

Environmental Derivatives, Risk Analysis, and Conservation Management

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Abstract

Two key challenges in conservation management are: (1) how to quantify and manage the risk that natural populations will fall below critical thresholds and (2) how to fund recovery plans should a population do so. Statistically estimated, process-based simulation models of two distinct fish populations are used to forecast the species population levels, and capture the risk of crossing a management defined trigger point. We show how to calculate the environmental derivative price, which is the amount a risk-neutral investor would require for promising a pay-out should the species abundance fall below the trigger level. The approach provides the potential for environmental derivatives to support species recovery, and a method for measuring the underlying “health” of a managed population and calculating risk-cost tradeoffs among alternative management strategies.

Introduction

Conservation management agencies regularly attempt to manage natural assets within specific limits, and constantly face the risk of crossing these limits, triggering costly restoration activities. Both public agencies and private industries, faced with paying for these actions, are usually unwilling or unable to secure funds for this purpose (Holl & Howarth 2000), which in turn leads to social and political pressures to ignore trigger points or delay the response, resulting in further, and at times extreme, damage. Faced with this risk, managers must therefore ask: How do management decisions affect risk? What risk measures can be used to inform management decisions? And, what can be done to share the financial risk in the event a threshold is crossed?

Similar issues are routinely addressed in other areas including agriculture, commodities, and finance, with market-based mechanisms and financial instruments, which transfer risk to a willing second party. Environmental management is increasingly looking at such approaches to manage risk (Dalton 2005; Fenichel *et al.* 2008; Mandel *et al.* 2009; Sethi 2010; Sethi *et al.* 2012; Sullivan 2013). For example, Mandel *et al.* (2010) suggested a class of products called derivatives could be used like assurance bonds (Costanza & Perrings 1990), to align the incentives of investors and stakeholders with the recovery and conservation objectives for species like the endangered red-cockaded woodpecker (*Picoides borealis*). We suggest that derivatives can be used to manage the financial risk of recovery and restoration, and ensure

that conservation managers use effective management strategies.

Derivatives are widely used to manage or hedge risk in financial and commodity markets. They are also used to manage risk associated with environmental conditions, such as weather (Jewson *et al.* 2005). The environmental derivative we envisage, analogous to a financial derivative called an option, would operate in such a way that one party, called the owner, would pay another party, called the writer, to incur the risk of funding recovery operations. The writer is contractually obliged to make a pay-out to the owner for recovery efforts if the underlying asset, for example, a red-cockaded woodpecker population, falls or remains below a pre-defined trigger point, called the strike, prior to an expiry date. However, if the population stayed above the trigger point, no pay-out would be required and the writer (investor) would keep their payment.

Derivatives have acquired a poor reputation because their speculative and reckless use contributed to the recent global financial crisis. However, they are in essence a form of insurance and continue to be used widely and responsibly in that role. An important point highlighted by the global financial crisis is that pricing derivatives, or any form of insurance contract, requires accurate quantification of risk. The widespread failure of statistical models to accurately quantify financial risks contributed to the global financial crisis (Salmon 2009), and a lack of robust risk measurement methods represents a substantial barrier to their use for conservation. We show that stochastic population models are a well-established platform for objectively measuring the risk of crossing trigger points, and calculating the derivative payment price.

The use of environmental derivatives, based on objectively characterizing risk, offers multiple direct and indirect benefits for conservation management. Directly, it ensures that funds are available to implement agreed rebuilding initiatives if assets drop below trigger points. Indirectly, it pressures managers to invest in effective conservation strategies. For example, managers are typically faced with a choice of strategies having different risk profiles, and may be under pressure to adopt a strategy that promises higher economic returns, but higher risk of population collapse. Managers may also, less obviously, be under pressure to reduce investment in monitoring and assessment needed to underpin the strategy chosen. The requirement that a management agency insure against the risk of population collapse using environmental derivatives, at a price that increases in proportion to risk, offers a countervailing pressure that favors risk-averse strategies.

In this article, we outline risk assessment methods that can be used to develop environmental derivatives for

conservation purposes and calculate prices for derivatives associated with three management strategies. The risk assessment and pricing methods outlined here offer a direct financial measure of the benefits of investment in management procedures that reduce uncertainty and risk. The methods are illustrated for two marine fish populations.

Methods

The derivative price is the payment the writer (investor) of the contract requires for incurring the risk of a pay-out. Consequently, the greater the probability that the population will fall below the threshold, the higher the derivative price should be. Probabilities were calculated from stochastic simulations forecast from a statistically estimated process-based population dynamics model (biological model) of two fish species, school whiting (*Silago flindersi*) and tiger flathead (*Platycephalus richardsoni*). These species were chosen based on their life history characteristics, their current estimated status, and the uncertainty associated with that estimate. School whiting is a fast growing short-lived species, whose spawning biomass is currently thought to be at a relatively high fraction (0.6) of the undisturbed spawning biomass (Day 2010). The longer-lived tiger flathead is generally thought to be at a lower (0.4), but more certain level (Klaer 2010).

Derivative prices accounted for observation error, and were generated for three management control strategies (Appendix), each involving a data collection and estimation procedure performed by an observation model, and a decision procedure to set an allowable harvest that reflects a management objective of balancing conservation and economic goals. Each strategy is currently used by the management agency on a range of species, and represented different operating costs (for monitoring and assessment): management control 1 is the costliest, and sets allowable harvest based on an estimated population size using annually collected age, growth and mortality data; management control 2 sets allowable harvest based on a population size estimated from annually collected age data; and management control 3 represents the cheapest procedure by setting allowable harvest based on annually collected catch-rate data.

