Balancing conservation and commerce: A shadow value viability approach for governing bycatch

Pierce Donovan [a],[*], Michael Springborn [b]

[a] *Economics, Connecticut College, United States of America*
[b] *Environmental Science and Policy, University of California, Davis, United States of America*

ARTICLE INFO

ABSTRACT

The losses from extinction events are not well-known, making an expected net benefits approach to conservation problems difficult to implement. A viable control strategy instead focuses on limiting the risk of extinction to some acceptably low level at the least possible cost. Here we describe a shadow value viability approach for solving conservation problems with irreversible thresholds with dynamic programming. A social planner calculates the minimal (virtual) level of loss from extinction that would trigger sufficient action to avoid extinction with the desired confidence. The cost-effective policy then arises from acting as if the resulting shadow value is real. We demonstrate the method in a numerical application to the conservation of the Pacific leatherback turtle population, which co-mingles with the Pacific swordfish fishery. We show how the cost-effective outcome can be achieved among decentralized fishers by using the planner's shadow value to set market-based instruments for managing turtle bycatch. This approach translates the species viability objective into economic terms so conservation and commercial harvest can be rationally integrated.

1. Estimating—and avoiding—a loss due to species extinction

Natural resource management under the threat of catastrophe presents particular challenges. While the costs of preventive action are usually fairly clear, the scale of the benefits from avoiding most disasters is not well-known. Without good information on this essential input to maximizing net benefits, management insights relying on this approach will be unavailable or poorly justified.

Consider the example of social losses from extinction of a species, including how they are measured and inform decision making. Eliciting this value directly from people is problematic in the same way that – in the context of the value of a statistical life (VSL) literature – eliciting the value of a "whole human life" is problematic (Viscusi and Aldy, 2003).[1] With the VSL, economists instead target the willingness-to-pay (WTP) for marginal changes in the risk of death; a similar marginal measure is appropriate for species viability (Montgomery et al., 1994).

In the context of conservation, when eliciting willingness to pay for protection, researchers often make one of two simplifying assumptions for tractability: (1) each marginal individual animal holds the same value, or (2) the population value is given by its

---

[1] Even if we could measure the presumably huge amounts of money people would be willing to pay to avoid a species extinction, this would not provide enough information to decision-makers concerning how much conservation action is warranted as population levels change, or alternatively, what population abundances we should aim for Eiswerth and van Kooten (2009).

status classification (e.g., threatened or endangered) effectively making some marginal animals worthless and others at the transition between classifications hugely valuable. Neither of these strategies reflect the ecological reality, but are essentially required by WTP approaches because eliciting marginal WTP at different population levels over a wide range would be both difficult and expensive. But this marginal valuation is almost certainly not constant over a wide range of stock levels. Additional individuals provide significant extinction risk reduction benefits in small populations, while for large populations, the contribution is smaller. Yet WTP estimates as a continuous function of the population are generally unavailable for the reasons above; almost nothing is known about the form of the marginal preservation benefit function (Eiswerth and van Kooten, 2009; Ojea and Loureiro, 2010).

In the absence of sufficient information on benefits, a logical approach to management is to avoid extinction with some margin of safety at minimal cost. This approach is also likely to appeal to wildlife managers, who are typically more comfortable with choosing a viability target than monetizing the value of species (regardless of whether one is more tractable than the other from a theoretical or empirical perspective). While the decision maker must still choose a level of confidence with which the desired outcome is achieved, Lichtenberg and Zilberman (1988) argue that such a margin of safety approach is broadly appealing for three reasons: practicality, broad familiarity stemming from similarity to statistical significance methods, and close correspondence to the way in which regulations are actually constructed.

Despite this appeal, until recently, techniques for cost-effective, ongoing avoidance of a disastrous threshold – hereafter called the "viability problem" – have lagged far behind standard net benefit maximization. The difficulty arises from the need for joint-chance constraints that combine probabilistic outcomes (e.g., extinction avoidance) over multiple periods. The "rolling window" nature of the time horizon – in which every year the decision-maker is continually-concerned with species viability over the next T years (as opposed to relaxing as time advances towards the end of the first T years) – undermines typical dynamic programming techniques.

