Assessing the risk of alternative management strategies in a Mediterranean fishery: protecting the younger vs reducing fishing effort

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A stochastic age-structured population model was developed to explore biologically favourable levels of effort and closing periods within the sardine pelagic fishery in the eastern Mediterranean Sea. Results suggested that the developed age-structured model captured the observed biomass fluctuations and catches reasonably well and represents the first comprehensive investigation of alternative management strategies for eastern Mediterranean sardine fishery that include stochasticity. The present study provided direct evidence for the importance of the correct timing of the temporal fishing ban. Significant benefits were found both in terms of biomass and catch from a corrective shift in the fishing closed period. The current findings suggested that protecting the younger age groups from fishing in the period October–December, by shifting the ban period earlier than December may profit, biologically, the stock and economically the fishing sector. Progressive reductions in fishing mortality/effort also yield significant positive biological and fishery benefits in the short term.

Keywords: sardine; fisheries management; stochastic model; ecosystem approach; technical measures

1. Introduction

The Mediterranean fishery is multispecific and this is also the case for the eastern Mediterranean purse seine fishery although some seasonal targeting also occurs. The sardine (Sardina pilchardus) is among the main target species comprising more than approximately 15% of the total pelagic landings (anchovy Engraulis encrasicolus and horse mackerel Trachurus trachurus are the two others, [27]). Purse seining is the main fishing method for pelagic species since pelagic trawling is prohibited. Management regulations for small pelagic fish, currently in force, include mesh size regulations, technical measures such as closed seasons/areas and fishing prohibitions within specific distances from the coast [19]. In the last decade, sardine catches in the eastern Mediterranean exhibit a decreasing trend and the stock has been recognized as fully exploited [4].

The control and management of such overfished species is a task of high priority for fishery managers. As a result, numerous modelling studies worldwide examined and proposed different
management actions that could prove beneficial for the sustainability and recovery of depleted and overexploited stocks. Fishing scenarios that are often investigated include, among others, closed fishing seasons [5, 8], marine protected areas [16], imposition of total allowance catches and fishing effort reduction schemes [11].

Managing fish stocks using modelling approaches is characterized by several uncertainties that can be attributed to several types of errors (measurement, process, model structure and operator) [7, 17]. The parameters included in the modelling process are known imprecisely and are subject to natural variability having a strong effect on the assessment and implementation of fishing strategies [15]. Stochastic fish models are often implemented in an attempt to handle such uncertainties and define sustainable exploitation scenario with less risk [10, 18, 22, 28]. A risk analysis is usually performed to calculate the probabilities within which the biomass, the catch and the exploitation rate will fall below or above a given reference point or threshold [20, 24].

In this study, a stochastic version of the age-structured McKendrick–Von Foerster population model [1] is implemented to simulate the dynamics of sardine stock in the North Aegean Sea (eastern Mediterranean). The deterministic McKendrick–Von Foerster age-structured population model has been successfully applied to several systems and currently was implemented to anchovy fishery in the north Aegean sea [23]. The main advantage of the current model is the continuous time scale with which the life cycle is represented by synthesizing the mortality and reproduction processes at each age group.

The aim of the paper is: (1) to apply a stochastic age-structured model for assessing the status of the sardine stock in the study area and evaluate the effectiveness of the current management measures, (2) to demonstrate a series of alternative pragmatic fishing scenarios that can be used for management advice and (3) to perform a kind of uncertainty analysis to assess the impact of the proposed management actions to the short-term sustainability of the sardine stock.

2. Methodology and data

2.1. Growth equation

The weight-at-age model used here, combines the growth in length Von Bertalanffy equation [9],

\[ L(a) = L_{\text{max}} - (L_{\text{max}} - L_0)e^{-k(a-a_0)}, \]

and the allometric weight–length relationship

\[ G(a) = a_w(L(a))^{b_w}. \]

Substituting Equation (1) into Equation (2), the growth in weight of fish \( G(a) \) with age \( a \) is represented by the equation

\[ G(a) = a_w(L_{\text{max}} - (L_{\text{max}} - L_0)e^{-k(a-a_0)})^{b_w}. \]

The growth parameters used in the presented study were derived from [25]. The values and the notation of the related parameters are given in Table 1. Since no sex discrimination of data is available, the weight–age model equation is the same for both male and female fish.

2.2. Stochastic population dynamics

The dynamics of the sardine population is described by a stochastic partial differential equation. It is an age-structured continuous population model which is derived from the deterministic
Table 1. Growth, population, reproduction and numerical scheme parameters used for the base run scenario.

| Symbol | Parameter | Value |
|--------|-----------|-------|
| \( L_0 \) \(^b\) | Length at birth | 3.5 mm |
| \( L_{\text{max}} \) \(^b\) | Maximum length | 195 mm |
| \( a_b \) | Age at birth | 0 |
| \( k_b \) | Curvature parameter | 0.39 year \(^{-1}\) |
| \( \alpha_b \) \(^b\) | Parameter | 0.00003 |
| \( b_{wb} \) | Parameter | 3.2144 |

**Natural mortality**

\( m_1 \) \(^a\) 0 < age \leq 35 days 0.21 day \(^{-1}\)

\( m_2 \) \(^d\) 35 < age \leq 182 days 0.10 day \(^{-1}\)

