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Economic Effects of Global Warming under Stock Growth Uncertainty: The European Sardine Fishery

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Abstract

Global warming of the oceans is expected to alter the environmental conditions that determine the growth of a fishery resource. Most climate change studies are based on models and scenarios that focus on economic growth, or they concentrate on simulating the potential losses or cost to fisheries due to climate change. However, analysis that addresses model optimization problems to better understand of the complex dynamics of climate change and marine ecosystems is still lacking. In this paper a simple algorithm to compute transitional dynamics in order to quantify the effect of climate change on the European sardine fishery is presented. The model results indicate that global warming will not necessarily lead to a monotonic decrease in the expected biomass levels. Our results show that if the resource is exploited optimally then in the short run, increases in the surface temperature of the fishery ground are compatible with higher expected biomass and economic profit.

Keywords*: Global warming, stock growth uncertainty, European sardine fishery, Transitional dynamics*

Introduction

Marine social-ecological systems are in decline (MEA 2005; Branch et al. 2010; Gelcich et al. 2010; MRAG 2010; FAO 2012). Climate change will complicate the challenges currently facing global fisheries, as it has begun to alter ocean conditions, particularly water temperature and biogeochemistry (Cheung et al. 2009).

The number of empirical studies related to climate change in fisheries has increased dramatically in recent years. Results seem to suggest that climate change is altering the behavior of commercial fisheries (Lehodey et al. 2006; Drinkwater et al. 2010; Wang et al. 2010) and productivity of the stocks (Hannesson 2007). It also seems to be causing changes in biotic and physiological characteristics of species (Schmittner 2005), and the distribution of many species of fish (Poff et al. 2002). These changes are unpredictable and can affect the behavior of stocks, which in turn can negatively impact the environmental services they provide (Worm et al. 2006; Cheung et al. 2009).

One effect of global warming is that the water temperature of the oceans is altered (IPCC 2007). Increased temperature reduces the ability of oceans to capture CO_2, and the oceans become more acidic; this acidity subsequently reduces the concentrations of carbon ions and influences the biological capacity of the oceans (Caldeira and Wickett 2003). Moreover, global warming of the oceans is expected to alter the environmental conditions that determine the growth of the fishery resource (Johannessen and Miles 2011; Pascoe et al. 2011; Vinegar et al. 2011), because recruitment of many exploited fishes and invertebrates is correlated with environmental conditions (Cushing 1975). For this reason, numerous studies have focused on the potential impact of climate change on Earth and its natural resources (Rockström et al. 2009), and in particular on fishery resources (Arnason 2007; Trathan et al. 2007). Such studies assume that changes in ocean temperature will change the natural growth rate of the resource (Hannesson et al. 2006; Garza-Gil et al. 2011), which will have economic impacts on the fishing industry (Arnason 2007; Sumaila et al. 2011; Voss et al. 2011).

In particular, the economic consequences of climate change on fisheries might manifest themselves through changes in the price and value of catches, fishing costs, fishers' incomes, and earnings to fishing companies (Arnason 2007; Bosello et al. 2007). There are a number of research efforts currently underway to estimate the economic losses that might occur due to climate change (Eide 2007; Medel 2011; Sumaila et al. 2011), and the economic costs of adapting fisheries to climate change (Tseng and

Chen 2008). Most climate-change of studies is based on the models and scenarios on economic growth (Eboli et al. 2010), or concentrated on simulating the potential losses (Sumaila et al. 2011) or cost to fisheries due to climate change (Kavuncu 2007; Cinner et al. 2011). However, analysis that address model optimization problems may also lead to a better understanding of the complex dynamics of climate change and marine ecosystems (Crèpin et al. 2011).

This paper is structured as follows. Section 2 shows the implications of climate change and the transitional dynamics in fishery resources. Sections 3 to 5 present a stochastic bioeconomic model and its forward-looking economic solution to estimate the economic effects of climate change on the European sardine (*Sardina pilchardus*) fishery. Section 6 shows the results and discussion. Section 7 concludes.

Climate change and transitional dynamics of fishery resources

Analysing climate change involves studying systems that are in transition (van der Brugge et al. 2005; Voss et al. 2011). The growth rate of a fishery resource is subject to changing conditions under global warming. Therefore, the population can never be in equilibrium until the ocean temperature stabilizes. Technically, global warming alters the steady state of the biomass which adjusts to a new steady state situation; this adjustment process is called transitional dynamics. Thus, the system of equations used to describe the behavior of a social-ecological system must be modified to take into account the transitional dynamics of the system in order to analyse the impact of climate change.

Calculating the transitional dynamics of the system that are required to reach the new steady state is not an intractable problem (Da Rocha et al. 2012a and 2012b). Given an initial global warming scenario**,** once an event of climate change occurs we may set a time horizon large enough to ensure that the dynamics of the system attains again stability. This also allows truncating the transitional dynamics in the new steady state associated with the global warming scenario reached after the increase of temperature of the oceans. The solution is obtained by solving a finite system of difference equations. Although generally it is not possible to obtain analytical solutions, it is possible to solve the dynamics equations of the system using numerical methods.

Sometimes system dynamics are simulated as a succession of stationary states. For instance Garza-Gil et al. (2011) describes the steady state of a fishery affected by global warming as a situation where the biomass only is affected by the temperature which is an exogenous variable; a change in the temperature varies the stationary value of the stock. In a single-species case and without global warming affecting the fishery, the optimal adjustment path is monotonically increasing in both biomass and harvest whenever the actual biomass level is below that of optimal equilibrium and monotonically declining in both variables in the opposite case (Clark 1976). These adjustment paths are missed when the analysis is focused exclusively on steady state situations.

