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ARTICLE

Optimal harvest responses to environmental forecasts depend on resource knowledge and how it can be used

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Abstract: Managing natural resources under large-scale environmental fluctuations like the El Niño Southern Oscillation (ENSO) is likely to become increasingly important under climate change. Forecasts of environmental conditions are improving, but the best response to an unfavorable forecast remains unclear; many practitioners advocate reducing harvest as a more precautionary approach, while prior economic theory favors increasing harvest. Using logistic and age-structured fisheries models, we show that informational constraints — uncertain stock estimates and restrictions on harvest policies — play a central role in choosing how to respond to a forecasted shock. With perfect knowledge and no policy constraints, risk-neutral managers should increase harvest when a negative shock is forecast. However, informational constraints may drive the optimal response to a forecast of a negative shock toward or away from precaution. Precautionary forecast responses arise when informational constraints make the harvest policy insufficiently sensitive to the true resource status. In contrast, uncertainty about the stock size can lead to more aggressive forecast responses when stock dynamics are nonlinear and not all fish are susceptible to fishing.

Résumé : La gestion des ressources naturelles en réponse à des fluctuations environnementales à grande échelle comme l'oscillation australe El Niño (ENSO) sera vraisemblablement de plus en plus importante dans un contexte de changements climatiques. Les prédictions concernant les conditions environnementales s'améliorent, mais la meilleure réaction à une prédiction défavorable demeure incertaine; de nombreux spécialistes recommandent la réduction des prises comme approche prudente, alors que la théorie économique existante favorise une hausse des prises. En utilisant des modèles logistiques et de pêches structurés par âge, nous montrons que des contraintes associées à l'information, comme des estimations des stocks incertaines et des restrictions aux politiques de prises, jouent un rôle central dans la sélection de la réaction à un choc prédit. Avec des connaissances parfaites et aucune contrainte associée aux politiques, des gestionnaires ayant une approche neutre à l'égard du risque devraient accroître les prises quand un choc négatif est prédit. Cependant, des contraintes associées à l'information pourraient faire en sorte que la réaction optimale à une prédiction d'un choc négatif tende vers l'approche prudente ou s'en éloigne. Des réactions prudentes aux prédictions sont de mise quand des contraintes associées à l'information rendent les politiques en matière de prises trop peu sensibles à l'état réel des ressources. À l'inverse, l'incertitude associée à la taille des stocks peut mener à des réactions moins prudentes aux prédictions quand la dynamique des stocks est non linéaire et que tous les poissons ne sont pas susceptibles d'être pêchés. [Traduit par la Rédaction]

Introduction

Fluctuations in the physical ocean environment can have major effects on fish and fisheries (Brander 2007; Holland and Herrera 2009; Pinsky and Byler 2015; Dee et al. 2016). Many of the world's most productive ocean ecosystems are characterized by high environmental variability, due in part to climate fluctuations like El Niño Southern Oscillation (ENSO) or longer-term phenomena like the Pacific Decadal Oscillation and the North Atlantic Oscillation. When variable environmental conditions are ignored in management decisions, the consequences can be costly (Lindegren et al. 2013; Pershing et al. 2015). Designing fisheries management that is robust to these changes is increasingly critical given that the frequency and (or) intensity of environmental fluctuations are anticipated to increase with climate change (Lee and McPhaden 2010; Cai et al. 2014; Wang et al. 2017).

Fortunately, our ability to forecast these events is also improving. Finer spatial resolution of models is reducing bias in temperature and other oceanographic predictions, which has enabled better mapping and modeling of species' habitat suitability (Stock et al. 2011, 2015; Saba et al. 2016; Kleisner et al. 2017), including better predictions of likely changes in distribution and abundance. Equally important, recent and ongoing advances in forecasting methods are facilitating earlier predictions of climate fluctuations like ENSO (Goddard et al 2001; Ludescher et al. 2013, 2014; Salinger et al. 2016) that would allow managers to alter current season harvest in anticipation of a shock the next season.

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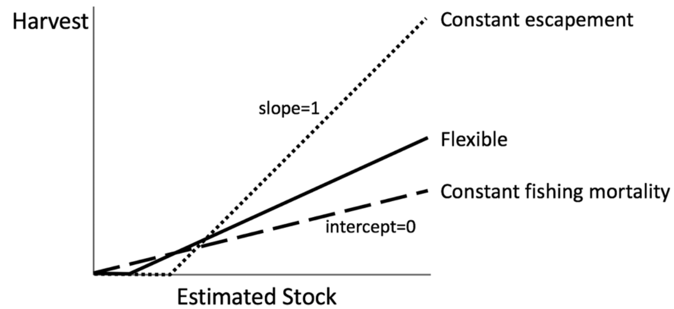
Surprisingly, there is no clear consensus on how a fishery manager should react to an environmental forecast. In particular, consider forecasts of short-term, "negative" environmental shocks that increase mortality and (or) depress growth for a target species; those shocks and species are the subject of this paper. A general perception among practitioners is that the appropriate response to a forecast of a negative environmental shock is to fish more conservatively, allowing fish stocks to build up before conditions deteriorate to reduce the risk of stock collapse (Pfaff et al. 1999; Broad et al 2002). However, the few theoretical analyses that have explicitly addressed this question for risk-neutral managers have found the opposite strategy to be optimal; harvest should decrease before positive shocks and increase prior to negative shocks (Parma 1990; Costello et al. 1998, 2001; Carson et al. 2009). The intuition is that fish left in the water for a negative shock will be less productive or die and therefore should be caught before that happens.