Prices were calculated for the different species, initial forecast conditions, and management controls. The approach is described in more detail in the Appendix, but can be summarized qualitatively as follows. The current population size and the biological parameters controlling the population dynamics are uncertain. Probability distributions for these variables were obtained by applying

a statistical estimation procedure based on historical observations. A large random sample from these probability distributions was used to initialize an ensemble of independent simulations. For each ensemble member, we simulated not only the population trajectory as defined by the biological model and its parameterization, but also the application of each management control. This gave a time series of the underlying population size, and a parallel time series of the estimated population size derived from the estimation component of the management control, because in a real world situation managers would not know the “true” population size, but only an estimate of it. Derivative prices were calculated as the expected pay-out, based on the ensemble of this estimated population size and the probability a pay-out would be triggered in any year throughout the contract term.

The pay-out conditions were defined by a financial option, which gives one party (the contract owner) the option to exercise the contract under specific conditions prior to an expiry or “maturity” date, and receive a pay-out from the second party (the contract writer; Hull 2009). For conservation management, we assume the contract owner (management agency) would have the “option” to exercise the contract and receive a pay-out from the contract writer if the average spawning biomass is seen to cross the trigger point, or strike, of 20% of the undisturbed level, at any time before maturity in 20 years, thus initiating recovery efforts. This is analogous to an American-style “put option” contract in financial risk management (Jewson *et al.* 2005). Prices were calculated from the estimated population size as the expected outcome of a \$100 pay-out, and represented the amount the contract writer would require, as a risk-neutral investor, from the contract owner, to incur the risk of a pay-out should the population be perceived to have crossed the management threshold. Prices were also calculated on the underlying population to show the effect of error in the population estimate on the derivative price.

In weather derivatives and financial options contracts, pay-out is usually proportional to the difference between the trigger and the asset state (Jewson *et al.* 2005; Hull 2009). Thus, an asset that falls to 19% of the undisturbed level would have a lower pay-out than if the asset fell to 15%, assuming a trigger point of 20%. Consequently, the contract owner has the choice or “option” either to exercise the contract and take the pay-out, or not, and wait in the hope that the asset declines further. The difficulty with this type of option when applied to natural assets is that it provides a perverse incentive to contract owners who might try to maximize their pay-out by waiting for the asset to decline further below the trigger point before exercising the contract. A derivative contract based on a constant pay-out as we have specified (Appendix) would

not lead to this behavior because there would be no financial incentive for the contract owner to wait for the asset to fall further.

Results

School whiting

The simulation results suggested all three controls are reasonably robust, in the sense that the ensemble mean of the “true” biomass is maintained above 60% of undisturbed levels, and the ensemble mean minus one ensemble standard deviation still stays above the trigger level of 20%, at least when starting from observed levels (Figure 1A-C). When initial mean population levels are artificially lowered to 30% of undisturbed levels, the management controls all lead to recovery of mean biomass to levels of 60% or higher (Figure 1D-F). Note that management control 2 is more conservative, and tends to maintain spawning population at around 80% of undisturbed levels.

For management control 1, the mean estimated population size was under-estimated in the long-term when forecast from the initial estimated state (Figure 1A). In contrast, it converged to the actual underlying state when the initial mean population levels were artificially lowered (Figure 1D). The reason for the difference is that the observation model interpreted the initial 2009 reduction in Figure 1D as a stochastic deviation resulting in a lower 2009 estimate than in Figure 1(A). Other data that came through to the observation model in Figure 1(D), however, indicated increasing productivity in the underlying population, which led to an estimate that increased through the projection period eventually coinciding with the actual underlying population state.

Management control 2 substantially under-estimated the population because the estimation procedure involved estimating the age-structure of the species, which consists of relatively few ages. Management control 3 only slightly under-estimated the true biomass level, but was much more variable because it relies on a simple index that is assumed to be proportional to abundance. As a result, the line marking the estimated mean less 1 standard deviation is quite close to the trigger level in Figure 1C. When the initial biomass was artificially lowered, the mean initial estimates from management controls 2 and 3 all fell below the trigger level, indicating a high probability of the need for recovery efforts

Tiger flathead

Management control 1 tended to maintain average “true” biomass at around 50% of undisturbed levels, with the

