Exploring the implications of the harvest control rule for Pacific sardine, accounting for predator dynamics: A MICE model

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Abstract

An ecosystem approach to forage fish management is required because forage fish support large fisheries, are prey for many valued species in marine food webs, and provide important social and cultural benefits to humans. Complex ecosystem models are often used to evaluate potential ecosystem consequences of forage fish fisheries, but there is seldom sufficient data to parameterize them, and full consideration of uncertainty is impossible. Models of Intermediate Complexity for Ecosystem assessment (MICE) provide a link between full ecosystem models and tactical (usually single-species) models typically used in fisheries management. MICE are ideal tools to form the basis for management strategy evaluations that compare the ability of candidate strategies to achieve goals related to target fisheries and broader ecosystem protection objectives. A MICE model is developed here for the California Current Ecosystem (CCE) that focuses on the fishery for the northern subpopulation of Pacific sardine (*Sardinops sajax*) and the indirect impacts of the fishery on place-based predators, in particular brown pelicans (*Pelecanus occidentalis*) and California sea lions

(*Zalophus californianus*), in the Southern California Bight. The model includes three forage species (sardine, northern anchovy *Engraulis mordax*, and 'other forage'), an 'other prey' category, and two predator species (brown pelican and California sea lion) and evaluates the impacts of variable forage availability on adult predator reproductive success and survival. Parameterization of the model is based on available monitoring data and assessment outputs. The model is then used to assess the ecosystem and fishery consequences of the current sardine management systems for Mexico, the USA, and Canada, with a focus on identifying which among a long list of sources of uncertainty in the system are most consequential for predictions of fishery impacts on predators. Key sources of uncertainty to consider in ecosystem assessments for the CCE are how prey abundance and availability impact predator demography, and the extent to which the dynamics of prey populations are driven by environmental factors. Data are available for some of these sources of uncertainty for CCE sardine management, but much uncertainty remains, necessitating exploration of sensitivity to alternative model formulations and parameter values when providing advice on management strategies to decision makers.

Keywords: northern anchovy, brown pelican, California sea lion, California Current, Ecosystem Based Fisheries Management, harvest strategies, Management Strategy Evaluation, Pacific sardine.

1. Introduction

Implementation of harvest control rules that are expected to achieve management goals is considered ‘best practice’ in fisheries management (FAO, 1996; Punt, 2006; Anon, 2014). Candidate management strategies (combinations of data collection schemes, methods for estimating the inputs for the harvest control rules, and the harvest control rules themselves) can be evaluated in terms of how well they satisfy management objectives using simulation, i.e., by applying the management strategy evaluation (MSE) approach (Smith, 1994; Punt et al., 2016). Management strategies have been broadly evaluated to achieve single-species objectives and, to a lesser extent, multi-species and ecosystem objectives (Punt et al., 2016).

An MSE involves several steps: (a) identification of the management objectives; (b) identification of a broad range of uncertainties to which the management strategy should be robust; (c) development of a set of models (often referred to as ‘operating models’) that provide a mathematical representation of the system to be managed; (d) specification of the parameters governing the operating model(s); (e) identification of candidate management strategies that could realistically be implemented for the system; (f) application of each management strategy to each operating model using simulation; and (g) summary and interpretation of the performance statistics. Of these steps, (c) and (d) are the most challenging technically because complex multi-species and spatially-explicit operating models require rich and diverse data inputs, which may not be available.

It is necessary, however, for operating models used in MSE to explicitly include ecosystem components if the management objectives include habitat protection, avoiding adverse impacts on threatened and endangered species, or indirect effects of fishery removals on other valued species. To this end, Plagányi et al. (2014) introduced ‘Models of Intermediate Complexity for Ecosystem assessments’ (MICE). The following ideas underlie MICE: restrict the model to focus on the main management questions under consideration, and include properties that advance their use as ecosystem assessment tools. MICE are particularly useful for addressing questions such as the effects of fisheries on predator-prey relationships. For example, MICE have been developed to address the effects of Cape fur seals (*Arctocephalus pusillus*) on the hake (*Merluccius capensis* and *M. paradoxus*) fishery off the west coast of South Africa (Punt and Butterworth, 1995), the inter-relationships of a multi-species prawn fishery off northern Australia (Dichmont et al., 2008), impacts of sardine fisheries on African penguins (*Spheniscus demersus*) (Robertson et al., 2015), and the interaction between crown of thorns starfish (*Acanthaster planci*) and coral reef ecosystems on Australia's Great Barrier Reef (Morello et al., 2014). The benefits to fisheries decision-making of MICE, as opposed to more complex ecosystem models, are that MICE tend be focused on a single question of interest, rather than whole-of-ecosystem models such as Atlantis (Fulton et al., 2007) and Ecopath with Ecosim (Walters et al., 1997; Pauly et al., 2000) (Plagányi et al., 2014). Furthermore, MICE are computationally simpler, allowing for exploration of a wider range of scenarios and more opportunity to incorporate uncertainty.

The California Current Ecosystem (CCE) off the west coast of North America is a dynamic upwelling system (Checkley and Barth, 2009), with important interactions between fisheries and the ecosystem, especially for small planktivorous pelagic fish such as northern anchovy (*Engraulis mordax*)[1] and Pacific sardine (*Sardinops sagax caerulea;* Clupeidae)[2]. The management objectives for these 'coastal pelagic species' (CPS) in the USA include (a) achieving 'optimum yield' (i.e., maximum sustainable yield as reduced by ecological and economic factors), (b) preventing overfishing, and (c) providing adequate forage for dependent species (PFMC, 2011). In relation to (c), sardine and anchovy are preyed on by dozens of upper trophic level predator species (Szoboszlai et al., 2015), including threatened and endangered species (e.g., southern resident killer whales *Orcinus orca*, humpback whales

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[1] Henceforth referred to as 'anchovy'

[2] Henceforth referred to as 'sardine'

Megaptera novaeangliae, marbled murrelet *Brachyramphus marmoratus*, salmon *Oncorhynchus spp.*, and yelloweye rockfish *Sebastes ruberrimus*), as well as species exhibiting recent declines in abundance (e.g., brown pelican *Pelecanus occidentalis*). The impact of "bottom-up" climate forcing on sardine and anchovy can be modelled owing to long-term data sets on density of both species, and there are available data on predator diets through time. Moreover, the management system for anchovy and sardine off the coasts of the USA and Canada is well-established and documented, so a robust MSE can be implemented.

Here, we develop a MICE model for the CCE to evaluate the USA and Canadian sardine harvest control rules and management questions related to the interactions of sardine with anchovy and a selected group of top predators. Although the model structure is general, the focus is on top predators of the Southern California Bight (southern CCE), and in particular the brown pelican for which most of the diet appears to be sardine and anchovy (Szoboszlai et al., 2015) and which have shown breeding failures in many recent years (S.P. Henry, US Fish & Wildlife Service, pers. commn). Our MICE model considers sardine and anchovy, 'other forage' species, 'other prey', and two predators (brown pelicans, and California sea lions *Zalophus californianus*). The information available for modelling purposes differs among species, but parameter values regarding prey species are based on fitting the model to data (c.f. Plagányi et al., 2014), to the extent possible, and parameter values regarding predator species are based primarily on literature values in the absence of formal assessments of these species.

The focus for the current paper is not on conducting a full evaluation of alternative harvest control rules for anchovy and sardine, but rather to understand the consequences of the current USA and Canadian harvest control rules for sardine in terms of the USA management objectives for CPS. Consequently, the paper presents a baseline version of the

MICE model, along with several variants that modify its specifications, specifically related to which sources of process error are modelled, the diets of the predators, demographic responses of predators to changes in prey availability, and the dynamics of the prey species, specifically their relationship to environmental drivers. The paper then outlines a set of model outputs that quantify the three major conceptual USA objectives for CPS and summarizes projections for each alternative MICE model formulation to determine how sensitive model outputs are to key model specifications. The results of the projections are then evaluated in terms of which areas of uncertainty have the greatest impact on evaluating harvest control rules for CPS in the CCE. Last, the MICE model is appraised in the context of the suite of modelling tools available for supporting management objectives.

2. Methods

2.1 History of sardine and anchovy fisheries

Pacific sardine is harvested off the coasts of Mexico, the USA, and Canada. The biomass and catch of sardine increased rapidly from the 1930s until the mid-1940s, and declined thereafter. The decline was likely due to a combination of environmental conditions leading to poor recruitment and high fishing mortality rates (Murphy, 1966). Rebuilding began during the 1980s, and by 1991 a directed fishery was re-established in the USA. Sardines were first re-observed in the diets of seabirds off central California in 1992 (Sydeman et al., 2001). The sardine population began to decline again around 2007 (Hill et al., 2015); the Canadian sardine fishery, which had been inconsequential before 1995, ceased in 2013, and the directed fishery in the USA was closed in 2015 because biomass was below the escapement threshold in the harvest control rule. The reason for the decline in abundance was primarily poor recruitment, a result of unfavourable environmental conditions (Hill et al., 2015).

The central subpopulation of northern anchovy is found from northern Baja California to northern California, but is found primarily in the southern California Bight. This subpopulation has been harvested commercially, primarily in the late 1970s and early 1980s. However, in common with sardine, catches in recent years have been low and recent evidence suggests that the biomass of this stock may be at historic lows (MacCall et al., 2016).

The population dynamics of sardine and anchovy, in common with those of many small pelagic fish species, are characterized by large changes in abundance, driven primarily by environmental conditions. The long-term nature of these fluctuations has been confirmed for anchovy and sardine in the CCE using samples of fish scales from sediment cores in the Santa Barbara Basin (Soutar and Issacs, 1969, 1974; Baumgartner et al., 1992).