\( \text{age - 0} \)^\(b\) 182 < age \leq 365 days 1.50 year \(^{-1}\)

\( \text{age - 1} \)^\(b\) 1 < age \leq 2 year 0.96 year \(^{-1}\)

\( \text{age - 2} \)^\(b\) 2 < age \leq 3 year 0.69 year \(^{-1}\)

\( \text{age - 3} \)^\(b\) 3 < age \leq 4.5 year 0.61 year \(^{-1}\)

**Fishing mortality**

\( f_y(t) \)^\(b\) Interannual fishing mortality 0.40 year \(^{-1}\)(2003)

0.66 year \(^{-1}\)(2004)

0.84 year \(^{-1}\)(2005)

0.66 year \(^{-1}\)(2006)

0.55 year \(^{-1}\)(2007)

0.55 year \(^{-1}\)(2008)

0.61 year \(^{-1}\)> (2008)

\( f_y(a) \)^\(a\) Fishing-at-age 0.2 (age-0), 2.88 (age-1), 0.84 (age-2), 0.08 (age-3)

\( f_s(t) \)^\(a\) Seasonality of fishing mortality 0 (season-1), 1.2 (season-2) 1.6 (season-3), 1.2 (season-4)

**Reproduction**

\( \left( \frac{G}{F} \right)(a) \)^\(c\) Batch fecundity 325 (1 \(\leq a \leq a_{\text{max}}\))

\( R^e \) Sex ratio 0.55

\( s_1 \)^\(c\) Maximum spawning frequency fraction 0.09

\( s_2 \)^\(d\) time-1 0.5

\( s_3 \)^\(d\) time-2 1

\( s_4 \)^\(d\) Curvature parameter 0.3

**Numerical scheme**

\( \Delta a \) Age step 0.056

\( \Delta t \) Time step 0.0051

\( a_{\text{max}} \) Maximum lifespan 4.5 years

\( T_{\text{run}} \) Simulation period 18 years

\(^a[3]\), \(^b[4,25]\), \(^c[26]\), \(^d\) This study.

McKendrick–Von Foerster model [14] following the methodology of [2]. For 0 < \( a \) < \( a_{\text{max}} \), \( t > 0 \) we have

\[
\frac{\partial n(a, t)}{\partial t} + \frac{\partial n(a, t)}{\partial a} = - (m(a)n(a, t) + f(a, t))n(a, t) - \left( \sqrt{(m(a) + f(a, t))n(a, t)} \right) \frac{\partial^2 W(a, t)}{\partial a \partial t},
\]

\[
n(0, t) = \int_0^{a_{\text{max}}} Dsf(a, t)n(a, t)G(a) \, da
\]

\[
+ \sqrt{\int_0^{a_{\text{max}}} Dsf(a, t)n(a, t)G(a) \, da} \, \frac{dW(t)}{dt}, \quad t > 0,
\]

\[
n(a, 0) = n_0(a), \quad 0 \leq a \leq a_{\text{max}}.
\]
Table 2. Notation of the population dynamics model.

| Variable | Notation | Units |
|----------|----------|-------|
| $a$      | Age      | Year  |
| $t$      | Time     | Year  |
| $n(a,t)$ | Density of age $a$ at time $t$ | Fish number |
| $n(0,t)$ | Density of newborns ($a = 0$) at time $t$ | Fish number |
| $m(a)$   | Natural mortality rate | $1/\text{year}$ |
| $f(a,t)$ | Fishing mortality rate | $1/\text{year}$ |
| $D_{sf}(a,t)$ | Daily specific fecundity rate | Fish number/\text{per fish gram} |
| $G(a)$   | Growth at age in terms of weight | Grams |
| $n_0(a)$ | Initial age distribution | Fish number |
| $a_{\text{max}}$ | Maximal age of the sardine species | Year |
| $W(a,t)$ | Independent two-dimensional Brownian sheet | Dimensionless |

The definitions of the variables and parameters used within the population model are given in Table 2.

2.2.1. Derivation of the stochastic age-structured model

The mathematical formulation of the system (3) is based on the stochastic derivation described in [1,2] where a general stochastic size model and a size–age-structured stochastic population model are produced from the deterministic one. For the consistency of the present study, we lined up the basic steps of the method, while in the Appendix A.1, the analytical steps for the age–structure case were reviewed.

Taking into account a randomness in births and deaths, the implementation of the methodology for the system (3) includes a sequence of steps. First, it is assumed that the variable $n(a,t)$ randomly varies with age $a$ and time $t$. A discrete stochastic model is formulated by listing the possible changes of the population along with the corresponding probabilities for a short time step $\Delta t$ and age step $\Delta a$. The expected mean change and square mean change are then calculated for the discrete stochastic process. As the time interval, $\Delta t$ decreases, the discrete stochastic model is transformed to a stochastic equation. Brownian sheets are substituted into the stochastic dynamic system for the Wiener processes and as the age intervals go to zero the derived age-structured stochastic model approximates the stochastic model.

The advantage of the present age-structured stochastic model is that it takes into account the randomness in the birth and death processes where a deterministic model does not. Also, the variability of the randomness is not manually chosen, but it intrinsically produced through its derivation from the deterministic and it is also dynamic in age and time.