Here we examine what might explain this apparent discrepancy between theory and practice. Clearly, different assumptions about managers' objectives (e.g., aversion to risk, conservation, or employment goals) will matter, but a number of other underexplored factors likely play a role. We focus our attention on two information constraints common to many fisheries: imperfect knowledge of the resource size and status, and limitations on how that information can be used via limited policy options for setting quotas. Imperfect information about stock levels is common in fisheries (Beddington et al. 2007), and fisheries management under uncertainty is the subject of much research (e.g., Sethi et al. 2005). For our purposes, greater uncertainty in stock size increases the threat of accidental collapse, which may influence the best forecast response. In addition, given an estimate of the underlying stock size, many fisheries are managed via harvest control rules, which restrict how stock estimates can affect harvest quotas (Deroba and Bence 2008). We examine two such restrictions: fixed end-of-season biomass (escapement) and constant fishing mortality. Since the optimal policy may involve mortality or biomass targets that are not fixed, these rules impose constraints on managers and distort how estimates of biomass affect quotas. Managers must account for these distortions when choosing how to respond to an environmental forecast, which may affect the optimal harvest response.

Specifically, in this paper we use models to analyze how these informational constraints affect optimal harvest responses to environmental forecasts. We identify those responses for a risk-neutral manager maximizing expected discounted harvest in two fisheries. First, we study a stylized fishery with logistic growth that is subject to an environmental shock, which negatively affects both the growth rate and carrying capacity. We use that model as an approximation to a wide range of fisheries to develop our intuition about our main question. Second, we examine an age-structured model of the Peruvian anchoveta (*Engraulis ringens*) fishery, the largest (6.5 million tonnes (t)·year^{-1} 2005–2014) and most valuable (US\$1.3 billion·year^{-1} 2005–2014) single species fishery in the world (FAO 2018; SAUP 2018). Anchoveta are known to respond to environmental variability and, in particular, to ENSO events (Chavez et al. 2003; Alheit and Ñiquen 2004; Bertrand et al. 2004). The biomass of anchoveta has been noted to be greater in upwelled cold coastal water and during cold-water La Niña years than in warm-water El Niño years. Anchoveta also feed on larger size classes of phytoplankton, which are more prevalent in cooler waters, and large-scale oceanic forcing is believed to contribute strongly to the population's range size (Swartzman et al. 2008). Altogether, upwelling dynamics and the patchy distribution of anchoveta create an inherently high level of uncertainty that make the fishery a relevant case study. Indeed, anchoveta managers and industry leaders in Peru have been among the pioneers to incorporate forecasts of future climate into fisheries management (Broad et al. 2002).

Fig. 1. Harvest control policies relating attempted harvest to estimated stock size. The flexible policy (solid line) places no restrictions on the slope and intercept; the constant escapement policy (dotted line) places no restrictions on the intercept but requires a slope of 1 above a minimum stock level; the constant fishing mortality policy (dashed line) requires an intercept of zero but does not constrain the slope.



Our analysis brings together several strands of work that separately address stochasticity, environmental forecasts, and the practical limitations just discussed. A large collection of literature examines management of stochastic fisheries without environmental forecasts (e.g., Reed 1979; Sethi et al. 2005). Our model nests the standard stochastic fishery model as a special case, also allowing managers to react to a temporary reduction in uncertainty offered by an environmental forecast. Some previous theoretical work has examined how forecasts of environmental shocks (Costello et al. 1998, 2001) or knowledge of impending regime shifts (Polasky et al. 2011) affect optimal harvest, but only under otherwise perfect information and without management constraints. A complementary literature has studied how uncertainty in stock size impacts optimal management in the absence of environmental forecasts or management constraints, illustrating particularly large effects on optimal fishing policy and profits (Clark and Kirkwood 1986; Weitzman 2002; Sethi et al. 2005). Finally, a long list of literature in optimization highlights the role of constraints; if one part of an optimal strategy cannot be implemented, the second-best solution may require changing other parts of the strategy in unexpected ways (Lipsey and Lancaster 1956; Bennear and Stavins 2007; Johannesen and Skonhoft 2009; Cabral et al. 2017). The primary contribution of this paper is to consider all of these issues jointly; how do environmental forecasts, which reduce one source of uncertainty, affect optimal management when uncertainty in stock size and management constraints remain? By comparing management with and without environmental forecasts, uncertain stock size, and policy constraints, we identify the role these fishery features play in determining optimal responses to and the value of environmental forecasts.

Methods

We use models to explore how the optimal harvest response to an environmental forecast depends on both imperfect stock estimates and policy constraints. In particular, we consider a resource manager who may respond to a forecast of a shock by adjusting harvest up or down by a percentage of her choosing. We examine how the sign and magnitude of her optimal adjustment depend on two model features. First, as in most fisheries, the manager must set harvest levels based on imperfect estimates of the true state of the resource. Second, we consider cases in which the manager's baseline policy is constrained to a constant escapement or a constant mortality rule (Fig. 1), except for the environmental forecast response just described (i.e., adjusting harvest up or down by any percentage). We then ask how these two informational limitations individually and jointly affect the optimal response to a forecast of environmental conditions when maximizing expected discounted harvest. We do so for two instances of a general model: a stylized fishery with logistic growth and an age-structured model of the Peruvian anchoveta fishery.