A shadow valuation-based dynamic programming method developed by Donovan et al. (2019) presents the computational framework needed to solve the viability problem and features an extended review of the relevant literature, including population viability analysis, related resource economic modeling, and the broader literature in viability theory. In this article, we provide new theoretical backbone for elements introduced numerically by Donovan et al. and extensive discussion of the mechanics and benefits of our method. We then show for the first time how our approach informs market-based instruments that achieve a cost-effective solution in a system of decentralized resource users, and investigate the sensitivity of this solution to two key, but exogenous economic parameters.

Our solution to the valuation and viability problems—*shadow value viability* (SVV)—allows a decision-maker to proceed in the absence of explicit information on the benefits of taking preventative action. In the case of endangered species management, the focus is on avoiding extinction with a given likelihood over some extended time horizon.

The SVV approach involves positing a hypothetical value, Ω, specifying a one-time loss from extinction when the endangered species population goes extinct. In a stochastic dynamic programming problem, we solve for the lowest value of Ω that would drive sufficient conservation effort to ensure survival with a given level of confidence. It is important to note that this value of Ω does not represent the true, real-world extinction loss but rather the minimum sufficient extinction loss that would trigger enough action to avoid extinction over the specified time horizon with the specified confidence.[2] In turn, Ω informs an expected present loss denoted by $\omega(X)$, i.e., a shadow value of the species population level equal to Ω weighted by the discounted probability that extinction occurs if the population size is X. We do not impose any assumptions as to the shape or scale of this function, but instead let these properties emerge as a result of the population dynamics and the cost structure of the problem. The marginal shadow value of extinction risk from species population decline (or growth) at any given population size – a critical value for decision-making – is then given by $\partial\omega(X)/\partial X$. These elements are illustrated in Fig. 1.

The SVV structure is relatively simple but powerful. Once inserted into the social planner's decision problem, the [frictive] joint chance constraint becomes simple to ensure using standard dynamic programming solution techniques (see Section 2.2). Then, turning to decentralized management, the shadow value informs the setting of market-based instruments (see Section 3.4).

In our numerical example, we illustrate these ideas in the context of sustainable multi-species fisheries management. Specifically, we provide a practical policy solution for the integrated management of the Pacific swordfish fishery and the protection of the endangered leatherback turtle. The current approach to protecting the leatherbacks employs inflexible management tools like marine protected areas (MPAs) and specific gear requirements. MPAs often have static boundaries, force fishing effort into less bountiful waters and need to be large in order to provide meaningful protection for ranging pelagic species. Gear standards can impose higher costs of compliance than necessary by forcing one facet of bycatch mitigation that is typically fixed over space, time and users.

Leatherback turtles can be maintained with this management scheme, but at an unnecessarily high cost to the fishery. Alternatively, market-based instruments provide greater flexibility in how fishers choose to avoid the leatherbacks and incentivize the adoption of new information and technologies, thus lowering opportunity costs. This is particularly relevant because the Magnuson–Stevens act requires that the costs of enforcing ecological objectives not be overly-burdensome. However, theory to inform the setting of market-based instruments for bycatch is lacking. The viable control framework provides a method for doing so that reflects the shadow value of changes in leatherback population from changes in the risk of extinction. Our market based policy instruments internalize the appropriate dynamic cost of bycatch needed to induce fisherman to choose the cost-effective trade-off with commercial fishery rents.