2.2.2. Natural mortality $m(a)$

In terms of natural mortality, the sardine population has been divided into six groups each having its own natural mortality value. Since there are no available data for the early life stages for sardine in the study area, mean values were unavoidably adopted [3]. The division of the early life groups was: $m_1$: 0–35 days and $m_2$: 35–182 days (Table 1). For the remaining age groups, natural mortalities values are presented in Table 1. Natural mortality parameters were derived from empirical equations where available, and were found to be age specific [4] and constant over the years of model implementation. For age group $m_2$, an average value between $m_1$ and $age – 0$ was imposed.
2.2.3. Fishing mortality $f(a,t)$

The fishing mortality function $f(a,t)$ followed the separability assumption and was described by the product of the following age ($a$) and time-dependent ($t$) factors:

$$f(a,t) = f_y(t)f_{ag}(a)f_s(t).$$

Averaged over the different age groups but specified for the 2003–2008 period, fishing mortalities values were available to parameterize the interannual variation of fishing mortality parameter $f_y(t)$ of the model. For year $> 2008$, a mean value over the 2003–2008 period was imposed for $f_y(t)$.

Since direct estimates of fishing mortality values per age group are not available, following the catch-at-age information as provided in [4] the values of $f_{ag}(a)$ term are also presented in Table 1.

Following also the seasonal distribution of fishing effort for sardine in the North Aegean sea (0% winter, 30% spring, 40% summer, 30% autumn) (HCMR database), we introduced the function $f_s(t)$ that parameterized the above information (season-1: December–February, season-2: March–May, season-3: June–August and season-4: September–November). Assuming that the distribution of fishing effort is similar across all years of the base run scenario, the values of $f_s(t)$ are given in Table 1.

2.2.4. Daily specific fecundity $Dsf(a,t)$

The daily egg production method (DEPM) is a well-developed method applied by biologists to provide valuable information on the characteristics of spawning habitats and reproductive parameters of fish stocks. The DEPM method has been applied for sardine in the central Aegean Sea for the estimation, among others, of the daily specific fecundity which will act a source of new eggs in our model. Thus, the daily specific fecundity function $Dsf(a,t)$ (number of eggs produced per gramme weight of the population) is calculated from the relationship [26]

$$Dsf(a,t) = \left( \frac{F}{G} \right)(a) \times R \times S(t),$$

where $a$ is the fish age, $(F/G)(a)$ denotes the relative fecundity (number of eggs $(F)$ per gram of weight $(G)$), $R$ is the sex ratio and $S(t)$ denotes the spawning frequency (the fraction of the mature females spawning every day).

During the peak of the spawning season, mean population relative batch fecundity $(F/G)(a)$ is fairly constant for sardine stocks in several ecosystems around the world [26]. In the model, we adopt a mean value for $(F/G)(a)$ (Table 1). The spawning period of sardine in the study area extends from November to April with a peak during December–January [25]. A normal-shaped function with a peak at $s_1$ is assumed to parameterize the spawning frequency during a year, taking the following form:

$$S(t) = s_1 \left( 1 - \frac{(t - s_2)^2}{(t - s_2)^2 + s_3} \right), \quad 0 < t < 1,$$

$t = \text{mod}(T, 1)$. The graph form of $S(t)$ is shown in Figure 1. This form is repeated for every year, but it is randomly varied as a part of $Dsf(a,t)$ due to the stochastic term of the model.

2.3. Fishing scenarios and beneficial analysis

Three types of alternative fishing management scenarios were investigated: (1) a shift in the existing fishing ban period, (2) a fixed reduction in the fishing pressure and (3) a gradual decrease...
in fishing mortality. All scenarios are projected over a 12 years period (2009–2020). Due to the stochastic form of the model, 500 repetitions were run for each scenario to allow for random output variations. The notation of the examined scenarios is listed in Table 3.

2.3.1. Shifting of the existing fishing ban period (Sc-1)

We examined the effect of shifting the existing closed period for fishing (December–March) to a different one. A shifting period from January to March was initially tested through the Sc-1.1 scenario. One period that has been proposed and tested as potentially beneficial for the sardine stock is the October–December period [4] (Sc-1.2). The main argument is that by this way the smaller length classes would be protected and thus could possibly have a positive effect on the status of the stock.

2.3.2. Reduction of fishing pressure (Sc-2)

To assess the likely effect of reduced fishing pressure, this scenario was run by assuming a fixed reduction in fishing mortality by 10% (Sc-2.1) and 20% (Sc-2.2) for the entire projection period.
2.3.3. **Gradual reduction of fishing effort (Sc-3)**

We examine the effect of a progressive annual reduction of fishing mortality for a 5-year period and a fixed mortality rate (i.e. that of the final fifth year) for the remaining projection period (Table 3). Two options were applied, first a 5% annual reduction of fishing mortality for the first 5 years (overall first 5-year reduction equals 25%) and then is kept reduced at the last year level (Sc-3.1) and the same experiment with 8% annual reduction (overall first 5-year reduction equals 40%) (Sc-3.2).