2.2 Overview of the MICE

The MICE model is a spatially-structured model (see Fig. 1 for its spatial structure and Fig. 2 for a conceptual summary) that includes separate components for prey and predators. The model includes two predator species (brown pelicans and California sea lions), which were chosen because they are of management interest and anchovy and sardine constitute an appreciable fraction of their diets (Fig. 3). Both brown pelicans and California sea lions are site-based, central place foraging predators, which must balance the demands of provisioning for themselves versus provisioning for their offspring while foraging from a fixed, central location (Orians and Pearson, 1979). Therefore, the reproductive success of these species is likely more sensitive to changes in prey abundance than the reproductive success of more mobile predators. The distributions in the CCE of both sardine and anchovy contract during periods of low population size (Mais, 1974; MacCall, 1990), resulting in low availability for some central place foragers in certain locations. This contraction may be even more pronounced during periods of low combined sardine and anchovy abundance. Sardine and anchovy predators with greater mobility while breeding, such as dogfish (*Squalus acanthias)* and humpback whales, are likely less impacted by low forage abundance because of their ability to move greater distances to areas of relatively higher sardine and anchovy (or other prey) abundance, with less risk to their reproductive success. Furthermore, in contrast to brown pelicans, diets of dogfish (Brodeur et al., 2014) and humpback whale (Clapham et al., 1997; Rice, 1963) show switches between sardine and anchovy depending on availability.

The MICE model includes the following four prey groups: sardine, anchovy, ‘other forage’, and ‘other prey’. The group ‘other forage’ is a collection of small fish, including other small pelagic fishes and the juvenile stages of other fish (e.g., age-0 *Sebastes* spp.) and invertebrate species (e.g., euphausiids and squids), and is modelled to allow for stochasticity in absolute abundance of prey. The group ‘other prey[3]’ is minimally important for brown pelican, but fairly substantial in the diets of California sea lions (Fig. 3). Only sardine is fished in the model and removals are based on close approximations to current sardine management practices. Although anchovy is subject to a minor fishery in the CCE (catches have been extremely low, typically < 10,000 tons, since the early 1980s), this was ignored to reduce model complexity. The model only considers the impact of variation in prey biomass on the survival and reproductive rates of brown pelican and California sea lions, and not the impact of changes in predator numbers on the dynamics of the prey species. This is because only a small component (< 10%; Koehn et al., in press) of the predation mortality on the prey species in the MICE is due to the predators included in the model. The consequences of changing predator numbers for prey species, and associated conclusions regarding fishing impacts, are more suitable for evaluation using a more complex ecosystem model such as Atlantis (Fulton et al., 2007). The results from the MICE can be used to structure such more complex models, as discussed in Section 4.

Model parameters are either calculated from other variables, based on literature values, or estimated from available data (Supplementary Tables A.1 and A.2). It is possible to set the values of the parameters for each component of the model (largely) separately, because in the

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[3] ‘Other prey’ is made up of broad group of species, with the largest component being squids and Pacific whiting (*Merluccius productus*).

model sardine are impacted by fishing and natural processes, but not by the predators, so the sardine component can be parameterized using the results from stock assessments (e.g., Hill et al., 2009, 2011, 2015). The same is also (largely) the case for anchovy, although recruitment of anchovy also depends on the biomass of sardine. Thus, the values for the parameters of the MICE were not obtained by fitting it to the available data in a single optimization process (e.g., Punt and Butterworth, 1995; Morello et al., 2014); however, this is appropriate given the prey species are largely independent.

Prey are modelled with 48 time-steps within each year, whereas predators are modelled on a yearly time-step. Time-steps differ between prey and predators owing to the slower dynamics of the predators. The model year ranges from 1 July to 30 June to match the quota year for the USA sardine fishery. All species are assumed to be at unfished equilibrium at the start of the projection period, but model results are presented only for those years occurring after a 50-year 'burn-in' period, therefore the consequences of this assumption are minor.

2.3 The prey model[4]

2.3.1 Basic dynamics

The prey species are governed by the following spatial age-structured population dynamics model in which spatial distribution is pre-specified:

$$N^A_{y,t,a} = \delta^A_{y,t,a} \begin{cases} \sum\limits_A N^A_{y,t-1,a}\, e^{-Z^A_{y,t-1,a}} & \text{if } t > 1 \\ N_{y,1,0} & \text{if } t = 1 \text{ and } a = 0 \\ \sum\limits_A N^A_{y-1,48,a}\, e^{-Z^A_{y-1,48,a}} & \text{if } t = 1 \text{ and } 0 < a < x^N \\ \sum\limits_A N^A_{y-1,48,x^N}\, e^{-Z'^A_{y-1,48,x^N}} + \sum\limits_A N^A_{y-1,48,x^N-1}\, e^{-Z^A_{y-1,48,x^N-1}} & \text{if } t = 1 \text{ and } a = x^N \end{cases} \quad (1)$$

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[4] The dependence of variables on species (i.e., subscripts for prey or predator) is generally omitted in this section for ease of presentation.

where $N_{y,t,a}^{A}$ is the number of animals of age a in area A at the start of time-step t of year y, $Z_{y,t,a}^{A}$ is the total mortality for animals of age a in area A during time-step t of year y:

$$Z_{y,t,a}^{A} = M/48 + S_a F_{y,t}^{A} \qquad (2)$$

M is the rate of natural mortality (assumed to be independent of time-step and area), S_a is fishery selectivity on animals of age a, $F_{y,t}^{A}$ is the full-selection fishing mortality on animals in area A during time-step t of year y, $N_{y,1,0}$ is the number of age-0 animals at the start of year y, $\delta_{y,t,a}^{A}$ is the proportion of animals of age a in area A at the start of time-step t of year y, and x^N is the maximum age-class considered in the model (treated as a plus-group).

2.3.2 Stock and recruitment

Recruitment occurs in the middle of July (the start of the model year). The stock-recruitment relationship for sardine includes an environmental driver, so that the simulated extent of variation in biomass in the absence of exploitation matches the variation observed in historical scale deposits in the Santa Barbara Basin, i.e.:

$$N_{y,1,0} = \alpha \tilde{B}_y \, e^{-\beta \tilde{B}_y + \gamma G_y + \varepsilon_y^{\text{Sardine}} - (\sigma_R^{\text{Sardine}})^2/2} \qquad \varepsilon_y \sim N(0;\sigma_R^2) \qquad (3)$$

where α, β, γ are the parameters of the stock-recruitment relationship, $\tilde{B}_y$ is the spawning biomass at the start of year y, i.e.:

$$\tilde{B}_y = \sum_{a=a_{\text{m}}^{N}}^{x^N} w_a \sum_{A} N_{y,1,a}^{A} \qquad (4)$$

a_{m}^{N} is the age-at-maturity, w_a is the weight of an animal of age a at the start of the year, G_y is the value during year y of the environmental driver, $\varepsilon_y^{\text{sardine}}$ is the deviation during year y

about the deterministic stock-recruitment relationship, and $\sigma_R^{\text{sardine}}$ is the extent of variation in random log-deviations about the stock-recruitment relationship for sardine. Recruitment of sardine occurs only to the southern areas (1-5; Fig. 1), i.e.:

$$\delta^{A}_{y,1,0} = \begin{cases} 0.2 & \text{if } A \in (1,2,3,4,5) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The stock-recruitment relationship for anchovy depends on the biomass of sardine, and allows for the possibility that recruitment is zero, i.e.:

$$N_{y,1,0} = \begin{cases} 0 & \text{if recruitment if zero} \\ \alpha_1 \tilde{B}_y \, e^{-\beta_1 \tilde{B}_y + \varepsilon_y^{\text{anchovy}}} & \text{if non-zero recruitment and } B_y^{1+,\text{sardine}} < 500{,}000t \\ \alpha_2 \tilde{B}_y \, e^{-\beta_2 \tilde{B}_y + \varepsilon_y^{\text{anchovy}}} & \text{if non-zero recruitment and } B_y^{1+,\text{sardine}} \geq 500{,}000t \end{cases} \tag{6}$$

where $\alpha_1, \beta_1, \alpha_2, \beta_2$ are the parameters of the stock-recruitment relationship, and $B_y^{1+,\text{sardine}}$ is biomass of sardine aged 1 and older at the start of year *y*:

$$B_y^{1+,\text{sardine}} = \sum_{a=1}^{x^{\text{sardine}}} w_a^{\text{sardine}} \sum_A N_{y,1,a}^{A,\text{sardine}} \tag{7}$$

The probability of zero recruitment is 0.224 (the observed proportion of historical anchovy recruitments that are zero; MacCall et al., 2016), and the probability of zero recruitments is independent of year. The values for $\varepsilon_y^{\text{anchovy}}$ are resampled randomly from the residuals about the fit of Eqn 6 to the anchovy stock and recruitment data. Recruitment of anchovy only occurs to the California Bight (area 4; Fig. 1).

No stock-recruitment or environmentally-driven relationship is set for ‘other forage’, as this component is made up of several species. Therefore, age-0 abundance for ‘other forage’ is assumed to be an auto-correlated random variable selected from a log-normal distribution, i.e.:

$$N_{y,0}=e^{\varepsilon_y^{\text{other}}-(\sigma_R^{\text{other}})^2/2} \qquad \varepsilon_y^{\text{other}}=\rho_R^{\text{other}}\,\varepsilon_{y-1}^{\text{other}}+\sqrt{1-(\rho_R^{\text{other}})^2}\,\eta_y \quad \eta_y\sim N(0;(\sigma_R^{\text{other}})^2) \tag{8}$$

where ρ_R^{other} determines the extent of auto-correlation in recruitment for 'other forage', and σ_R^{other} is the extent of variation in random log-deviations about the stock-recruitment relationship for 'other forage'. Recruitment of 'other forage' occurs equally to all areas.