Building on the basic framework of Donovan et al. (2019), this article makes several contributions. First, we show how the SVV approach can be used not just for centrally-controlled resource problems (as in Donovan et al.) but also decentralized problems with

---

[2] If the former value was known, the SVV approach could be used to find an economically-efficient level of viability, rather than a least-cost program given a specified viability goal (as we solve for here). However, as previously discussed, such a value is unlikely to be available.
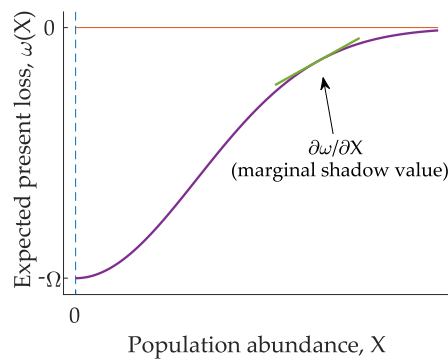
Fig. 1. An illustration of the shadow value function representing the expected present loss due to extinction. At extinction $(X = 0)$, a hypothetical loss of magnitude Ω is realized. With an increase in the population X away from extinction (to the right), this loss is discounted both in time and by the likelihood of transitioning closer to extinction at a later period. For ever-higher abundances, $\omega(X)$ decreases in magnitude.

multiple resource users. Second, while Donovan et al. was mostly computational, here we formalize and make explicit several central elements of the SVV problem. We derive analytically an expression for the shadow value function, $\omega(X_t)$, showing its dependence on the probability of extinction, the minimum sufficient extinction loss (Ω), and the discount factor. We provide a deeper treatment of the SVV problem's rolling window feature (introduced above) through graphical illustration, explanation of how time-consistency for the decision-maker is maintained, and how the resulting dynamic programming problem still admits a fixed-point. Finally, we show the dependency of SVV results to the choices of time and risk preferences, specifically the discount rate (r) and confidence (Δ). Notably, we find that expected annual profits increase as the regulator seeks preservation with greater confidence, exhibiting a *negative* annual opportunity cost to maintain a higher Δ (since the higher confidence can be maintained with less constraint on fishing effort in the long run). However, as expected, when accounting for transitions from a given starting level of the at-risk species population, the opportunity cost is positive (the expected present value of long-run profit is lower) on average $3.6M per confidence point (0.01). We explain why this opportunity cost for each unit of additional confidence, or "viability supply curve", is not monotonic across each individual unit. Overall, in exploring sensitivity to preference parameters, the viability supply curve and implications for setting policy instruments, we lay out the connections between the SVV approach and more familiar economic models.

Viability-style problems extend to a broad set of applications beyond conservation. Management objectives that aim to stay above (or below) a particular threshold over time with some margin of safety are abundant in natural resource management and elsewhere. Notable examples include maintaining viable populations for endangered species (illustrated here and in Donovan et al. (2019)), global warming below a maximum (Fitzpatrick and Kelly, 2017; Donovan, 2021), water levels below flooding (Alais et al., 2017), water pollution below eutrophication (Rougé et al., 2013), groundwater contamination (Lichtenberg et al., 1989), and zoonotic disease prevalence away from outbreak levels (Shiferaw et al., 2017). Each of these applications center on managing resources to avoid a threshold with dire but inestimable consequences. The shadow value viability approach translates the implied value of avoiding these thresholds into the benefits of reducing risk on the margin, enabling these urgent issues to be investigated within an intuitive economic framework to identify optimal management and in certain cases – as elaborated in this paper – set policy instruments.

Next we develop our theoretical framework and the insights that come from it. After presenting the SVV approach, we use Section 3 to review the bycatch management problem and our application to the Pacific swordfish fishery. We present numerical findings in Section 4 and discuss future opportunities for applying viable control in Section 5.

2. A theoretical model of viable control

The standard economic approach to natural resource management involves maximizing the difference between the present value of long-run benefits and costs, whether we are thinking about live species, water, fossil fuels or other environmental assets. This is effective when the payoff given a particular path of the natural resource is predictable. But when certain disastrous and irreversible outcomes are difficult to value – such as the extinction of a species – a reasonable alternative is the viable control approach: seek an acceptably small likelihood of the outcome with minimized management costs.[3] This probabilistic constraint requires simultaneous consideration of all periods over an extended time frame (e.g. species survival horizon) which undermines most solution algorithms for finding an optimal feedback policy. Such viable control problems simplified the constraint (e.g. via linearization, Ono et al. (2015)) until recent advances presented a new way forward (Donovan et al., 2019). Here, we explore the results of a relatively simple viable control model for a single vulnerable species and highlight the model's useful features.