Nevertheless, simulating a situation of flux using a succession of stationary situations may be a reasonably robust approximation in some circumstances. For example when the initial state of the system is under equilibrium (i.e., steady state) and that global warming follows a very slow pattern the transitional dynamics to the steady state can be neglected. However, this simplification has two important limitations. First, given that climate change began before the period of analysis, resources have been subjected to changing environmental conditions; even if the changes are very gradual and imperceptible, the system is not in equilibrium. Second, climate change might not be the only factor of uncertainty in terms of environmental conditions, which would mean that the system is always fluctuating around the hypothetical steady state. Therefore, the initial conditions of the ecosystem would not have been close to the steady state. In the case of the European sardine (*Sardina pilchardus*), the population likely is affected by various environmental conditions. The spawning stock biomass (SSB) has declined since 2006 due to the lack of strong recruitments in recent years. As a result, SSB in 2011 was 67% below the long-term average (ICES 2011a).

Due to these limitations the approach we follow in this article is not to simulate as a succession of stationary states. By the contrary, we focus on transitional dynamics to a new steady state. In a stochastic context, climate change induces consequences longer than the oscillating frequency and the relevant analysis has not to be based on the final situation but on the transition to this point.

In this paper we provide a forward-looking algorithm for estimating the impact of foreseeable ocean temperature changes on the economic exploitation of fishery stocks subject to growth uncertainty. We first describe the bio-economic model, and then we describe the equations used to quantify the economic effects of climate change and the algorithm used to solve them numerically. As a case study, we apply the algorithm to the European sardine fishery.

The bio-economic model

In this section, we introduce global warming using the stochastic model of Da Rocha et al. (2011). We assume that the size of the resource at period $t+1$, X_{t+1}, is the difference between the growth of the resource, $G=(1+\varepsilon_t)aX_t^{b+cT_t}$ and the catches for the period t, h_t:

$$X_{t+1}=(1+\varepsilon_t)aX_t^{b+cT_t}-h_t, \qquad (1)$$

where a, b and c are biological constant parameters, T_t is the sea surface temperature at period t, and ε_t measures the effect of other environmental factors on the growth of the resource. We assume that ε_t is an independent and identically distributed (i.i.d.) stochastic variable with $E\varepsilon_t=0$ and $E\varepsilon_t^2=\sigma_\varepsilon$.

Notice, first that $b+cT_t$ represents the elasticity of the gross stock growth, i.e. if the stock increases 1% then next period stock increases a $(b+cT_t)$%. This means that changes in the surface temperature affect the evolution of the stock through the elasticity of the gross stock growth, in particular through parameter *c.* Although the elasticity of the growth function can also be affected by other motives apart from temperature. This is represented by the parameter *b*. Second, $(1+\varepsilon_t)a$ can be interpreted as the productivity of the resource at time t, which can be affected by other environmental shocks apart from those of temperature.

Catches depend on a Cobb-Douglas technology, which is a function of the amount of fishing effort measured through the number of fishing days, e_t, the size of the resource, X_t, and fleet productivity, γ, which is assumed to be constant across time:

$$h_t=\gamma X_t^{\beta_1}e_t^{\beta_2}, \qquad (2)$$

where β_1 and β_2 represent the stock and effort elasticity, respectively.

At the time when management decisions are made for the time period, the regulator knows the size of the resource, X_t, sea surface temperature, T_t, and the realization of the stochastic variable, ε_t. Moreover, the regulator is forward looking: (S)he knows the future evolution of the sea surface temperature which is exogenously given by:

$$T_t = \begin{cases} T_{t-1} + \Delta T & \forall t < \bar{t} \\ T_{t-1} & \forall t \geq \bar{t} \end{cases}, \qquad (3)$$

where, $\bar{t}$ is the estimated period of time required for global warming to stabilize.

Before solving the model, note that the bio-economic system cannot attain stationarity at any time before sea temperature stabilizes. Stationarity in this bio-economic model means that the stock keeps constant along time. As long as $t < \bar{t}$, the sea temperature is changing according with (3) and this implies that the stocks also varies according to (1) and (2).

A forward-looking economic solution

We propose a forward-looking economic solution based on the following premises. At any date t the economic problem consists of choosing optimal catches to maximise economic profits $ph_t - we_t$, discounted at the initial moment where *p* is the market price of the fish and *w* is the cost of the fishing effort. This aim is attained taking into account stock growth (equation (1)), fishing technology (equation (2)), and, more importantly, that sea surface temperature will not be constant before $\bar{t}$ (equation (3)). Formally:

$$\max_{\{h_t, X_{t+1}\}_{t=0,\ldots,\infty}} \quad \sum_{t=0}^{\infty} \delta^t \underset{t}{E}\left(ph_t - we_t\right),$$

$$s.t. \quad \begin{cases} X_{t+1} = (1+\varepsilon_t) a X_t^{b+cT_t} - h_t & \forall t \\ h_t = \gamma X_t^{\beta_1} e_t^{\beta_2} & \forall t \\ T_t = T_{t-1} + \Delta T & \forall t < \bar{t} \\ T_t = T_{t-1} & \forall t \geq \bar{t} \\ X_t \geq 0 & \forall t \\ X_0, T_0, \Delta T \ \ are\ given \ \ and \ \ \varepsilon_t \ \ is \ \ i.i.d. \end{cases}, \qquad (4)$$

where δ denotes the discount factor and $\underset{t}{E}$ represents the expectation of future variables that are estimated based on the information available at period *t* about the future evolution of sea surface temperature and natural resource growth shocks.

