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Enhancing the utility of known-biomass production models: a case study of the Bay of Biscay and Iberian Coast ecoregion

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Summary: Our general purpose is to support the use of known-biomass production models (KBPMs), illustrating their usefulness by addressing the evolution of surplus production (SP) over time and the factors affecting it (e.g. environment). We also demonstrate the utility of KBPMs for multispecies management objectives or for estimating maximum sustainable yield reference points without a stock recruitment function, among other worthwhile applications. To do so, we present different uses of KBPMs, illustrating their application on demersal species in the International Council for the Exploration of the Sea (ICES) area, specifically for megrim, white anglerfish and European hake stocks. The proposed analytical approach involved fitting single-species and multispecies KBPMs, conducting retrospective analyses and assessing the effects of environmental variability on SP. The findings show that, in general, stock SP increased after a decline in biomass and SP, except for white anglerfish in the southern area. Megrim stocks are the least productive, while hake and northern anglerfish are the most productive. Retrospective analysis revealed SP shifts in northern hake stock for reasons other than biomass variability. Hence, the North Atlantic Oscillation and the Atlantic Multidecadal Oscillation (AMO), two key climate variability modes in the North Atlantic, were tested for their links to SP, revealing a positive connection between SP and AMO, although further research is necessary. Beyond the specific results of our particular KBPM application, our main conclusion is that KBPMs can serve as a tool complementary to more complex assessment models for resolving unaddressed issues and crosschecking available assessment results.

Keywords: KBPMs; stock assessment models; environmental effects; biological reference points; multispecies; surplus production evolution.

Realzando la utilidad de los modelos de producción de biomasa conocida: un caso de estudio en la Ecorregión del Golfo de Vizcaya y la Costa Ibérica

Resumen: Nuestro objetivo principal es promover el uso de los modelos de producción de biomasa conocida (KBPMs, por su sigla en inglés), destacando su utilidad para abordar la evolución de la producción excedente (SP, por sus siglas en inglés) a lo largo del tiempo y los factores que inciden en ella, como los aspectos ambientales. También demostramos la utilidad de los KBPMs en objetivos de gestión multiespecífica o en la estimación de puntos de referencia vinculados al rendimiento máximo sostenible, prescindiendo de una relación stock-reclutamiento, entre otras aplicaciones de interés. Con este propósito, se exponen diversos usos de los KBPM, ejemplificándolos a través de su aplicación en especies demersales de la zona ICES (International Council for the Exploration of the Sea), específicamente en las poblaciones de gallo, rape blanco y merluza europea. El enfoque analítico propuesto implica el ajuste de KBPM monoespecíficos y multiespecíficos, la realización de análisis retrospectivos y la evaluación de los efectos de la variabilidad ambiental en la SP. Los resultados muestran que, en términos generales, la SP de los *stocks* ha experimentado un aumento después de una disminución en la biomasa y la SP, con la excepción del rape blanco en la zona sur. Las poblaciones de gallo muestran la menor productividad, mientras que las de merluza y rape del norte son las más productivas. El análisis retrospectivo revela cambios en la SP del *stock* de merluza norte debidos a razones distintas a la variabilidad en la biomasa. Por lo tanto, se exploró la relación entre la Oscilación del Atlántico Norte (NAO) y la Oscilación Multidecenal del Atlántico (AMO), dos modos clave de variabilidad climática en el Atlántico Norte, y se identificó una relación positiva entre la SP y la AMO. No obstante, es necesario continuar con investigaciones adicionales para comprender completamente este comportamiento. Más allá de los resultados específicos derivados de nuestra aplicación de los KBPM, nuestra conclusión principal es que los KBPM pueden constituir una herramienta complementaria a modelos de evaluación más complejos, tanto para resolver cuestiones no abordadas como para cotejar con los resultados de evaluación disponibles.

Palabras clave: KBPM; modelos de evaluación de *stocks*; efectos medioambientales; puntos de referencia biológicos; multiespecies; evolución de la producción excedentaria.

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INTRODUCTION

Populations of marine resources have recently undergone many changes in their size, abundance, biomass and spatial distribution. In order to understand the population dynamics of these resources, marine scientists have proposed statistical and mathematical models called stock assessment models. These models allow us to analyse population dynamics and see the effect of any perturbations (Beverton and Holt 1957). This analysis leads to a decision about whether a particular effort or catch level is sustainable for a given future time (Hilborn and Walters 1992). When addressing management objectives, it is of crucial interest to define the desirable states for a fishery in terms of target reference points.

Data-rich stock assessment models such as the Globally Applicable Area-Disaggregated General Ecosystem Toolbox (GADGET), stock synthesis (SS), Assessment for All (a4a) and virtual population analysis require adequate knowledge of the biology and exploitation levels of the studied stock, historical time series of catches structured by age or length, and fishing effort by gear and sector, among other inputs. However, this kind of information is usually deficient or inadequate for the vast majority of stocks. This is why recent years have seen great interest in the use and development of new methods to ascertain the situation of data-poor stocks (Chrysafi and Kuparinen 2015, Pennino et al. 2022, Cousido-Rocha et al. 2022a). In particular, the International Council for the Exploration of the Sea (ICES) Workshop on the Development of Quantitative Assessment Methodologies based on Life-history Traits, Exploitation Characteristics and other Relevant Parameters for Data-limited Stocks (WKLIFE), (ICES 2015) identified and discussed three categories of data-limited approach: (1) length-based methods, (2) catch-only methods, and (3) methods based on catch and catch-per-unit-effort (CPUE) or on other fishery-independent biomass indices. This third group of methods is represented by surplus production (SP) models, which are the only data-limited method that provides an evaluation of exploitation and stock status based on maximum sustainable yield (MSY) reference points, and catch predictions based on alternative scenarios (Cousido-Rocha et al. 2022b). In current practice, SP models are extensively used for the assessment of data-limited/moderate stocks of different fish species because they are the simplest analytical models for stock assessment, including all aspects of production in a single function (Prager 1992). The minimum data necessary to estimate the parameters of these models are the time series of an index of relative abundance (derived from a scientific survey or CPUE), and the associated catch data (Pedersen et al. 2017, Winker et al. 2018).