---

[3] The viable control problem as stated is a fairly narrow definition that is a part of a much larger field of study. For a broader discussion of viability theory and the viable control literature, see Baumgärtner and Quaas (2009) and Oubraham and Zaccour (2018). For three representative applications of viability theory in fisheries management, look to De Lara and Martinet (2009), Doyen et al. (2012), and Martinet et al. (2016).
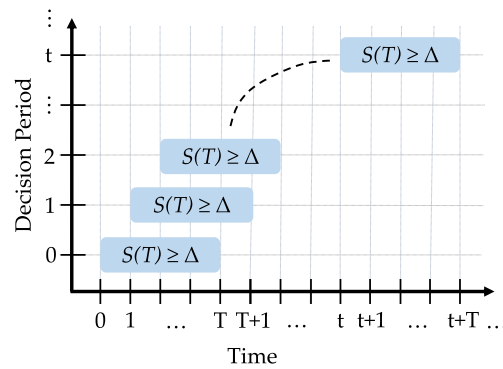
Fig. 2. A viability program naturally features a rolling time horizon: at time 0 survivorship is sought for the next T periods (bottom-left shaded box) while knowing that at time 1 survivorship will be sought for time 1 through $T + 1$ (the next shaded box to the northeast), and so on. (Conditional arguments of S have been suppressed here for simplicity.)

2.1. Thinking realistically about species viability

We seek to manage a vulnerable species to meet a conservation goal over an extended *viability horizon, T*. Since long-term viability of struggling species can rarely be guaranteed, we represent this goal as a constraint on the likelihood of species survival over T periods. This *viability constraint* is written

$$S(T \mid X_t, A(X)) \equiv \Pr\left\{ \bigcap_{\tau=t}^{t+T} (X_\tau > 0) \;\middle|\; A(X) \right\} \geq \Delta, \tag{1}$$

which requires that our vulnerable species will make it through year T with at least $\Delta * 100\%$ likelihood.[4] The survival function depends on an initial state X_t and a management policy $A(X)$ specified over any given state, and implicitly relies on the dynamics of the population of vulnerable species. In general, an increase in population or a conservation action increases $S(\cdot)$. Requiring a longer time horizon or higher level of confidence will decrease it.

The pair $\{T, \Delta\}$ reflects a social preference or, more generally, a policy target as they are often found in policy language in population management plans. Importantly, even though we initially take these to be exogenous in our model, the setting of these parameters already considers both the local system of interest as well as its interactions with the rest of the economy. Thus economic considerations are already (implicitly or explicitly) baked-in to the viability constraint of our cost-effective conservation problem. In Section 4.3, we investigate and discuss the sensitivity of the viability program to changes in these viability parameters.

Considering many periods complicates the assessment of viability because we are now concerned with limiting the distribution of many (T) joint outcomes. This constraint could be imposed with a constant likelihood of survival in each period that jointly meets Δ over the target horizon (i.e. linearization), but this artificially reduces the number of feasible paths that satisfy the joint-chance constraint. Joint-ness is central to the problem—an exceptionally good outcome in one period opens up slightly more wiggle room to absorb a bad shock in the future, while a bad intermediate outcome requires increased effort later.

A subtle but crucial element of this type of conservation problem – and ongoing viability problems in general – is that we are continually-concerned with the next T periods into the future on a rolling basis as depicted in Fig. 2. At time 0, survivorship is sought for the next T periods given that after moving forward to time 1, survivorship will be sought for time 1 through $T + 1$. If instead the viability horizon did not roll forward with time, by $T - 1$ the manager would only be concerned with survival for one last year, which is inconsistent with the realities of most resource management objectives, including conservation (Donovan et al., 2019). Additionally, an infinite horizon viability constraint is impractical, since there is always some non-zero likelihood of transitioning to degraded populations each period (Bulte and van Kooten, 2001). Furthermore, the decision maker (not just the modeler) must also take this rolling window into account so that the policy is time-consistent.