For both fisheries, we construct a discrete-time model with four steps in each period. First, the fish population undergoes natural growth and mortality according to the current environmental state, producing a fishable population for the current season. Second, a manager receives information on the current state of the fishery and a forecast of the environmental state in the next period. Third, the manager chooses and applies a harvest level by plugging the information just received into the harvest control rule selected prior to the first period. Finally, the environmental state updates to a new value for the following period.

Our approach can be formalized as follows. Denote the start-of-season biomass in each of one or more age classes in period t by S_{at} and the vector of all age-specific biomass in period t by $\boldsymbol{S}_t$. Reproduction, individual growth, and natural mortality prior to harvest give a fishable population $\boldsymbol{B}_t$ with biomass B_{at} in age class a based on population dynamics: $B_{at} = g_a(\boldsymbol{S}_t, Q_t)$. In general $g_a(\cdot)$ depends on the current environmental state Q_t. In what follows, we model Q_t as a binary variable taking value 1 if environmental conditions are unfavorable, and 0 otherwise. While both environmental shocks and forecasts of them vary in intensity, we use a binary variable for illustrative purposes to emphasize the sign of the harvest response.

After natural growth occurs, the manager observes an estimate $\boldsymbol{B}_t^{\mathrm{est}}$ of $\boldsymbol{B}_t$ and a forecast q_t of Q_{t+1} and chooses harvest accordingly. Each element of $\boldsymbol{B}_t^{\mathrm{est}}$ is subject to observation error, with $B_{at}^{\mathrm{est}} = Z_{at}B_{at}$, where Z_{at} is an independently and identically distributed lognormal random variable with mean 1 and standard deviation σ_o. To simplify discussion, we focus primarily on perfect forecasts ($q_t = Q_{t+1}$), though we briefly present results for certain imperfect forecasts with $P(q_t = Q_{t+1}|Q_{t+1}) < 1$. For reference, recent methods (Ludescher et al. 2014) correctly predict the timing of El Niño events approximately 76% of the time.

With this information, the manager sets a harvest quota according to rules of the following form:

$$h_t = \left(\phi + \boldsymbol{\gamma}^T\boldsymbol{B}_t^{\mathrm{est}}\right)(1 + \lambda q_t) \tag{1}$$

In short, the quota is linear in the estimated population in each age class. The manager chooses the intercept ϕ and slope vector $\boldsymbol{\gamma}$ to determine how biomass estimates influence the quota. In addition, the manager can adjust harvest up ($\lambda > 0$) or down ($-1 \leq \lambda < 0$) by a multiplicative factor if bad environmental conditions are forecast for the next period. We consider three harvest policies of this general type (Fig. 1). The first allows the manager to choose all parameters freely (the "flexible" policy); the second restricts choices for $\boldsymbol{\gamma}$ to target a constant escapement when no shock is forecast (the "constant escapement" policy); and the third restricts ϕ to harvest a constant fraction of the fishable biomass when no shock is forecast (the "constant fishing mortality" policy). While the possibility of an environmental forecast response means the restricted policies are not strictly constant escapement and constant mortality policies since escapement and mortality may vary with q_t, we use those names to simplify explanation.

Once a harvest quota is chosen, start-of-season biomass S_{at+1} and environmental conditions Q_{t+1} for the following period are determined as follows:

$$S_{at+1} = \max\left(B_{at} - h_t\frac{\eta_a B_{at}}{\boldsymbol{\eta}^T\boldsymbol{B}_t}, 0\right), \quad Q_{t+1} = f(Q_t) \tag{2}$$

Harvest is removed from susceptible age classes in proportion to their fishable biomass $\eta_a B_{at}$ as a share of overall fishable biomass $\boldsymbol{\eta}^T\boldsymbol{B}_t$, where $\boldsymbol{\eta}$ is a binary selectivity vector with element η_a taking value 1 if age class a is susceptible to fishing, and 0 otherwise. Note harvesting the entire quota may not be feasible due to imperfect stock estimates ($B_{at}^{\mathrm{est}} \neq B_{at}$). To reflect this discrepancy, define realized harvest h_t^{real} as

$$h_t^{\mathrm{real}}(h_t, \boldsymbol{B}_t) = \sum_a (B_{at} - S_{at+1}) \tag{3}$$

The environmental state updates according to a stochastic transition process $f(Q_t)$.

Given these dynamics and any policy constraints, the manager chooses harvest rule parameters ϕ, $\boldsymbol{\gamma}$, and λ to maximize the discounted sum of expected benefits received from the fishery:

$$\max_{\phi,\boldsymbol{\gamma},\lambda} \sum_{t=0}^{T} \delta^t E\left\{u\left[h_t\left(\boldsymbol{B}_t^{\mathrm{est}}, q_t; \phi, \boldsymbol{\gamma}, \lambda\right), \boldsymbol{B}_t\right]\right\} \tag{4}$$

where $\delta \in [0, 1]$ is a discount factor, and T is the planning horizon (results below reflect $\delta = 0.95$ and $T = 100$). We focus our attention on the case of maximizing expected discounted harvests, for which $u(h_t, \boldsymbol{B}_t) = h_t^{\mathrm{real}}(h_t, \boldsymbol{B}_t)$. This choice implies the manager values each pound of fish caught in a year equally and is risk neutral, allowing for comparison with prior theoretical studies. Assuming instead that managers prefer to avoid risk would favor smoothing harvests across time and hence more conservative responses to unfavorable environmental forecasts, but those effects are well studied and are not the focus of our efforts (see online Supplementary material[1]). We solve the manager's problem numerically using Monte Carlo simulation with 100 000 samples. Each sample is a potential realization of all random variables (environmental shocks, stock estimation error, and any environmental forecast error) across the entire planning horizon. We then find control rule parameters ϕ, $\boldsymbol{\gamma}$, and λ that maximize the sample average analog of eq. 4 across those samples. We also compute the relative value of the environmental forecast, defined as the average increase in total discounted harvest with the forecast as a share of average total discounted harvest without the forecast.