2.4 The predator model

2.4.1 Basic dynamics

The predators are modelled using age-structured models where either (or both) survival or reproduction depend on the biomass of prey. The number of births to a predator species is thus a function of the number of mature animals and the density-dependence on the birth rate (or equivalently the survival rate of age-0 animals), as well as the impact of prey abundance on reproductive rate, i.e.:

$$P_{y,a}=\begin{cases} P_y^m\phi_y(1+(\Phi-1)(1-(\phi_y P_y^{1+}/K^{1+})^z))e^{\varepsilon_y^P-(\sigma_R^P)^2/2} & \text{if } a=0\\ P_{y-1,a-1}\,\Omega_{a-1}\,\tilde{\Omega}_{y-1} & \text{if } 1\le a<x^P\\ (P_{y-1,x^P-1}\Omega_{x^P-1}+P_{y-1,x^P}\,\Omega_{x^P})\tilde{\Omega}_{y-1} & \text{if } a=x^P \end{cases} \tag{9}$$

where $P_{y,a}$ is the number of predators of age *a* at the start of year *y*, Ω_a is the survival rate for predators of age *a* in the absence of prey-related effects, $\tilde{\Omega}_y$ is the impact of prey on the survival rate of predators during year *y*, x^P is the maximum age modelled (treated as a plus group), P_y^m is the number of mature animals, i.e.:

$$P_y^m=\sum_{a=a_{\text{m}}^P}^{x^P}P_{y,a} \tag{10}$$

a_{m}^p is the age-at-maturity, P_y^{1+} and K^{1+} are, respectively, the number of predators aged 1 and older at the start of year *y*, and in an unfished state (i.e., when $P_y=P_0$), i.e.:

$$P_y^{1+} = \sum_{a=1}^{x^P} P_{y,a} \qquad\qquad K^{1+} = \sum_{a=1}^{x^P} P_{0,a} \tag{11}$$

z is the degree of compensation (set to 2.39 so maximum production occurs at 60% of K^{1+}), Φ determines the extent of density-dependence in juvenile survival rate, ϕ_y is the impact of prey on the reproductive rate of the predators during year y, ε_y^P is the logarithm of the deviation between the actual and expected number of births $\varepsilon_y^P \sim N(0,(\sigma_R^P)^2)$, and σ_R^P determines the extent of variation in reproductive success.

2.4.2 Prey impacts on predators

The relationship between changes in predator reproductive success and the amount of prey available is given by:

$$\phi_y = \max\left[0, \frac{(1-\tilde{\theta}_1-\tilde{\theta}_2)\tilde{\theta}_3(P_y/P_0-\tilde{\theta}_1)}{(1-\tilde{\theta}_1)\tilde{\theta}_2(1-\tilde{\theta}_3)+(\tilde{\theta}_3(1-\tilde{\theta}_1)-\tilde{\theta}_2)(P_y/P_0-\tilde{\theta}_1)}\right] \tag{12}$$

where $\tilde{\theta}_1$ is the relative prey biomass at which the number of births is zero, $\tilde{\theta}_3$ is the value of ϕ_y when $D_y/D_0 = \tilde{\theta}_2$, and D_y is the total amount of prey available to the predator during year y, i.e.

$$D_y = O + \sum_s \tilde{B}_y^{s,1+}\,\omega^s \tag{13}$$

where the summation is over sardine, anchovy, and ‘other forage’, $\tilde{B}_y^{s,1+} = \bar{B}_y^{s,1+}\chi_y^s$ and χ_y^s is beta random variable with mean $(\tau_1+\tau_2\bar{B}_y^{s,1+})^{-1}$ where τ_1 and τ_2 are the parameters of the relationship between the total biomass of a prey species and the biomass of that prey available to predators, and $\bar{B}_y^{s,1+}$ is the 1+ biomass of prey species *s* in the areas associated with the predators (areas $A_1 - A_2$, time-steps t_1 to t_2) during year y[5], i.e.:

$$\bar{B}_y^{s,1+} = \sum_{A=A_1}^{A_2} \sum_{t=t_1}^{t_2} \sum_{a=1}^{x} w_a^s \, N_{y,t,a}^{s,A} \tag{14}$$

D_0 is the average value of Eqn 13 under unfished conditions (obtained by conducting multiple 2,000 year projections without fishing and averaging the value of D_y over years and replicate simulations), O is the proportion of 'other food' in the diet of the predator, and ω^s is the preference that the predator has for prey species *s*. The value of ω^s is set so that the predicted diet proportions match the observed diet proportions (Fig. 3) when all of the prey species are at their average unfished levels, i.e.:

$$\omega^s = \Gamma_0^s / \tilde{B}_0^{s,1+} \tag{15}$$

$\tilde{B}_0^{s,1+}$ is the average biomass of prey species *s* from Eqn 14, accounting for the availability of prey to predators, and Γ_0^s is the expected proportion that prey species *s* is of the diet of the predator. The quantity χ_y^s allows the proportion of a prey species *s* available to a place-based predator to change as a function of biomass of the prey species.

A relationship of the form of Equation 12 is also assumed between predator survival and prey abundance[6], i.e.:

$$\tilde{\Omega}_y = \max\left[0, \frac{(1-\theta_1-\theta_2)\theta_3(D_y/D_0-\theta_1)}{(1-\theta_1)\theta_2(1-\theta_3)+(\theta_3(1-\theta_1)-\theta_2)(D_y/D_0-\theta_1)}\right] \tag{16}$$

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[5] The (albeit limited) data on the diet of brown pelican (e.g. Sunada et al., 1981) suggests they eat a range of age-classes of forage species, with the size-composition of anchovy in pelican diets matching that of the commercial fishery, and including animals of ages 1+.

[6] This choice of functional form leads to a similar relationship between predator survival rate and prey biomass (Supplementary Figure A.8) to that used by Robinson et al. (2015), except that natural mortality under Eqn 16 is much higher at very low prey biomass (<1% of P_0)

where θ_1 is the relative prey biomass at which survival is zero, and θ_3 is the fraction of the survival when $D_y = D_0$ that occurs when $D_y / D_0 = \theta_2$.

2.5 Catches and implementation of the control rules for sardine

To quantify the impacts of sardine management strategies, fishing mortality rates are specified for each model area (Fig. 1). Sardine fisheries management is not coordinated across national boundaries, and therefore three 'fisheries' are considered: (1) off the Pacific coast of Mexico (the three southernmost areas); (2) the USA fishery (areas 4, 5, 6, 9, 10, and 11), and (3) off the coast of British Columbia, Canada (the two northernmost areas).

The catch (in mass) of sardine from area *A* during time-step *t* of year *y*, $C^A_{y,t}$, is given by:

$$C^A_{y,t} = \sum_a \frac{S_a F^A_{y,t}}{Z^A_{y,t,a}} w_{a+t-0.5} N^A_{y,t,a} (1 - e^{-Z^A_{y,t,a}}) \qquad (17)$$

where $w_{a+t-0.5}$ is the weight of a sardine of age *a* in the middle of time-step *t*.

The maximum fishing mortality rates by area for each time-step are constrained to not exceed 0.05yr^{-1}. This allows a maximum annual fishing mortality rate by area of 2.4yr^{-1}, which exceeds estimated maximum coastwide fishing mortality rates, even during historical periods when the fishery was unregulated and there were more vessels (Murphy, 1966).

2.5.1 Mexico

Harvest control rules based on the results of stock assessments are not used to set management regulations for sardine in Mexico, although a minimum size limit is in effect. The projections for the sardine fishery off Mexico are therefore based on a constant fishing mortality rate distributed across areas 1, 2, and 3 (Fig. 1) by time-step within the year, with fishing mortality proportional to the actual catch by time-step in those three areas. This fishing mortality rate is selected so that the long-term model-predicted catch in mass matches the average catch mass reported for Mexico for 1999 – 2009 from Hill et al. (2015).

2.5.2 USA

USA fisheries for anchovy and sardine were managed by the State of California until 2000 when management authority was transferred to the Pacific Fishery Management Council (PFMC) (Hill et al., 2009, 2011, 2015). Harvest Guidelines (HG; catch limits) for sardine off the USA developed by the PFMC are set as the minimum of the Acceptable Biological Catch (ABC) and the output of the HG control rule (PFMC, 2013). The HG control rule is:

$$\mathrm{HG}_y = \min(\max((B_y^{obs} - \mathrm{Cutoff})\ \mathrm{x}\ \mathrm{Distribution}\ \mathrm{x}\ \tilde{E}_y, 0), \mathrm{Maxcat}) \qquad (18)$$

where B_y^{obs} is the estimate of the biomass of sardine aged 1 and older at the start of year *y* obtained from a stock assessment model such as that of Hill et al. (2015); Cutoff is 150,000 mt, and is the escapement threshold below which directed fishing is prohibited; Maxcat is the maximum catch, set to 200,000 mt; Distribution is the average proportion of the coastwide biomass in USA waters, set to 0.87, irrespective of the true proportion in USA waters; $\tilde{E}_y$ is a temperature-dependent exploitation fraction (Eqn 19) bounded by 0.05 and 0.2.

$$E_y = -18.46452 + 3.5209\bar{I}_y - 0.19723\bar{I}_y^2 + 0.0041863\bar{I}_y^3 \qquad (19)$$

$\bar{I}_y$ is the average temperature for years *y, y-1*, and *y-2*. The purpose of Cutoff is to protect the stock when biomass is low. The ABC is:

$$\mathrm{ABC} = \min(\max(E_y,0), 0.241)\ \mathrm{x}\ B_y^{obs}\ \mathrm{x\ Distribution\ x}\ 0.90592 \qquad (20)$$

0.90592 accounts for scientific uncertainty (Ralston et al., 2011) and 0.241 is the maximum value for the exploitation rate when calculating overfishing limits (PFMC, 2013). Consistent with current practice, an allowance is made for an incidental catch of 2,000 mt annually even when the direct fishery for sardine is closed.

Observation uncertainty in both the stock assessment estimate of biomass and the temperature used in the harvest control rule adds error to the outcome of the harvest control rule. The estimate of biomass on which the harvest control rules for sardine (USA and Canada) is generated from a log-normal distribution with mean given by the total +1 biomass, i.e.

$$B_y^{obs} = B_y^{1+,\mathrm{sardine}}\, e^{\upsilon_y - \sigma_B^2/2}; \qquad \upsilon_y = \rho_B \upsilon_{y-1} + \sqrt{1-\rho_B^2}\,\eta_y \qquad \eta_y \sim N(0;\sigma_B^2) \tag{21}$$

where σ_B is the extent of variation in biomass about the true 1+ biomass in log space (Table A.3; Ralston et al., 2011) and ρ_B is the extent of temporal autocorrelation in estimates of biomass. The temperature used when computing E_y (Eqn 19), I_y, is assumed to be a normally distributed index of G_y, i.e.:

$$I_y = \bar{T} + V_y + \varepsilon_y^I \quad \varepsilon_y^I \sim N(0;\sigma_I^2) \tag{22}$$

where σ_I is the measurement error for temperature, $\bar{T}$ is mean temperature (15.65^{0}C), V_y is the index of the environmental factor that drives recruitment, i.e.:

$$V_y = \rho_V V_{y-1} + \tilde{A}(1-\rho_V)G_y + \sqrt{1+\rho_V^2}\,\varepsilon_y^V \qquad \varepsilon_y^V \sim N(0;\sigma_V^2) \tag{23}$$

ρ_V is the extent of temporal autocorrelation in the temperature index, $\tilde{A}$ is a parameter to scale G to the temperature index, and σ_V is the variation in deviations about the relationship between G and V. The values for ρ_V, $\tilde{A}$, σ_V, and σ_I (See Section 1.2.1 of Supplementary

Appendix A) were obtained by fitting Eqns 22 and 23 to CalCOFI index data (Hurtado-Ferro and Punt, 2014).