2.3.4. **Beneficial analysis**

For assessing the effect of the simulated scenario, compared with the base run scenario, we applied the Mann–Whitney–Wilcoxon (MWW) non-parametric statistical test [12]. The MWW-test, as applied in the present model, tested the alternative hypothesis whether we have an increase in the median biomass or/catch of a given scenario compared to the null hypothesis where an equality of medians holds. By this way, the management measure can be considered effective from the statistical point of view, meaning that the median of the sardine biomass or/catch derived from the scenario run is higher compared with the base run. For the implementation of the statistical test, we performed a left-sided test using the \([p,h]=\text{ranksum}\) function of Matlab [21] that returns the result of the hypothesis test performed at the significance level. Value of \(h = 0\) denotes a logical value indicating the test decision, i.e. indicates that the null hypothesis (‘medians are equal’) cannot be rejected at the 5% level, while \(h = 1\) indicates that the null hypothesis can be rejected at the 5% significance level.

3. **Implementation**

3.1. **Initialization**

Following the availability of the data the starting date for the simulations was set as 1 June 2003. The plot of the initial distribution of the population \(n_0(a)\) is shown in Figure 2.

3.2. **Numerical scheme**

To obtain the numerical simulations of the system (3), an upwind scheme was applied following the numerical method described in [23], which also solved the stochastic part of (3) using the Euler–Maruama approximation [1,13]. The details of the applied numerical scheme are described in the Appendix A.2.

3.3. **Simulated outputs**

In order to test and validate models performance, we run simulations on both the sardine biomass and annual catches. The simulated sardine biomass \(B(t)\) in tonnes at time \(t\) is computed using the relationship

\[
B(t) = \int_{a_{0.5}}^{a_{\text{max}}} n(a,t)G(a)da, \quad t > 0.
\]  

(4)

The lower part of the integral \(a_{0.5}\) is chosen so that the simulation will be comparable with the sardine acoustic biomass estimates of June 2003–2006 and 2008.
Figure 2. Initial distribution of the population. The initial values are derived from [4].

The catch in grams during a time interval \([t, t + \Delta t]\) is given by the integral

\[
C_{\Delta t} = \int_0^{a_{\text{max}}} c(a, \Delta t) G(a) \, da, \tag{5}
\]

where

\[
c(a, \Delta t) = \frac{f(a, t)}{m(a) + f(a, t)} (n(a, t) - n(a, t + \Delta t)) \Delta t
\]

\[
+ \frac{f(a, t)}{m(a) + f(a, t)} \left( \sqrt{(n(a, t) - n(a, t + \Delta t)) \Delta t} \right) \eta. \tag{6}
\]

The term \(c(a, \Delta t)\) denotes the population of age \(a\) that is fished during the period \([t, t + \Delta]\), \(G(a)\) expresses the growth in weight and \(\eta \sim N(0, 1)\).

Due to the stochastic form of the model, it was essential to consider the propagated uncertainty of the sardine biomass driven by the input uncertainties. Therefore, for the projected sardine biomass obtained from the 500 repetitions, we calculated the following terms as proposed in [6]: (a) the mean \((m)\) of the repetitions was used as an estimate of the projected sardine biomass, \(P_{\text{SB}}\), (b) the standard deviation \((\text{std})\) was used as the standard uncertainty associated with \(P_{\text{SB}}\), (c) the probability that the \(P_{\text{SB}}\) will fall into the standard expanded uncertainty interval \(I_{SB} = [m - \text{std}, m + \text{std}]\) and (d) the standard fractional uncertainty \(Q_{SB}\) which is defined as the ratio of \(m\) to \(\text{std}\).

4. Results

4.1. Base run scenario

In Figure 3, the sardine biomass estimates derived from the simulations and the acoustic surveys are presented. In all cases, the biomass fell within the range of acoustic data (black dotted lines with 95% confidence intervals) with the mean biomass levels lying between 18,390 and 27,550.
Figure 3. The black line shows the mean simulated sardine biomass from 500 runs, the dark grey shaded area covers the 25%–75%th percentile, while the light grey shaded area covers the 5–25%th and 75–95%th percentiles. The dot lines with the error bars represent the estimated biomass from acoustics with the corresponding 95% confidence intervals [4].

tonnes. Overall, the model reproduced reasonably well the annual cycle of sardine dynamics characterized by a seasonality due to species’ spawning strategy. The eggs that are produced during the winter period grow causing an increase in biomass till the first half of the year where biomass reaches its highest value. The combined effects of fishing mortality and the lack of egg productivity in the subsequent months cause a decrease in biomass in the second half of the year. In order to accommodate the high variability of the small pelagic species alongside the precautionary principle, it was decided to tune the model to fall into the lower bounds of biomass estimates for 2006 and 2008.

The performance of the model during the 2003–2008 period was examined by comparing the simulated catches to the annual landings (Figure 4). Box plots represent the modelled annual catch over 500 simulations. The top and bottom lines of the box plot is the interquartile range and the black line of each box plot is the median. Black dot points correspond to the reported annual landings. The mean catch outputs follow the reported mean annual catch levels. Overall, a good agreement was observed between them. A vertical section of Figure 3 at any time period corresponds to a sample of values for sardine biomass that can be represented by an empirical probability distribution histogram. Such a histogram can be summarized using statistical measures and can also define the uncertainty of the propagated simulation. Considering June 2013 as a reference period, the sample biomass distribution is shown in Figure 5. The statistical and uncertainty measures of the projected sardine biomass histogram at June 2013 are also presented in Table 4. With a mean biomass of $m = 22,559.2$ tonnes, we noticed that the fractional uncertainty of the mean is $Q_{SB} = 0.25$, while the probability of the $P_{SB}$ sardine biomass to fall within the uncertainty interval $I_{SB} = [16,462.4, 28,657.3]$ is 0.67.