Based on SP models, an alternative line of research called known-biomass production models (KBPMs) was developed from the idea that, for an unfished stock, the calculation of annual SP is the difference between the biomass in one year and the previous one (MacCall 2002). KBPMs are an alternative to traditional production models (Schaefer 1957, Prager 1992), which use a time series of known biomass (i.e. biomass estimates produced by a data-rich stock assessment model) instead of historical fishing effort or indices of relative biomass, such as CPUE, to avoid estimation of a catchability coefficient to relate the abundance index to a true (inferred) abundance. Therefore, KBPMs calculate SP from the known biomass and observed catches.

These models relate aggregate measures of annual SP (the amount of production available to be fished each year without changing the biomass of the stock) to the current total biomass and provide estimates of MSY and related reference points (Jacobson et al. 2002, MacCall 2002). The main characteristic of KBPMs is that they require a prior model adjustment, which provides a historical biomass series. This raises a first question about their usefulness: If we already have a model that defines the stock status, what does this alternative provide?

Despite requiring a prior model adjustment, KBPMs can be a useful tool not only for crosschecking the available assessment results but also for dealing with other scientific questions related to the evolution of SP over time and the factors (e.g. environmental ones) that affect it, multispecies management objectives and estimation of MSY reference points without a stock recruitment function, among other worthwhile applications (Jacobson et al. 2002, Mueter and Megrey 2006, Bundy et al. 2012). More precisely, KBPMs give the chance to explore the evolution of SP over time and factors that affect it, such as biomass, offering a view on whether the change in biomass can be explained only by catches or whether similar biomass levels provide similar surplus production over time. They can also serve as a diagnostic tool for whether stock collapse has been caused by overfishing or by a previous decline in SP for reasons other than biomass decline (Hilborn 2001, Jacobson et al. 2001, Walters et al. 2008). Additionally, KBPMs have been used for the estimation of MSY biological reference points (BRPs). SP model parameters are based on known biomass and catches, so MSY reference points can be calculated from the production model parameter estimates. KBPMs provide an estimation of MSY reference points without a stock recruitment function, providing a valuable crosscheck to assess the sensitivity of the results of stock-recruitment models such as MSY, fishing at MSY (F_{msy}) and biomass at MSY (B_{msy}) (Jacobson et al. 2002, MacCall 2002, Sparholt et al. 2021).

KBPMs have also proven their usefulness for multispecies management objectives. A KBPM approach has been applied to analyse the dynamic of total aggregated biomass and catch of all targeted fish species in a community, thus defining a simple data-limited ecosystem model to assess ecosystem status (Bundy et al. 2012, Mueter and Megrey 2006).

In addition, KBPMs can be complemented with environmental factors to explain variations in production arising from factors other than biomass (Bundy et al. 2012). Some KBPMs that include environmental and biological covariates have been used to consider that marine ecosystems are dynamic and, hence, their overall productivity depends on multiple drivers related to climatic, anthropogenic and ecological influences (Mueter and Megrey 2006).

Finally, KBPM formulations can also be used to perform a sensitivity analysis. For example, Hilborn (2001) conducted a sensitivity analysis of the catchability coefficient by exploring the consequences of different biomass values, which, in turn, become different catchability coefficient estimates.

Despite these useful applications of KBPMs, very few studies implement this approach in practice. Perhaps this is because the scientific community has not yet realized the potential of these models. Our primary objective is to contribute to the scientific community by providing a comprehensive review of KBPMs, highlighting their advantages and illustrating their use in three different demersal species: two megrim (*Lepidorhombus whiffiagonis*) stocks, two white anglerfish (*Lophius piscatorius*) stocks, and two European hake (*Merluccius merluccius*) stocks in the Bay of Biscay and Iberian Coast ecoregion. The second aim is to take advantage of the KBPM results for these demersal species to achieve a better understanding of the species dynamics.

The proposed analytical approach consists of (1) a single-species KBPM fit; (2) for stocks that show possible production changes in the individual KBPM fits, a retrospective analysis to determine whether such changes have arisen for reasons other than biomass variability; (3) implementation of multispecies KBPMs; and (4) analysis of the possible effects of environmental variables on stock status. Hence, this analytical approach covers important topics for both present and future applications of the KBPM approach.

MATERIALS AND METHODS

Case study: modelling commercial stocks in the Bay of Biscay and Iberian Coast ecoregion

The study area includes the ICES subareas 3–4 and 6–9, covering the Iberian Peninsula and Bay of Biscay ecoregion and the Celtic Sea ecoregion (ICES 2021). Overall, these ecoregions are characterized by marked seasonal mixing and a stratification of water masses typical of temperate seas. Modifications to this pattern may be due to wind-driven upwelling, river runoff and tidal processes, which increase the system's productivity with large variations across the region (ICES 2021). Habitats far from the coast are shaped by the influence of Atlantic waters in the Bay of Biscay and western Iberia (Abad et al. 2020).

The target species studied were megrim (*Lepidorhombus whiffiagonis*), white anglerfish (*Lophius piscatorius*) and European hake (*Merluccius merluccius*). These species are generally targeted together in a mixed fishery and have traditionally been considered of great commercial importance for fishing because of their high economic value.

All species are widely distributed throughout Atlantic shelf waters, and the selected stocks are assessed by the ICES in two units, northern and southern stocks, which are the ones we used in our study.

Dataset

Data were obtained from the ICES database (https://www.ices.dk) through the *icesSAG* package (Colin et al. 2022) of R software (R Core Team 2021). Indeed, this package allows access to the web services of the ICES database and download of the required data directly in R. For this study, spawning stock biomass (SSB, in tonnes) and annual catches (in tonnes) were collected for each stock for the time period reported in Table 1.

In order to test the potential effect of environmental variability on stock dynamics, we used two indices: the Atlantic Multidecadal Oscillation (AMO) and the North Atlantic Oscillation (NAO). The AMO is a long-term climatic variability index, which is defined as the North Atlantic sea surface temperature anomaly between Greenland and the Equator. The AMO provides an ongoing series of long-duration changes in sea surface temperature of the North Atlantic Ocean, with cool and warm phases that may last for 20 to 40 years at a time (Kerr 2000, Enfield et al. 2001). Its inclusion allows us to address longer-term variations that can influence fish population dynamics. We also included the NAO index in our study because it is one of the major sources of climate variability in the northern hemisphere (Hurrell 1995). The NAO serves as a comprehensive representation of the winter maritime climate (e.g. swell) and the trajectories of storms as they pass over the North Atlantic and therefore has a major influence on wind and precipitation in our region (Hurrell and Deser 2009). We obtained the NAO

Table 1. – List of the stocks analysed in the Bay the Biscay and Iberian Coast ecoregion. The time period for which spawning stock biomass was available is also reported for each stock.

