



Bayesian joint longitudinal models for assessing the exploitation rates of sardine stock in the Mediterranean Sea

Gabriel Calvo¹ · Carmen Armero¹ · Luigi Spezia² · Maria Grazia Pennino³

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Abstract

The European sardine is a pelagic species of great ecological importance for the conservation of the Mediterranean Sea as well as economic importance for the Mediterranean countries. Its fishing has suffered a significant decline in recent years due to various economic, cultural and ecological reasons. This paper focuses on the evolution of sardine catches in the Mediterranean Sea from 1985 to 2018 according to the fishing Mediterranean country and the type of fishing practised, artisanal and industrial. We propose three Bayesian longitudinal linear mixed models to assess differences in the temporal evolution of artisanal and industrial fisheries between and within countries. Overall results confirm that Mediterranean fishery time series are highly diverse along their dynamics and this heterogeneity is persistent throughout the time. Furthermore, our results highlight a positive correlation between artisanal and industrial fishing. Finally, the study observes a consistent decreasing time trend in the quantity of fish landings. Although the causes of this feature could be also linked to economic motivations (such as a reduction in demand or the reorientation of fleets towards more commercially beneficial species), it may indicate a potential risk to the stock of this species in the Mediterranean Sea.

Keywords Autoregressive processes · Joint linear mixed models · Pelagic ecosystem · Serial correlation

1 Introduction

Small pelagic fish species are key elements of the Mediterranean pelagic ecosystem due to their high bulk biomass at the mid-trophic level, which provides an

important energy connection between the lower and the upper trophic levels (Albo-Puigserver et al. 2015). These species have shown to be essential in the coupling between the pelagic and the demersal environment, as they are prey for pelagic predators such as tuna, cetaceans, pelagic birds, and demersal predators such as hakes (Mellon-Duval et al. 2017; Navarro et al. 2017). Small pelagic fishing usually live in dense shoals, making gear such as mid-water pelagic trawls and purse seines particularly efficient for their capture.

Fluctuations in populations of small pelagics can therefore have serious ecological and socio-economic consequences. The population dynamics of these species could be strongly influenced by natural environmental fluctuations (bottom-up control) and mortality (top-down control) (Checkley et al. 2017). Catches in the Mediterranean Sea are dominated by small pelagics, representing nearly 49% of the harvest (Saraux et al. 2014). Among them, the European sardine (*Sardina pilchardus*) is possibly the most important species both ecologically and economically.

✉ Gabriel Calvo
gabriel.calvo@uv.es

Carmen Armero
carmen.armero@uv.es

Luigi Spezia
luigi.spezia@bioss.ac.uk

Maria Grazia Pennino
grazia.pennino@ieo.es

¹ Departament d'Estadística i Investigació Operativa, Universitat de València, C/Dr. Moliner 50, 46100 Burjassot, Valencia, Spain

² Biomathematics and Statistics Scotland, AB15 8QH Aberdeen, UK

³ Instituto Español de Oceanografía, Centro Oceanográfico de Vigo, Subida a Radio Faro, 50-52, 36390 Vigo, Pontevedra, Spain

In recent years, the European sardine has undergone a shocking process of fragility, with a drastic reduction in body weight (about two thirds) and a much shorter life span than 20 years ago, which can be a reflection of its reduction in catches. This decline is the result of a complex process probably caused by many factors, the combination of which has led to this negative process (Brosset et al. 2017; Brigolin et al. 2018). Many theories were raised within the fishery scientific community: an increase in hungry sardine-eating predators such as bluefin tuna, whose population is increasing in the Mediterranean Sea, and dolphins. Another important element is the reduction of plankton, their food source. In the last few years, these marine microorganisms have been drastically reduced and have become less nutritious. This is a result of global warming, as plankton generally feed on nutrients from cold, deep waters. In addition, there has also been a recent proliferation of jellyfish blooms, predators of eggs and larval stages of sardines and also competitors for plankton. The shrinking size of sardines, the fact that most sardines are sold fresh rather than frozen, the changing economic relationship that generates their sales, dominated lately by large retail chains that virtually control their demand, and changing consumer preferences and intergenerational differences have all contributed, to a greater or lesser extent, to a fall in sardine prices and catches in the market that threatens the viability of the less powerful fishing fleets.

It is also important to note that the declining trend in European sardine landings may lie in different factors (Coll et al. 2024; Chen et al. 2021; Basilone et al. 2021). For instance, there could be a refocusing of fishing fleets on other economically more profitable species (such as anchovy), the abandonment of fishing by shipowners without replacement, a lack of demand due to a

reorientation of the processing industry, or changes in consumption patterns and habits.

Figure 1 describes the quantity, in thousands of tonnes (tt), of sardine caught by the main Mediterranean fishing countries from 1985 to 2018. This graph shows very interesting information. Two distinct behaviours can be reported. On the one hand, we observe that from 1985 to around 2005 the quantity of sardines fished experienced a notable decrease, going from around 350 to 250 tt. In 2006 and 2007 we can appreciate a slight upturn, but from that date onward there is again a decrease that seems to have stabilised in recent years at around 225 tt.

At regional level, strong declines in sardine landings have been reported in different Mediterranean areas (Coll et al. 2019). However, no study has been performed to assess sardine landings dynamics at a large-scale. Although working at a fine scale and regional level (e.g. Mediterranean eco-regions or subareas) has several advantages, large-scale analysis is also essential to provide a broader and complementary perspective of non-localised drivers of fisheries where sardine fish stocks are shared among countries, and reduce the bias of landings misallocation (Stergiou et al. 2016). Understanding fish population dynamics is a major goal of fisheries ecology.

Pennino et al. (2017) stated that Mediterranean fisheries are highly diverse and geographically varied, not only because of the existence of different marine environments, but also because of diverse socio-economic situations, and fisheries status. The two most important types of commercial fishing in the Mediterranean are artisanal and industrial, defined in terms of small-scale and large-scale commercial fisheries, respectively (Zeller and Pauly 2016).

This is a statistical article that focuses on the evolution of sardine catches in the Mediterranean Sea from 1985 to 2018 according to the Mediterranean fishing country and the type of fishing practised. The main objective is to detect and analyse general patterns of the joint temporal evolution of artisanal and industrial fisheries, as well as relevant individual characteristics of the different Mediterranean countries. This is a quantitative overview that provides a different perspective on the problem than a purely biological, economic or ecological one.