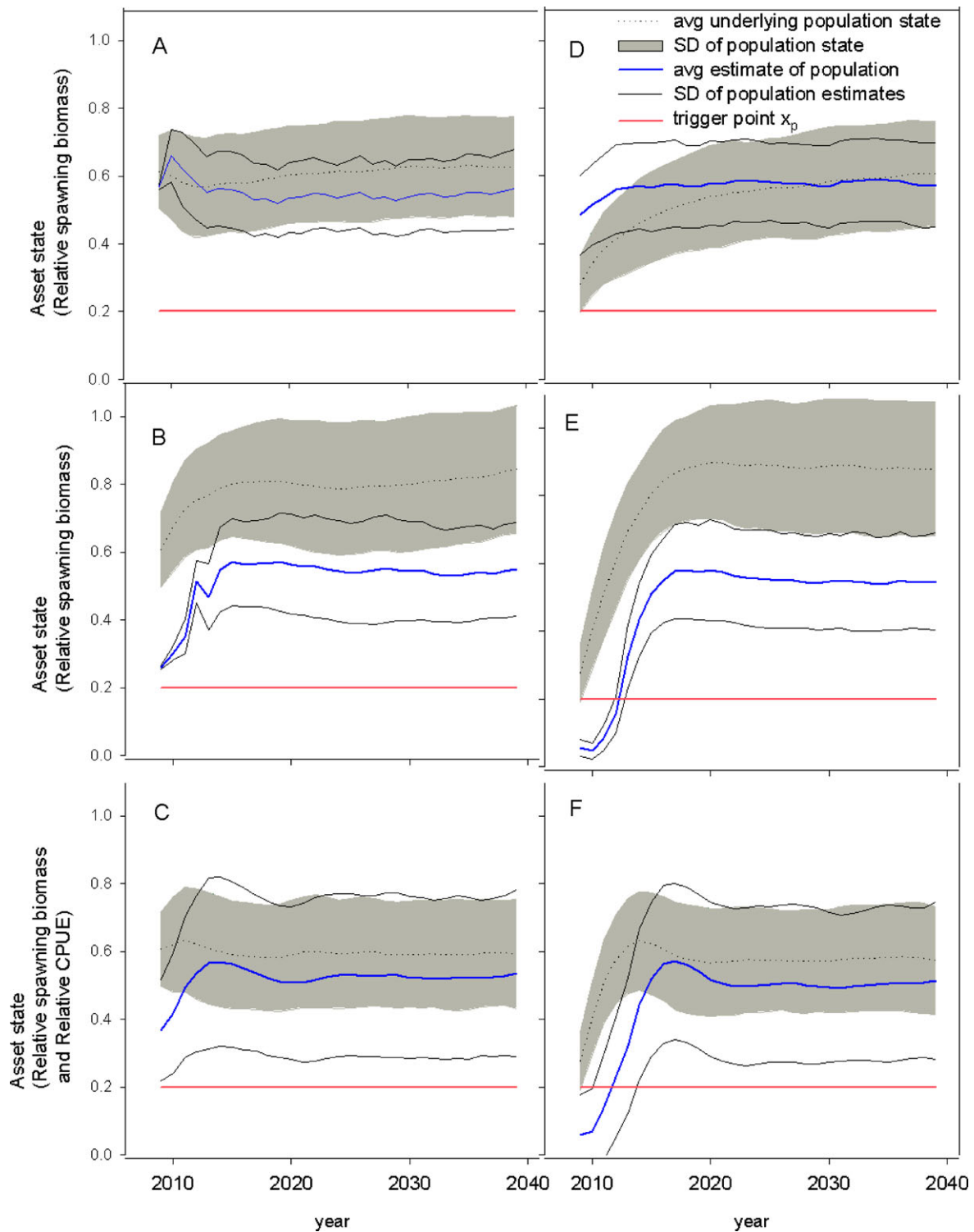


Figure 1 Average school whiting spawning biomass trajectory (relative to undisturbed levels) from the underlying simulation model (dotted line, shaded area \pm SD) and the observation model estimated biomass in each year (blue line) when the forecast started at the current estimated state (A–C) and at a lower state (D–F). Panels A and D represent the population under management control 1, B and E under management control 2, and C and F under management control 3. The average estimated spawning biomass calculated from the catch-rate (blue line; C and F) is scaled so that the target catch-rate is 48% of undisturbed levels. Solid lines are the between-simulation SD in the observation model estimates. Red lines correspond to the management trigger point.