Stock code	Description	Time period
Northern hake	European hake (*Merluccius merluccius*) in subareas 4, 6, and 7, and in divisions 3.a, 8.a–b, and 8.d, Northern stock (Greater North Sea, Celtic Seas and the northern Bay of Biscay)	1978-2021
Southern hake	European hake (*Merluccius merluccius*) in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	1982-2019
Northern anglerfish	White anglerfish (*Lophius piscatorius*) in subarea 7 and in divisions 8.a-b and 8.d (Celtic Seas, Bay of Biscay)	1986-2021
Southern anglerfish	White anglerfish (*Lophius piscatorius*) in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	1980-2021
Northern megrim	Megrim (*Lepidorhombus whiffiagonis*) in divisions 7.b-k, 8.a-b and 8.d (west and southwest of Ireland, Bay of Biscay)	1984-2021
Southern megrim	Megrim (*Lepidorhombus whiffiagonis*) in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	1986-2021

and AMO annual averages from the NOAA (available at https://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml).

Data analyses

For a better understanding of the stock dynamics of the three demersal species considered in the study, the proposed analytical strategy involved four steps: (1) annual SP was calculated and KBPMs were fitted to each of the six stock units listed in Table 1; (2) for the stocks that showed possible production changes in the individual KBPM fit, a retrospective analysis was performed to determine whether such changes had occurred for reasons other than biomass variability; (3) multispecies KBPMs were implemented to analyse the dynamics of the southern and northern communities of the Bay of Biscay and Iberian Coast ecoregion, and also of the global component aggregating both areas; and (4) the AMO and NAO indices were included in KBPMs to assess the environmental influence on stock status for the stocks identified in (2) as experiencing production change caused by factors other than biomass variability.

Known-biomass production models

The only data requirements for SP models with known biomass are the time series for catch and biomass (estimated values of biomass produced by a data-rich stock assessment model). Traditional SP models estimate biomass as "exploitable biomass", that is, as the fraction of biomass accessible to fishing gears based on their selectivity. For production models with a known biomass, estimates of exploitable biomass are not available, but total biomass is available in some cases and SSB is always available. Hence, annual SP is calculated for each stock as:

$$SP_t = SSB_{t+1} - SSB_t + C_t \qquad (1)$$

for $t=1, .., T$, where T is the last year of the catch time series, SSB_t the spawning biomass at the beginning of year t, and C_t the catch during year t. Then, the average annual spawning biomass $\overline{SSB_t}$ that produced SP_t is computed as $\overline{SSB_t} = (SSB_t + SSB_{t+1})/2$. The surplus production–biomass relationship is fitted based on $\overline{SSB_t}$ and SP_t as follows:

$$SP_t = a\,\overline{SSB_t} + b\,\overline{SSB_t}^{\,\nu} + \varepsilon_t, \qquad (2)$$

for $t=1, .., T$, where a, b, and ν are model parameters and ε_t are model residuals that are assumed to be normally distributed. The parameter ν is the shape parameter introduced by Pella and Tomlinson (1969) to allow asymmetry in the SP curve. The asymmetry parameter, ν, is difficult to estimate accurately, so henceforth we assume $\nu=2$, which corresponds to the symmetric SP curve of the Schaefer formulation (1957).

The BRP estimates derived from model (2) are $SSB_0=-a/b$ (where SSB_0 is the maximum value of SSB when SP=0, which is the maximum unfished equilibrium SSB), $SSB_{msy}=SSB_0/2$ (where SSB_{msy} is the value of SSB when SP=MSY), $MSY=aSSB_{msy}+bSSB_{msy}^2$ and $F_{msy} = a/2$. The parameter a is algebraically equivalent to the intrinsic population growth rate in the logistic population growth model (Prager 1992, Jacobson et al. 2002). Finally, the data-rich estimates of SSB and the exploitation rate in the final year were compared with the reference points derived from KBPMs to draw conclusions regarding stock status. These results were crosschecked with the conclusions obtained from the data-rich stock BRPs.

Retrospective analysis

In order to identify possible changes in SP caused by reasons other than biomass variability, a retrospective analysis was performed for the stocks that showed possible population changes in the individual KBPM fits. Retrospective patterns are usually defined as systematic changes in the estimates of assessment model–derived quantities that occur as additional years of data are removed from a stock assessment (Hurtado-Ferro et al. 2015). Here, we performed a retrospective analysis by removing three years at a time (2020-2017-2014-

2011-2008-2005) for northern hake (northern stock 7-8abd), and assessing whether the model fit changed in relation to parameters *a* and *b*. We focus on this stock because, as we will see in the KBPM fit results, it is the one which exhibits a significant, abrupt and sustained change in SP and SSB.

Multispecies KBPMs

Ecosystem-based fisheries management (EBFM) has been proposed as a place-based rather than a species-based management approach (Fogarty 2014) that can account for fishery effects on food web structure and function, biodiversity balance and yield objectives, in addition to improving management in systems characterized by large seasonal, decadal and long-term climate variability, such as the Atlantic Ocean.

One possibility of KBPMs is that they can be easily fitted as multispecies stock assessment models by aggregating each stock biomass and catch time series per year (Bundy et al. 2012). This possibility could allow assessment of the species community, defining ecosystem-level reference points and identifying the ecosystem status following EBFM requirements (Mueter and Megrey 2006). Here, we performed a multispecies approximation, aggregating southern stocks (in Iberian Peninsula Atlantic waters) and northern stocks (northwards) into two components so as to assess these two parts of the ecosystems separately. Additionally, northern and southern stocks were also aggregated into a single component to assess the status of the demersal community.

Despite its simplicity, the KBPM multispecies approach provides estimates of multispecies MSY reference points that are more appropriate than the sum of single-species MSYs, providing an alternative approach to setting limits on overall removals from an exploited species complex (Mueter and Megrey 2006).