The statistical framework of this study are the longitudinal linear mixed models. The term longitudinal indicates that each individual of the sample is measured repeatedly on the same outcome at several points in time. Each Mediterranean country was considered as an individual and the annual sardine landings formed a set of individual time series (1985 to 2018), one for each country and type of fishing. The assumption that all of the information about the response variable is generated by a function common to all individuals of the target population is not realistic. Ignoring individual heterogeneity among countries could



Fig. 1 Annual thousands of tons of European sardine caught by the main Mediterranean fishing countries from 1985 to 2018. Data come from Sea Around Us (www.seaaroundus.org)

lead to inconsistent and inefficient estimates of the parameters of interest (Pinheiro and Bates 2000). As a result, our longitudinal models will include not only common population information and measurement error terms, as described by Diggle et al. (2002), but also random effects to account for specific country characteristics.

Statistical estimation is carried out within the Bayesian inferential framework. Consequently, we assume a definition of probability that allows assigning probability distributions to all unknown quantities, such as parameters, random effects, hyperparameters, etc. In particular, a prior distribution is always the starting point of the inferential process that we will update with the experimental information through the Bayes theorem to obtain the posterior distribution for the relevant unknown quantities of the model. This posterior distribution is the key element for the posterior analysis about the relevant outcomes of the process. The Bayesian framework is appropriate for conducting environmental research, as evidenced by Lye (1990), Perreault et al. (2000) and Tongal and Boojj (2023), among others.

The contributions of the paper are twofold. On the methodological side, we developed an approach in the fishery framework for jointly modelling several longitudinal response variables. This approach connects individual information by considering correlation parameters that measure the linear relationships between the random effects of the different responses within each individual. Secondly, on the applied fishery side, we demonstrated, among all the heterogeneous behaviours of the countries, a decline in landing quantity for both the artisanal and the industrial fishing in the Mediterranean Sea over the past three decades. In addition, we found a positive synergistic relationship between the two types of fisheries within each country.

This paper is organised as follows. Section 2 presents the data on artisanal and industrial sardine catches from 1985 to 2018 corresponding to the Mediterranean countries that participate in the study. Section 3 discusses the general joint Bayesian statistical framework and introduces three modelling approaches that seem appropriate for analysing the study's data. Section 4 deals with the approximation of the subsequent posterior distributions via Markov Chain Monte Carlo methods (MCMC). It also presents a discussion comparing the three proposed models, and a final subsection that analyses the possible synergistic relationships between the two types of fisheries in the different countries studied. The paper ends with some concluding remarks.

2 Sardine fisheries in the Mediterranean Sea

Annual landings data (tonnes) from 1985 to 2018 of European sardine caught by artisanal and industrial methods by Mediterranean countries have been extracted from Sea Around Us (www.seaaroundus.org). Countries participating in the study are Albania, Algeria, Bosnia and Herzegovina, Croatia, France, Greece, Italy, Montenegro, Morocco, Slovenia, Spain and Turkey (See Fig. 2).

Data from European countries recognised as sovereign from 2010 by the international community (Bosnia and Herzegovina, Croatia, Montenegro, and Slovenia) were imputed from 1985 to 2010 (Zeller and Pauly 2016) based on information from Exclusive Economic Zones (EEZ), which was linked to these countries after reconstructing data by means of several sources.

According to Zeller and Pauly (2016), in the Sea Around Us dataset, both artisanal and industrial sectors are predominantly commercial. Additionally, the size of the vessel is not explicitly considered to differentiate between artisanal and industrial fishing. However, in the latter, larger vessels are common. In particular, artisanal fishing consists not only of small-scale methods (such as hand lines and gillnets) and fixed gears (like weirs and traps), but also is limited to coastal areas within a maximum range of 50 km from the coast or 200 m in depth. Another characteristic of this method is that a small fraction of the catch is consumed or given away by the crew. In contrast, industrial boats can fish in waters of other countries or in the open sea. They are motorized vessels that require significant investments in their construction, maintenance, and operation.

Figure 3 shows two spaghetti plots. The top figure shows the annual amount of sardines caught by artisanal fishing from 1985 to 2018 in those Mediterranean countries that retain this type of fishery. The bottom figure displays the same quantity but for the annual amount of sardines caught by industrial methods. The first thing that strikes is how few sardines are caught by traditional methods compared to those caught by industrial fishing. There is only one notable situation, such as that of Algeria, which has a positive evolution of its traditional fisheries. Note that not all countries have both types of fisheries (Bosnia and Herzegovina has no registered industrial fisheries and Albania has not registered artisanal fisheries).

The behaviour of the countries is very different both in relation to the quantity of sardines caught by industrial methods at the beginning of the study (year 1985) and in their evolution over time. Countries such as Italy and Algeria are particularly striking. Italy started out as the country that fished the most sardines at the beginning of the study, exceeding the 150 tonne barrier the first years. From



Fig. 2 Countries bordering the Mediterranean Sea. Photo by Ian Macky, PAT Atlas, <https://ian.macky.net/pat/map/medi/mediblu.gif>

the mid-1980s onwards, it experienced a significant decrease, fishing less than 50 tonnes per year from 1998 onwards. Although it seems to have recovered in recent years, it is still below the annual level of 50 tonnes of sardines fished. Algeria started the study in the group of low fishing countries but experienced strong growth until the end of the 1980s. Since then it has maintained a fairly stable behaviour until around 2008 when it has seen a drastic reduction in its sardine catches. Spain has also exhibited a consistent decline in industrial fishing activity since around 1995, without showing any signs of recovery since then. A weak recovery seems to have been observed in some countries in recent years. Bosnia and Herzegovina is the country that fishes the least quantity of sardines. It only reports industrial fishing but has experienced a notable expansion in the most recent years. Turkey also increased fishing significantly between the 70s and the 90s, and it is currently, along with Algeria, Croatia, Greece and Morocco one of the largest sardine fisheries. France and Slovenia have lowered substantially their catches in the recent years.

It is important to note that no information was recorded neither for Spain’s artisanal fishing until 2010, nor for Turkey’s since 2000. This does not necessarily imply that these fisheries did not exist during the indicated years. In fact, to conduct our analysis, we have treated the absence

of these data from Spain and Turkey as missing data. That is, we believe that there was fishing activity, but it could not be recorded for unknown reasons.