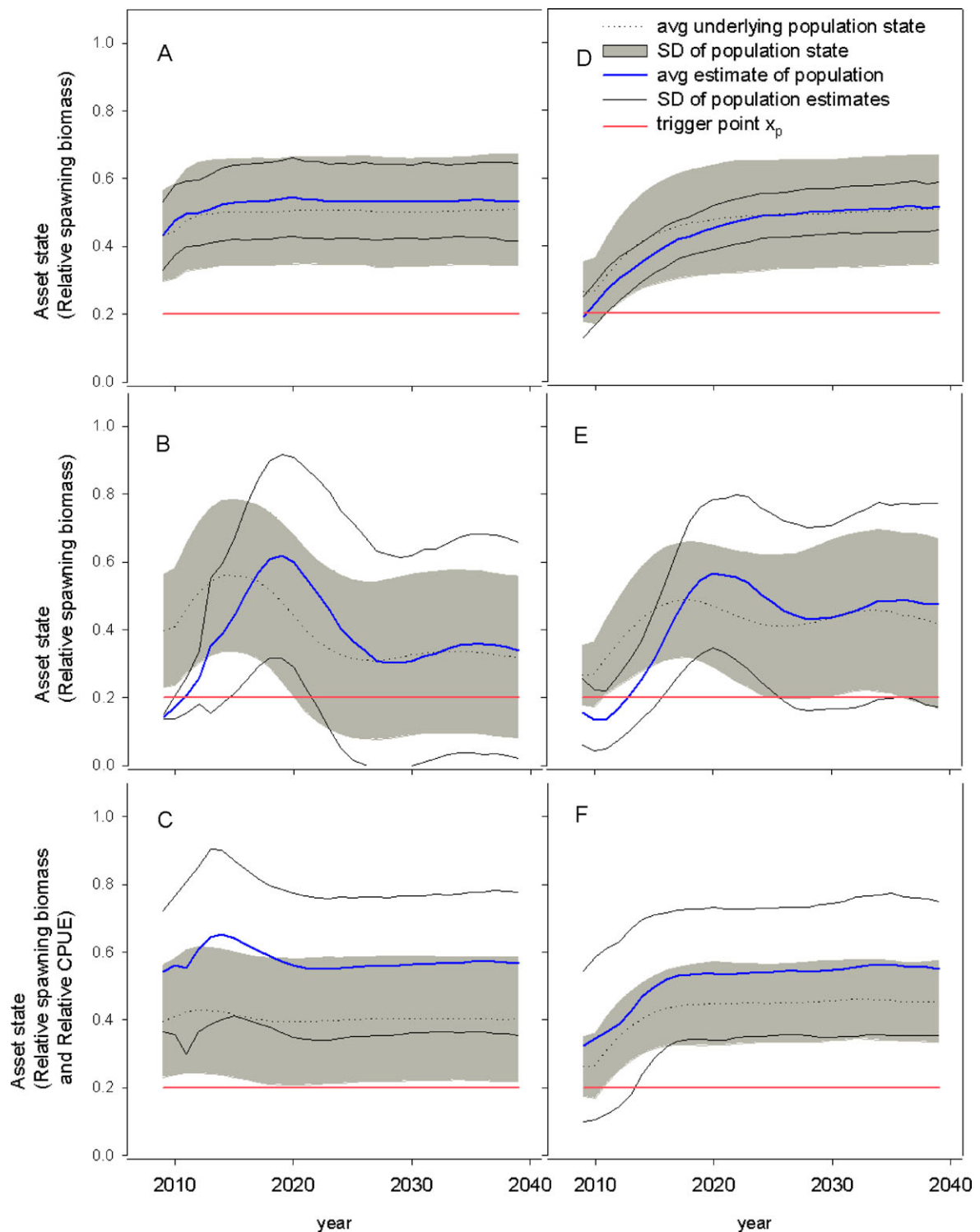


Figure 2 Average tiger flathead spawning biomass trajectory (relative to undisturbed levels) from the underlying simulation model (dotted line, shaded area \pm SD) and the observation model estimated biomass in each year (blue line) when the forecast started at the current estimated state (A–C) and at a lower state (D–F). Panels A and D represent the population under management control 1, B and E under management control 2, and C and F under management control 3. The average estimated spawning biomass calculated from the catch-rate (blue line; C and F) is scaled so that the target catch-rate is 48% of undisturbed levels. Solid lines are the between-simulation SD in the observation model estimates. Red lines correspond to the management trigger point.

mean less one standard deviation above the 20% trigger level (Figure 2A). The observation model slightly overestimated biomass, but seemed to be more sensitive to a decrease in initial biomass (Figure 2D). Management controls 2 and 3 were less robust for this species, with mean true biomass declining to around 40% or less of undisturbed levels, and the mean less one standard deviation at or below the trigger level (Figure 2B and C). Biomass estimates were highly variable for management control 2 (Figure 2B and E). The biomass was greatly overestimated for management control 3 (Figure 2C and F), mainly because the analysis procedure is not a formal statistical estimate, but instead relies on a general heuristic.

Prices

Several estimates of the underlying population were consistently biased. School whiting under management control 2, for example, showed the greatest under-estimated status (Figure 1B and E). Biases in population estimates will lead to distortions in price, and potential “errors” in management, triggering payouts and rebuilding when they are not necessary, or failing to trigger rebuilding when it is needed. The effect of these biases on derivative prices can be shown by comparing derivative prices calculated from the estimated biomass that would be used in practice (i.e., the practical price; Figure 3), with derivative prices calculated from the underlying biomass (i.e., the underlying price; Figure 3), on which the estimates were based.

Derivative prices ranged between \$0.03 and close to \$99.99, depending on the species, initial conditions and management control (Figure 3). A price of \$100 is the theoretically maximum price, signifying the population is expected to cross the trigger point and initiate a \$100 pay-out immediately and with 100% certainty. All prices were less than this maximum, but four cases gave prices above \$85 (Figure 3) because the average estimated spawning biomass started below the 20% threshold (Figures 1E and F, 2B and E).

Risk-management tradeoffs

The prices shown in Figure 3 show the interactive effects of species dynamics (school whiting, tiger flathead), initial state (current best estimate, artificially lowered) and management control method. As expected, higher prices result when the initial biomass is lower, because the probability of triggering a payout is higher. Nevertheless, there is a strong interaction with management control. For instance, management control 1 leads to lower practical prices than management controls 2 and 3 under almost all conditions. It is also more expensive to implement.

The penalties for using “cheap” management controls, in terms of higher contract prices or “insurance premiums,” therefore would be substantial.

Management control 1 offers a price advantage (lower risk) for both species when forecast from the current best estimate of the state, suggesting that the “true” biomass is more likely to stay above the trigger point (Figure 3A and C). There is little or no difference in the underlying price among management controls when the forecasts start from a lower initial state, suggesting that the differences in practical prices are due to differences in the management controls, particularly the bias and spread in the biomass estimates (Figure 3B and D).

Discussion

Conservation management must address many risks. There is the conservation risk that a population has fallen below a threshold, and there is the financial risk that restoration and recovery efforts require financial support. Risk is generally regarded as being composed of two parts: the probability of an event, and its consequence. We calculated the conservation risk of crossing a management trigger point in the derivative prices, as the expected cost. Probability was captured using a statistically fitted, process-based, population dynamics model, projected stochastically under different management controls. The consequence of the event was based on the financial risk management concept of a put option, which specifies a pay-out to be exercised if the asset falls below the trigger level.

The derivative prices we calculated have a natural extension to a risk market. We suggest that derivatives, specifically the *environmental put options* defined here, could be used in a risk market to hedge against the risk of unforeseen environmental events.

The obvious direct purpose of an environmental derivative market is to address the financial risk associated with conservation management. A market in environmental put options would operate to transfer the financial risk of recovery, which can be large, to investors willing to bear it. It also creates a class of investors with a financial incentive in the conservation status of the population (Mandel *et al.* 2010).

By providing a funding source, an environmental derivatives market would more likely result in management intervention, if it is needed. Currently, in the absence of such a fund, recovery efforts require unbudgeted expenditure from government, or foregone income and potentially prolonged, severe losses to those that rely on the asset, two outcomes with strong opposition. The failure to implement these efforts, however, would result in further asset degradation.