Testing environmental variability on stock status

In addition to modelling SP as a function of spawning biomass, we also investigated the relationships between SP and the NAO and AMO environmental indices in order to test whether productivity changes in response to environmental fluctuations for the stocks identified as undergoing a production change caused by reasons other than biomass variability. Environmental effects are modelled as either additive effects (Bundy et al. 2012) or multiplicative effects (Mueter and Megrey 2006) as follows:

Additive model:

$$SP_t = a\,\overline{SSB_t} + b\overline{SSB_t}^{\nu} + cX_{t-lag} + \varepsilon_t \qquad (3)$$

Multiplicative model:

$$SP_t = exp\left(cX_{t-lag}\right)\left(a\,\overline{SSB_t} + b\overline{SSB_t}^{\nu}\right) + \varepsilon_t \qquad (4)$$

for *t=1, .., T*, where X_{t-lag} is the environmental covariate measured in year $t-lag$, where lag is a value selected from the sequence 1, …, n_{lag} according to the highest Pearson correlation among the SP_t and X_{t-lag} time series, and n_{lag} is the maximum number of lags for which it is considered that a correlation may exist. More precisely, Pearson's correlation between X_{t-lag} and SP_t time series for lag from 1 to =4 was computed, and then the was finally set equal to the one corresponding to the highest correlation.

The models were fitted using R software (R Core Team 2021). To fit the non-linear models, we used the *nls* (non-linear least square) function. The R code for the analytical strategy is available at this GitHub repository (https://github.com/IMPRESSPROJECT/Known-biomass-production-models-the-case-study-of-the-Bay-the-Biscay-and-Iberian-Coast-Ecoregion).

Predicted values derived from the original fit without environmental covariables, Equation (2), and from both environmental fits were compared with the observed SP values through the following error measures: mean absolute percentage error (MAPE) and root mean square error (RMSE).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\widehat{SP}_t - SP_t)^2}{T}},$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\left(\frac{(\widehat{SP}_t - SP_t)^2}{SP_t}\right)\right|,$$

where *T* is the total length of the time SP series, $\widehat{SP}_t$ the predicted SP at time *t* and $|\cdot|$ the absolute value function. In addition, we also compared performance of the models according to the Akaike information criterion (AIC).

$$AIC = 2k - 2ln\left(\hat{L}\right),$$

where *k* is the number of estimated parameters in the model and $\hat{L}$ the maximized value of the likelihood function for the model.

RESULTS

Known-biomass production models

The average annual spawning biomass, annual SP and model fit for these data were computed for each individual stock (Fig. 1). According to Walters et al. (2008), several patterns can be identified based on a visual inspection of $\overline{SSB_t}$ and SP_t pairs: (*i*) stationary (production varying randomly around a mean production curve); (*ii*) upward or clockwise hooks–cycles (increasing production and stock followed by a decrease in production and stock, or decreasing production and stock followed by an increase in stock and production); and (*iii*) downward or counterclockwise hooks–cycles (higher production rates during stock declines than during subsequent recoveries).

Northern anglerfish and both hake stocks (southern and northern) show clockwise hooks–cycles. More precisely, when biomass decreases, SP is below expected;

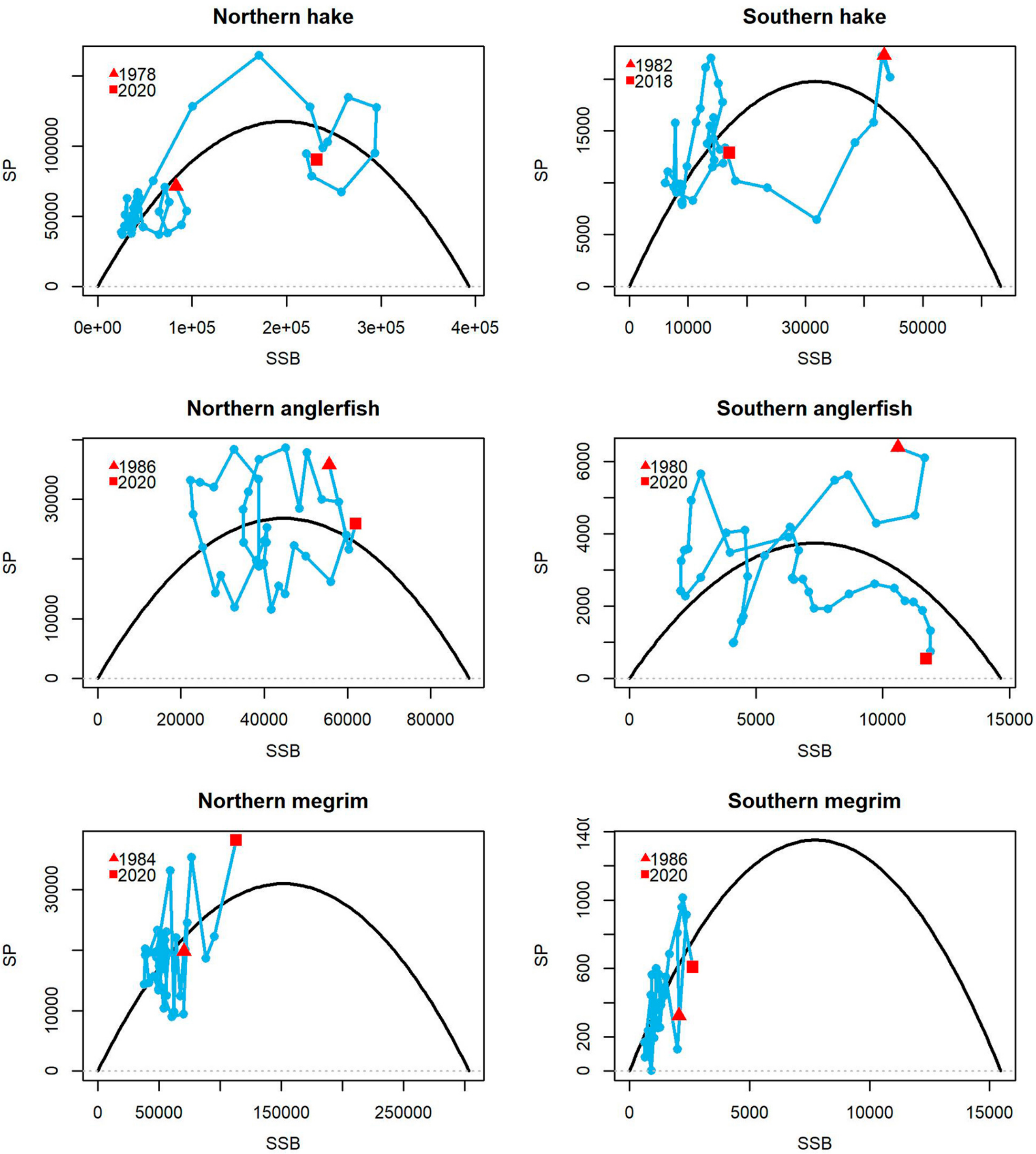

Fig. 1. – Single-species KBPM fits, average annual spawning biomass and annual surplus production for each individual stock.