In order to solve the maximization problem (4), we rewrite catches and effort as:

$$h_t(\varepsilon_t, T_t, X_t, X_{t+1}) = (1+\varepsilon_t) a X_t^{b+cT_t} - X_{t+1}, \tag{5}$$

and

$$e_t(\varepsilon_t, T_t, X_t, X_{t+1}) = \left[\frac{(1+\varepsilon_t) a X_t^{b+cT_t} - X_{t+1}}{\gamma X_t^{\beta_1}} \right]^{1/\beta_2}, \tag{6}$$

Therefore, the economic problem can be expressed in terms of a sequence of state variables, $\left\{ \varepsilon_t, T_t, X_t \right\}_{t=0}^{\infty}$, such that:

$$\max_{\{X_{t+1}\}_{t=0,\ldots,\infty}} \sum_{t=0}^{\infty} \delta^t \underset{t}{E} \left[p h_t(\varepsilon_t, T_t, X_t, X_{t+1}) - w e_t(\varepsilon_t, T_t, X_t, X_{t+1}) \right]. \tag{7}$$

The first order conditions of the maximization problem (5) are an infinity set of equations given by:

$$-\frac{\partial \left(p h_t - w e_t \right)}{\partial X_{t+1}} = \delta \underset{t}{E} \left[p \frac{\partial h_{t+1}}{\partial X_{t+1}} - w \frac{\partial e_{t+1}}{\partial X_{t+1}} \right] \qquad \forall t = 0,1,\ldots,\infty . \tag{8}$$

Equation (8) characterises the optimal harvesting rule by equalising, for each and every period t, present marginal profits of increase in one unit harvesting today:

$$-\frac{\partial \left(p h_t - w e_t \right)}{\partial X_{t+1}} = p - \frac{w}{\beta_2} \frac{e_t}{h_t}, \tag{9}$$

with the expected marginal costs tomorrow:

$$\delta E_t\left[p\frac{\partial h_{t+1}}{\partial X_{t+1}} - w\frac{\partial e_{t+1}}{\partial X_{t+1}} \right] = \\ \delta E_t\left\{ p(b+cT_{t+1})\frac{h_{t+1}+X_{t+2}}{X_{t+1}} - \frac{w}{\beta_2}\frac{e_{t+1}}{X_{t+1}}\left[(b+cT_{t+1})\frac{h_{t+1}+X_{t+2}}{h_{t+1}} - \beta_1 \right] \right\}. \quad (10)$$

Finally note that expression (8) is an equation in differences of order two: given the initial conditions of the resource X_t, surface ocean temperature T_t, and stochastic growth ε_t, the optimal size of the resource at the next period X_{t+1} depends on the optimal biomass level two time periods ahead, X_{t+2}. Moreover, optimal harvesting today depends on expectations about surface ocean temperature in the next period T_{t+1} and the other environmental factors, ε_{t+1}, tomorrow.

A particular solution: the steady state

As stated above, it is possible to define a stationary solution only when surface ocean temperature and natural resource growth are stationary. Therefore, we assume that there exists a date $t = ss$ greater than $\bar{t}$ for which $T_{ss} = T_t = T_{t+1}$ and $\varepsilon_t = E\varepsilon_{t+1} = 0$. A steady state solution, $X_{ss} = X_t = X_{t+1}$, verifies:

$$p = \frac{w}{\beta_2}\frac{e_{ss}}{h_{ss}}\left[1 - \delta\beta_1 \frac{h_{ss}}{X_{ss} - \delta(b+cT_{ss})(h_{ss}+X_{ss})} \right], \quad (11)$$

where $h_{ss} = aX_{ss}^{b+cT_{ss}} - X_{ss}$ and $e_{ss} = \left(\frac{h_{ss}}{\gamma X_{ss}^{\beta_1}} \right)^{1/\beta_2}$. Note that this stationary solution depends on the surface ocean temperature. If climate change reduces the natural growth through parameter c then, an increase in surface ocean temperature reduces the natural growth rate. Therefore, stationary biomass (and economic profits) decreases as surface ocean temperature increases (Medel 2011). Notice also that natural resource growth also may be affected by other factors apart from temperature which are summarized in parameter b. So any external environmental factor that decrease *b* leads to reduce the biomass and profits in the long run.

The numerical algorithm

The optimal trajectories derived from the maximization problem (1) are the optimal paths for $\{X_{t+1}\}_{t=0}^{\infty}$ that satisfy the infinity set of equations that characterizes the first order conditions given by the system of equations (8). To make it computationally tractable, we assume that these optimal trajectories converge to the stationary solution in a finite number of periods T_N. That is, given the initial condictions, X_0, the first order conditions are truncated such that $X_{T_N} = X_{T_N+1} = X_{ss}$. Note that the optimal trajectories are contingent on the shocks affecting the initial conditions. Thus, we assume that ε_t is equal to:

$$\varepsilon_t = \sigma(2u_t - 1), \tag{12}$$

where u_t follows a uniform distribution on [0,1] and σ is the variance of X_t.