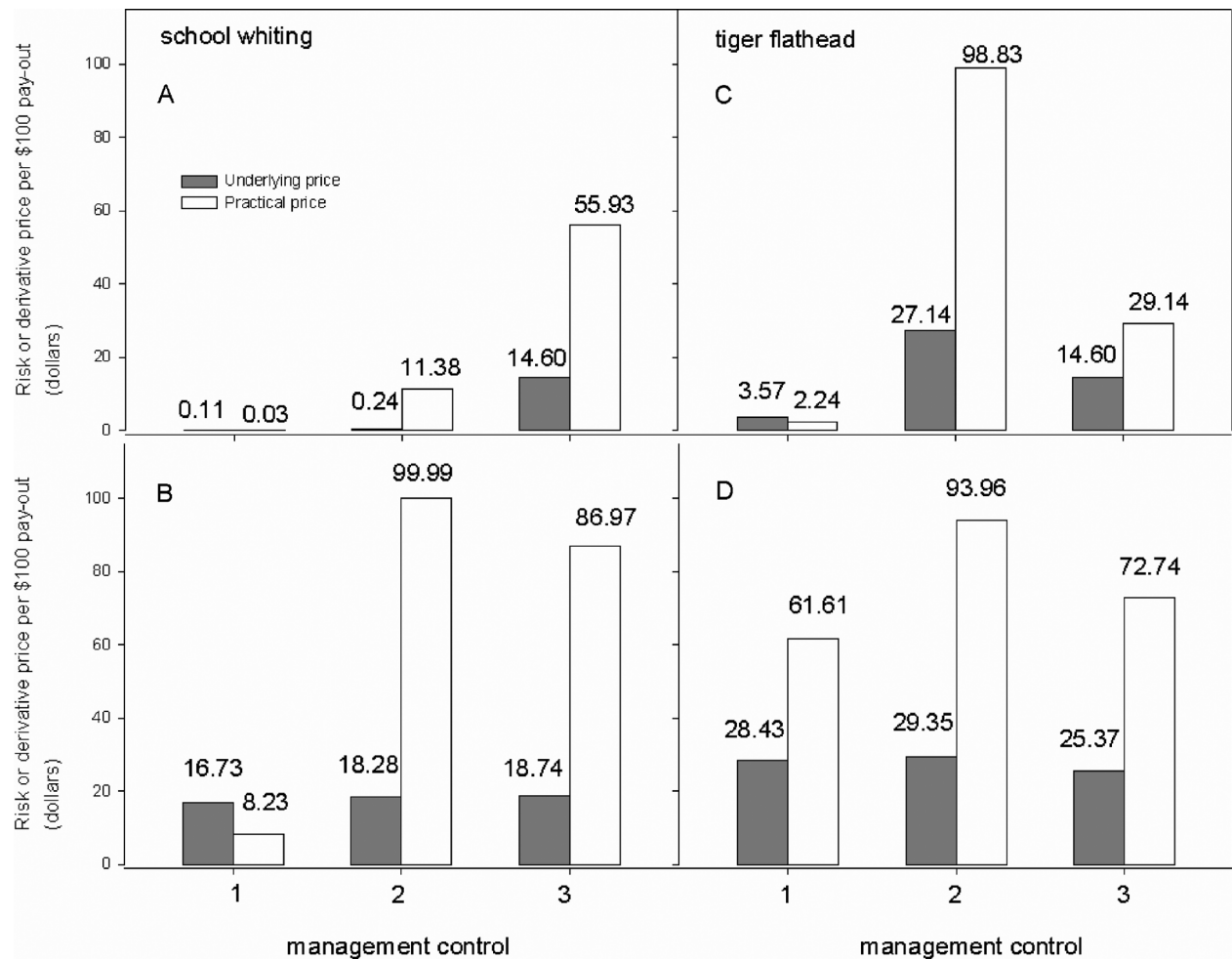


Figure 3 The practical price determined from the estimated spawning biomass and the underlying price determined from the underlying spawning biomass of environmental American style derivative contracts with 20-year maturity dates, under three management controls for school whiting (A and B) and tiger flathead (C and D) when the forecast started at the current estimated state (A and C) and the lower state (B and D).

A derivative market would rely strongly on an accurate, open, price calculation because any information asymmetry on the potential outcome of a population would be financially advantageous, by providing an arbitrage opportunity to one party. Since a management agency faces an incentive to trigger a pay-out, counterparties would want independent verification, which provides incentive for third-party involvement. The models we used represented the best understanding of the population dynamics, and associated uncertainty in predicting the future population states. Such models are well established for exploring population viability and the implications of management (Morris & Doak 2002; Bunnefeld *et al.* 2011; Doyen *et al.* 2012).

Derivatives can be applied to any natural asset with an associated stochastic model (Burgman *et al.* 1993; Lande

et al. 2003) including whales (Moore & Barlow 2011), sea turtles (Chaloupka 2002), grizzly bears (Knight & Eberhardt 1984), emperor penguins (Jenouvrier *et al.* 2009) and albatross (Zador *et al.* 2008). In all applications, management trigger points would be required to define the risk threshold (Regan *et al.* 2005; Farrier *et al.* 2007) and the pay-out conditions. These could be set at an ultimate level of extinction or extirpation, or at an abundance level representing a degree of precaution against such an event. The fisheries conservation examples we have shown were selected because the stochastic models and management trigger points were well developed and already used for management purposes.