With this general structure in place, we next describe the two specific cases we analyze: a stylized fishery with logistic growth and an age-structured model of the Peruvian anchoveta fishery.

Logistic growth fishery

A stylized fishery with logistic growth can be modeled as a population with a single age class susceptible to fishing ($\boldsymbol{\eta}^T = [1]$) and the following update rule:

$$B_{1t} = S_{1t} + r_{Q_t}S_{1t}\left(1 - \frac{S_{1t}}{K_{Q_t}}\right) \tag{5}$$

Here the intrinsic growth rate r_{Q_t} and carrying capacity K_{Q_t} may both depend on environmental conditions Q_t. In particular, we assume the shock reduces both intrinsic growth and carrying capacity by a fraction w: $r_{Q_t} = r(1 - wQ_t)$ and $K_{Q_t} = K(1 - wQ_t)$. This might happen, for example, if the shock causes an abrupt, temporary reduction in food density, since both intrinsic growth and carrying capacity might reasonably be linearly related to that density (see online Supplementary material[1]). A larger value of w indicates a more severe shock. The environmental state is unfavorable in period $t + 1$ with probability 0.5; current envi-

[1]Supplementary data are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfas-2018-0283.

ronmental conditions have no effect on those in the next period. A constant escapement policy can be imposed by requiring $\boldsymbol{\gamma}^T = [1]$, while a constant fishing mortality policy entails $\phi = 0$.

Peruvian anchoveta

Our model of the Peruvian anchoveta is based on models developed by el Instituto del Mar del Perú (IMARPE), the research institution tasked by the Peruvian government with monitoring the anchoveta population and making fishery management recommendations (IMARPE 2010). Simulated trajectories of the model closely match a 27-year time series of anchoveta biomass in Peru. The model runs on a 6-month time step, tracking the biomass in each of three age classes. Anchoveta older than age class 3 (>18 months old) represent less than 4% of the catch, and are therefore neglected.

The general framework above can be specialized to the anchoveta fishery as follows:

$$(6) \qquad B_{1t} = \alpha_{Q_t}(S_{2t} + S_{3t})\mathrm{e}^{-\beta_{Q_t}(S_{2t}+S_{3t})}$$

$$(7) \qquad B_{at} = \omega_{a-1,a}\mathrm{e}^{-0.5M_{a-1,Q_t}} S_{a-1t} \quad \text{for } a \in \{2,3\}$$

Here, α_{Q_t} and β_{Q_t} are parameters of the Ricker stock–recruitment relationship, both of which depend on the current environmental state Q_t. The $\omega_{a\text{-}1,a}$ parameters determine natural growth, while M_{a-1,Q_t} determines natural mortality of fish entering age class a; we further assume mortality of the first age class depends on Q_t while $M_{2,Q_t} = M_2$ does not. Only age classes 2 and 3 are susceptible to fishing, so that $\boldsymbol{\eta}^T = [0, 1, 1]$.

The environmental state, which represents ENSO in this case, takes value 1 in period $t + 1$ with probability

$$(8) \qquad p(Q_{t+1} = 1|Q_t) = \begin{cases} 0.5 & \text{if } Q_t = 1 \\ 0.07 & \text{otherwise} \end{cases}$$

These probabilities correspond to El Niño having a characteristic return time of 7 years (14 seasons) and a characteristic length of 1 year (two seasons). See the online Supplementary material[1] for details and results with alternate probabilities.

In this setting, the constant escapement policy restriction can be imposed by requiring $\boldsymbol{\gamma}^T = [0, 1, 1]$, while a constant fishing mortality policy again entails $\phi = 0$.

Results

For the logistic growth fishery, the optimal response to an unfavorable environmental forecast may be either aggressive (increase harvest) or conservative (decrease harvest) depending on the degree of uncertainty in stock size (Fig. 2). With perfect information about the stock size and no constraints on policy parameters, the optimal response to an unfavorable forecast of a shock that reduces growth and carrying capacity by 10% is to increase harvest (by up to 26%), consistent with the theoretical literature. However, we find that increasing uncertainty in stock size alone leads to a less aggressive harvest response, and sufficiently large uncertainty can lead to a net reduction in harvest in response to the environmental forecast (up to 18% decrease). These effects are magnified when the harvest policy is constrained to a constant escapement policy; the optimal harvest response becomes precautionary at lower levels of uncertainty in stock size, reaching larger relative reductions (up to 63% decrease). Under a constant mortality policy, the harvest response is dampened but always aggressive, ranging from a 7% increase under perfect information to nearly no response at high levels of uncertainty in stock size.