Taking this into account, solving the model consists of choosing X_1, X_2, ..., X_{T_N-1} such that the system of equations under the first order condition is satisfied. This system of $T_N - 1$ nonlinear equations with $T_N - 1$ unknowns is written as:

$$p-\frac{w}{\beta_2}\frac{\left[(1+\varepsilon_0)aX_0^{b+cT_1}-X_1\right]^{1/\beta_2-1}}{\gamma X_0^{\beta_1/\beta_2}}=\delta p(b+cT_1)\int_0^1\left[(1+\sigma(2u-1))aX_1^{b+cT_1-1}\right]du-$$

$$-\delta\frac{w}{\beta_2 X_1}\int_0^1\left[\frac{(1+\sigma(2u-1))aX_1^{b+cT_1}-X_2}{\gamma X_1^{\beta_1}}\right]^{1/\beta_2}\left[\frac{(b+cT_1)(1+\sigma(2u-1))aX_1^{b+cT_1}}{(1+\sigma(2u-1))aX_1^{b+cT_1}-X_2}-\beta_1\right]du$$

.....

$$p-\frac{w}{\beta_2}\frac{1}{\gamma X_t^{\beta_1/\beta_2}}\int_0^1\left[(1+\sigma(2u-1))aX_t^{b+cT_t}-X_{t+1}\right]^{1/\beta_2-1}du=$$

$$+\delta p(b+cT_{t+1})\int_0^1\left[(1+\sigma(2u-1))aX_{t+1}^{b+cT_{t+1}-1}\right]du-$$

$$-\delta\frac{w}{\beta_2 X_{t+1}}\int_0^1\left[\frac{(1+\sigma(2u-1))aX_{t+1}^{b+cT_{t+1}}-X_{t+2}}{\gamma X_{t+1}^{\beta_1}}\right]^{1/\beta_2}\left[\frac{(b+cT_{t+1})(1+\sigma(2u-1))aX_{t+1}^{b+cT_t}}{(1+\sigma(2u-1))aX_{t+1}^{b+cT_1}-X_{t+2}}-\beta_1\right]du$$

.....

$$p-\frac{w}{\beta_2}\frac{1}{\gamma X_{T_{N-1}}^{\beta_1/\beta_2}}\int_0^1\left[(1+\sigma(2u-1))aX_{T_N-1}^{b+cT_{N-1}}-X_{ss}\right]^{1/\beta_2-1}du=$$

$$+\delta p(b+cT_{ss})\int_0^1\left[(1+\sigma(2u-1))aX_{ss}^{b+cT_{ss}-1}\right]du-$$

$$-\delta\frac{w}{\beta_2 X_{ss}}\int_0^1\left[\frac{(1+\sigma(2u-1))aX_{ss}^{b+cT_{ss}}-X_{ss}}{\gamma X_{ss}^{\beta_1}}\right]^{1/\beta_2}\left[\frac{(b+cT_{ss})(1+\sigma(2u-1))aX_{ss}^{b+cT_{ss}}}{(1+\sigma(2u-1))aX_{ss}^{b+cT_{ss}}-X_{ss}}-\beta_1\right]du.$$

(*13*)

And it can be solved by using standard numerical methods. At any time point, natural growth is affected by the shock, thus the optimal trajectory should be recalculated for each period once the drawn is known. This numerical method is known as Model Predictive Control (Garcia et al. 1989; Mayne et al. 2000).

Notice that the above algorithm takes into account the transitional dynamics towards the steady state which is reached after the temperature stabilizes. This approach differs from the one use in Garza-Gil et al. (2011), they used the steady state equation (11) for calculating the steady state biomass associated to different values of temperature. However, this approach makes no full sense if the temperature has not reached its long-run stabilized value.

Application of the model to the European sardine fishery

To obtain numerical results, we applied the algorithm to the European sardine fishery. In 2010, the atmosphere over the Iberian Peninsula was warm with respect to the long-term mean: The average temperature was 0.35 ^{o}C above the mean during the reference period (1971–2000). However, it also was the coolest year since 1996 (ICES 2011b). The Iberian Peninsula is a fishing ground that is especially sensitive to the effect of climate change (Garza-Gil et al. 2011). Moreover, small pelagic fish species like the European sardine are subject to high biomass fluctuations. In its last assessment, ICES (2010) reported that SSB in 2011 was 67% below the long-term average. In our application of the model to the European sardine fishery, we considered four finite time horizon scenarios similar to those suggested by Garza-Gil et al. (2011) (Figure 1):

a) *Scenario I:* The contra factual scenario, in which surface ocean temperature remains constant at 2010 levels;

b) *Scenario II:* Sea surface temperature will increase at the same rate as in the last few decades, which is 0.027 ºC per year (Garza-Gil et al. 2011);

c) *Scenario III:* Sea surface temperature will increase twice as fast as in recent decades (i.e., 2 x 0.027 ºC); and finally

d) *Scenario IV*: Sea surface temperature will increase more slowly than in recent decades (i.e., 4/5 x 0.027 ºC).