4.2. Scenario results

The median plots of the sardine biomass for the base run scenario alongside the corresponding explored scenarios are shown in Figure 6. Evidently, all the examined scenarios except Sc-1.1 increased the species biomass through time.
The annual catches for base run and examined scenarios are presented in Figure 7. The modified fishing ban period and the step-wise 5-year reduction of $F$ by 8% resulted in the highest increase in fishery catches. The gradual decrease of $F$ had an anticipated negative initial impact on the fishery. Soon after, however, this was followed by a period of significantly improved catches.

To examine further the observed differences in the biomass medians and catches and assess the statistical significance of these differences, we used the MWW non-parametric statistical test.

The results of the MWW test for the projected 2010–2020 period are summarized in Table 5. The following decision pairs were considered essential: (a) (1,0) which indicated a biological benefit (light grey cells), (b) (0,1) which implied a fisheries benefit (dark grey cells) and (c) (1,1) which suggested both biological and fisheries benefit (bold pair) from the applied scenario.
Table 4. Summary statistics of forecasted sardine biomass distribution.

| Parameters                  | June 2013 |
|-----------------------------|-----------|
| Mean (m)                    | 22,559.2  |
| Median                      | 21,666.4  |
| Standard deviation (std)    | 6097.5    |
| Skewness                    | 0.93      |
| Interquantile               | 7998.1    |
| 5% percentile               | 14,277.1  |
| 95% percentile              | 32,770.2  |
| Fractional uncertainty ($Q_{SB}$) | 0.25 |
| Uncertainty interval ($I_{SB}$) | [16,462.4, 28,657.3] |
| $Pr(P_{SB} \in I_{SB})$     | 0.67      |

Figure 6. Plots of median biomass for the base run (black line) and examined scenarios. Black vertical dot lines represent the reference dates (June 2014 and June 2020) to provide risk analysis.

Figure 7. Plots of median annual yields for the base run (black dots) and examined scenarios.
Table 5. MWW non-parametric statistical test, comparison of the base run with the various scenarios over the 2009–2020 period.

| Year | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|------|------|------|------|------|------|------|------|------|------|------|------|
| Sc-1.1 | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) | (0,0) |
| Sc-1.2 | (0,0) | (0,0) | (0,1) | (0,1) | (1,1) | (0,1) | (1,1) | (1,1) | (1,1) | (1,1) | (1,1) |
| Sc-2.1 | (0,0) | (0,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) |
| Sc-2.2 | (0,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) |
| Sc-3.1 | (0,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,1) |
| Sc-3.2 | (0,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,0) | (1,1) |

Note: Values of $h = (h_{\text{bio}}, h_{\text{cat}})$ are shown, where $h_{\text{bio}}$ corresponds to biomass and $h_{\text{cat}}$ the annual catches decision test value.

Table 6. Probability of sardine biomass (SB) to become greater than mean biomass of base run scenario with assigned standard uncertainty.

| Year | 2014   | 2020   |
|------|--------|--------|
| Sc-1.1 | 0.41 (0.14) | 0.35 (0.11) |
| Sc-1.2 | 0.54 (0.14) | 0.62 (0.20) |
| Sc-2.1 | 0.62 (0.17) | 0.62 (0.19) |
| Sc-2.2 | 0.72 (0.15) | 0.80 (0.24) |
| Sc-3.1 | 0.69 (0.16) | 0.84 (0.24) |
| Sc-3.2 | 0.67 (0.23) | 0.94 (0.30) |

The January–March period fishing ban scenario did not provide any improvement either in the biomass or the catch of the species. On the contrary, the October–December closing period scenario proved to be beneficial for both the species and its fishery. Improved catches were obtained already from the third simulation year (2012) and increased stock levels were recorded in the sixth simulation year (2015). Both species biomass and catches remained higher than the corresponding of the base run scenario for the last four simulation years. Importantly, the probability of the mean biomass to be higher than the base run was 62% in the final simulation year for the October–December fishing ban scenario.

The fixed reduction of fishing mortality scenarios exhibited a similar effect on stock and fishery. The stock biomass levels increased and remained statistically higher than the original biomass after the second simulation year i.e. 2012. Species biomass and catches were concurrently significantly higher than the base run scenario only in 2018. The biomass of the fixed 20% $F$ cut had 80% probability of being greater than the original biomass.

The fishing mortality gradual reduction scenarios demonstrated analogous results to the previous ones. Statistically significant higher values were obtained: (a) for the catches in the last three years (two for scenario 3.1) and (b) for the stock biomass from the second simulation year for both sub-scenarios. Catches decreased rapidly with the implementation of $F$ cuts but the fishery soon recovered to levels higher than the base run. Noticeably, the sardine biomass in the final simulation year had 94% chances to be higher than the original biomass.