The value of the environmental forecast as a share of harvest (Fig. 3) clearly depends on the type of harvest control rule used. The environmental forecast value may be up to 3% for the flexible harvest control rule and up to 15% for the constant escapement policy, but has little worth under a constant mortality policy. The value tends to be largest when the harvest response is most conservative, which occurs with high growth and high uncertainty in stock size.

Modifying aspects of the logistic growth model produces mostly predictable results. The same general patterns hold when the ef-

Fig. 2. The optimal response to a perfect forecast of bad environmental conditions in the logistic growth model as a function of uncertainty in stock size (x axis) and stock growth rate (y axis), for flexible (top panel), constant escapement (middle panel), and constant mortality (bottom panel) harvest policies. Figures reflect $K = 150$, $\delta = 0.95$. Blue colors indicate increased harvest when a shock is forecast, red colors indicate reduced harvest, and white indicates no response. Darker colors indicate stronger responses. [Colour online.]

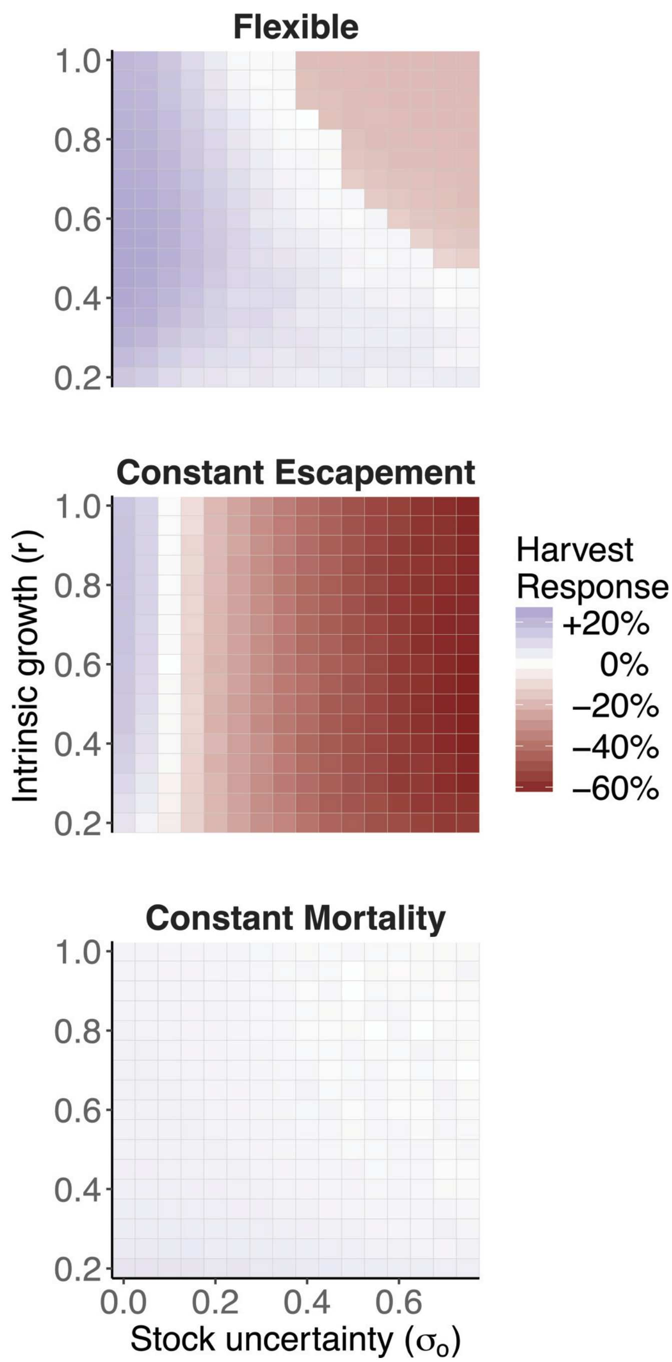


Fig. 3. The value of a perfect forecast (as a percentage of harvest without the forecast) of bad environmental conditions in the logistic growth model as a function of uncertainty in stock size (*x* axis) and stock growth rate (*y* axis), for flexible (top panel), constant escapement (middle panel), and constant mortality (bottom panel) harvest policies. Figures reflect $K = 150$, $\delta = 0.95$. Darker colors indicate larger environmental forecast value. [Colour online.]