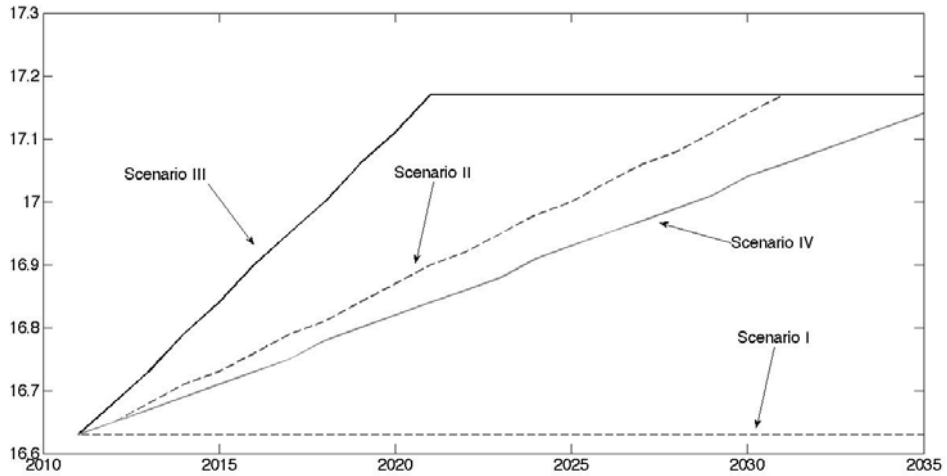

Figure 1 shows four simulations of the surface ocean temperature for scenarios I to IV. We consider an initial surface ocean temperature is 16.63 ºC. This temperature evolves according with the scenarios II, III and IV until stabilize at a value of 17.16 ºC. Both values correspond with the lowest and highest values considered by Garza-Gil et al. (2011). Scenarios III and IV were used mainly to perform sensitivity analyses. Under these scenarios, surface ocean temperature would stabilise at the same level as that in Scenario II, but equilibrium would occur at different times.

In order to compute the optimal solution, we assumed that, on average, the initial conditions were 67% below the deterministic stationary biomass associated with the initial surface ocean temperature of 16.63 ºC in 2010. This assumption is based on biologist studies that assess that SSB in 2010 was 67% below the long-term average (ICES, 2010) and on the temperature evolution considered by Garza-Gil et al. (2011). Formally, $\underset{2010}{E} X_{2010} = .33 \times X_{ss}(T = 16.63)$. Finally, data used for the parameterization of the bio-economic model were taken from Garza-Gil et al. (2011). Table 1 summarises these values.

Table 1. Parameters and variables used in the model

Parameter/variable	Concept	Value
Natural Growth		
a	Constant(*)	569.6500
b	Independent elasticity term	0.9919
c	Temperature elasticity term	0.0269
σ	Stochastic variable	0.2500
Technology		
α	Fleet productivity	28.9595
β_1	Stock elasticity	0.0830
β_2	Effort elasticity	0.6887
Economics values		
p	Price (euros)	613.0700
w	Fishing effort cost (euros)	912.4700

Source: Garza-Gil et al. (2011). (*) Long term average Spawning Stock Biomass.

We ran 1000 simulations using the same realizations for the shock for each of the four scenarios. As initial conditions for each simulation, we used the biomass at date 2010 distorted by the realization of the shock in period one, $X_0 = \varepsilon_1 \underset{2010}{E} X_{2010}$, and a time horizon equal to 45 periods. These conditions were chosen to guarantee that convergence to the stationary solution associated with the final surface ocean temperature would occur. Once the optimal expected value of the biomass in the next period was obtained, we updated the initial conditions using the realisation of the shock in period two, ε_2, and the

temperature of period two under each scenario. That is $X_1 = \varepsilon_2 \underset{2011}{E} X_{2011}(T_{2011})$. And so on. Overall, the algorithm was run for 45 periods × 1000 simulations × 4 scenarios.

Results and discussion

In this section detailed results from the bioeconomic model are presented and discussed.

Figure 2 compares the optimal expected biomass values (solid black line) obtained for each scenario with a succession of pseudo steady states (dashed line). The optimal expected biomass has been calculated using the algorithm expressed in (13) in order to capture the transitional dynamics toward the stationary values. The succession of pseudo steady states shows the value of the steady states associated to different long-run temperature levels according with the deterministic equation (11). We call this solution pseudo steady states because they would only represent steady states if the temperature were stable at this value. Red dashes line indicates when the fishery ground will be in a stationary distribution if the resource is exploited optimally. In this analysis it is considered that this situation is reached when the temperature stabilize at a value of 17.16 ºC. This value corresponds with the highest value considered by Garza-Gil et al. (2011). Notice that the period in wich this stabilized temperature is reached is different for each scenario.

These results exhibit different patterns for each scenario. First, note that the optimal path does not follow the most rapid approach (the bang-bang solution), and the fishery will be out of the stationary distribution for a long time. Of course, slow global change scenarios reach the long run level later than faster global change scenarios.

Second, global warming does not necessarily led to a monotonic decrease in the expected biomass levels, as myopic analysis based on pseudo steady states predicts. The optimal path exhibits an inverted U-shaped form. During the first 5 years the optimal sardine biomass levels (as well as the optimal profit levels) increase as the sea surface temperature increases. After that sardine biomass decreases until the long run (40 years) level is reached. This optimal biomass level is higher than that in the initial condition but lower than that at the initial steady state. If global change reduces fishery productivity, reducing the biomass level by increasing catches along the optimal transition path will be optimal.