The USA catch is allocated by time-step proportional to the actual catch by month (four time-steps per months, with catches equal by time-step within month) for 2006 to 2010, years during which catches were the highest in the last 30 years. The allocation of the catch by time-step to area first assumes that the catch in areas 7 and 8 is zero, to reflect reality, while the catch by area for the remaining areas in the USA is set using the equation:

$$C^A_{y,t} = C_{y,t} \frac{\hat{B}^A_{y,t}\,\psi^A_t}{\sum\limits_{A'} \hat{B}^{A'}_{y,t}\,\psi^{A'}_t}; \qquad \psi^A_t = \frac{\bar{C}^A_t / \hat{B}^A_{0,\mathrm{t}}}{\sum\limits_{A'} \bar{C}^{A'}_t / \hat{B}^{A'}_{0,t}} \tag{24}$$

where $\bar{C}^A_t$ is the mean (over 2006-2010) catch of sardine in area *A* during time-step *t*, $\hat{B}^A_{0,t}$ is the mean biomass of sardine in area *A* during time-step *t* in the unfished state (computed by projecting the model forward without catches and selecting a set of (simulated) years when the population was at a high level given the biomass of sardine was high during 2006-2010), $C_{y,t}$ is the catch limit for year *y* and time-step *t*, and $\hat{B}^A_{y,t}$ is the available biomass to the fishery in area *A* at the start of time-step *t* of year *y*, i.e.:

$$\hat{B}^A_{y,t} = \sum_a w_{a+t-0.5}\, S_a N^A_{y,t,a} \tag{25}$$

2.5.3. Canada

The catch limit for Canada is set to 5% of the difference between the estimate of biomass of sardine aged 1 and older and 150,000 mt (Nathan Taylor, DFO, pers. commn). This control rule can lead to unrealistically high catch limits when the stock is at very high abundance. It is unlikely that the Canadian fleet could take the entire catch limit based on this control rule, so the modeled catch limit for Canada is constrained to be less than 22,000 mt (the highest catch taken off Canada since 1980; Hill et al., 2015). The algorithm used to partition the Canadian catch to time-step and area is the same as that used for the USA fishery.

2.6 Performance metrics

The focus for the simulations, following PFMC (1998) and Hurtado-Ferro and Punt (2014), is the long-term behaviour of the system. The ability of the management system (the combination of the harvest control rules by nation) to satisfy management objectives included in the USA CPS management plan (PFMC, 2011) is quantified using a set of performance metrics that address maximizing yield, preventing the stock declining to the very low levels, and minimizing impacts on predators.

The performance metrics for the fishery system are (a) the mean catch of sardine (all countries), (b) the mean catch of sardine (USA, Mexico, and Canada separately), and (c) the probability that the total catch of sardine is less than 50,000 mt. These performance metrics are based on the performance metrics reported by Hurtado-Ferro and Punt (2014), which were selected by the PFMC when they evaluated candidate harvest control rules for Pacific sardine in 2014. The performance metrics for sardine and anchovy are also based on selections (for sardine) by the PFMC: (a) mean biomass (anchovy and sardine), (b) probability that the biomass of sardine is larger than 400,000 mt, and (c) probability that the biomass of sardine drops below 150,000 mt. The following additional performance metrics are reported for each predator species to further understand the impact of the sardine fishery: (a) the mean number of mature animals relative to carrying capacity, (b) the probability that the number of mature animals drops below half of carrying capacity, and (c) the probability that the number of mature animals drops below one-tenth of carrying capacity.

Each projection is 2,000 years long and results are based on 50 replicates. The replicates differ due to the values for the environmental driver and the recruitment deviations (prey and predators), due to the errors when measuring biomass and calculating catch limits, and due to stochastic variation in the distribution of sardine. The performance metrics are based on aggregating the results of all projections, but ignoring the first 50 years of each projection as that represents a ‘burn in’. The projection length is adequate to ensure that the projections include a sufficient number of productivity regimes that the initial conditions are negligible. The selection of 50 replicates was justified by conducting projections with an increasing number of replicates and examining when the values for performance metrics converged (Supplementary Figure A.10).

2.7 Scenarios

The MICE model was used to explore the impacts of harvest on the performance metrics outlined in Section 2.6, under 23 scenarios (Table 1). The baseline scenario assumes that predator reproductive rates are related to prey abundance (Eqn 12). The scenarios examine the implications of alternatives to the baseline assumptions, as well as the implications of eliminating various sources of uncertainty. Each sensitivity scenario was conducted for two cases: (a) no harvest and (b) harvest based on the harvest control rules in Section 2.5.

2.7.1 Scenarios related to the predators

Scenarios 1 - 10 explore the sensitivity of the results to aspects of the predator component of the model. Scenarios 1-4 explore the sensitivity to the form of the relationship between prey abundance and reproductive rate, given the limited information on how predator reproductive rate may change with prey abundance (Fig. A.8). Scenario 5 explores how the predator performance metrics change when predator survival, rather than predator reproductive rate, is impacted by changes in prey abundance. There is a limited range of plausible values for the parameters of Eqn 16 given the constraint that the predator populations remain extant under zero harvest. Scenario 5 therefore sets θ_1 to zero and θ_3 to 0.95 in Eqn 16 because setting these parameters to the values used for the baseline relationship between prey abundance and predator reproductive rate renders the predators extinct even in the absence of fishing. Scenarios 6 and 7 consider the effects of different assumptions about predator diets, because estimates of the diets of the four predator species are uncertain, owing to small sample sizes, issues with seasonal representativeness of data collection, as well as changes over time in diets. Consequently, the estimates of the proportion of sardine and anchovy in predator diets can differ among studies and among years within a single study (e.g., Velarde et al., 2013). Scenario 8 examines the impact of allowing for random variation in predator reproductive rate, while Scenarios 9 and 10 explore the consequences of greater and lesser density-dependence in the reproductive rate.

2.7.2 Scenarios related to the prey

Scenarios 11 – 21 concern the prey component of the model. Scenario 11 drops all random variation about the prey stock-recruitment relationships. Scenario 12 increases natural mortality for sardine from M=0.4 to M=0.6 yr^{-1} to reflect that M=0.4 yr^{-1} represents a period when key predator species (e.g., humpback whales and sea lions) were at low abundance but increasing (Carretta et al., 2013). Increasing M leads to greater fluctuations in sardine abundance; therefore, this scenario also changes how much recruitment varies among regimes so that the coefficient of variation (CV) of biomass remains similar to that for the baseline scenario. The remaining scenarios for sardine consider lesser variability in the prey available to predators by ignoring the variation in spatial distribution (Scenario 13) and by assuming that the stock-recruitment relationship is not environmentally-driven (Scenario 14). To ensure comparability with the baseline scenario, Scenario 14 involves modifying the values for the parameters of the stock-recruitment relationship for sardine so that the mean sardine biomass in the absence of a fishery is the same as when there are regime shifts in recruitment.

Scenario 15- 17 change the form of the stock-recruitment relationship for anchovy. Scenario 15 explores the possibility that the difference in anchovy stock-recruitment relationships between 1951-89 and 1990+ in Supplementary Fig. A.6 is spurious; in addition, the current formulation of the MICE implicitly creates a negative correlation between anchovy and sardine recruitment, which will tend to provide a portfolio effect to predators, buffering them from declines. Scenario 15 therefore assumes that the anchovy stock-recruitment relationship is independent of sardine abundance. Scenario 16 examines an alternative model of anchovy recruitment by assuming that it follows Eqn 3, with the value of γ (the scalar that determines the extent to which the environment drives deviations in recruitment about the stock-recruitment relationship) chosen so that expected anchovy biomass under unfished conditions matches that for baseline scenario. Scenario 17 bases the anchovy stock-recruitment relationship on fitting to the estimates of spawning biomass and recruitment from the assessment conducted by Methot (1989) rather than on Eqn 6.

The baseline analyses assume that the ‘other prey’ component of the diet is constant. However, in reality the species that constitute this component vary over time and space. Scenario 18 explores this assumption by treating ‘other prey’ as ‘other forage’, thereby allowing all components of the diet to vary over time. The baseline analysis ignores temporal correlation in recruitment of ‘other forage’ ($\rho_R = 0$ in Eqn 8). However, several studies (e.g., Miller and McGowan, 2013; Koslow et al., 2015) have shown species covariance and low frequency variability across a broad spectrum of candidates for ‘other forage’. Scenario 19 therefore involves setting the extent of temporal correlation in recruitment of ‘other forage’ to 0.707 so that half the variation in recruitment of ‘other forage’ can be attributed to autocorrelation. Scenario 20 examines autocorrelation in recruitment for ‘other forage’ further, by assuming that recruitment has two levels that are correlated with the environmental driver for sardine, with a level of variation in recruitment that matches the baseline level for ‘other forage’. The variation in the biomass of ‘other forage’ in the baseline scenario is less than that of sardine or anchovy. Scenario 21 therefore explores the consequences of higher variation in recruitment for ‘other forage’ and hence more variation in the biomass of this group.

2.7.3 Scenarios related to the assessments

There is no evidence for a retrospective pattern in the assessment results (e.g., Hill et al., 2015), justifying the choice $\rho_B = 0$ in Eqn 21. However, the lack of retrospective pattern does not guarantee a lack of assessment bias (Hurtado-Ferro et al., 2015) and estimates of biomass from assessments tend to be auto-correlated (Wiedenmann et al., 2015). Scenario 22 therefore examines the consequences of a substantial amount of autocorrelation (the upper end of the range inferred from Wiedenmann et al., 2015, i.e., $\rho_B = 0.9$). The final sensitivity scenario (23) removes all sources of observation error to quantify the relative impact of observation vs. process error.