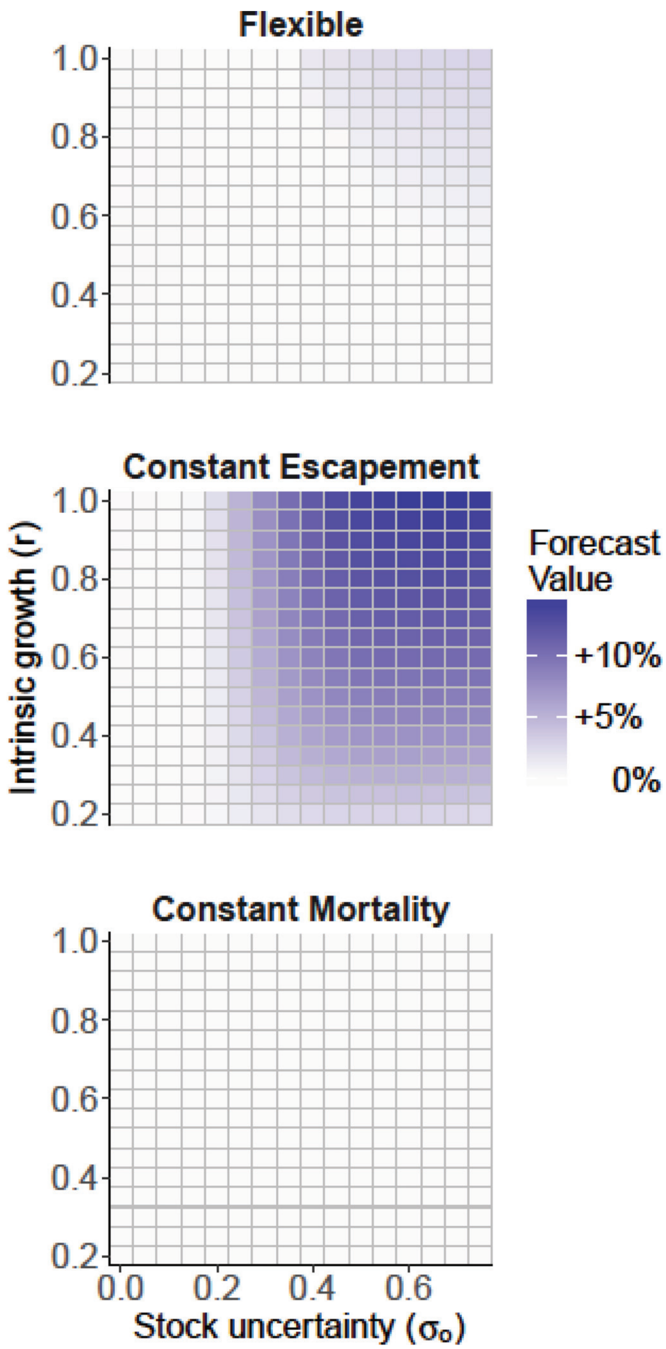


Fig. 4. The optimal response to an uninformative, completely random forecast ($P(q_t = Q_{t+1}) = 0.5$) of bad environmental conditions in the logistic growth model as a function of uncertainty in stock size (*x* axis) and stock growth rate (*y* axis), for flexible (top panel), constant escapement (middle panel), and constant mortality (bottom panel) harvest policies. Figures reflect $K = 150$, $\delta = 0.95$. Darker colors indicate stronger reduced harvest, and white indicates no response. [Colour online.]

fect of the shock is larger (e.g., a 40% reduction in growth and carrying capacity; Fig. S1[1]). If the management objective were to favor less variance in harvest due to risk aversion or preferences for steadier harvest through time, the optimal policy predictably becomes conservative at lower levels of uncertainty (Fig. S2[1]), with the most conservative harvest response occurring under high growth and uncertainty. Finally, if the environmental forecast is uninformative, such that a shock is predicted with probability 0.5, a response (reduced harvest) is only warranted when a constant escapement policy is mandated (Fig. 4).

For the Peruvian anchoveta fishery, across all historical regimes, the optimal response to a perfect forecast of an El Niño event in the following season is to increase current harvest (Fig. 5; stock parameters for the three regimes are provided in Table 1). The magnitude of that increase ranges from 12% to 54%. Figure 5

Fig. 5. The optimal harvest response (*y* axis) under the flexible harvest policy to a perfect forecast of El Niño in the anchoveta fishery during the 1961–1970 (red), 1971–1991 (blue), and 1992–2009 (black) regimes as a function of uncertainty in stock size (*x* axis). Stock parameters for the three regimes are provided in Table 1. [Colour online.]

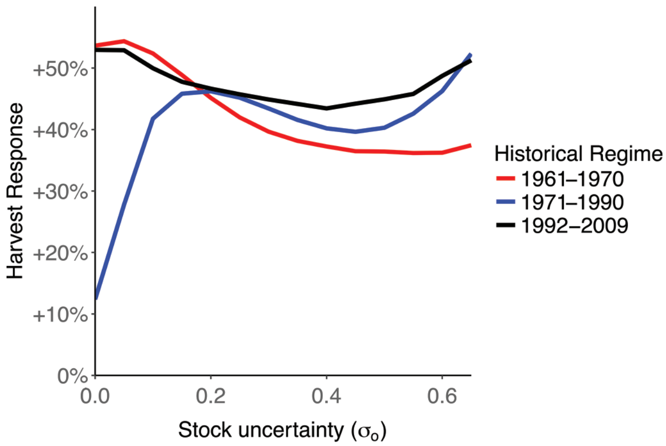


Table 1. Parameters for anchoveta population dynamics in three recent regimes.

Parameter	Regime 1 (1961–1970)	Regime 2 (1971–1990)	Regime 3 (1992–2009)
α_{normal}	0.71	0.58	0.56
α_{ENSO}	0.82	0.65	0.63
β_{normal}	7.33×10^{-8}	2.24×10^{-7}	1.19×10^{-7}
β_{ENSO}	1.28×10^{-7}	3.86×10^{-7}	2.05×10^{-7}
$M_{\{1,\text{normal}\}}$	1.59	1.27	1.20
$M_{\{1,\text{ENSO}\}}$	1.89	1.50	1.42
M_2	1.53	0.94	1.06
ω_{12}	6.56	6.56	6.56
ω_{23}	1.87	1.87	1.87

Note: See eqs. 6 and 7 for parameter definitions. α and β are parameters of the Ricker stock–recruitment relationship; *M* governs natural mortality; ω determines natural growth between age classes.

shows an increase in uncertainty in stock size has more complex effects on the harvest response, with nonmonotonic effects that vary across regimes. With a flexible harvest policy, the maximum value of a perfect environmental forecast in the anchoveta fishery is approximately 1% of harvest across all regimes, which occurs at low levels of uncertainty in stock size. In a fishery averaging approximately 8 million t of harvest per year during the 1992–2009 regime, that value equates to an extra 80 000 t or US$3 million per year (SAUP 2018). Harvest responses are qualitatively similar but smaller in magnitude (see online Supplementary material, Fig. S3[1]) when forecasts are imperfect with accuracy similar to that in recent models (Ludescher et al. 2014).