then, when SP surpasses what is expected, biomass increases again. A counterclockwise hooks–cycle is observed for southern anglerfish; higher production rates during SSB decline were detected from 1980 to 1994, then the general pattern was an increase in SSB and a decrease in SP.

The $\overline{SSB_t}$ and SP_t pairs of the northern and southern megrim correspond to the left side of the symmetric Schaefer curve, which leads us to conclude that the maximum SP in these stocks is estimated with high uncertainty. A clockwise hooks–cycle was observed for northern and southern megrim: when SP was below expected, the SSB decreased until SP crossed the expected value and then SSB increased.

The KBPM fit information (Fig. 1) is completed by the biological reference point estimates derived in Table 2 and the parameter estimates included in the Supplementary Material (Table S1). The comparison of the last year of SSB and F (exploitation rate derived from the prior data-rich stock assessment fit) with the corresponding KBPM reference points (SSB_{msy} and F_{msy}) allows us to discuss the actual stock status compared with BRP independently of a specific stock recruitment function. Additionally, the conclusions derived from the KBPM BRPs can be crosschecked with the data-rich stock assessment outcomes. As mentioned above, this information can be easily obtained using the *icesSAG* package (code available on GitHub repository). For southern and northern megrims and anglerfish, the F value in the last year was below F_{msy} for both estimates (data-rich and KBPM), leading to the same conclusion about their exploitation status. However,

Table 2. – Biological reference points derived from single-species KBPMs and last year of SSB and F data-rich stock assessment estimates. For comparative purposes, the data-rich fishing mortality at maximum sustainable yield (F_{msy}) is also provided.

	KBPMs					Data-rich		
Stock	SSB_0	SSB_{msy}	F_{msy}	MSY	MSY/SSB_0	Last year SSB	Last year F	F_{msy}
Northern hake	393338	196669	0.6	117554	0.3	224675	0.26	0.26
Southern hake	63290	31645	0.62	19765	0.31	16619	0.60	0.25
Northern anglerfish	89240	44620	0.6	26797	0.3	59807	0.23	0.28
Southern anglerfish	14656	7328	0.51	3738	0.26	11802	0.083	0.24
Northern megrim	303858	151929	0.2	31009	0.1	100112	0.14	0.19
Southern megrim	15465	7732	0.17	1351	0.09	2498	0.12	0.19

although both lead to the same final conclusions, it is worth mentioning that for anglerfish the KBPM's F_{msy} is considerably higher than the data-rich one, whereas for megrims both estimates were closer to each other. For northern hake the conclusions obtained from the two approaches do not coincide because the data-rich model concluded that stock is exploited at F_{msy}, whereas KBPM concluded that fishing pressure is considerably below F_{msy}. Finally, for the southern hake stock the F value in the last year was above the data-rich F_{msy} but not above the KBPM F_{msy} value, leading to different conclusions about the fishing pressure applied to this stock.

The MSY/SSB_0 ratio is informative about current stock productivity, and according to the values in Table 2, megrim stocks can be classified as the least productive stocks of those studied, whereas hake (northern and southern) and northern anglerfish are the most productive.

The substantial, abrupt and persistent change in SP and SSB detected in northern hake stock can lead to the hypothesis that, in addition to biomass variability, there are other reasons for this shift, which is why we performed a retrospective analysis of this stock.

Retrospective analysis

A retrospective analysis was performed by removing three years at a time (2020-2017-2014-2011-2008-2005) for northern hake stock (northern stock 7-8abd). Figure 2 reports on the retrospective analysis, Table 3 provides the corresponding reference points, and the Supplementary Material (Table S2) provides the parameter estimates.

The first and second retrospective fits (end of years 2017 and 2014) showed a slight increase in MSY, which was clearer in the third retrospective fit (end of year 2011), with a value of 136261 (an increase of 16% in relation to the value in the 1978-2020 fit), whereas stock productivity remained stable (MSY/SSB_0 around 0.3) and SSB_0 and SSB_{msy} increased. Conversely, the fourth and fifth retrospective fits (end of years 2008 and 2005) showed an increase in productivity (around 60% in relation to the original MSY/SSB_0 value), whereas the corresponding SSB_0 and SSB_{msy} decreased by around 68% in relation to the original fit values (end of year 2020). The retrospective fits lead to the conclusion that from 2005 to 2017 the carrying capacity increased, whereas the relative productivity decreased even though the SSB increased. Consequently, this ret-

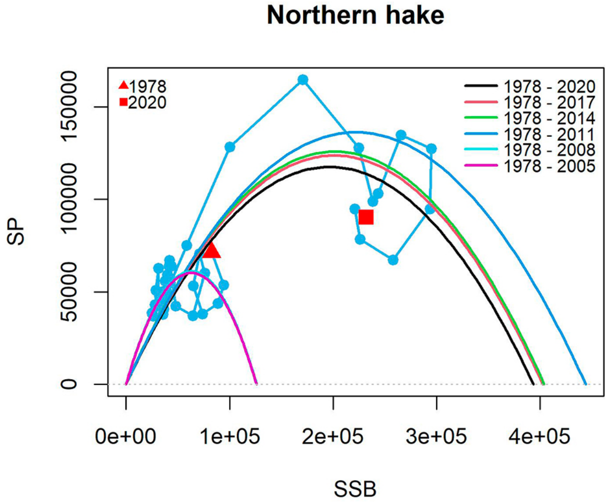

Fig. 2. – A retrospective analysis by removing three years at a time (2020-2017-2014-2011-2008-2005) for northern hake (*Merluccius merluccius*).