Table 6 shows the probability that the scenario biomass will be larger than the mean base run biomass. It is observed that the last three scenarios had the largest probability of attaining biomass levels higher than the base run scenario.

5. Discussion/conclusions

The advantage of the present age-structured stochastic model is that, contrary to a deterministic model, it incorporated the randomness in the birth, death and reproduction processes. The
variability of the randomness was not subjectively chosen, but rather was intrinsically produced through its deterministic derivation that was further dynamic in age and time. The fisheries management system in the Mediterranean depends heavily on direct effort restrictions via the control of fishing effort/mortality and technical measures including restricted entry. In the present work, we used a stochastic age-structured population operating model developed in the MATLAB framework to explore biologically favourable levels of effort and closing periods within the sardine fishery and the impact of these various scenarios on the stock from a more biologically focussed perspective. This work represents the first comprehensive investigation of alternative management strategies for eastern Mediterranean sardine fisheries that include stochasticity. The stock assessment process that has been recently implemented for the sardine stock in the north Aegean Sea suffered from various uncertainties that have been highlighted in [4]. For example a simplistic assumption made was that of constant natural mortality across ages that can have a strong impact on small pelagic stock assessment process. The present work relaxed this assumption by simulating the population dynamics of sardine having considered the impact of uncertainty derived from varying mortality and fecundity rates in the model parameters and without imposing a fixed variability in the uncertainty of the parameters.

The current base run results of the model captured the basic characteristics of the sardine fishery (biomass, catch) adequately. The shift in the fishing closing period, i.e. October–December (instead of December–February), proved to be beneficial from both a biological and fishery perspective. The fishery improved the catches and, thus its profits after 3 years. The stock’s biomass increased significantly above the status quo level after 6 years and despite the higher catch rates attained by the fishing industry. In addition, there were 62\% greater chances for the sardine biomass to be greater than the original biomass in 2020. These findings are in agreement with observations on the composition of landings during the last decade, revealing a higher proportion of smaller individuals towards the end (i.e. October–November) of the existing temporal closure (HCMR database). The present results suggest that protecting these younger age groups from fishing by shifting the fishing ban period earlier than December may profit, biologically, the stock and economically the fishing sector.

The direct reduction of the exerted fishing mortality of the fleet had a positive effect on stock’s biomass level. The current findings showed that substantial reductions in fishing effort and resulting fishing mortality would be required to obtain statistically significant increases in biomass in 2–3 years. The fishing sector will be affected by such an effort/mortality reduction. The fleet catches will initially drop but will soon recover to improved levels. However, these levels will be significantly higher than the catches of the base run scenario only in one of the 11 simulation years. Evidently, such a management scenario will advance the recovery of the overexploited sardine stock to sustainable levels but the benefit for the fishery will only be marginal.

The gradual reduction of fishing mortality could also be effective in the recovery of the overexploited sardine stock in the Aegean Sea. Under such a management strategy, the fleet will steadily apply less effort (than the base run scenario) and eventually the stock will rebuild to higher levels and sooner (faster than the base run scenario). The probability of the sardine biomass being larger than the mean biomass of the base run scenario in the final simulation year 2020 was 94\%, being the larger realization among the scenarios tested. As anticipated, the fishery catches will initially drop but will progressively increase in the last 3 years of the 11-year simulation period. This could have an adverse effect on the implementation of such a management measure as it will have important socioeconomic implications. One way to ease the transition towards the decreased fishing effort regime will be to introduce some form of compensation or the right incentives for the stakeholders to comply and accept the loss on their income due to the reduced catches.

Results suggested that the developed age-structured model captured the observed biomass fluctuations reasonably well. However, small pelagic species are susceptible to environmental fluctuations. The short time series of the available biological data limited the use of any meaningful
environmental variable. There is a clear need to conduct further research to extend the datasets and include additional information (such as prey availability, oceanographic and environmental data).

The existing management system has proven inadequate to safeguard simultaneously the biological and the socioeconomic prosperity of the pelagic ecosystem in the North Aegean Sea. However, our results highlight that recovery is possible without substantial changes in the management system. The present study provided direct evidence for the importance of the correct timing of the temporal fishing ban. Results showed significant benefits both in terms of biomass and catch from a corrective shift in the fishing closed period. Such a modification will also be easier to implement, as it will require minimum, if any, adjustments for the fishermen. Progressive reductions in fishing mortality/effort were also found appropriate to produce significant positive biological and fishery results in the short term. However, for these latter to be implemented, substantial management changes and socioeconomic incentives may be required.