While increased harvest is the best response to a forecast of an El Niño event in all anchoveta regimes, this is not a general property of age-structured fisheries. Consistent with the results for the logistic growth fishery, a net conservative response to an environmental forecast is possible with uncertainty in stock size under other parameterizations (e.g., if recruitment is increased; Fig. S4[1]).

Discussion

Our results highlight the potential for a forecast of environmental conditions that are unfavorable for a stock to elicit either a conservative or an aggressive response in the management of a natural resource. Consistent with prior theoretical results, in an idealized world with perfect information about the size of the stock and no policy constraints, the optimal harvest response is aggressive in both fishery models we examine. For the negative shocks we consider, that finding matches economic intuition; poor future conditions mean a fish left in the water will be less productive, so it makes sense to harvest more today and invest the benefits in other more productive uses. A corollary of that result is that harvest should be lower when environmental conditions next season are expected to be favorable (no shock), a practice managers of the anchoveta fishery in Peru have successfully followed by reducing harvest at the end of El Niño warm-water events. However, realistic limitations on the quality and use of biomass estimates can have dramatic effects on the optimal harvest response to a forecast of a shock. We find many cases in which the optimal response to a forecast of poor environmental conditions is to reduce harvest. This reversal of the optimal response is consistent with earlier work on management under multiple sources of uncertainty (Sethi et al. 2005), in which sources of uncertainty interact in substantive ways. Here, an environmental forecast represents a reduction in uncertainty pertaining to growth, the effects of which depend crucially upon the remaining uncertainty around stock size.

The primary force driving a precautionary reaction to an environmental forecast in the face of uncertainty in stock size is the threat of stock collapse. When stock estimates are uncertain, the harvest policy intuitively should respond less to those estimates. However, when a shock reduces stock levels, this insensitivity can lead to harvest that exceeds the true stock size. Knowing this, the manager has an incentive to harvest less when a shock is forecast so that the relatively insensitive harvest policy is less likely to lead to collapse after the shock occurs. This incentive is notably absent in prior work on harvest responses to environmental forecasts (e.g., Costello et al. 1998) in which a manager with perfect information cannot accidentally drive the stock to collapse after a shock and so need not use a forecast response to reduce the risk of accidental collapse.

The effect of uncertainty in stock size is more complex in the anchoveta fishery; increased uncertainty may lead to either more or less aggressive harvest. This contrast stems from two important differences in the fisheries. First, because the youngest age class of anchoveta is not susceptible to fishing, it is more difficult for a manager to accidentally drive the population to extinction. Thus, the potential downside to an aggressive response to an El Niño forecast is limited in our model (but a lower probability, multiseason shock could still lead to extinction). This effect is likely relevant for many fisheries; technological regulations limiting catch of younger and (or) smaller fish (e.g., via minimum mesh sizes) are common. Second, while logistic growth implies linear reductions in marginal recruitment under a shock, Ricker recruitment in the anchoveta model implies the reduction in marginal recruitment under El Niño has both concave and convex regions. As a result, in the anchoveta fishery, greater uncertainty in stock size can increase expected reductions in growth under El Niño, favoring more aggressive harvest (see online Supplementary material[1]). Together, these factors can make a more aggressive response to an El Niño forecast appropriate even under uncertainty in stock size. For context, some estimates of uncertainty regarding stock levels put σ near 0.21 (see online Supplementary material[1]).

The policy limitations we examine may either exaggerate or counteract the effect of uncertainty in stock size on the optimal environmental forecast response. Both results are best understood via the earlier observation that the optimal harvest policy intuitively should respond less to a noisy stock assessment. The policy constraints we consider have the effect of forcing the manager to overreact (constant escapement) or underreact (constant mortality) to stock assessments (see Fig. 1). One way to compensate for this overreaction (or underreaction) is to reduce (or increase) harvest whenever a forecast of bad environmental conditions occurs. Doing so brings the responsiveness of the harvest policy closer to the unconstrained level, at least in expectation. This is most easily seen mathematically for the logistic growth fishery, for which the overall coefficient on the stock assessment is $\gamma(1 + \lambda q_t)$. In the presence of uncertainty in stock size, constant escapement requires γ to be larger than the optimal level, and so the overall coefficient can be brought closer to its optimal level by choosing $\lambda < 0$. The overall effect is to flatten the harvest response to noisy biomass estimates, which also smooths harvests across time.