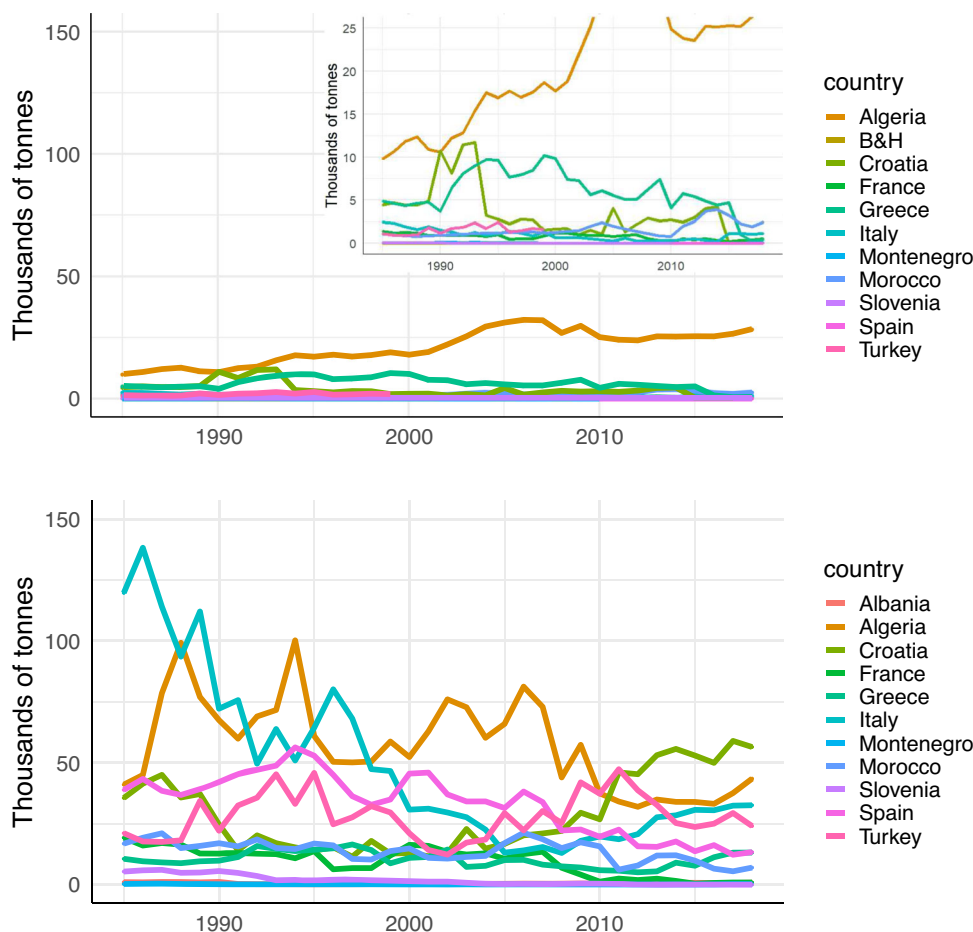
3 Joint Bayesian longitudinal modelling

Let $(y_{ij}^{(1)}, y_{ij}^{(2)})$ be the bivariate random vector describing the response of individual i , $i = 1, \dots, N$ at time t_{ij} , $j = 1, 2, \dots, n_i$. Consider the random vector $(\mathbf{y}^{(1)}, \mathbf{y}^{(2)})' = \{(\mathbf{y}_i^{(1)}, \mathbf{y}_i^{(2)})', i = 1, \dots, N\}$, where $(\mathbf{y}_i^{(1)}, \mathbf{y}_i^{(2)}) = \{(y_{ij}^{(1)}, y_{ij}^{(2)})', j = 1, \dots, n_i\}$.

As in Verbeke and Davidian (2009) and Armero et al. (2018), we assume a Bayesian share-parameter framework to jointly model both responses that uses random effects to generate an association structure between both longitudinal measures. To this effect, a Bayesian joint longitudinal model (BJLM) for $(\mathbf{y}^{(1)}, \mathbf{y}^{(2)})'$ is specified via the joint probability distribution

$$\begin{aligned}
 f(\mathbf{y}^{(1)}, \mathbf{y}^{(2)}, \boldsymbol{\theta}, \boldsymbol{\phi}) &= f(\mathbf{y}^{(1)}, \mathbf{y}^{(2)} \mid \boldsymbol{\theta}, \boldsymbol{\phi}) f(\boldsymbol{\phi} \mid \boldsymbol{\theta}) \pi(\boldsymbol{\theta}) \\
 &= f(\mathbf{y}^{(1)} \mid \boldsymbol{\theta}, \boldsymbol{\phi}) f(\mathbf{y}^{(2)} \mid \boldsymbol{\theta}, \boldsymbol{\phi}) f(\boldsymbol{\phi} \mid \boldsymbol{\theta}) \pi(\boldsymbol{\theta}) \\
 &= \left(\prod_{i=1}^N f(\mathbf{y}_i^{(1)} \mid \boldsymbol{\theta}, \boldsymbol{\phi}_i) f(\mathbf{y}_i^{(2)} \mid \boldsymbol{\theta}, \boldsymbol{\phi}_i) \right) \left(\prod_{i=1}^N f(\boldsymbol{\phi}_i \mid \boldsymbol{\theta}) \right) \pi(\boldsymbol{\theta}),
 \end{aligned}
 \tag{1}$$

Fig. 3 Annual tons of European sardine (*Sardina pilchardus*) per country, from 1985 to 2018. From top to bottom: artisanal and industrial fishing



where $f(y_i^{(c)} | \theta, \phi_i)$ is the conditional probability distribution of $y_i^{(c)}$ given the vector ϕ_i of the random effects associated with individual i and the vector θ of the parameters and hyperparameters of the model; $f(\phi_i | \theta)$ is the conditional probability distribution of ϕ_i given θ ; and $\pi(\theta)$ a prior distribution for θ . Conditional independence between both responses and random effects corresponding to individuals is assumed.

This BJLM works in the framework of the normal distribution, so the i -th component of the sampling probability distribution is:

$$\begin{aligned} f(y_i^{(1)} | \theta, \phi_i) &= \mathcal{N}(\mu_i^{(1)}, \Sigma_i^{(1)}) \\ f(y_i^{(2)} | \theta, \phi_i) &= \mathcal{N}(\mu_i^{(2)}, \Sigma_i^{(2)}), \end{aligned} \tag{2}$$

where $\mu_i^{(c)}$ is the conditional mean of $y_i^{(c)}$ given (θ, ϕ_i) and $\Sigma_i^{(c)}$ its conditional variance-covariance matrix whose (j, l) th element is $\text{Cov}(y_{ij}^{(c)}, y_{il}^{(c)} | \theta, \phi)$.