3. Results

3.1 Model validation

The ability of the model to adequately represent the system was evaluated by conducting 2,000-year projections in which there was no exploitation using the baseline scenario. Adequate model performance was defined as producing time-trajectories of anchovy and sardine biomass that show behaviour consistent with the trends in scale deposition density, as well as predator populations that remained extant in the absence of exploitation of prey. Predator reproductive success should vary over time, and there should be occasional major declines in abundance for brown pelican because brown pelican feed primarily on sardine and anchovy in contrast to sea lions, which feed on a range of prey species.

Both anchovy and sardine exhibit considerable variation in 1+ biomass (Fig. 4 columns 1 and 3), with high temporal autocorrelation, consistent with the scale deposition density data. The median (across simulations) CV of the biomass of sardine was 1.04 (95% simulation interval 0.79 – 1.40), which is consistent with the CV of the deposition data for sardine (CV=1.27). In contrast, the 1+ biomass of 'other forage' does not exhibit high correlation – this is not unexpected given the way recruitment is generated for this species group (Eqn 8). Sardine and anchovy recruitment is also highly variable, but with occasional outlying estimates that lead to major spikes in 1+ biomass (such spikes are also evident in the scale deposition data for sardines; Fig. A.5).

The numbers of mature brown pelicans vary over time in response to changes in prey, a result consistent with the model of MacCall (1984). The numbers of mature brown pelicans exhibit far more temporal variation than those of sea lions (Fig. 5). This increased variability occurs even though the reproductive rate of both predators varies over time to some extent. The level of variation is largest for brown pelicans, reflecting in particular their dependence on sardine and anchovy (Fig. 3). However, even given the variation in reproductive rate, the population of brown pelicans remained extant for all simulations in the absence of fishing. The relative lack of variation for sea lions is attributable to the fact that much of their diet consists of 'other prey' (Fig. 3), which is constant in the baseline scenario.

The relationship between reproductive rate for brown pelicans (numbers of age-0 animals divided by the number of animals that have reached the age at maturity) and total prey, as well as the biomass of each prey species available to brown pelicans, showed increased variability at low prey biomasses (Fig. 6). The overall relationship between reproductive rate and prey is as expected from Eqn 9. The probability of very low reproductive rates occurs when the total prey abundance is 15% or less of unfished levels and 10% or less of unfished levels for sardine and anchovy (Fig. 6). Reproductive rate can exceed the rate when the population is at carrying capacity owing to the impacts of density-dependence, which directly impact the reproductive rate (Eqn 9). Reproductive failure for brown pelican occurs for a wide range of ‘other forage’ biomass, indicating that ‘other forage’ are not key drivers of the dynamics of brown pelican (see Supplementary Figure A.11 for these relationships for sea lions).

3.2 Baseline simulations with sardine catches

Fifty replicate 2,000-year projections were conducted using catch limits for the USA, Canada, and Mexico areas based on the harvest control rules in Section 2.5. Figure 7 shows time-trajectories of catch (in mass) by nation for three replicates. Catches by the USA and Canada are constrained by Maxcat (the USA) and 22,000 mt (Canada), respectively. In contrast, the catches off Mexico are related to the sardine biomass off Mexico and are unconstrained in the simulations.

The first two rows of Tables 2 and 3 contrast the values of the performance metrics when there is no harvest and when harvest is based on the nation-specific harvest control rules. The mean catch for the baseline scenario is 167,000 mt, of which 34,800 mt is taken by Mexico, 118,600 mt by the USA, and 13,600 mt by Canada. These mean values should be interpreted within the context of the variation in catches over time, which can be substantial (Fig. 7). This variation implies that catches (in total) are less than 50,000 mt in 34% of years (Table 2), with low and even zero catches frequent for the USA and Canadian fisheries (Fig. 7). The average sardine and anchovy biomasses are close to their unfished levels even under the simulated management system (> 90% of unfished levels). This is in large part due to the upper limit on catches imposed under the USA and Canadian harvest control rules, which means that fishing mortality is highest for intermediate sardine biomass levels. This is reflected in the difference in the medians of the distribution of 1+ biomass relative to the unfished 1+ biomass between the no-fishing and with-fishing cases (0.88 for sardine and 0.85

for anchovy) which are lower than the means of those distributions (0.96 for sardine and 0.93 for anchovy). There is consequently a larger impact of fishing on the probability of the sardine 1+ biomass dropping below 150,000 mt and being above 400,000 mt (changes of four and seven percentage points with fishing) than on mean sardine biomass. This impacts the pelican population, with reductions in mean abundance[7] and an increase in the probability of the mature population dropping below 50% and 10% of carrying capacity when there is fishing. The model predicted a lesser impact of fishing on the numbers of sea lions; therefore, the following sections focus only on impacts to brown pelicans.

3.3 Sensitivity to model structure assumptions

3.3.1 Catches and prey populations

The largest impacts on fishery and sardine/anchovy performance metrics occur in response to higher natural mortality for sardine (Scenario 12) and no regime-like shifts in recruitment (Scenario 14; Table 2). The lower catches (and higher probability of catches less than 50,000 mt) for Scenario 12 occur primarily because the average biomass is lower with higher natural mortality. Catches are much higher, and the probability of catch less than 50,000 mt is essentially zero, when there are no regime-shifts in sardine recruitment. This is not unexpected because the biomass of sardine never naturally drops to low levels owing to poor regimes for Scenario 14 (thereby avoiding fishery closures) while the lack of very high biomass levels has little impact on average catches because the catches by the USA and Canadian fisheries are capped. The increase in the probability of the biomass of sardine dropping below 150,000 mt as a result of harvesting ranges between 4.4% and 7.7% among scenarios (except for Scenario 14 when it is zero), while the reduction in the probability of the biomass of sardine exceeding 400,000 mt as a result of harvesting ranges from 6.0% and

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[7] The mean value of N/K^{1+} is not 1 under the no fishery case in Table 3 because Eqn 9 is a concave function so reductions in reproductive rate due to low prey abundance are not exactly balanced by increases in this rate at equivalent high prey abundance.

8.2% among scenarios, except for Scenario 14 for which it is always 1 (i.e., the biomass of sardine always exceeds 400,000 mt).

3.3.2 Brown pelican

Predator performance metrics were most sensitive to changes in the predator/prey relationship (Table 3). In particular, reducing the effects of prey on predator reproductive rate by setting $\tilde{\theta}_1$ to zero (Scenario 1) leads to the conclusion that fishing for sardine will have essentially no impact on the number of brown pelicans. The effect of increasing $\tilde{\theta}_3$ from 0.95 to 0.98 (Scenario 3, also reducing the effects of prey on predator reproductive rate) has a similar (but smaller) effect. In contrast, increasing the effects of prey on predator reproductive rate by increasing $\tilde{\theta}_1$ from 0.15 to 0.3 (Scenario 2) or reducing $\tilde{\theta}_3$ from 0.95 to 0.7 (Scenario 4) leads to fewer brown pelicans, with or without fishing. However, the effects of fishing are exacerbated for Scenarios 2 and 4 compared to the baseline scenario, with the differences in the probability of the brown pelicans dropping below half of carrying capacity between the no-fishing and with-fishing cases increasing from 1.1% to 7.8% (Scenario 2) and to 4.7% (Scenario 4). There are fewer brown pelicans even in the absence of a fishery when prey abundance impacts predator survival rate (Scenario 5), but as was the case for Scenarios 2 and 4, the relative impact of fishing is greater for Scenario 5 than for the baseline scenario (e.g., a difference in mean N/K of 3.0% for Scenario 3 compared to 1.8% for the baseline scenario).

Increasing the proportion of sardine in the brown pelican diet (Scenario 6) leads to fewer brown pelicans even in the absence of fishing. This arises because, although the diet of brown pelican is more balanced between anchovy and sardine, the variability of sardine biomass is higher than that of anchovy (Fig. 4), leading ultimately to more a variable prey base and hence a lower expected reproductive rate. Unsurprisingly, given that sardine is fished, the impact of fishing is greater for Scenario 6 than for the baseline scenario (larger differences between the no-fishing and with-fishing cases). When the proportion of sardine in the diet is halved and the proportion of anchovy increased (Scenario 7), the impact of fishing sardine on brown pelican numbers is reduced relative to Scenario 6 and the baseline scenario.

There is very little impact of ignoring random variation in predator reproductive success (Scenario 8). Lower predator productivity (Scenario 9) leads to lower average numbers of mature brown pelicans compared to the baseline scenario even in the absence of catches, but also to a larger impact of fishing on the probability of being below half of carrying capacity (3.5% versus 1.1% in the baseline scenario.) Higher predator productivity (Scenario 10) leads, as expected, to higher average population sizes and more resilience to fishing.

Changing the assumptions and parameter values related to the prey species (Scenarios 11-21) generally has lesser impacts on the performance metrics related to brown pelicans than changing the assumptions and parameter values related to brown pelicans themselves (Scenarios 1-10). Differences between the no-fishing and with-fishing cases were increased under higher natural mortality of sardine (Scenario 12) and when recruitment of 'other forage' is correlated with that of sardine (Scenario 20). Reduced effects of fishing occurred when there are no regime shifts in recruitment (Scenario 14), anchovy recruitment is unrelated to sardine biomass (Scenario 15), recruitment of anchovy follows an environmental signal (Scenario 16), and anchovy recruitment is based on a stock-recruitment relationship estimated from the results of the Methot (1983) assessment (Scenario 17). All of these scenarios are cases that lead to less variability in forage.

Changes in data available for assessment purposes and setting of catch limits (Scenarios 22 and 23) have little impact on the performance metrics for brown pelican.