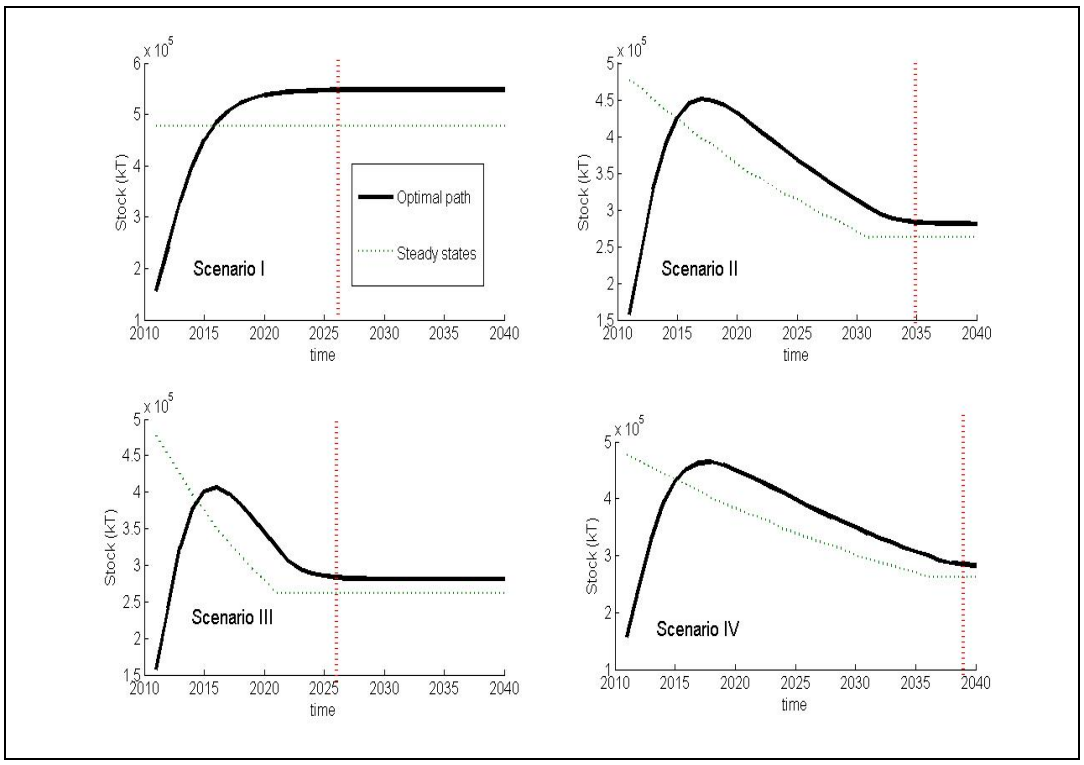

Figure 2: Expected biomass under each scenario: Scenario I (No global warming), Scenario II (Benchmark global warming), Scenario III (Fast global warming), and Scenario IV (Slow global warming). Solid black line represents the optimal biomass taking into account the transitional dynamics toward the steady state. Green dashed line is the steady state biomass if the associated temperature would have reached its stabilized value. Red vertical dashed line indicates the date when the stock distribution stabilizes.

Moreover, by assuming that the initial conditions of the fishery are close to the pseudo steady state, net present profits between 2010 and 2050 are overestimated in the four scenarios. That is, if the resource is below its stationary level, a succession of pseudo steady states overestimates the profits of the initial conditions of the stock and underestimates the effect of global warming. In our numerical simulations under the benchmark global warming (scenario II), net present value of profits associated to the succession of pseudo steady states are 4.49% higher than the optimal net expected profits based on the initial conditions of the fishery.

Figures 3 and 4 show the cumulative distributions of the biomass and profits, respectively. In both figures variables are illustrated for scenarios with no global warming (scenario I, grey solid line) and with the benchmark global warming (scenario II, black solid line). The y-axis expresses the probability of the variable being lower than abscises value.

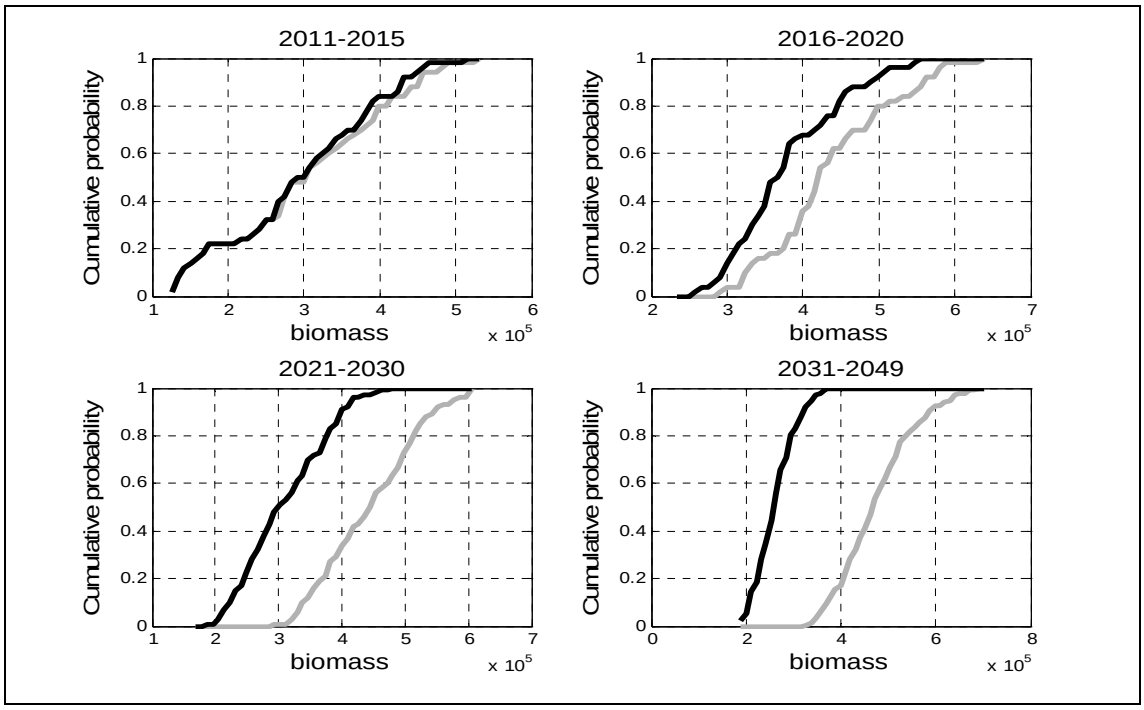

Figure 3: Cumulative probability distributions of biomass under Scenario I (No global warming, grey line) and Scenario II (Benchmark global warming, black line). The y-axis expresses the probability of the biomass being lower than abscises value.