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References

[1] E.J. Allen, Modeling with Ito Stochastic Differential Equations, Springer, Dordrecht, 2007.
[2] E.J. Allen, Derivation of stochastic partial differential equations for size- and age-structured populations, J. Biol. Dyn. 3 (2009), pp. 73–86.
[3] P. Alvarez and M. Chifflet, The fate of eggs and larvae of three pelagic species, mackerel (Scomber scombrus), horse mackerel (Trachurus trachurus) and sardine (Sardina pilchardus) in relation to prevailing currents in the Bay of Biscay: Could they affect larval survival? Sci. Mar. 76(3) (2012), pp. 573–586.
[4] K. Antonakakis, M. Giannoulaki, A. Machias, S. Somarakis, S. Sanchez, L. Ibaibarriaga, and A. Uriarte, Assessment of the sardine (Sardina pilchardus Walbaum, 1792) fishery in the eastern Mediterranean basin (North Aegean Sea), Med. Mar. Sci. 122 (2011), pp. 333–357.
[5] C.J. Arendse, A. Govendera, and G.M. Branch, Are closed fishing seasons an effective means of increasing reproductive output? A per-recruit simulation using the limpet Cymbula granatina as a case history, Fish. Res. 85 (2007), pp. 93–100.
[6] S.A. Bell, A beginner’s guide to uncertainty in measurement, National Physical Laboratory, Teddington, Middles., 2001.
[7] A. Charles, Living with uncertainty in fisheries: analytical methods, management priorities and the Canadian groundfishery experience, Fish. Res. 37 (1998), pp. 37–50.
[8] W. Chen, M. Al-Husaini, and M. Al-Foudari, Using age-structured models to develop a stock recovery strategy for Kuwait’s shrimp fishery, Fish. Res. 2–3 (2007), pp. 276–284.
[9] J.E. Cloern and F.H. Nichols, A von Bertalanffy growth model with a seasonally varying coefficient, J. Fish. Res. Board Can. 35 (1978), pp. 1479–1482.
[10] J.M. Da-Rocha, M.D. Garza-Gil, and M.M. Varela-Lafuente, A model of fishing periods applied to the European sardine fishery, Fish. Res. 109 (2011), pp. 16–24.
[11] N. Fouzai, M. Coll, I. Palomera, A. Santojanni, E. Arneri, and V. Christensen, Fishing management scenarios to rebuild exploited resources and ecosystems of the Northern-Central Adriatic (Mediterranean Sea), J. Mar. Sys. (2012), pp. 102–105.
[12] J.D. Gibbons and S. Chakraborti, Nonparametric Statistical Inference, 4th ed., Marcel Dekker, New York, 2003.
[13] D.J. Higham, An algorithmic introduction to numerical simulation of stochastic differential equations, Siam Rev., Soc. Ind. App. Math. 43 (2001), pp. 525–546.
[14] H. Hoppensteadt, Mathematical theories of populations demographics, genetics, and epidemics series, CBMS-NSF Regional Conference Series in Applied Mathematics, New York, 1975.
[15] H. Hoshino, E.J. Milner-Gulland, and R.M. Hillary, Bioeconomic adaptive management procedures for short-lived species: A case study of Pacific saury (Cololabis saira) and Japanese common squid (Todarodes pacificus), Fish. Res. 121–122 (2012), pp. 17–30.
[16] S. Guénette and T.J. Pitcher, An age-structured model showing the benefits of marine reserves in controlling overexploitation, Fish. Res. 39 (1999), pp. 295–303.
[17] Y. Jiao, Y. Chen, and J. Wroblewski, An application of the composite risk assessment method in assessing fisheries stock status, Fish. Res. 72 (2005), pp. 173–183.
Appendix A.1

For the derivation of the mathematical model, we mainly use the deterministic structure in [14] as well as the stochastic derivation (construction and analysis) from [2]. Thus, first we consider the changes of the population within a small time interval $\Delta t$. Dividing the population into $A$ age intervals $[a_{j-1}, a_j]$ for $j = 1, 2, \ldots, A$, where $a_j = j \Delta a$, $\Delta a = a_{\text{max}}/A$ and considering that $n_j(t)$ is the population level at time $t$ with age from $a_{j-1}$ to $a_j$, the potential population changes will have to be documented. For $n_j(t) > 1$, there is a probability 1 for $n_{j-1}(t)/\Delta a$ individuals to change age from age-class $j-1$ to $j$. Also, defining as $m_j$ and $f_j$ the natural and fishing mortalities rates for age-class $j$, there is a probability of $n_j(t)(m_j + f_j)\Delta a$ for a death in time $\Delta t$ for age-class $j$, while the occurrence of birth for the first age-class has a probability $\sum_{k=2}^{A} D_{sfj} n_k G_k \Delta t$. All the possible changes are listed in Table A1.

The mean and mean square of these changes for $j > 1$ are

$$E(\Delta n_j) = \frac{n_{j-1} - n_j}{\Delta a} - (m_j + f_j)n_j \Delta t,$$

$$E((\Delta n_j)^2) = (m_j + f_j)n_j \Delta t.$$

For $j = 1$,

$$E(\Delta n_1) = \sum_{j=2}^{A} D_{sfj} n_j G_j \Delta t - n_1 \frac{\Delta t}{\Delta a},$$

$$E((\Delta n_1)^2) = \sum_{j=2}^{A} D_{sfj} n_j G_j \Delta t.$$

Table A1. Potential changes of $n_j(t)$ for $j > 1$ and $n_1(t)$ during time $\Delta t$.