Table 3. – Biological reference points derived the retrospective analysis by removing three years at a time (2020-2017-2014-2011-2008-2005) from northern hake.

Time period	SSB_0	SSB_{msy}	F_{msy}	MSY	MSY/SSB_0
1978-2020	393338	196669	0.6	117554	0.3
1978-2017	402399	201200	0.62	123769	0.31
1978-2014	403821	201910	0.62	125868	0.31
1978-2011	443932	221966	0.61	136261	0.31
1978-2008	126068	63034	0.97	60993	0.48
1978-2005	125964	62982	0.96	60236	0.48

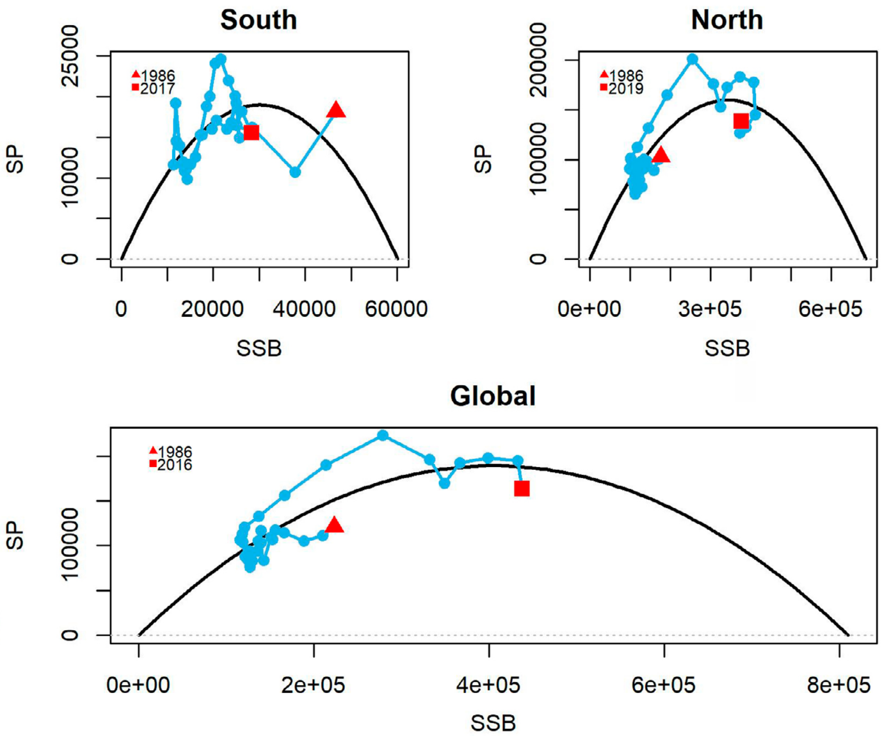

Fig. 3. – Multispecies KBPM fit, average annual spawning biomass and annual surplus production for aggregating stocks in south and north ICES areas, and also in global one component containing both south and north areas.

rospective analysis of the production curve using KBPMs identifies a pattern in the dynamics of the northern hake stock that requires thorough examination to uncover its underlying causes. Step (4) of our analytical approach aimed to investigate whether these variations could be attributable to environmental fluctuations.

Multispecies KBPMs

We conducted a multispecies approximation, aggregating the northern and southern stocks into two components to be assessed separately (Fig. 3, Table 4 and Table S3 in the Supplementary Material). Furthermore, the global area was also analysed through a single component aggregating northern and southern stocks (Fig. 3, Table 4 and Table S3 in the Supplementary Material). This practical usage of KBPM allows the demersal community status to be analysed from an ecosystem point of view. Northern and southern demersal community patterns are clockwise hooks–cycles (decreasing production and SSB followed by an increase in both production and SSB). The global community pattern is clearly determined by the northern community because of its high size in relation to the southern one. Additionally, this simple empirical approach provides multispecies MSY BRPs (Table 4). In particular, based on the MSY/SSB_0 values, it can be concluded that the southern demersal community exhibits greater productivity than its northern counterpart (MSY/SSB_0 values of 0.32 and 0.23, respectively), with the MSY northern community value being approximately eight times that of the southern one (Table 4).

Table 4. – Biological reference points derived for the multispecies KBPMs implemented to analyse the dynamic of the south and north communities of the Bay the Biscay and Iberian Coast Ecoregion. An additional fit was also carried out for the global community (south and north aggregation).

Stock	SSB_0	SSB_{msy}	F_{msy}	MSY	MSY/ SSB_0
South	60121	30061	0.63	18967	0.32
North	686856	343428	0.47	159759	0.23
Global	810366	405183	0.47	189143	0.23

Testing the environmental variability in stock status

The relationship between SP and the NAO and AMO environmental variables was investigated for northern hake because drivers of production changes in marine fish communities can include climate forcing. The scatter plot between the values of SP and the environmental covariates at different year lags from 1 to 4 was derived and the corresponding correlation was calculated (Fig. 4). The maximum correlation value corresponded to lag 4 of the AMO covariable, so additive model and multiplicative environmental models, Equations (3) and (4), were fitted including this covariable. A significant environmental effect was found in the multiplicative model, where c=6.358e-01, whereas the environmental effect in the additive model was not significant (Table S4 in the Supplementary Material).