The costs we defined for a contract were arbitrarily set to \$100. A higher aggregate pay-out would require multiple contracts, which would spread the risk, allowing

more parties to participate. The total number of such contracts would depend on several factors, including the direct costs of restoring the asset, and the potential losses in economic returns (e.g., tourism) and ecosystem services incurred from crossing the threshold.

Even if a functional derivatives market operated to manage the financial risk associated with conservation, the question remains as to whether a derivatives market could actually reduce conservation risk by reducing the probability of an asset crossing a threshold. We believe that a derivatives market would achieve this by clearly quantifying the effects of management. Typically, the costs of investment in management are relatively clear, but the benefits are frequently left unquantified. A market with a suitable method for computing derivative prices, of the kind presented here, would strongly penalize high risk management activities, including underinvestment in monitoring and assessment, by attaching high derivative prices to them. In principle, with appropriate regulation and compliance measures, this could be sufficient to reduce conservation risk. If, for example, marine fisheries were required to take out derivative protection against over-use with derivative prices based on the projected management strategy, and payout conditional on compliance with the strategy, then the financial penalty for using poor, high-risk management, and data collection strategies, or for not complying with more rigorous strategies, would be severe. Verified compliance with a management strategy would prevent management from engaging in moral hazard, and taking increased risks, in the assurance or hope of a financial pay-out (Mumford *et al.* 2009).

We acknowledge that environmental derivatives would be difficult to apply to all natural assets. A market requires affordable prices for management agencies, which implies that the risk of the asset crossing the threshold should not be excessive. The trade-off between high derivative prices and the cost of effective management and monitoring implies that natural assets with highly variable or uncertain population dynamics, or high management and monitoring costs would probably not be affordable to management agencies. Such cases where sophisticated management procedures are too costly, and weak management results in expensive derivative prices, would nevertheless indicate that economic and conservation objectives are not reconcilable.

The biggest difference between the use of derivatives in environmental management described here and the use in financial markets is that the state of the underlying natural asset is not certain, whereas the state of an underlying asset in a financial market is typically known with great certainty through the market price. The consequences for an environmental derivatives market are that

errors can be made in exercising a contract based on the perceived status (Mapstone 1995). For example, the perceived status could be below the trigger level when the actual status is above it, or alternatively the status may appear to be above the trigger when in fact it is below. This discrepancy is indicated in our example as the difference between the underlying and practical prices. In the real world, only the practical price, calculated from the estimated state of the underlying asset, would be available, without any knowledge of how accurately it would measure the risk.

To reduce the danger of such errors, trigger levels and payout conditions could be adjusted to achieve an agreed level of precaution. Conservation objectives often consist of both a threshold and a tolerance level (Mapstone *et al.* 2008), with tolerance defined in terms of a probability the threshold will not be crossed. In our example, we defined a threshold of 20% of the undisturbed state, and the tolerance was considered as the average biomass from the simulations, which represents about the 50th percentile. Increasing the threshold, say to 30%, or reducing the tolerance to ensure each simulation had only a 5% chance of crossing the threshold would accordingly increase the derivative price. For tiger flathead under management control 1 and assumed to be at the currently estimated state, the price of a contract would increase from \$2.24 to \$7.99 for the increased threshold, and \$52.20 for the reduced tolerance.

The derivative prices we calculated quantified the risk associated with available management controls. In general, the most data- and computationally demanding, and potentially most costly, management control resulted in lower prices or risk values. A comparison of these management strategies in terms of implementation costs would allow for a detailed risk-cost trade-off analysis that is typically not undertaken by management (Restrepo *et al.* 1992; Goldstein *et al.* 2008; Dowling *et al.* 2013). We find that the environmental derivative price is a leading indicator of the current and future health of an environmental asset, and a valuable and quantifiable key performance indicator for managers.

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Appendix

Since actual recovery costs are difficult to estimate, and are species- and situation-specific, a standard payout was set to \$100. The prices we calculate therefore reflect the payment price the investor would require for each \$100 promised in pay-out, should the asset cross the trigger point prompting recovery operations.

Forecast results

Prices were calculated based on an ensemble of 1,000 stochastic projections from a simulation model of two fish species in the Australian Southern and Eastern Scalefish and Shark Fishery (SESSF), subject to management control procedures in a management strategy evaluation framework (cf. Bunnefeld *et al.* 2011). Two scenarios were examined to explore the effect of the initial population state on the derivative price:

- (1) Forecasts started at the current estimate of state, or
- (2) Forecasts started from a lower initial state constructed by artificially increasing historical exploitation rates.

Model forecasts of these populations, derived from Fay *et al.* (2011), represented a data generation step to which we applied the price calculations (Fig. A1). Each of the 1,000 simulations was based on an alternative parameter vector sampled from a Bayesian posterior distribution (e.g., Fay & Tuck 2011). Model generated data consisted of the spawning biomass, $X_{k,t}$, of the underlying biological model in simulation k at time t , and an estimate of it, $x_{k,t}$, by an embedded observation model with coupled management control in each year of a forecast starting in 2009 (Fig. A1).

Three observation models and associated management controls were used based on those currently operating in the SESSF:

- (1) **Management control 1** set harvest levels annually using a decision rule (Fig. A2 A) that seeks to achieve a catch target of Maximum Economic Yield (MEY; Grafton *et al.* 2007; Smith *et al.* 2008). The annual harvest prescribed by the decision rule is based on the estimated spawning biomass determined from Stock Synthesis (Methot & Wetzel 2013) as an embedded observation model. The estimate of population size from this observation model used catch per unit effort (catch-rate), and age-, and length-composition data that were sampled from the underlying biological model.
- (2) **Management control 2** set harvest levels annually using a decision rule (Fig. A2 B) that seeks to achieve

a catch target of MEY based on an observation model that estimated current fishing mortality (F_{cur}) from the age-structure of recent catches. The population status was determined from the equilibrium spawning biomass associated with the estimated current fishing mortality (Cordue 2012), where current fishing mortality is based on a modified catch curve analysis applied to age-composition data captured from the underlying biological model (Wayte & Klaer 2010).