4. Discussion

4.1 Main findings

A principal finding of the work was the relative vulnerability of brown pelicans to declines in sardine and anchovy, in contrast to weaker responses by sea lions. This may have been expected *a priori* due to the higher diet proportion of anchovy and sardine in brown pelican diets, as well as a more limited foraging ambit to surface and near-surface waters (whereas sea lions can forage at depth), but it also illustrates that a broad range of prey are available in the California Current –though undoubtedly more available to sea lions than to pelicans. The relatively large number of forage species in this region and diverse pathways for energy transfer from lower to higher trophic levels has been identified by other authors (Miller et al., 2010; Ruzicka et al., 2012; Koehn et al. in press) and contrasts with descriptions of other 'wasp waist' upwelling systems (Cury et al., 2000). Understanding whether species within this forage assemblage are temporally out of phase or simply not in phase has been debated (MacCall, 2009, Field et al., 2009), and remains a topic of investigation. Our sensitivity tests exploring temporal properties of anchovy and 'other forage' recruitment illustrate that the answer to this debate has greater influence on more sensitive brown pelican in comparison with a far-ranging marine mammal (sea lion).

Brown pelicans exhibited strong declines in reproductive success, but only at quite low abundance of sardine and anchovy (<10% of unfished levels), lower than the "1/3 of Bmax" threshold suggested by other authors (Cury et al., 2011). However, due to the dynamic and cyclical population dynamics of sardine and anchovy in nature (Baumgartner et al., 1992) and in our model, these low abundances of sardine and anchovy are not uncommon. In fact, current sardine stock size is < 10% of peak 2007 abundance (Hill et al. 2015) and anchovy in the Southern California Bight may be at <1% of the peak abundances observed in the 1960s-1980s (MacCall et al., 2016). Perhaps fortunately, brown pelican diet data suggest they depend more heavily on anchovy than sardine, and our work suggests this adds some stability to pelican population dynamics, since anchovy exhibit less extreme population fluctuations than sardine. Corresponding to the recent decline in both anchovy and sardine, brown pelican reproductive success has been zero or extremely low from 2009-2015.

Lindegren et al. (2013) demonstrated that sardine and anchovy populations are driven by climate cycles and density dependence, moderated by fishing effects, and here we observe these same effects at higher trophic levels, exemplified by brown pelicans. For instance, model results indicate climate alone (without fishing) drove declines of brown pelicans to less than half of carrying capacity in 4% of years, or up to 23% of years if higher dependence of pelican reproduction on prey is assumed. Fishing under the existing harvest control rules increased the frequency of this decline to 5% of years, or up to 31% of years if higher dependence of pelican reproduction on prey is assumed. The results illustrate that strong declines in predators with high dietary dependencies and limited forage range are possible and even expected in unfished systems, and that fishing influences this decline but to a lesser extent than climate-driven prey availability.

4.2 A MICE model in context

Scenario results allowed an appraisal of which factors impact the performance metrics to greatest extent, and hence which should be the focus for both additional data collection, and inclusion in other models of the impact of fishing on forage species in an ecosystem context. Specifically, the values of performance metrics related to the fishery are most sensitive to how bottom-up forcing impacts the dynamics of sardine (i.e., the environmental driver of recruitment and to a lesser extent the natural mortality rate for sardine and variation about the stock-recruitment relationships), a conclusion also drawn by Hurtado-Ferro and Punt (2014) using a single-species projection model with no spatial structure. The values of the performance metrics for the predators are most sensitive to the parameters of the relationship between reproductive success or survival and prey biomass. The availability of some data on the relationship between reproductive success and prey biomass (e.g., Fig. A.8) suggests that it is possible to impose some bounds on the values for these parameters, at least for this system. As expected, the performance metrics for brown pelican are impacted by the assumed productivity of the predator species (the extent of density-dependence in reproductive rate), but not variability in reproductive rate.

The focus for the results was on three species, sardine, anchovy, and brown pelicans, one of which (sardine) was explicitly managed. Although the model was fairly simple, it nevertheless included several sources of process error and sensitivity of the results was explored to some of the model specifications that are not well informed by data. MICE are meant to be simple, to target a small, specific set of questions, and to be fitted to available data. This MICE model is one component of a multi-model-based research effort to understand the implications of sardine fishing on the CCE. Atlantis (I. Kaplan, pers. commn), physics-to-fish (Fiechter et al., 2015; Rose et al., 2015), and Ecosim-with-Ecopath (Field et al., 2006) models as well as single-species models (Hurtado-Ferro and Punt, 2014) were also developed. The full suite of models allows the robustness of the results from the MICE to be evaluated and for the results from the MICE to inform the development of models tailored to different questions such as the impact of harvest of predators on the dynamics of prey species.

The sardine and anchovy models were fitted to available data on recruitment and spawning stock size, and a particular feature of the MICE model was that scenarios considered various hypotheses for how bottom-up forcing impacts forage species in the CCE (sensitivity tests 11-21). The parameters related to these hypotheses were based on information on variation in the prey biomasses from scale deposition data, under the assumption that the deposition data are reflective of total population biomass. There are only a few similar data sets worldwide (Field et al., 2009). MICE for systems without such data would have to consider scenarios based on a range of values for the parameters of the model to cover the plausible range. However, as noted below, the models for sardine and anchovy are limited in how natural mortality is modelled as well as in terms of the plasticity of their life-history parameters. Similarly, movement of sardine and anchovy while qualitatively reasonable was not based on, for example, fitting movement models to tagging data.

There are substantially fewer data for the predators, and no attempt was made, for example, to estimate key productivity-related parameters such as $\lambda_{\max}$, which were set by proxy. Consequently, it was necessary to conduct many sensitivity tests related to the specifications for the predator model (Table 1). A key driver of the performance metrics was the relationship between prey biomass and reproductive rate or survival. The parameters of the former relationship were estimated from data on reproductive success for colonies of brown pelican (Fig. A.8). However, the values for these parameters remain uncertain. There are few data on adult survival for predator species, including for the predator species included in the MICE model, which meant, for example, that it was necessary to hypothesize values for the parameters of the relationship between survival and prey biomass. In principle, it would be possible to estimate these values using available data on survival from tagging (e.g., Robinson et al., 2015), were such data available.

4.3 MICE and MSE

Punt et al. (2016) outline best practices guidelines for MSE. The MICE model in this paper is generally consistent with these guidelines. In particular, the performance metrics are based on input from decision makers and a broad set of scenarios and uncertainties are considered, including those related to spatial structure, predator-prey interactions, and environmental drivers. However, there are aspects of the current MICE model that do not follow the guidelines. In particular, limited account is taken of parameter uncertainty, for example, that associated with the parameters of the stock-recruitment relationships for sardine and anchovy. Punt et al. (2016) recommend that parameter uncertainty for each scenario be quantified using Bayesian methods. This could have been achieved (given specifications for priors), but it would have meant conducting many more than 50 replicate projections and preliminary results suggests that, in common with many MSEs, there is much more between-scenario variation in performance metrics than within-scenario variation due to parameter uncertainty.

Punt et al. (2016) also recommend simulating the management strategy as it would be applied in reality. This is achieved here by simulating the actual harvest control rules. However, the actual stock assessment for sardine (a maximum likelihood integrated analysis model implemented in Stock Synthesis; Methot and Wetzel, 2013) was not simulated but was rather approximated, based in part on the results of Hurtado-Ferro et al. (2015). The results of those simulations and generic evaluations of assessment performance (e.g. Wiedenmann et al., 2015) could be used to refine the way the biomass estimates used in harvest control rules are generated. This approach to evaluating management strategies is consistent with the recommendations of Punt et al. (2016) who note that ‘In cases in which the management strategy is complex, this may be impossible computationally, in which case a simplification of the assessment method is needed – the nature of the simplification should be based on simulation analyses.’

4.4 Caveats and future work

The MICE model makes several assumptions given the desire to obtain a model where the parameter values are determined largely by available information. As a result, it makes several assumptions that are likely to be invalid. Key amongst these are:

- Natural mortality of the prey species is assumed to be constant over age and time. This assumption is necessary given that only a small fraction of the CCE is included in the MICE model. In particular, the model does not include predation by the primary predators of sardine (humpback whales, sea lions, hake *Merluccius productus*, and dogfish) and anchovy (salmon, common murre *Uria aalge*, dogfish, and humpback whales), based on the contribution of these predators to forage total mortality (Koehn et al in press). The impact of this assumption could be assessed using alternative modelling frameworks such as Atlantis.

- Weight-at-age is constant over time. There is evidence that growth of both sardine and anchovy have changed over time (e.g., Bindman, 1986; Hill et al., 2009). While the model could be extended to allow weight-at-age to be stochastic, it is likely that variation over time in weight-at-age is the result of density-dependence and/or the availability of food. This variation could be included in the model given available data.
- The relationship for survival or reproductive success of predators is based on a single study that was for brown pelican (Fig. A.8). It is unclear if this relationship should be assumed for sea lions.
- Spawning frequency and batch size should ideally be accounted for in the density-independent biomass component of the prey stock-recruitment relationships, while the density-dependent component could reflect total (or 1+) biomass. This would, however, require modifying the method used to assess sardine.

The current baseline version of the model could be extended. In particular, while the baseline model includes an environmental driver of sardine recruitment (and indirectly of anchovy recruitment because anchovy recruitment is a function of sardine biomass), it ignores the possibility of long-term climate effects on the environment. Such effects could include trends in temperature, but also changes in distribution. The model includes a single stock of sardine, but there are multiple stocks of sardine along the west of coast of North America and two of these stocks are found at various times during the year off Southern California (Demer and Zwolinski, 2014a). There is no assessment for the southern subpopulation of Pacific sardine so this stock could not be explicitly included in the present model; rather a single stock was modelled. Finally, the model of how prey impacts predator populations does not account for spatial changes in predator populations in response to changes in prey density. Such changes could be modelled given the future availability of data on the spatial distribution of prey and predators.

The paper has explored the implications of a single set of harvest control rules. Alternative control rules could involve different values for the parameters of the current USA and Canadian harvest control rules (e.g., cutoff, Distribution, Maxcat), and whether the rules should involve an environmentally-determined exploitation fraction. For example, Demer and Zwolinksi (2014b) developed a control rule that aims to keep the exploitation rate below that implied by the USA harvest guideline control rule (without 'Distribution') irrespective of whether Mexico, Canada, and USA can reach agreement on a management system. In principle, future work could also examine management strategies for sardine and anchovy that account for interactions among these species (c.f., de Oliveira and Butterworth, 2004).