The fully specification of the Bayesian model is completed with the elicitation of a prior distribution $\pi(\theta)$ for θ and the conditional distribution $f(\phi_i | \theta)$, $i = 1, \dots, N$. Once the Bayesian model is fully specified and the data \mathcal{D}

(i.e., the observations of $(y_{ij}^{(1)}, y_{ij}^{(2)})$) are obtained, the next step of the Bayesian protocol is to compute the posterior distribution $\pi(\theta, \phi | \mathcal{D})$ via the Bayes theorem. This distribution is the basis of the statistical analysis and the starting point of the posterior distribution of any relevant measure of performance of the model depending on (θ, ϕ) .

3.1 Longitudinal modelling for the total European sardine landings

Let $y_{ij}^{(A)}$ represent the total tonnage of sardines caught in country i during year t_{ij} using artisanal methods, and let $y_{ij}^{(I)}$ represent the total tonnage of sardines caught using industrial methods. Both quantities are measured on a logarithmic scale. This study considers a time scale based on the calendar, with $t_i = (0, \dots, 34)$ denoting the range of years. Time zero ($t_{i1} = 0$) corresponds to the initial year of the study, specifically, 1985.

We will consider three BLJM (i.e., models \mathcal{M}_1 , \mathcal{M}_2 , and \mathcal{M}_3) for analysing the evolution of artisanal and industrial fisheries within the general methodological framework explained in the previous section. Model \mathcal{M}_1 is

a basic homoscedastic linear mixed model with the natural covariate time and random effects. Models \mathcal{M}_2 and \mathcal{M}_3 account for serial correlation in terms of autoregressive elements, whose inclusion is justified by a strong dependence of each year’s fishing activity on previous years and the large number of observations per country. In particular, \mathcal{M}_2 and \mathcal{M}_3 introduce autoregressive terms in the conditional means and the variance-covariance matrices of the sampling probability distribution in (2), respectively. The models are defined as follows:

Model

$$\mathcal{M}_1 \quad \begin{aligned} f(y_i^{(A)} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) &= \mathcal{N}(\mathbf{I} \beta_0^{(A)} + \mathbf{I} b_{0i}^{(A)} + \mathbf{t} \beta_1^{(A)} + \mathbf{t} b_{1i}^{(A)}, \sigma^{(A)^2} \mathbf{I}), \\ f(y_i^{(I)} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) &= \mathcal{N}(\mathbf{I} \beta_0^{(I)} + \mathbf{I} b_{0i}^{(I)} + \mathbf{t} \beta_1^{(I)} + \mathbf{t} b_{1i}^{(I)}, \sigma^{(I)^2} \mathbf{I}), \end{aligned} \quad (3)$$

where \mathbf{I} is a vector of ones of dimension 35, $\mathbf{t} = (0, 1, \dots, 34)'$, $\beta_0^{(A)}$ and $\beta_0^{(I)}$ common intercepts for artisanal and industrial fishing, respectively as well as $\beta_1^{(A)}$ and $\beta_1^{(I)}$ for the subsequent common slopes. Individual random intercepts $b_{0i}^{(A)}$ and $b_{0i}^{(I)}$, and random slopes $b_{1i}^{(A)}$ and $b_{1i}^{(I)}$ are conditionally independent and normally distributed as $(b_{0i}^{(A)}, b_{0i}^{(I)} | \Sigma_0) \sim \mathcal{N}(0, \Sigma_0)$ and $(b_{1i}^{(A)}, b_{1i}^{(I)} | \Sigma_1) \sim \mathcal{N}(0, \Sigma_1)$. Variance-covariance matrix Σ_0 includes the correlation coefficient ρ_0 between $b_{0i}^{(A)}$ and $b_{0i}^{(I)}$ as well as its respective variances $\sigma_0^{(A)^2}$ and $\sigma_0^{(I)^2}$. Analogously, ρ_1 and both variances $\sigma_1^{(A)^2}$ and $\sigma_1^{(I)^2}$ for Σ_1 . This model is homoscedastic. Therefore the variability associated with the random measurements is always equal and constant, $\sigma^{(A)^2} \mathbf{I}$ and $\sigma^{(I)^2} \mathbf{I}$ for artisanal and industrial, respectively, where \mathbf{I} represents the 35×35 unit matrix.

Model \mathcal{M}_1 is completed with the elicitation of a prior distribution for the parameters and hyperparameters of the model. We assume a non-informative prior scenario, which gives the maximum prominence to the data, as well as prior independence. We specify normal distributions with large standard deviation for the common regression coefficients, $\pi(\beta_0) = \pi(\beta_1) = \mathcal{N}(0, 10^2)$ and uniform distribution $\mathcal{U}(0, 10)$ for all standard deviation terms, $\sigma^{(A)}$, $\sigma^{(I)}$, $\sigma_0^{(A)}$, $\sigma_0^{(I)}$, $\sigma_1^{(A)}$, and $\sigma_1^{(I)}$. Prior distributions for correlation terms ρ_0 and ρ_1 are chosen as uniform $\mathcal{U}(-1, 1)$.

Model

$$\mathcal{M}_2 \quad \begin{aligned} f(y_i^{(A)} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) &= \mathcal{N}(\mathbf{I} \beta_0^{(A)} + \mathbf{I} b_{0i}^{(A)} + \mathbf{t} \beta_1^{(A)} + \mathbf{t} b_{1i}^{(A)}, \Sigma^{(A)}), \\ f(y_i^{(I)} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) &= \mathcal{N}(\mathbf{I} \beta_0^{(I)} + \mathbf{I} b_{0i}^{(I)} + \mathbf{t} \beta_1^{(I)} + \mathbf{t} b_{1i}^{(I)}, \Sigma^{(I)}). \end{aligned} \quad (4)$$

In this model, the means of both conditional distributions are expressed as in model \mathcal{M}_1 . The element (j, l) of the

conditional variance-covariance matrix $\Sigma^{(\cdot)}$ is defined as follows:

$$\text{Cov}(y_{ij}^{(\cdot)}, y_{il}^{(\cdot)} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) = \sigma^{(\cdot)^2} \sum_{k=1}^{\min(j,l)} \rho^{(\cdot)^2(k+(t_{ij}-t_{ik})+(t_{il}-t_{ik}))}, \quad (5)$$

where $\rho^{(\cdot)}$ is the coefficient of the autoregressive term of a heteroscedastic AR(1).