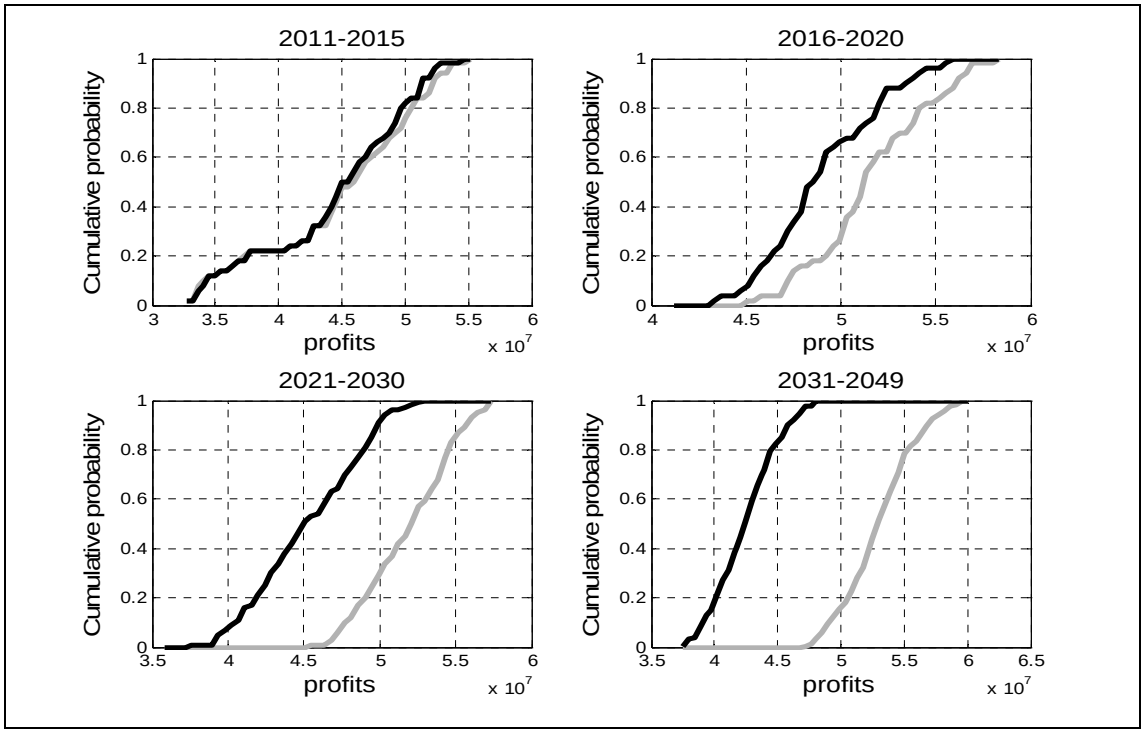

Figure 4: Cumulative probability distributions of profits under Scenario I (No global warming, grey line) and Scenario II (Benchmark global warming, black line). The y-axis expresses the probability of the profits being lower than abscises value.

Figure 3 shows that in the first 5 years, the probability than the biomass with climate change would be below the levels without climate change is less than 5%. Of course, this probability increases as the time horizon increases. In the long run (between 2031 and 2049), biomass will be (with probability one) lower than 400,000 tonnes, but it also can be higher than in 2011.

This result has important implications in terms of quantification of the expected economic effects of climate change on the European sardine stock. Stationary analysis predicts that annual profits will decrease by 1.27% during the 2010–2030 period (Garza-Gil et al. 2011). However, Figure 4 shows that in the short run (2011–2015) the distribution of profits will not be affected by changes in surface ocean temperature.