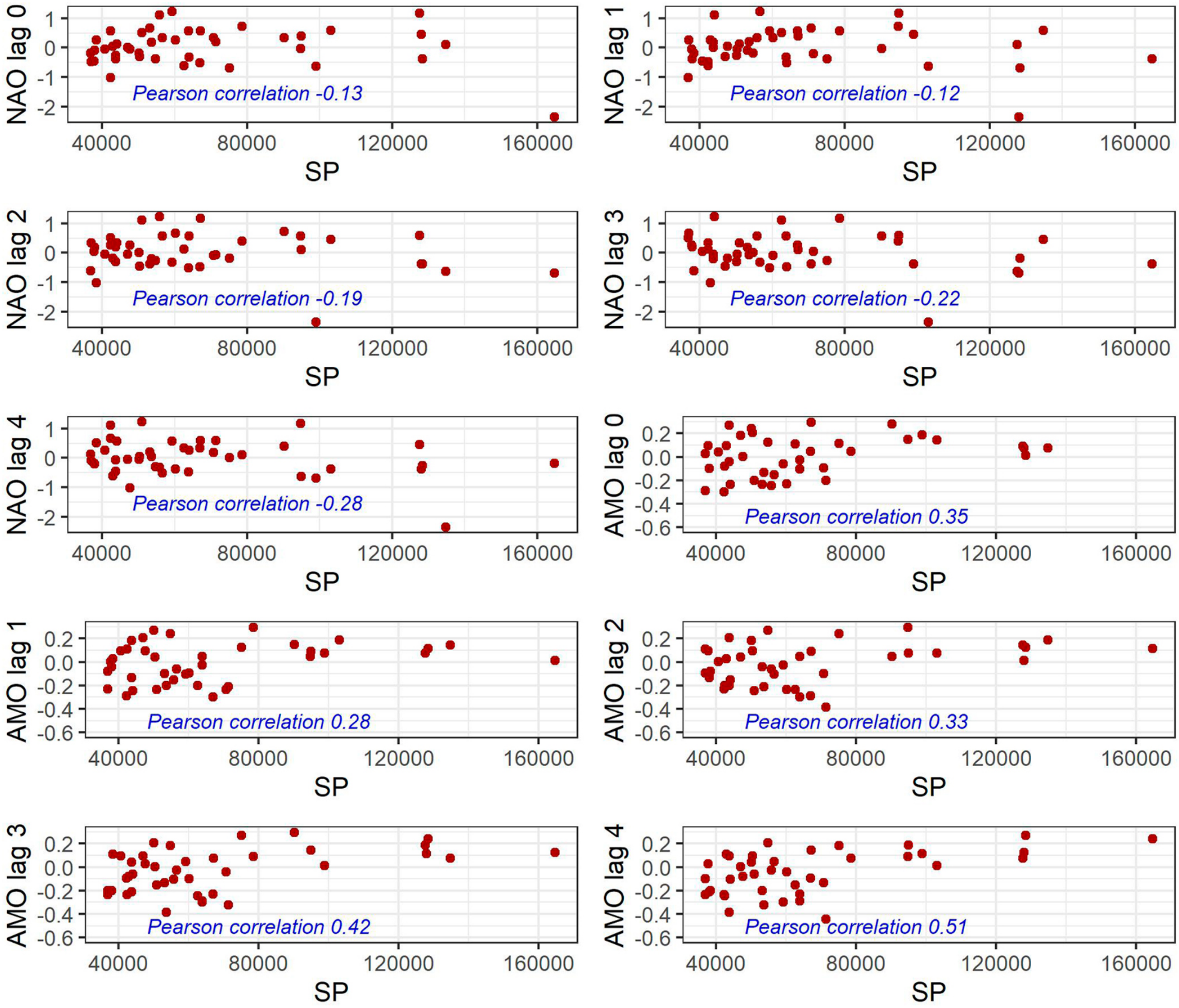

Fig. 4. – Scatter plots and Pearson correlation between the surplus production and the environmental covariables values (AMO and NAO) at different lags from 1 to 4.

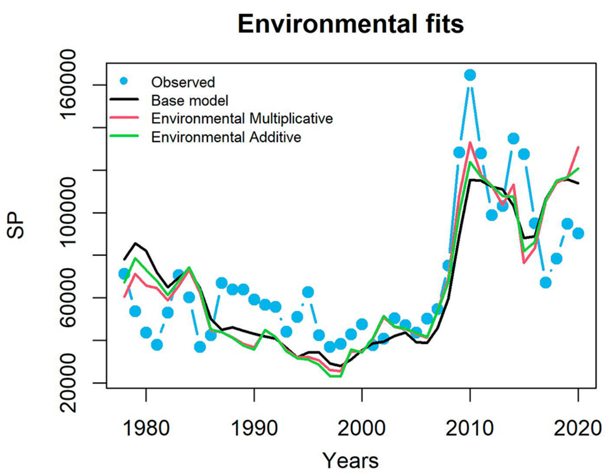

Fig. 5. – Plot of the predicted values derived from the original fit without an environmental covariable, and from the environmental fits (multiplicative and additive) with the observed SP values.

Table 5. – Performance comparison of the environmental models (additive and multiplicative) and the base fit without an environmental covariable. The Akaike information criterion (AIC), Mean Absolute Percentage Error (MAPE) and root mean square error values (RMSE) are reported.

Model	AIC	MAPE	RMSE
Additive: Equation (3)	985.05	0.27	20789
Multiplicative: Equation (4)	981.41	0.25	19927
Base fit (2)	985.76	0.27	21455

The predicted values derived from the original fit without the environmental covariable, Equation (2), and from both environmental fits were reported with the observed SP values (Fig. 5). Graphically, we found no clear differences, so the MAPE and RMSE measures were computed and reported for each of the models in Table 5 with the AIC values. The lowest values of AIC, MASE and MAPE corresponded to the multiplicative model; however, the differences between the error measure values of the different models were minimal. This finding leads to the conclusion that although the multiplicative model detected an environmental effect on stock production, this does not seem to be the main factor explaining the change in stock SP, or that more local environmental covariables would have to be included in the model to identify the environmental factor as a main one.

DISCUSSION

Known-biomass production models are a useful tool that could be used in addition to traditional data-rich stock assessment models. Indeed, by using a set of complementary tools such as KBPMs, we are more likely to consider the full range of possibilities and are less likely to over- or underexploit stocks due to misunderstandings of their status and dynamics. Furthermore, due to their computational efficiency, KBPMs can be classified as a quick and easy tool for complementing the data-rich view of stock status. Because of their simplicity, fewer applications of judgement are required, making them much more reproducible than other methods.

In addition to being a complementary tool providing another perspective on stock status, they can also be applied to address issues that cannot be easily tackled using traditional stock assessment models, such as assessing SP evolution over time and the factors affecting it (e.g. environmental factors), identifying multispecies management objectives and estimating MSY points without a stock recruitment function, among other noteworthy applications outlined in the introduction and exemplified throughout the analysis conducted in this study.