To clarify the derivation of matrix (5), we formulate this model in an alternative way by conditioning y_{ij} on y_{ij-1} (Chi and Reinsel 1989), assuming, for the sake of simplicity, that the response variable is univariate:

$$\begin{aligned} (y_{i1} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) &= \mu_{i1} + \epsilon_{i1}, \\ (y_{ij} | y_{ij-1}, \boldsymbol{\theta}, \boldsymbol{\phi}_i) &= \mu_{ij} + \rho(y_{ij-1} - \mu_{ij-1}) + \epsilon_{ij}, \quad j = 2, \dots, 35 \end{aligned} \quad (6)$$

where the measurement errors are normally distributed, denoted as $(\epsilon_{ij} | \sigma) \sim \mathcal{N}(0, \sigma^2)$, and $\mu_{ij} = \beta_0 + b_{0i} + t_{ij}(\beta_1 + b_{1i})$ for any measurement j of country i .

Additionally, this model can be expressed by means of an autoregressive process of the term $(y_{ij} - \mu_{ij})$ as follows

$$\begin{aligned} (y_{i1} - \mu_{i1}) &= \epsilon_{i1}, \\ (y_{ij} - \mu_{ij}) &= \rho(y_{ij-1} - \mu_{ij-1}) + \epsilon_{ij}, \quad j = 2, \dots, 35. \end{aligned} \quad (7)$$

Moving forward, this autoregressive process can be rewritten as a moving average process:

$$(y_{ij} - \mu_{ij}) = \sum_{k=1}^j \rho^{(t_{ij}-t_{ik})} \epsilon_{ik}. \quad (8)$$

Thus, the variance of this term is

$$V(y_{ij} - \mu_{ij}) = \sum_{k=1}^j \rho^{2(t_{ij}-t_{ik})} \sigma^2,$$

which is always finite in our case, given that the data in the study are balanced, and the number of measurements for each country is 35. Additionally, this variance is the summation of a finite geometric series with a ratio value ρ^2 between 0 and 1.

Finally, the calculation of the elements of the variance-covariance matrix in (5) is straightforward:

$$\text{Cov}(y_{ij}, y_{il} | \boldsymbol{\theta}, \boldsymbol{\phi}_i) = \sigma^2 \sum_{k=1}^{\min(j,l)} \rho^{(t_{ij}-t_{ik})+(t_{il}-t_{ik})}.$$

We chose this specific matrix, i.e., a heteroscedastic autoregressive error matrix, instead of considering matrices as those described in Hedeker and Gibbons (2006), to avoid potential confusion between the random intercept and the error at the initial time.

In addition, we have selected a uniform prior distribution, $\mathcal{U}(-1, 1)$, for the autoregressive coefficients $\rho^{(A)}$ and

$\rho^{(l)}$. By enforcing $|\rho^{(A)}|$ and $|\rho^{(l)}|$ to be less than 1, we place limits on the values of the elements in the variance-covariance matrix. The prior distribution for the remaining parameters and hyperparameters in this model follows the same approach as model \mathcal{M}_1 .

Model

$$\begin{aligned} \mathcal{M}_3 \quad f(y_i^{(A)} | \theta, \phi_i) &= \mathcal{N}(\mathbf{I} \beta_0^{(A)} + \mathbf{I} b_{0i}^{(A)} + \mathbf{t} \beta_1^{(A)} + \mathbf{t} b_{1i}^{(A)} + \mathbf{w}_i^{(A)}, \sigma^{(A)^2} \mathbf{I}), \\ f(y_i^{(l)} | \theta, \phi_i) &= \mathcal{N}(\mathbf{I} \beta_0^{(l)} + \mathbf{I} b_{0i}^{(l)} + \mathbf{t} \beta_1^{(l)} + \mathbf{t} b_{1i}^{(l)} + \mathbf{w}_i^{(l)}, \sigma^{(l)^2} \mathbf{I}). \end{aligned} \quad (9)$$

This model is similar to model \mathcal{M}_1 but includes a latent autoregressive term $\mathbf{w}_i^{(\cdot)} = (w_i(t_{i1})^{(\cdot)}, \dots, w_i(t_{in_i})^{(\cdot)})'$ in the conditional mean, where each $w_i(t_{ij})^{(\cdot)}$, $j = 2, \dots, n_i$, is a realisation at time t_{ij} from a Gaussian process with mean $\rho w_i(t_{i,j-1})$ and variance σ_w^2 , where $(w_i(t_{i1}) | \sigma_w) \sim \mathcal{N}(0, \sigma_w^2)$ (Diggle et al. 2002). That is, $\mathbf{w}_i^{(\cdot)}$ is a vector of time correlated noises. Again, the prior distribution for the parameters and hyperparameters of this model is as in model \mathcal{M}_1 to which we add the marginal prior distribution, $\mathcal{U}(-1, 1)$ for the correlation coefficients $\rho^{(A)}$ and $\rho^{(l)}$, and $\mathcal{U}(0, 100)$ for the standard deviations, $\sigma_w^{(A)}$ and $\sigma_w^{(l)}$, of the autoregressive term in the conditional means.

4 Posterior inferences

The posterior distribution associated with models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3 has been approximated via MCMC sampling (Tanner 2012) through JAGS software (Plummer 2003) (version 4.0.5). In particular, we used the `runjags` package developed by Denwood (2016) to parallelise the simulation process, running three parallel chains for each model with a total of 5,000,000 iterations and a burn-in of 1,000,000 iterations. To reduce autocorrelation in the sample, we also thinned the chains by storing every 5000th iteration. The computations were performed on a computer with an Intel i9 processor, 32 GB of RAM, and running Windows 10 Enterprise LTSC. The full inferential analysis, performed by an R code, and the data are publicly available as supplementary material in the GitHub repository at https://github.com/gcalvobayarri/European_sardine_analysis.git.

Table 1 shows a basic description of the approximated posterior distribution of the parameters and hyperparameters of the models under study. The first thing that strikes us is the consistency of the results obtained with the three models. All of them present similar results for their outcomes in relation to the initial behaviour of the different countries, their time trends, and the strong impact of the autoregressive terms in models \mathcal{M}_2 and \mathcal{M}_3 . Very few differences can be observed in the estimates of the

regression coefficients in both types of fisheries. In all of them, a smooth but negative time trend is discernible which indicates a decreasing pattern in the amount of sardine fishing in recent decades. This is a consistent situation with the behaviour shown by the data in Fig. 1.