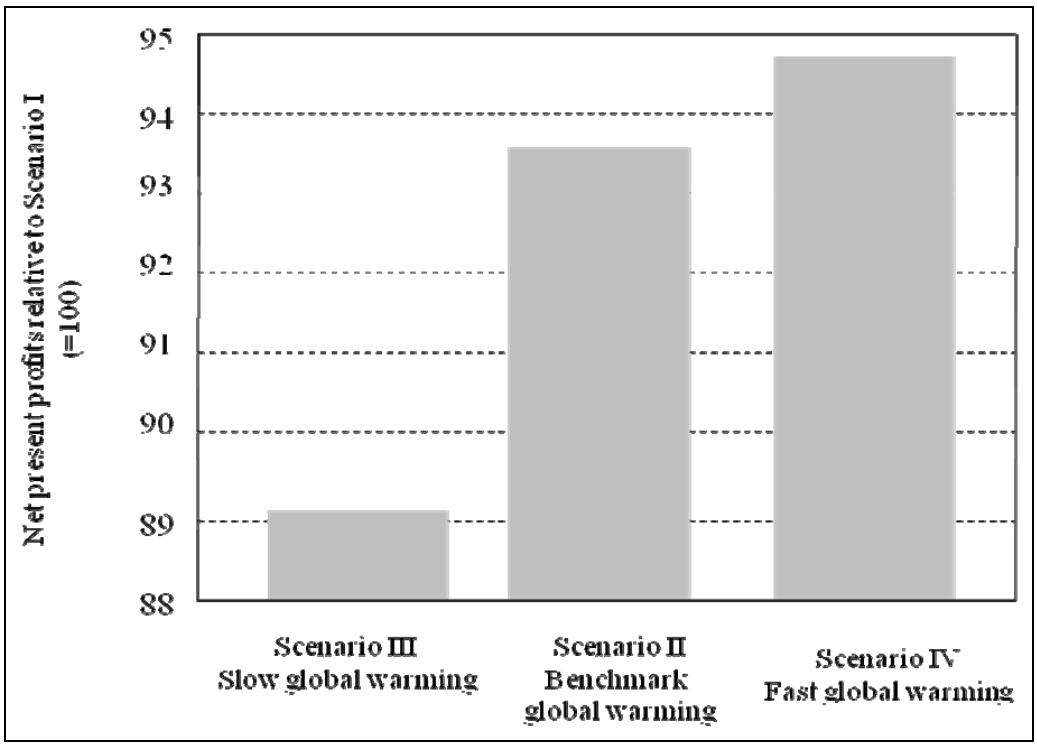

Figure 5: Economic effects of global warming on the European sardine fishery. Estimated net present profits for the period 2011-2030 considering a discount rate of 5%. Results for Scenario II (Benchmark global warming), Scenario II (Fast global warming), and Scenario III (Slow global warming) are relatives to Scenario I (No global warming) which correspond to index 100.

To quantify the economic impact of climate change on the fishery, we summarise the distribution in only one statistic: net present profits. As in Garza-Gil et al. (2011), we use a time horizon that extends to 2030 (this is the time horizon proposed in the Spanish Plan of Adaptation to Climate Change; MMA

2006) and a discount rate equal to 5%. Figure 5 shows that during the next 20 years, the economic impact of climate change on expected net present profits will be equal to a reduction of less than 7%, which is equivalent to an annual decrease of a 0.36%. Therefore the quantification of the economic impact taking into account the transitional dynamics implied by the global warming process reduces the losses predicted by the pseudo steady state analysis in more than a 30%.

Conclusions

Global warming may generates slow or abrupt transitions between climate regimes. While surface ocean temperature is increasing, fishery grounds are subject to potential changes in environmental factors. As a result, natural productivity of marine resource is not stationary. Therefore, to estimate the effect of climate change, the dynamic transitions of the bio-economic system must be computed.

In this paper we provide a simple algorithm to compute transitional dynamics in order to quantify the effect of climate change on fisheries subject to fluctuations. Given the initial conditions of the fishery ground and assuming that the system converges in a finite number of periods to a new climate regime, the transition can be solved by using standard numerical methods.

What do we learn when we compute the transition instead of a succession of steady states? First, in a single-species case and without global warming effects on the fishery, the optimal adjustment path is monotonically increasing in both biomass and harvest whenever the actual biomass level is below that of optimal equilibrium and monotonically declining in both variables in the opposite case (Clark 1976). Second, global warming does not necessarily lead to a monotonic decrease in the expected biomass levels, as myopic analysis based on steady states predicts. Our model results show that in the short run (5-10 years), increases in the surface temperature of the Iberian Atlantic fishery ground are compatible with higher expected biomass and economic profit levels when the resource is optimally exploited. Third, small pelagic species are subject to other environmental factors apart from temperature changes that affect natural productivity. In other words, sardine biomass is affected by other environmental variables that can mitigate the reduction in natural growth caused by climate change. Therefore, the effect of climate change must be measured in terms of the cumulative distribution of biomass generated by endogenous regulatory decisions and exogenous shocks under each possible climate regime.

Finally, there are four simplifications of the model used that can be improved in future research. First, we have assumed that climate change will increase sea surface temperature at a constant rate in the future until a stabilized value is reached. It is clear that climate change may vary the sea temperature with different patterns. Further research including different paths for the evolution of the temperature may be interested from the economic and ecological point of view.

Second, the European sardine fishery is regulated by using a mixture of fisheries management measures simultaneously: gear restrictions, minimum sizes, area closures, and fishing periods (season length). Here, the assumption is that the fishery is regulated by fixing an annual target harvest. However, it is possible to quantify the economic effect of climate change using a more realistic model that includes daily quotas (or trip limits) and fishing periods (the overall limits on the fishing season) together with the target harvest to regulate the fishery ground (Da Rocha and Gutierrez 2012).

Third, the ICES assessment of the European sardine stock uses age-structured populations models instead of biomass models as the one used in this article. Optimal management based on the optimization of bioeconomic age-structured population models has been developed in recent years (Tahvonen 2009; Da Rocha et al. 2010, 2012a and 2012b; Da Rocha and Gutierrez 2011 and 2013), and thus it may be possible to compute transitions between climate regimes using age-structured models (Voss et al. 2011). Therefore, further research that connects climate change and environmental factors with age-structured models is needed to predict sardine dynamics under optimal exploitation considerations.

Furthermore, in many cases the effect of other environmental factor could be even higher than those related to the sea ocean temperature. For instance it may happen that a stock migrates following temperature modification to another new environmental conditions and this affect to its growth. New research taking into account this kind of effect may be useful for some species. Also more plausible future scenarios about the evolution of the sea ocean temperature may be interesting to simulate when new research on marine ecosystems come to light.

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