4.5 Conclusions and next steps

The analyses of this paper quantify the effects of the sardine management system (Mexico, USA, and Canada) on two predator populations. These effects need to be interpreted relative to those of an unimpacted system because while fishing impacts the dynamics of the prey populations and hence predator populations, the dynamics of prey populations are also driven to a substantial extent by environmental factors as well. Not unexpectedly, the key factors influencing the predator populations are how prey populations impact predator numbers (reproduction and/or survival) and the extent to which prey populations are driven by environmental factors. Data are available for some of these sources for the CCE, but much uncertainty remains, necessitating exploration of sensitivity to alternative model formulations and parameter values when providing advice on the choice of management strategies to decision makers. The areas of sensitivity highlight areas where additional data collection is needed. In particular, the results clearly support continuing monitoring of predator diets as well as of predator reproductive success. Monitoring of predator survival, e.g., through tagging, has the potential to substantially improve understanding of the impact fisheries have on place-based predators.

The next steps for this work include developing alternative models, with different levels of complexity for the sardine-anchovy-predators system, specifically an Atlantis model, and ensuring inclusion of those factors found influential by the MICE modelling. End-to-end models such as Atlantis allow evaluation of impacts on a broader set of predators, competitors, and prey of sardine and anchovy (Kaplan et al., 2013), though typically without the extent of sensitivity and uncertainty quantification provided by MICE. Projections of the sardine management system (or variants thereof) will then be undertaken to assess whether the quantitative predictions of the MICE are robust to model structure.

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Effect of heating rates on the crystallization process of $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy

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Abstract: $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy prepared by a single roller melt spinning was annealed at 550, 600, 650 and 750 °C for 1h under different heating rates. The thermal property, microstructure and magnetic property of alloys are investigated by simultaneous thermal analyzer (STA), X-ray diffraction (XRD), transmission electron microscopy (TEM) and vibrating sample magnetometer (VSM). At the same heating temperature, the crystallization of amorphous alloy is different along with the change of heating rate. The relationship between the heating rate and the microstructure is studied. The heating rates affect the distribution of elements and result in the difference in the crystallization products. Coercivity($\boldsymbol{H}_c$) of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy at the initial crystallization stage can be improved by the decrease of heating rate.

Keywords: heating rates; crystallization process; microstructure

1. Introduction

Fe-based nanocrystalline soft magnetic alloys are very popular by power conversion applications due to their excellent soft magnetic properties, which consists of ultrafine crystalline grains embedded within a residual amorphous phase. The soft magnetic characterization arises from the presence of intergranular magnetic coupling between adjacent nanocrystals(α-Fe) through the residual amorphous phase[1].

Nanocomposite magnetic materials are synthesized by the partial crystallization of an amorphous alloy precursor [2]. Studying the effect of annealing conditions on the structure of alloys is helpful not only to realize the origin of excellent soft magnetic properties, but also to optimize the heat-treatment conditions[3]. The strong relation between nanocrystalline microstructure parameters and the soft magnetic properties of these systems provokes the study of the mechanisms of nanocrystallization from the amorphous precursors, becoming a very important task for tailoring the final desired microstructure [4]. Works show that the heat treatments of amorphous alloys depended on heat and duration of treatment [5-8] (temperature, holding time and heating rate etc.). Some reports show that the heating rate has a significant effect on the microstructure of alloys. Gao et al. studied the relationship between the heating rate and the microstructure of $Nd_7Fe_{86}Nb_1B_6$ ribbons[8]. They found that the intermediate metastable phases $Nd_2Fe_{23}B_3$ and $Nd_3Fe_{62}B_{14}$ were present in the initial crystallization stage under the slow heating rate of 10°C/min and not observed under the high heating rate of 90°C/min. Vijayan et al. studied the effect of heating rate on the phase transition and crystallization kinetics of $Ag_2Se_{0.2}Te_{0.8}$ alloy[9]. The bulk alloy underwent a structural phase transition with hysteresis influenced by the heating rates.

The interest of this work is focused on the effect of heating rates on the crystallization process of $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy. The α-Mn type phase is observed when $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy is annealed under high heating rates. We expect determine the suitable parameters of heat treatment and obtain the nanostructures, thus to the enhancement of soft magnetic properties.

2. Experimental details

$Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy was prepared by a single roller melt spinning and annealed at 550, 600, 650 and 700 °C for 1h under 4, 10, 20 and 35 °C/min, then furnace cooling naturally. The annealing scheme for the $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy is shown in Fig.1. The thermal analysis was investigated by simultaneous thermal analyzer (STA, 449F5). Structural characterizations of samples were examined by X-ray diffraction (XRD, D/max 2500/PC, Cu-Kα, λ=1.5406Å) and transmission electron microscopy (TEM, JEM-2100E). Coercivity was measured by vibrating sample magnetometer (VSM, Lake Shore M7407).

3. Results and discussion

There are all three exothermic peaks in the STA curves under different heating rates. It is worth noting that the width of the second exothermic peak (T_{p2}) under 20 °C/min is broader compared with other STA curves and the third exothermic peak (T_{p3}) is very weak. The span ΔT_p between the first exothermic peak (T_{p1}) and T_{p2} decreases with increasing heating rate.

XRD patterns of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy as-quenched and annealed at 550, 600, 650 and 700 °C under different heating rates are shown in Fig. 3. No crystalline peaks are observed in the alloy as-quenched, indicating that the alloy forms amorphous.

When the alloy is annealed at 550 °C under 4 °C/min, only α-Fe(Co) crystallization phase precipitates from amorphous matrix. The α-Fe(Co) and α-Mn type phases are observed at 550°C under10, 20 and 35 °C/min. The fraction of the crystallization phase strongly depends on the heating rates. As the increase of heating rates, the content of α-Fe(Co) phase decreases and the content of α-Mn type phase increases. The crystallization processes of the alloys annealed under high heating rates are complex. The crystallization of amorphous alloy is affected by heating rate and heating temperature. At the same heating temperature, the crystallization of amorphous alloy is different along with the change of heating rate.

Crystallization is a solid state phase transformation often controlled by nucleation and growth kinetics[10], which is usually dependent on atomic diffusion. The subjacent idea is the following: a different heating rate will expose the material to high temperatures during different times and consequently the diffusivity of the elements will be affected [4]. When the alloys annealed at 550 °C under the heating rate of 4 °C/min, only α-Fe(Co) phase nucleates. Zr atomic radius is large and the diffusion rate is slow at low heating rate, resulting in that Zr still retains in the remained amorphous matrix. The lattice constants of α-Fe(Co) of alloys after annealing at 550, 600, 650 and 700 °C under 4 °C/min are 2.8558(3), 2.8577(1), 2.8522(1) and 2.8494(1) Å, respectively. The lattice constants of pure α-Fe and pure α-FeCo are 2.8664 and 2.8550 Å, respectively. It is inferred that the Co element dissolves in α-Fe. With increasing annealing temperature, the lattice constants decrease. Above 650 °C, the lattice constants of α-Fe(Co) are lower than that of pure α-FeCo. Therefore, B element also dissolves in α-Fe(Co) at high temperature. When the alloy annealed under the heating rate of 10 °C/min and 20 °C/min, both α-Fe(Co) and α-Mn type phases nucleate together. The lattice constants of α-Fe(Co) of alloys after annealing at 550, 600, 650 and 700 °C under 10 °C/min are 2.8537(5), 2.8534(2), 2.8508(1) and 2.8523(1) Å, respectively. The lattice constants of α-Fe(Co) of alloys after annealing at 550, 600, 650 and 700 °C under 20 °C/min are 2.8532(7), 2.8525(2), 2.8482(1) and 2.8417(1) Å, respectively. The lattice constants of α-Fe(Co) under 10 and 20 °C/min are still lower than those of pure α-FeCo. It is inferred that one part of B element dissolves in α-Fe(Co). The diffusion rate of Zr element increases with increasing heating rate. A part of Zr with Fe and B direct nucleates into α-Mn type phase. The other part of Zr still retains in the remained amorphous matrix. When the alloy annealed at 550 and 600 °C under the heating rate of 35 °C/min, a little of α-Fe(Co) phase and lots of α-Mn type phase are observed. The intermediate α-Mn type phase is metastable and transforms into α-Fe solid solution at 650 °C, which is also observed in the primary crystallization processes of other Fe-based alloys [11-13]. The lattice constants of α-Fe(Co) of alloys after annealing at 650 and 700 °C under 35 °C/min are 2.8538(1) and 2.8640(1) Å, respectively. After annealing at 700 °C, the lattice constant increases obviously. Co, Zr and B atoms are rejected from α-Fe solid solution and generate $ZrCo_3B_2$ and Co_2Zr_3 phases at last.

Combining with Fig. 2 and Fig. 3, the three exothermic peaks of STA curve under 4 °C/min correspond to the formations of α-Fe(Co), the precipitation of ZrO_2 phase and the precipitation of $CoZr_2$, respectively. The three exothermic peaks of STA curve under 10 °C/min correspond to the formations of α-Fe(Co, B) and α-Mn type phases, the transformation of α-Mn type phase and the precipitations of ZrB et al. phases, respectively. The first exothermic peak of STA curve under 20 °C/min corresponds to the formations of α-Fe(Co, B) and α-Mn type phases. T_{p2} of the STA curve is broad and the T_{p3} is very weak. It should be that the transformation of α-Mn type phase into α-Fe(Co, B) is not complete and the ZrB et al. phases already precipitate. The three exothermic peaks of STA curve under 35 °C/min correspond to the formations of a little of α-Fe(Co) and lots of α-Mn type phases, the transformation of α-Mn type phase and the precipitations of $ZrCo_3B_2$ et al. phases, respectively. The crystallization processes of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy annealed under different heating rates are shown in Table 1.

From Fig. 3(a), only α-Fe(Co) phase precipitates when the alloy is annealed at 550 °C under 4 °C/min. In order to confirm it, the corresponding TEM image and the corresponding selected-area electron diffraction pattern are taken in Fig. 4(a). The planes of α-Fe(Co) phase are marked in the electron diffraction pattern. With increasing the heating rate at 550°C, the α-Mn type phase precipitates and the content of α-Mn type phase increases. In order to known the morphology of α-Mn type phase well, the TEM image and the corresponding selected-area electron diffraction pattern of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy annealed at 550 °C under 35 °C/min are taken in Fig. 4(b). The planes of α-Mn type phase are marked in the electron diffraction pattern. The crystalline volume fraction of alloy annealed at 550 °C under 4°C/min are more than that of the alloy annealed at 550 °C under 35 °C/min.