Posterior estimation of the variances associated with the random effects of the intercept and the slope of the artisanal and industrial fisheries are also very similar, mainly for models \mathcal{M}_2 and \mathcal{M}_3 . It is worth noting the great heterogeneity shown by the different Mediterranean countries at the beginning of the study in both types of fisheries as well as the fact that the greatest heterogeneity is shown by the artisanal fishery, which moves in much smaller dimensions than the industrial fishery. The association between the amount of artisanal and industrial fishing in the different countries, expressed through the information on ρ_0 and ρ_1 , is not very strong either at the beginning or during the study period, but the results indicate a positive association between them. This is an important issue that we will be fully described later.

The correlation $\rho^{(\cdot)}$ parameters involved in the autoregressive terms of models \mathcal{M}_2 and \mathcal{M}_3 are not comparable. In the case of \mathcal{M}_2 they are associated with the variance-covariance matrices of the sampling model while in \mathcal{M}_3 they are on the conditional mean. In both cases, they play a relevant role in the estimated model, with positive posterior means very close to one: 0.913 and 0.938 in \mathcal{M}_2 , and 0.953 and 0.947 in \mathcal{M}_3 for artisanal and industrial fisheries, respectively.

The variability associated with the measurement error in \mathcal{M}_1 is large (posterior means 0.662 and 0.486 for artisanal and industrial fisheries, respectively). These values are somewhat lower in the case of \mathcal{M}_2 due to the inclusion of the autoregressive term in the conditional matrix. The relevant difference happens with \mathcal{M}_3 in which the inclusion of the autoregressive term in the conditional mean takes away a large amount of the measurement error variability.

4.1 Model comparison

All of the three proposed models seem reasonable and show consistent and robust results. However, we would like to be able to choose one of the three as the most appropriate and most compatible with the data. Model checking is an essential issue of any statistical analysis. The existing literature on this subject is abundant and multifaceted due to the great quantity and disparity of criteria proposed (Vehtari and Ojanen 2012).

It is not our aim to study this issue in depth because it is beyond the scope of this paper. Here, we would like to briefly discuss this subject and obtain some results that will

Table 1 Summary of the approximated posterior distribution of the parameters and hyperparameters in models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3

	\mathcal{M}_1			\mathcal{M}_2			\mathcal{M}_3		
	Mean	Sd	0.95CI	Mean	Sd	0.95CI	Mean	Sd	0.95CI
$\beta_0^{(A)}$	5.759	1.253	(3.197,8.239)	5.365	1.340	(2.379, 7.794)	5.375	1.169	(2.936, 7.590)
$\beta_1^{(A)}$	-0.022	0.026	(-0.074,0.031)	-0.029	0.031	(-0.090 0.031)	-0.029	0.031	(-0.090, 0.031)
$\sigma_0^{(A)}$	3.837	1.144	(2.333,6.780)	3.848	1.198	(2.258,6.969)	3.781	1.075	(2.269, 6.434)
$\sigma_1^{(A)}$	0.083	0.026	(0.049,0.144)	0.081	0.034	(0.019,0.158)	0.080	0.036	(0.016, 0.162)
$\sigma^{(A)}$	0.662	0.027	(0.612,0.718)	0.522	0.022	(0.480,0.567)	0.181	0.049	(0.063, 0.0.259)
$\rho^{(A)}$	-	-	-	0.913	0.053	(0.804 0.994)	0.953	0.038	(0.861, 0.998)
$\sigma_w^{(A)}$	-	-	-	-	-	-	0.455	0.036	(0.389, 0.528)
$\beta_0^{(I)}$	9.249	0.768	(7.668,10.777)	9.019	0.783	(7.215,10.363)	9.105	0.662	(7.652,10.291)
$\beta_1^{(I)}$	-0.032	0.024	(-0.079,0.017)	-0.033	0.025	(-0.081, 0.018)	-0.035	0.023	(0.080,0.010)
$\sigma_0^{(I)}$	2.398	0.692	(1.488,4.111)	2.198	0.717	(1.294 3.927)	2.109	0.603	(1.285,3.620)
$\sigma_1^{(I)}$	0.074	0.022	(0.045,0.127)	0.070	0.025	(0.032,0.130)	0.070	0.025	(0.030,0.130)
$\sigma^{(I)}$	0.486	0.018	(0.453,0.524)	0.341	0.013	(0.317,0.368)	0.064	0.037	(0.003,0.136)
$\rho^{(I)}$	-	-	-	0.938	0.037	(0.862, 0.997)	0.947	0.035	(0.872, 0.998)
$\sigma_w^{(I)}$	-	-	-	-	-	-	0.327	0.019	(0.288, 0.362)
ρ_0	0.237	0.325	(-0.420, 0.807)	0.393	0.318	(-0.319, 0.889)	0.369	0.313	(-0.335, 0.867)
ρ_1	0.422	0.285	(-0.245 0.853)	0.404	0.371	(-0.473, 0.930)	0.397	0.387	(-0.514, 0.942)

help us to compare our three models. In this regard, we will focus on three methods that are quite popular in the Bayesian reasoning: The penalised expected deviance (PED), the Bayes factor (BF) and the conditional predictive ordinate (CPO). PED was proposed by Plummer (2008). It is based on the deviance information criterion (DIC) (Spiegelhalter et al. 2002) that combines the expected deviance as a measure of fit and the effective number of parameters of the model as a measure of their complexity. The complexity penalty used by PED is higher than that of DIC so it is to be understood that PED will generally favour simpler models than DIC. The Bayes factor is regarded as the conceptual solution to model selection problems but presents many practical problems. According to Kass and Raftery (1985); Berger and Pericchi (1996), it is defined in terms of prior predictive distributions evaluated on the observed data (evidence) which can be interpreted as the support provided by the data in favour of the subsequent model. We will use the R package `bridge-sampling` (Gronau et al. 2020) that uses bridge sampling (Meng and Wong 1996; Meng and Schilling 2002) to approximate the evidence from each of the three models examined. Finally, as in Gelfand and Dey (1994), we use the cross-validated predictive density to assess our models. In our case, it is defined as the conditional posterior density of a future artisanal and industrial tonnage of sardines

Table 2 Approximated PED for models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3 and mean (standard deviation) of ten replicates of the approximate evidence, in logarithmic scale, for models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3