Below we develop and solve a model in which the decision-maker ensures the viability objective is met over the next T years while "knowing" that (1) in the next period they will again work to ensure the objective is met over the next T years, and (2) this finite time horizon continues to roll in this fashion over infinite time. This "knowing" is not modeled explicitly but rather instituted by the combined use of a finite horizon viability constraint that must hold for all relevant states at every timestep, and an infinite time optimization problem with a stationary policy defined over these states. In this way, decisions are made time-consistent, i.e., expectations about future actions at future states are accurate.

---

[4] Extinction ($X = 0$) is a natural threshold to use to describe non-survival, but we are not limited to this case. If little is known about dynamics below some proposed minimum viable population, a "quasi-extinction" threshold can be imposed, e.g. Donovan et al. (2019).

Even for the most charismatic megafauna, conservation management efforts will typically be limited by physical, biological, or political constraints. We define $\overline{A}(X)$ as the maximally-conservationist action that can be taken at state X. This allows us to further define the *viability kernel* (Doyen and De Lara, 2010),

$$\{X\}_k \text{ s.t. } S\left(T \mid X_t, \overline{A}(X)\right) \geq \Delta, \ \forall \ X_t \in \{X\}_k. \tag{2}$$

The viability kernel $\{X\}_k$ is the set of all possible starting states X_t for which satisfying the viability constraint is feasible. The lowest population for which viability is feasible – i.e. the minimum viable population conditional on the maximally-conservationist action – will just bind the viability constraint, and any improved states from there will more than satisfy it. Outside of the viability kernel, conservation action may be taken but there is no available program that can satisfy the viability constraint with confidence at or above Δ.

We seek a solution specifying action that efficiently scales as the population state varies from near to far from extinction. Next, we develop a decision model to identify the cost-effective feedback policy to achieve viability. The resulting program will endogenously push population levels into a zone safely above extinction; just how far will depend on the strength of the stochastic component of the population dynamics, opportunity costs, constraints on actions, and the preferences given by the viability horizon and confidence.

2.2. Long-term management for viable populations

The manager's objective is to maximize the net present value of their actions, conditional on meeting a viability constraint over the next T years on a rolling basis:

$$\max_{A_t} \mathbb{E}_\epsilon \left[\sum_{t=0}^{\infty} \beta^t \cdot \pi(A_t, X_t) \right], \tag{3}$$

$$\text{s.t. } X_{t+1} = G(A_t, X_t, \epsilon_t) \qquad \text{(stochastic dynamics)}$$
$$\quad\quad S\left(T \mid X_t, A(X)\right) \geq \Delta \qquad \text{(viability)}$$
$$\quad\quad X_t \in \{X\}_k \qquad \text{(kernel)},$$

with per-period profits $\pi(\cdot)$, discount factor β, stochastic (ϵ) population dynamics $G(\cdot)$, and the viability constraint (Eq. (2)). In a strictly-conservation problem, $\pi(\cdot)$ might capture management costs in the field (e.g. Donovan et al. (2019)). In the resource extraction context considered in this article, it captures profits net opportunity costs. The population X_t is bounded below by extinction and the management problem ends if extinction occurs. In our model we assume that increasing action $A(X)$ raises $\pi(\cdot)$ at the expense of conservation, though the opposite approach can easily be taken. The optimal policy is denoted $A^*(X_t) = A^*$.[5]

The decision problem in Eq. (3) is presented in a standard way (e.g. as one might see in Judd (1998)), albeit one that leaves implicit some of the complexities of the rolling horizon. For example, A_t is selected each period given both an updated state (X_t) and updated window for the viability constraint (in effect over the next T periods). While the manager may currently face a single state, they still need to know the implications of moving to any other feasible state in future periods, where again they will seek to solve the same problem. Thus we are concerned with an optimal policy function $A^*(X_t)$ that maximizes the manager's value for *any* current state within the viability kernel.