| Change ($\Delta n_j$) | Probability |
|-----------------------|-------------|
| $n_{j-1}\Delta t/\Delta a$ | 1           |
| $-n_j\Delta t/\Delta a$ | 1           |
| $-1$ | ($m_j + f_j)n_j \Delta t$ |
| Change ($\Delta n_1$) | Probability |
| $1$ | $\sum_{k=2}^{A} D_{sfj} n_k G_k \Delta t$ |
| $-n_1\Delta t/\Delta a$ | 1           |
The above relations compose a discrete stochastic model which satisfies the Itô system [2],
\[ d n_j(t) = \frac{-n_j - n_{j-1}}{\Delta a} dt - (m_j + f_j)n_j dt - \sqrt{(m_j + f_j)n_j} d\bar{W}_j(t) \quad \text{for } j = 2, 3, \ldots, A, \]
\[ d n_1(t) = \sum_{j=2}^{A} Ds_j n_j G_j dt - \frac{n_1}{\Delta a} dt + \sum_{j=2}^{A} Ds_j n_j G_j dW(t), \]
where \( W(t), \bar{W}_j(t) \) are independent Wiener processes for \( j = 2, 3, \ldots, A \). Applying a Brownian sheet \( W(a, t) \), the above system equations can be written as
\[ \frac{d n_j(t)}{dt} = \frac{-n_j - n_{j-1}}{\Delta a} - (m_j + f_j)n_j - \sqrt{(m_j + f_j)n_j} \frac{1}{\Delta a} \int_0^{\eta} \bar{W}(a, t) da + \sum_{j=2}^{A} Ds_j n_j G_j dW(t), \]
\[ \frac{d n_1(t)}{dt} = \sum_{j=2}^{A} Ds_j n_j G_j - \frac{n_1}{\Delta a} + \sum_{j=2}^{A} Ds_j n_j G_j dW(t). \]

Allowing the age-interval \( \Delta a \) to approach zero, we conclude to the stochastic partial differential equation for the age-structured model. If we let \( n_j(t) = n(a_j, t) \Delta a \), then for \( 0 < a < a_{\max} \) and \( t > 0 \),
\[ \frac{\partial n(a, t)}{\partial t} = -\frac{\partial n(a, t)}{\partial a} - (m(a) + f(a, t))n(a, t) - \sqrt{(m(a) + f(a, t))n(a, t)} \frac{\partial^2 W(a, t)}{\partial a \partial t}, \]
\[ n(0, t) = \int_0^{a_{\max}} Ds_j n(a, t) G(a) da + \sqrt{\int_0^{a_{\max}} Ds_j n(a, t) G(a) da} \frac{dW(t)}{dt}, \quad t > 0, \]
\[ n(a, 0) = n_0(a), \quad 0 \leq a \leq a_{\max}. \]

**Appendix A.2**

In order to implement the numerical method, a spatial grid for age \( a \) and time \( t \) is introduced. Thus, \( a_j = j \Delta a, j = 0, 1, \ldots, A \), where \( \Delta a = a_{\max}/A \) is the mesh size and \( j \) is a positive integer. We also consider a fixed time interval \( 0 \leq t \leq T_{\text{run}} \). The time step is denoted by \( \Delta t \), where \( t_i = i \Delta t, i = 0, 1, 2, \ldots, N_{\text{run}}, \) with \( N_{\text{run}} = [T_{\text{run}}/\Delta t] \), are the discrete time levels.

For a time step \( \Delta t \) and an age step \( \Delta a \), we consider \( n_{j,i} \approx n(a_j, t_i) \) is the approximation to the exact solution \( n(a, t) \) of the problem (1) at the point \( (a_j, t_i) \) and \( n_{j,i} \geq n(a_j, t_i) \) is the numerical approximation of the initial distribution \( n(a, 0) \).

Also, we use the notation \( I \) to denote the integral approximation of the birth term \( n(0, t) \), i.e. \( n_{j,i} \approx n(a_j, t_i) \), which is
\[ I(n_{j,i}) = \sum_{j=0}^{J'j} Ds_j f(a_j, t_i)n_j G(a_j) \Delta a + \sqrt{\sum_{j=0}^{J'j} Ds_j f(a_j, t_i)n_j G(a_j) \Delta a} \delta_j, \]
where the symbol \(^\prime\) means that the first and last terms of the sum are halved, i.e. the trapezoidal rule is used. The numerical scheme for the problem (1) and Equations (4) and (5), for \( i = 0, 1, 2, \ldots, N_{\text{run}} \) and \( j = 1, \ldots, A \) is the following:
\[ n_{j,i+1} = n_{j,i} - \frac{\Delta t}{\Delta a} [n_j - n_{j-1}] - \Delta t (m(a_j) + f(a_j, t_i))n_j - \sqrt{(m(a_j) + f(a_j, t_i))n_j}\Delta w_j, \]
\[ n_{0,i+1} = I(n_{0,i}), \]
\[ B_i = \sum_{j=0}^{J'} n_j G(a_j) \Delta a, \]
\[ C_{i+1} = C_{i, a_0} + \sum_{j=0}^{J'} \Delta a \frac{f(a_j, t_i)}{m(a_j) + f(a_j, t_i)} G(a_j) n_{j,i} \Delta t \]
\[ + \sum_{j=0}^{J'} \Delta a \frac{f(a_j, t_i)}{m(a_j) + f(a_j, t_i)} G(a_j) \sqrt{(n_j - n_{j,i}) \Delta t} \cdot w_{j,i}. \]

where \( w_{j,i} \sim N(0, 1) \).

The values of the numerical scheme parameters \( \Delta a, \Delta t, T_{\text{run}}, N_{\text{run}} \) are listed in Table 1.