To highlight the intuition behind the effects of the constant escapement restriction, consider what happens if the environmental forecast is random, meaning a shock is predicted with probability 0.5 regardless of the true conditions for the next season. This special case corresponds to a standard stochastic fishery model. In this case, the environmental forecast contains no useful information, and so the manager should not and does not respond in the absence of policy constraints (Fig. 4, top panel). However, when a manager is restricted to a constant escapement policy, the optimal response to an uninformative environmental forecast is still to reduce harvest — dramatically so for high levels of uncertainty in stock size (Fig. 4, middle panel). This result highlights the phenomenon described above; since the environmental forecast is completely uninformative, the flexibility afforded by the forecast adjustment parameter λ can only be used for one thing: to compensate for inflexibility in the choice of the stock assessment coefficient γ.

Overall, our results also suggest that refinements in how some fisheries policies treat uncertainty may be necessary. As one example in the United States, National Standard 1 in the Magnuson–Stevens Act encourages reducing fishing mortality under higher "scientific uncertainty" — which includes both the stock and growth uncertainties we consider. However, we find an environmental forecast that reduces uncertainty in growth (in an unfavorable way) may necessitate either an increase or a decrease in harvest compared with the case when no forecast is available. Similarly, an increase in uncertainty in stock size induces a more conservative harvest response in the logistic growth model, but may result in a more aggressive response in the anchoveta model. In general, the effect of a change in uncertainty on optimal harvest depends on which type of uncertainty is changing, what other sources of uncertainty are present, harvest policy constraints, and details of biological dynamics and susceptibility of different age classes to fishing. Even if some managers are already aware of this nuance, not all large-scale policies reflect that understanding.

In all of these cases, the modest relative values of the environmental forecasts we examine should be interpreted with caution. First, small relative values in a large fishery such as the Peruvian anchoveta fishery translate into large absolute values. Second, in many cases, including for El Niño events, environmental forecasts are likely to benefit multiple fisheries or even multiple economic sectors, so that benefit–cost analyses for forecasting efforts must factor in the full suite of benefits or allocate a fraction of the forecast costs to a single fishery. Finally, the objective function we study is linear in harvest; nonlinear benefits (e.g., due to risk aversion costs of searching for schools) or other forms of socioeconomic or biological realism may substantively alter the environmental forecast value as well as the best forecast response.

Our analysis prompts several interesting extensions and directions for future work. First, there are numerous biological and environmental considerations that merit additional investigation. Multispecies fishery considerations, depensation, migration in response to the shock, or alternate life histories of the target species all could affect the appropriate harvest response to an environmental forecast. Similarly, environmental shocks vary in intensity, shock probabilities may depend on environmental conditions in prior seasons, and shocks could affect adult survival, growth, or catchability in addition to recruitment. The effects of shocks on populations and the impact of an environmental forecast on optimal harvest may be quite different when considering those factors. For example, slower-growing, longer-lived species may be much less affected by temporary shocks, warranting little to no response to a forecast of such an event.

Second, there are a range of other factors, beyond the two highlighted in this study, that could prevent a manager from achieving optimal results. For example, parameters of a control rule may not be chosen optimally, and the effects of the environmental shock may not be understood perfectly. The manager's imperfect understanding of the system may also be structural in nature, with uncertainty not just over biomass or environmental conditions, but also over which model best describes the fishery. In those cases, an approach that allows integration of multiple models, such as ensemble modeling, may be useful (see, e.g., Stewart and Hicks 2018). There may also be lags in the use of information; stock estimates take time and may not reflect current population levels, or delays in regulatory processes may mean quotas are set based on older forecasts. All of these limitations could affect whether a manager responds aggressively or conservatively to an environmental forecast.

Third, some fisheries are managed with more sophisticated policies than the ones we consider here, including "ramped" harvest control rules that shrink the target fishing mortality linearly below a biomass threshold (e.g., Eikeset et al. 2013). The optimal environmental forecast response for such rules is likely to differ, at least quantitatively, from those presented here, though the forecast response for ramped policies is likely to lie between that for the flexible and constant mortality policies (see online Supplemental material, Fig. S5[1]).

Finally, while we focus primarily on perfect forecasts of environmental conditions one season ahead, noisy and (or) multiseason forecasts may be of interest. We briefly examine imperfect environmental forecasts, but an intermediate model of forecast noise could account for uncertainty that depends on current and prior conditions. Regarding forecast horizon, previous models have shown that environmental forecasts of conditions more than one season ahead do not add value to management (Costello et al. 2001). However, more complex models including socioeconomic factors such as capital adjustment costs might find that more advanced environmental forecasts do provide added value.

From an implementation perspective, a manager opting to increase or decrease harvest in response to a forecasted shock may face opposition from resource users. Opposition might arise, for example, due to asymmetries in information between the manager and fishers. Similarly, fishers who value a steady stream of harvest or consistent employment may prefer precautionary harvest responses that avoid boom and bust cycles, even when maximization of expected discounted benefits might favor the opposite. While we do not study political economy and related issues, institutions that help communicate information and objectives or help fishers smooth income across time are likely to be important in making the most of environmental forecast information.

Looking ahead, responses to environmental forecasts are likely to play an increasingly central role in fisheries, many of which will continue to face the information constraints about stock status we consider here. Climate change is driving increased variability and more extreme environmental disturbances for many locations around the world (Timmermann et al. 1999; IPCC 2007; Easterling et al. 2000), creating a growing need for dynamic management for fisheries and other resources that adjusts for these fluctuations. The science of environmental forecasting is evolving rapidly as improvements in remote sensing technology are coupled with sophisticated climate and earth systems models and time series analysis. Our findings show that accounting for uncertainty and policy constraints will be critical to ensuring that management responds to environmental forecasts in the appropriate direction.

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