towards sustainable exploitation of the Bay of Biscay ecosystem, because in addition to providing a tool for long-term management, it is also a first step towards developing a tool that might provide advice for sustainable multispecies management. One extension of the current study would be to join this model with a similar one for northern hake and linking them using the trophic relationships identified between the two species in the study area (Mahe *et al.*, 2007; Velasco, 2007), producing a multispecies Gadget model where anchovy is consumed by hake in the Bay of Biscay. Once a multispecies model has been fitted and reasonable results have been obtained, they might also be ready for use as a multispecies operating model for management strategy evaluation (MSE; Howell and Bogstad, 2010). The MSE approach has already been used in the analysis of these two stocks, also including economic considerations in the analysis. However, there has never been an attempt to implement the multispecies relationships between them, and it might prove interesting to ascertain how this relationship might affect the management procedure of the stocks. Parallel effort should be made in simulating the local and global environmental variables that are currently being studied, and several climate models are being developed aimed at deriving climate scenarios soon that are more realistic. The expected result might well be a good proxy for the integrated assessment that European member states need to develop following the Marine Strategy Framework Directive (MSFD) to achieve Good Environmental Status (GES) in European marine waters by 2020. This might well provide a complete toolbox that will link some of the current efforts to move towards sustainable use of available resources of our ecosystem.

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