	\mathcal{M}_1	\mathcal{M}_2	\mathcal{M}_3
PED	1226	804	161
log(Evidence)	-802.52 (0.37)	-531.91 (0.01)	-517.93 (1.02)

caught of country i in an hypothetical replicated experiment

$$f(\mathbf{y}_i^{pred(A)}, \mathbf{y}_i^{pred(I)} | \mathcal{D}^{-(i)}) = \int f(\mathbf{y}_i^{pred(A)}, \mathbf{y}_i^{pred(I)} | \boldsymbol{\theta}, \boldsymbol{\phi}) \pi(\boldsymbol{\theta}, \boldsymbol{\phi} | \mathcal{D}^{-(i)}) d(\boldsymbol{\theta}, \boldsymbol{\phi})$$

where $\mathcal{D}^{-(i)}$ are all the data in \mathcal{D} except for the observations of country i (leave-one-out procedure). The fundamental idea underlying this proposal assumes that if the estimated model is correct, the observations of each country can be considered as a random value from the subsequent cross-validated predictive density (Chen et al. 2000). In this predictive framework, we consider the CPO for country i , i. e. CPO_i , defined as the value of $f(\mathbf{y}_i^{pred(A)}, \mathbf{y}_i^{pred(I)} | \mathcal{D}^{-(i)})$ at the observed $(\mathbf{y}_i^{(A)}, \mathbf{y}_i^{(I)})$ data. Large CPO_i values are supportive of the model as they indicate a good agreement between the data and the model.

Table 2 shows the PED value for models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3 as well as the sample and standard deviation of ten replicates of the approximated evidence, in the logarithmic scale. Both criteria point to \mathcal{M}_3 as the best model, followed in both cases by \mathcal{M}_2 . It seems clear that the two models with autoregressive elements perform better than the basic model, the PED is clearly in favour of \mathcal{M}_3 , but the differences are narrower in the case of the logarithm of the evidence.

Table 3 includes the CPO, in logarithmic scale, for each of the countries in the study associated with models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3 . This latter model records the highest CPO values in all countries except Montenegro. In this country, the highest CPO is obtained with \mathcal{M}_2 , although the differences between the CPO of this country with both models is quite small. \mathcal{M}_1 has the smallest CPO values in all countries with a large difference compared to ones from \mathcal{M}_2 and \mathcal{M}_3 . Spain is in all models by far the most different country from the rest, followed by Slovenia and Croatia. The CPO values obtained suggest that the model most compatible with the data is also \mathcal{M}_3 .

The inclusion of an autoregressive term in the model clearly seems to be a good decision, and better on the conditional mean than on the variance. If we had to choose one model it would be \mathcal{M}_3 .

4.2 Association and country-specific fishing patterns

As a complement to the statistical analysis carried out, we now turn to \mathcal{M}_3 and present some of the derived results. We recall that $\beta_1^{(A)}$ and $\beta_1^{(I)}$ is, respectively, the regression

slope associated with time in the conditional mean of the total tonnage (in logarithmic scale) of sardines caught by artisanal and industrial methods. The subsequent posterior mean and standard deviation of $\beta_1^{(A)}$ is -0.029 and 0.031 and -0.035 and 0.023 for $\beta_1^{(I)}$. Figure 4 shows the marginal posterior distribution of $\beta_1^{(A)}$ and $\beta_1^{(I)}$ and shows in the shaded part the posterior probability that the subsequent β_1 is negative, 0.912 and 0.857 , for the artisanal and industrial fishery, respectively. These values give strong support to a decreasing trend for both types of fisheries.

As mentioned before, an interesting issue of our study is the possible association between the specific characteristics of artisanal and industrial fisheries in the different countries of the study: do both types of fisheries have a synergistic relationship and generate a mutually cooperative relationship? Or, on the contrary, are they negatively associated, and therefore it is to be expected that high values for industrial fisheries are linked to low values for artisanal fisheries and vice versa?.

Figure 5 shows the mean of the posterior distribution of the random effects associated with the intercept and slope of each of the countries in the study. Slovenia, Montenegro and Spain started the study with low levels associated with small-scale fisheries, below the level of the other countries in the study. These countries behave very differently with respect to industrial fishing: above, at the average and below the rest of the countries in the study. This is the case for Spain, Slovenia and Montenegro, respectively. Algeria has a level of artisanal fishing well above the rest but its level of industrial fishing is in the average of the countries studied. The rest of the countries have specific characteristics above the average of the countries in the study, both in artisanal and industrial fishing. Italy and Algeria stand out as the countries with a higher level associated with industrial and artisanal fishing than the rest. In particular, it is worth noting that Spain is the country with the greatest imbalance, in favour of industrial fishing over artisanal fishing at the beginning of the study.

The evolution of artisanal and industrial fisheries has not been the same. Spain, Italy, Greece, France and, especially, Croatia exhibit decreasing dynamics for artisanal fisheries while in the other countries, Algeria, Morocco, Montenegro and Turkey, the trends are positive. It seems that artisanal fisheries are in recession in the economically stronger countries. Industrial fisheries show a positive trend in almost all countries except France and Italy. The countries with the highest pattern of industrial fishing are Turkey and Algeria. Although the association between sardine catches and artisanal and industrial fishing is not very strong, it is generally positive, so there seems to be a certain synergy between both types of fishing, although not in all countries,

Table 3 CPO's, in logarithmic scale, for the different countries in the study computed from models \mathcal{M}_1 , \mathcal{M}_2 and \mathcal{M}_3

Log CPO			
	\mathcal{M}_1	\mathcal{M}_2	\mathcal{M}_3
Algeria	-35.45	-28.30	-25.29
Croatia	-125.88	-86.74	-76.46
France	-65.40	-46.63	-45.44
Greece	-53.00	-31.54	-30.06
Italy	-51.68	-34.94	-31.74
Montenegro	-50.86	-37.40	-37.94
Morocco	-38.19	-29.56	-27.31
Slovenia	-97.49	-95.91	-95.28
Spain	-353.48	-169.58	-163.76
Turkey	-189.13	-44.60	-35.94