- (3) **Management control 3** set harvest levels annually based on a decision rule (Fig. A2 C) that seeks to achieve a catch target of MEY using catch-rate data generated from the underlying biological model. The observation model calculated the population status based on a general heuristic, as the average catch-rate of the five most recent years scaled to a target catch-rate thought to correspond to the spawning biomass at MEY (Little *et al.* 2011).

Catches taken from the underlying population model in each forecast year differed from those prescribed by the decision rule (Fig. A1) because the actual catch in a given year may differ from those prescribed by management (Patterson & Résimont 2007). This difference was determined from a relationship that fitted actual annual landings in the fishery as a function of what was prescribed (Fig. A3).

Price calculation

Price, defined as the expected recovery cost, was calculated as the statistical expectation of an investor pay-out, discounted to present value, from the $k = 1,000$ forecasts over the first 20 years of the forecast period.

Prices were calculated using the estimated biomass (Fig. A1) from the observation model $x_{k,t}$ in each forecast year t , and thus represented risk of the management controls. Prices were calculated in two steps. The first step involved defining the financial cost or pay-off from the model results at time t , in forecast k , as:

$$I_{k,t} = \begin{cases} 0 & \text{if } x_{k,t} \geq x_p \\ C & \text{if } x_{k,t} < x_p \end{cases} \quad (1)$$

with x_p the trigger point, set to 20% of the estimated average undisturbed biomass, the value currently used by management (Smith *et al.* 2008) and C set to \$100. This was followed in the second step by calculating the expected value of the pay-off $I_{k,t}$, discounted to present value, as $E[\hat{I}] = \frac{1}{1000} \sum_{k=1}^{1000} \hat{I}_k$, where \hat{I}_k is the maximum discounted pay-off across all time periods in model forecast k , $\hat{I}_k = \max_{t=0 \dots T} (e^{-\delta t} I_{k,t})$. This ensures that the expected cost or pay-off represents the first time the asset crosses

the trigger point. The parameter δ is the discount rate, which was set to 7%, to reflect the opportunity cost of the derivative to other investments.

Derivative prices in practice would be calculated based on the estimated biomass $x_{k,t}$ (the practical price), but we

can also calculate the derivative price on the actual underlying biomass $X_{k,t}$ (the underlying price) by replacing $x_{k,t}$ in Equation 1 with $X_{k,t}$. The difference between the prices shows the effect of observation error associated with the management control.

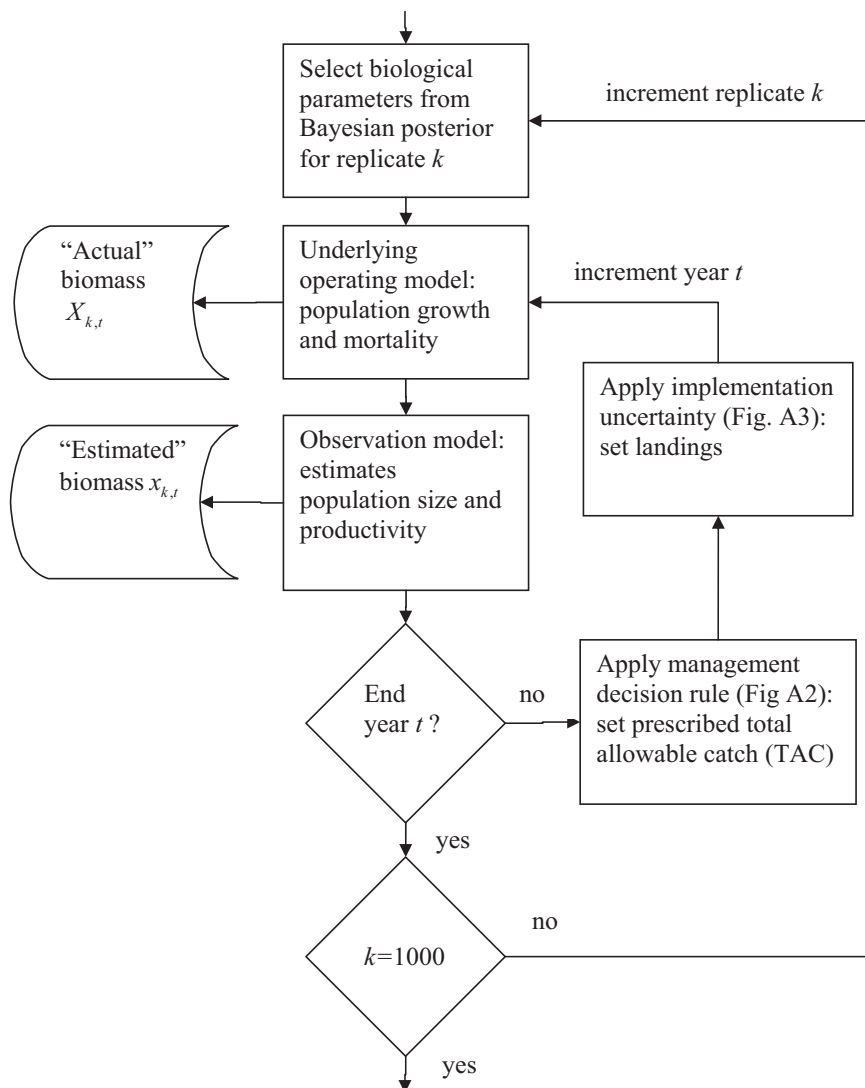


Figure A1 Flow chart summarizing the steps in data generation of 1,000 simulated spawning biomass forecasts, $X_{k,t}$, and the observation model estimates $x_{k,t}$ used for calculating derivative prices. Box shapes: denotes a simulation model process; denotes a conditional step in the simulation model; denotes model output that is saved for derivative price determination.