In particular, our study fitted single-species KBPMs to complement the data-rich view of stock status using the SP approach. The comparison of the F value in the last year with the corresponding reference points (data-rich F_{msy} and KBPM F_{msy}) allowed us to consider whether both approaches lead to the same conclusion about exploitation status. In particular, for southern hake, different conclusions were reached depending on the data-rich or KBPM reference points. Interestingly, due to a problem of retrospective bias, the assessment model corresponding to southern hake used in 2018 was recently replaced by a new model (ICES 2023), and the conclusion about fishing pressure of the new model agrees with the KBPM approach findings. Consequently, the contradictions observed between the previous data-rich model and KBPMs served as an indication of potential inaccuracies in the performance of the data-rich model. The alignment of the new model's results with KBPMs suggests that such inaccuracies have been solved in the new data-rich assessment model.

In addition to the conclusions obtained from comparisons between the two approaches (data-rich and KBPMs), KBPMs are themselves a diagnostic tool. An example of this is the case of southern anglerfish, in which a counterclockwise hook–cycle was observed, i.e. the SSB decreased while the SP remained more or less at the same level and then decreased when the SSB increased. There are alternative hypotheses for this behaviour, such as an environmental process that modifies the production curve over time. However, it does seem strange that this strong environmental driver only affects this stock. Under these circumstances, such counterintuitive behaviour could also indicate that there are issues in the data-rich stock assessment model which need to be addressed.

Another example is northern hake stock, whose KBPM showed a substantial, abrupt and persistent change in SP and SSB leading to the hypothesis that, in addition to biomass variability, there are other reasons for this shift. The retrospective analysis supports this hypothesis, concluding that from 2005 to 2017 the carrying capacity increased, whereas relative productivity decreased even when SSB increased. This behaviour could be explained by density-dependent phenomena (Hidalgo et al. 2009).

Drivers of SP shifts in marine fish communities may include climate forcing, so an analysis of environmental variability on stock status is of crucial interest. It is also possible to complement KBPMs with environmental factors to explain variations in production other than biomass. In fact, for northern hake, the correlation between SP and the NAO and AMO environmental variables was investigated, and the variable of maximum correlation was included in the environmental model (additive or multiplicative effect). However, although a significant effect on SP was detected, the differences between the environmental and original fit were not substantial. This may be due to the fact that more local environmental variables are required rather than the AMO and NAO global indices. Another possible reason is that the relationship between the environmental variable and SP is neither multiplicative nor additive. A future line of research is therefore to propose models that include non-linear smooth environmental effects.

Ecosystem-based management explicitly recognizes the complexity of ecosystems and the interconnections between their component parts, making their implementation challenging and costly in terms of time and human resources. The multispecies KBPM approach provides a simple data-limited ecosystem model for assessing ecosystem status. We illustrate this multispecies approximation by aggregating the northern and southern stocks into two components. This ecosystem overview leads us to conclude that both the southern and northern ecosystems are in a period of production and SSB increases after a historical period of decrease. So, multispecies KBPMs can be considered as an easy tool for exploring ecosystem behaviour before the development of a complex ecosystem model.

Summarizing, this research provides an overview of the uses of KBPM, including illustrations that analyse the status of several stocks of the Bay of Biscay and Iberian Coast ecoregion. This study leads to relevant conclusions for the stocks analysed and furthermore can be used as a guide for applying the KBPM approach to any other stock of interest. The corresponding code is available on GitHub to facilitate step-by-step replication of this study.

It is worth mentioning that some possible caveats of these models coincide with the ones detected for traditional SP models. For example, SSB time series that are too homogeneous, i.e. an SSB time series covering a limited range of levels, can lead to poor estimates of virgin biomass or maximum SP level. Furthermore, a related, specific KBPM issue appears when estimates of historical biomass values are available to estimate the virgin biomass, but their quality is questionable due to the data-rich model assumptions in the historical period, which often include fixing biological parameters to values derived from the literature or some prior knowledge (growth, natural mortality, stock recruitment steepness, etc.). The low quality of the biomass estimates in the historical part can lead to differences between the KBPM and data-rich conclusions. Also related to the biomass estimates, another consideration is the use of SSB as a measure of stock size to calculate yearly SP and fit the production curve. Since SSB is lower than total biomass it is expected that estimated yield and MSY may be underestimated. However, using the same reference measure as data-rich assessment models allows us to make more realistic comparisons.

It is also true that the KBPM multispecies approach carried out by aggregating the biomass and catches of the different stocks could lead to a multispecies behaviour that is mainly determined by the dominant species (large population size). An illustrative case of this can be seen in the results of the global community, which are evidently influenced by the results of the northern community. In particular, both F_{msy} and MSY/SSB_0 for the global community match the estimates derived from the northern community (Table 4). In other cases, however, this behaviour is not so clear, and refitting the production curve using the aggregated information makes it possible to estimate EBFM reference points that take account of the trade-offs between the different stock situations. For example, in the northern community, where there is no clear dominant stock, the reference points reflect the trade-offs between the status of hake, megrim and anglerfish. Specifically, while F_{msy} is 0.6 for northern hake, 0.6 for northern anglerfish and 0.2 for northern megrim individually, the combined SP curve gives an F_{msy} of 0.47 (see Tables 2 and 4). Consequently, there are situations in which refitting the SP curve to the aggregated data leads to a better understanding of the community. The multispecies KBPM therefore serves as a simple tool for investigating ecosystem behaviour before developing a complex ecosystem model, providing MSY reference points that are more appropriate than the sum of single species.

SUPPLEMENTARY MATERIAL

The following supplementary material is available through the online version of this article and at the following link:

Table S1. – Model estimates (*a* and *b*) derived from single-species KBPM fits.

Table S2. – Model estimates (*a* and *b*) derived from the retrospective analysis by removing three years at a time (2020-2017-2014-2011-2008-2005) from northern hake.

Table S3. – Model estimates (*a* and *b*) derived from multispecies KBPM fit, aggregating stocks in southern and northern ICES areas, and also the global one (both areas).

Table S4. – Model estimates (*a* and *b*) derived from the original fit without an environmental covariable, and from the environmental fits (multiplicative and additive) with the observed SP values.

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DECLARATION OF COMPETING INTEREST

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AUTHORSHIP CONTRIBUTION STATEMENT

Mohamed Yosri Zanni: Formal analysis, Writing – review & editing. Marta Cousido-Rocha: Conceptualization, Formal analysis, Methodology, Writing – original draft. Santiago Cerviño: Conceptualization, Funding acquisition, Writing – review & editing. Maria Grazia Pennino: Conceptualization, Funding acquisition, Writing – review & editing.

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