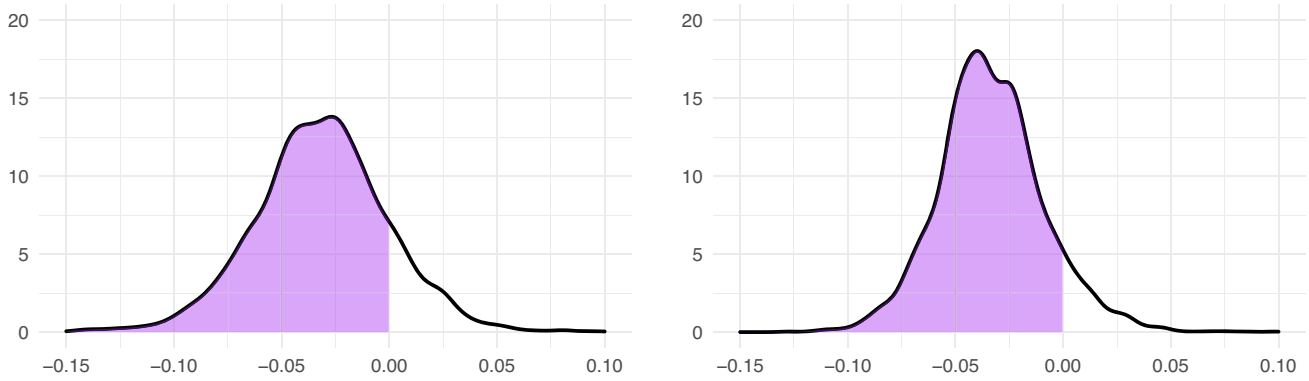


Fig. 4 Approximate marginal posterior distribution of $\beta_1^{(A)}$ and $\beta_1^{(I)}$, respectively, for model \mathcal{M}_3

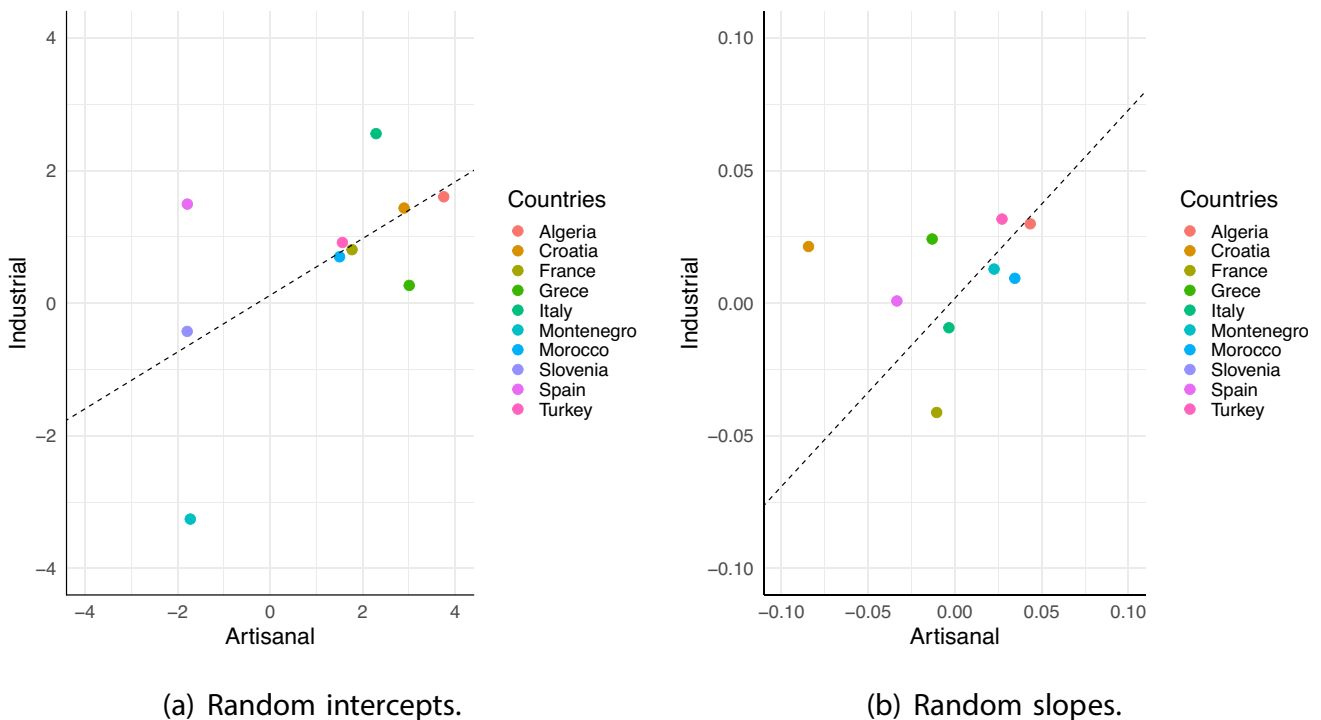


Fig. 5 Artisanal versus Industrial fishing. Approximate posterior mean of the random effects parameters from the model \mathcal{M}_3 and their estimated correlations (dashed lines): **a** random intercepts and **b** random trends

as in the case of Croatia that shows an apparent negative relationship.

5 Conclusions

We have presented a Bayesian joint longitudinal modelling to assess the temporal evolution of the European sardine landings, industrial and artisanal, in the Mediterranean countries from 1985 to 2018. These models dealt with general patterns as well as individual characteristics of the countries in the study. Therefore, these types of models

may contribute to improving the risk assessment of European sardine in the Mediterranean Sea.

Overall results confirmed that Mediterranean fisheries were highly diverse from the beginning of the time series and this heterogeneity still remains over time. This general result is in agreement with a recent study that analysed the convergence of the Mediterranean countries in terms of several ecological indicators (i.e. Marine Trophic Index, Fishing in Balance Index and Expansion Factor) during 1950–2010 (Pennino et al. 2017), showing strong temporal persistence in their fishery behaviours. Furthermore, the results demonstrate a general decline in European sardine fishing quantities in the Mediterranean Sea. Additionally,

there is a positive correlation observed between the landing dynamics of artisanal and industrial fishing within each country.

As mentioned in the introduction, the decline of sardine fisheries is a multifaceted issue that would need different approaches from different points of view. In addition, we know that the evidence of a declining trend in landings does not necessarily imply a potential risk for the stock, but there could also be other causes related to the economy, politics, or changes in demand and consumption.

Our study shows modest but interesting objectives because it provides quantitative information on the disparity in the evolution of industrial and artisanal sardine fishing in the different countries studied. Bayesian modelling is very flexible and would allow for the inclusion of additional information through baseline or temporal covariates. In this sense, it would be interesting to be able to feed our modelling with information related to the economic characteristics of the different countries and their fishing fleets, as well as geographical and environmental information on the areas where the sardine shoals are located.

The use of the official landings may be a limitation for this study as this data does not account for discards, by-catch and illegal, unreported and unregulated (IUU) catches. Despite these limitations, we believe the application of Bayesian longitudinal mixed model provides a novel way to assess changes in fisheries exploitation by different countries at large scale. This study represents a new standpoint from which to explore species fisheries exploitation time series under a probabilistic framework.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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