Fig. 5 shows the hysteresis loops at room temperature of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloys annealed at 550 °C under different heating rates. It is worth noting that the Coercivity(H_c) undergoes a significant increase from 13.1 Oe to 329.0 Oe, which is closely related to their microstructures. The alloy annealed at 550 °C under 4°C/min shows a soft magnetic characteristic, whose crystallization product is only α-Fe(Co) phase. As the increase of heating rate, H_c increases obviously, which is due to the increase of the content of α-Mn type phase. The results of VSM show that H_c of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy at the initial crystallization stage can be improved by the decrease of heating rate.

4. Conclusions

$Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy was prepared by a single roller melt spinning and annealed at 550, 600, 650 and 750 °C for 1h under different heating rates. The crystallization of amorphous alloy is affected by heating rate and heating temperature. At the same heating temperature, the microstructure of alloy is different along with the change of heating rate. The heating rates affect the distribution of elements and change the crystallization process. Coercivity(H_c) of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy annealed at 550 °C undergoes a significant increase from 13.1 Oe to 329 Oe, which is closely related to their microstructures. H_c of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy at the initial crystallization stage can be improved by the decrease of heating rate.

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Figure and Table captions

Fig.1. Annealing scheme for the $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy

(a)4 °C/min, (b)10 °C/min, (c)20 °C/min, (d)35 °C/min

Fig.2. STA traces of $Fe_{64}Co_{16}Zr_{10}B_{10}$ amorphous alloy under different heating rates.

(a)4 °C/min, (b)10 °C/min, (c)20 °C/min, (d)35 °C/min

Fig.3. XRD patterns of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy as-quenched and annealed at 550, 600, 650 and 700 °C under different heating rates

(a)4 °C/min, (b)10 °C/min, (c)20 °C/min, (d)35 °C/min

Fig.4. TEM images and the corresponding selected-area electron diffraction patterns of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy annealed at 550 °C under 4 °C/min(a) and 35 °C/min(b)

Fig.5. Hysteresis loops of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloys annealed at 550 °C under different heating rates

(a)4 °C/min, (b)10 °C/min, (c)20 °C/min, (d)35 °C/min

Table 1. The crystallization processes of $Fe_{64}Co_{16}Zr_{10}B_{10}$ alloy annealed under different heating rates

Table 1. The model scenarios considered to test sensitivity

Scenario	Description
Predators	
1	Change $\tilde{\theta}_1$ in Eqn 12 from 0.15 to zero, reducing the effects of prey on predator reproductive rate.
2	Change $\tilde{\theta}_1$ in Eqn 12 from 0.15 to 0.3, increasing the effects of prey on predator reproductive rate.
3	Change $\tilde{\theta}_3$ in Eqn 12 from 0.95 to 0.98, reducing the effects of prey on predator reproductive rate.
4	Change $\tilde{\theta}_3$ in Eqn 12 from 0.95 to 0.7, increasing the effects of prey on predator reproductive rate.
5	Prey abundance impacts predator survival rates instead of predator reproductive rates ($\theta_1 = 0, \theta_2 = 0.2, \theta_3 = 0.95$).
6	Double the contribution of sardine to the diet of the predators, and proportionally reduce the proportion of anchovy, 'other forage', and 'other prey' in the diet.
7	Halve the contribution of sardine to the diet of the predators and proportionally increase the proportion of anchovy, 'other forage', and 'other prey' in the diet.
8	No variability in reproductive rate, i.e. $\sigma_R^P = 0$ in Eqn 9
9	$\lambda_{\max}$ is half the baseline values.
10	$\lambda_{\max}$ is 50% higher than the baseline values.
All prey species	
11	No random variation in recruitment (but retain regime changes in mean recruitment for sardine, and anchovy stock-recruitment relationships that depend on the biomass of sardine), i.e. $\varepsilon_y^{\text{sardine}} = \varepsilon_y^{\text{anchovy}} = \varepsilon_y^{\text{other}} = 0$ and i $\varepsilon_y^{\text{sardine}} = \sigma_y^{\text{other}} = 0$ in Eqns 3, 6, and 8.
Sardine	
12	Natural mortality for sardine is 0.6yr^{-1} into the future
13	No stochasticity in the spatial distribution of sardine.
14	No regime shifts in sardine recruitment (i.e., γ=0) .
Anchovy	
15	Anchovy recruitment is unrelated to sardine biomass.
16	Recruitment of anchovy follows an environmental driver rather than being correlated with that of sardine, $\varepsilon_y^{\text{anchovy}} = \gamma G_y$
17	Anchovy recruitment based on the stock and recruitment data from Methot (1989)
Forage /'other forage'	
18	Ignore the 'other' component of the diet and subsume this fraction of the diet into 'other forage'.
19	Temporal autocorrelation in recruitment of 'other forage', i.e., $\rho_R^{\text{other}} = 0.707$

20	Recruitment of ‘other forage’ is correlated with that of sardine, i.e. $\varepsilon_y^{\text{other}} = \gamma G_y$
21	Recruitment variation for ‘other forage’, $\sigma_R = 1$
Other	
22	Allow for temporal auto-correlation in estimates of sardine biomass from the assessment ($\rho_B = 0.9$).
23	Ignore uncertainty associated with applying the harvest control rules, i.e. $\sigma_B = \sigma_I = \sigma_V = 0$.

Table 2. Values for key performance metrics related to catches and biomasses of anchovy and sardine for the baseline scenario, and for scenarios where the resulting biomass of sardine or anchovy differs from the baseline scenario. Values for the performance metrics are provided for two cases: (1) no catches, and (2) catches are based on the management system. The difference in the performance metrics between the no catch and catch cases are given in the last two columns. Mean Biomass is relative to the baseline scenario with no catches. Shaded cells represent the differences in performance metrics between the no catches and catches cases. Scenarios not shown did not vary parameters that impact fishery or sardine/anchovy performance metrics.

Scenario	Catches	Mean catch ('000 mt)				P (Catch < 50kt)	Mean Biomass		P (sardine < 150kt)	P (sardine > 400kt)
		Total	Mexico	US	Canada		Sardine	Anchovy		
Baseline	No	0	0	0	0		1	1	0.185	0.761
	Yes	167.0	34.8	118.6	13.6	0.342	0.957	0.929	0.233	0.692
									0.048	-0.069
11	No	0	0	0	0		1	1	0.170	0.776
	Yes	171.7	36.2	121.6	13.9	0.325	0.933	0.944	0.214	0.716
									0.044	-0.060
12	No	0	0	0	0		1	1	0.337	0.596
	Yes	125.7	25.2	90.1	10.4	0.494	0.868	0.916	0.414	0.514
									0.077	-0.082
14	No	0	0	0	0		1	1	0.000	1.000
	Yes	225.4	44.9	158.5	22.0	0.000	0.904	1.000	0.000	1.000
									0.000	0.000
22	No	0	0	0	0		1	1	0.185	0.761
	Yes	166.8	34.8	118.4	13.6	0.342	0.955	0.931	0.234	0.691
									0.049	-0.070
23	No	0	0	0	0		1	1	0.185	0.761
	Yes	169.6	34.8	121.2	13.6	0.334	0.954	0.928	0.230	0.691
									0.045	-0.070

Table 3. Values for key performance metrics related to brown pelican. Results are presented for the baseline scenario and then for each sensitivity scenario. Values for the performance metrics are provided when there are no catches, when catches are based on the management system and the difference in the performance metrics for the first two cases (i.e. ‘impact of fishing’).

Catches	Scenario	Mean *N* / *K*	P (N < 0.5K)	P (N < 0.1K)	Scenario	Mean *N* / *K*	P (N < 0.5K)	P (N < 0.1K)
No	Baseline	0.942	0.042	0.009	12	0.904	0.069	0.016
Yes		0.924	0.053	0.011		0.877	0.091	0.021
		-0.018	0.011	0.002		-0.027	0.022	0.005
No	1	0.995	0.000	0.000	13	0.942	0.042	0.009
Yes		0.994	0.000	0.000		0.924	0.053	0.011
		-0.001	0.000	0.000		-0.018	0.011	0.002
No	2	0.758	0.233	0.133	14	0.997	0.000	0.000
Yes		0.679	0.311	0.185		0.997	0.000	0.000
		-0.079	0.078	0.052		0.000	0.000	0.000
No	3	0.955	0.032	0.006	15	0.978	0.009	0.002
Yes		0.941	0.040	0.008		0.973	0.011	0.002
		-0.014	0.008	0.002		-0.005	0.002	0.000
No	4	0.848	0.130	0.050	16	0.990	0.001	0.000
Yes		0.798	0.177	0.066		0.987	0.001	0.000
		-0.050	0.047	0.016		-0.003	0.000	0.000
No	5	0.895	0.043	0.000	17	0.991	0.001	0.000
Yes		0.865	0.056	0.000		0.988	0.001	0.000
		-0.030	0.013	0.000		-0.003	0.000	0.000
No	6	0.872	0.122	0.055	18	0.942	0.041	0.009
Yes		0.831	0.162	0.075		0.924	0.052	0.011
		-0.041	0.040	0.020		-0.018	0.011	0.002
No	7	0.955	0.024	0.004	19	0.939	0.044	0.010
Yes		0.942	0.031	0.004		0.921	0.056	0.012
		-0.013	0.007	0.000		-0.018	0.012	0.002
No	8	0.942	0.041	0.009	20	0.890	0.097	0.037
Yes		0.925	0.053	0.011		0.859	0.124	0.043
		-0.017	0.012	0.002		-0.031	0.027	0.006
No	9	0.873	0.108	0.039	21	0.940	0.043	0.009
Yes		0.833	0.143	0.048		0.922	0.054	0.011
		-0.040	0.035	0.009		-0.018	0.011	0.002
No	10	0.972	0.017	0.003	22	0.942	0.042	0.009
Yes		0.964	0.022	0.003		0.924	0.053	0.011
		-0.008	0.005	0.000		-0.018	0.011	0.002
No	11	0.989	0.000	0.000	23	0.942	0.042	0.009
Yes		0.985	0.001	0.000		0.925	0.052	0.012
		-0.004	0.001	0.000		-0.017	0.010	0.003