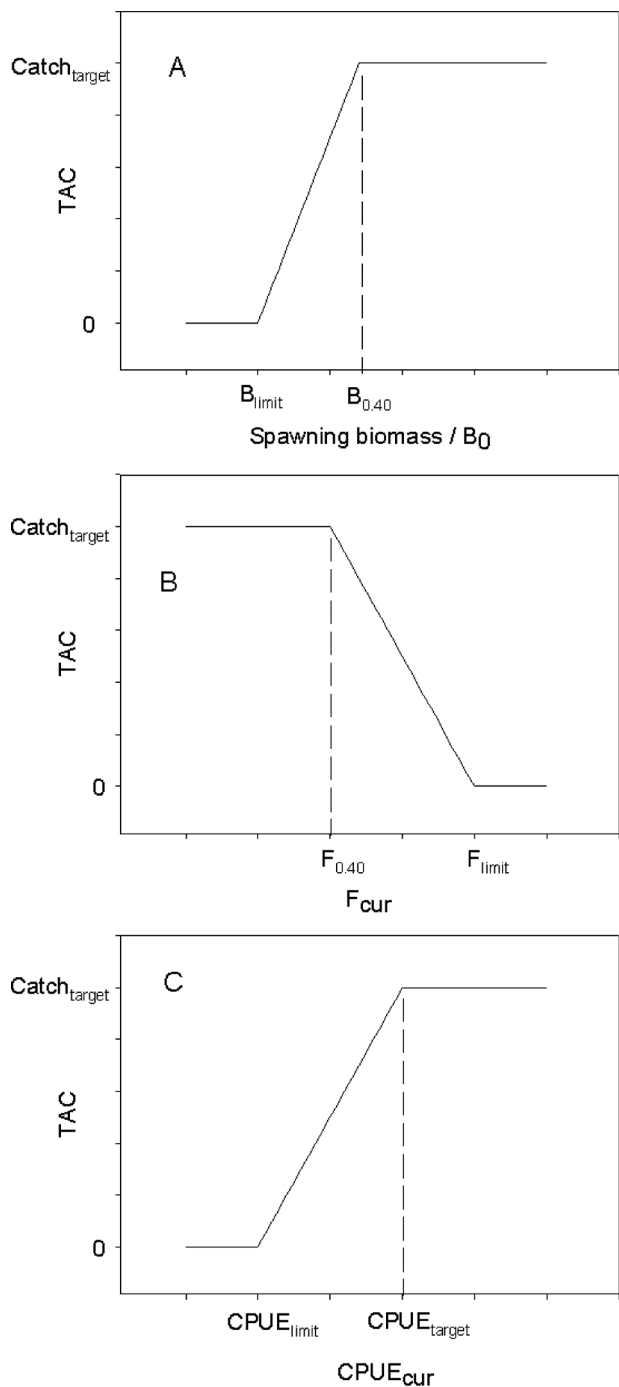


Figure A2 Decision rules for setting total allowable catch (TAC) based (A) on estimated spawning biomass relative to undisturbed level, B_0 for management control 1 where $B_{\text{limit}} = 0.20$, and $B_{0.40}$ = spawning biomass 40% B_0 (Smith *et al.* 2008); (B) current estimated fishing mortality F_{cur} where F_{limit} is the fishing mortality that leads to B_{limit} and $F_{0.4}$ is the fishing mortality that leads to $B_{0.40}$ for management control 2 (Wayte & Klaer 2010); and (C) current estimated catch-rate for management control 3 where $\text{CPUE}_{\text{limit}}$ is the catch-rate corresponding to B_{limit} and $\text{CPUE}_{\text{target}}$ is the catch-rate corresponding to MEY (Little *et al.* 2011).

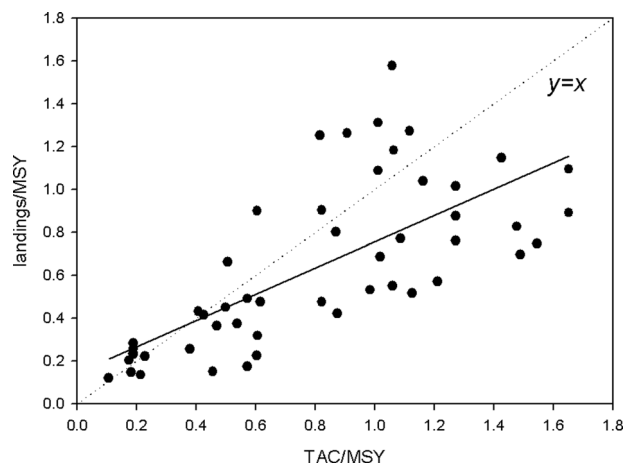


Figure A3 Scatter plot and fitted linear regression (solid line; $R^2 = 0.502$) of annual TAC against the annual landings, both scaled to the estimate of maximum sustained yield (MSY), for ten species in the SESSF: jackass morwong, blue warehou, redfish, tiger flathead, blue grenadier, pink ling, ocean perch, eastern gemfish, western gemfish, silver warehou. MSY was determined either from a statistical catch-at-age stock assessment when available, or from the target catches (Haddon 2010).

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