In a stochastic world, a feedback policy provides a contingency plan for responding to every possible future state we may find ourselves in, rather than a predetermined path over time. Thus we use dynamic programming to address the problem in Eq. (3). A cost-effective solution to the long-run management of viable populations involves solving for the fixed-point $V(X_t)$ of the following infinite-horizon Bellman equation,

$$V(X_t) = \max_{A_t} \left\{ \pi(A_t, X_t) + \beta \cdot \mathbb{E}_\epsilon \left[V(X_{t+1}) \mid A_t, X_t \right] \right\}, \tag{4}$$

$$\text{s.t. } X_{t+1} = G(A_t, X_t, \epsilon_t) \qquad \text{(stochastic dynamics)}$$
$$\quad\quad S\left(T \mid X_t, A(X)\right) \geq \Delta \qquad \text{(viability)}$$
$$\quad\quad X_t \in \{X\}_k \qquad \text{(kernel)},$$

however, this problem is computationally-intractable. Despite substantial attention to joint chance-constrained problems like Eq. (4) (e.g. Haight (1995), Newbold and Siikamäki (2009), Doyen and De Lara (2010), Ono et al. (2015), Alais et al. (2017)), to our knowledge, there is no exact solution method, and a brute-force approach would only be feasible for extremely trivial problems.

Donovan et al. (2019) find a solution to a slightly modified problem using a shadow value approach that involves an "inner" and "outer" optimization step. The inner step solves for the policy that maximizes present expected profits given any arbitrary shadow value specified for the loss incurred upon extinction. The outer step seeks the smallest shadow value that drives sufficient action to meet the viability goal. Formally, the outer step is,

$$\min \{\Omega\} \text{ s.t. } S\left(T \mid X_t, A^\Omega\right) \geq \Delta \text{ and } X_t \in \{X\}_k, \tag{5}$$

---

[5] Note that while population dynamics depend on action *at a particular time*, the viability function is dependent on the entire policy function.

where $A^{\Omega}(X_t) = A^{\Omega}$ solves the inner step, a profit maximization problem:

$$V^{\Omega}(X_t) = \max_{A_t} \left\{ \pi(A_t, X_t) + \beta \cdot \mathbb{E}_{\varepsilon} \left[V^{\Omega}(X_{t+1}) \mid A_t, X_t \right] \right\} \tag{6}$$

$$\text{s.t. } V^{\Omega}(0) = -\Omega \qquad \qquad \text{(extinction loss, } \Omega > 0 \text{)}$$

$$X_{t+1} = G(A_t, X_t, \varepsilon_t) \qquad \qquad \text{(stochastic dynamics).}$$

The solution to Eqs. (5) and (6) includes a fixed value for Ω – the smallest [hypothetical] extinction loss that would incentivize enough management action to satisfy the viability constraint – the policy A^{Ω}, and the fixed-point $V^{\Omega}(X_t)$.[6]

To inspect how the additional constraint $V^{\Omega}(0) = -\Omega$ modifies the value function, we can write out both values explicitly:

$$V(X_t) = \mathbb{E}_{T_f} \left[\sum_{\tau=t}^{t+T_f-1} \beta^{\tau-t} \cdot \pi(A^*, X_\tau) \mid X_t \right] \tag{7}$$

and,

$$V^{\Omega}(X_t) = \mathbb{E}_{\varepsilon} \left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \cdot \left(\pi(A^{\Omega}, X_\tau) \cdot \mathbb{1}(X_\tau > 0) - ((1-\beta) \cdot \Omega) \cdot \mathbb{1}(X_\tau = 0) \right) \mid X_t \right]$$

$$= \mathbb{E}_{T_f} \left[\sum_{\tau=t}^{t+T_f-1} \beta^{\tau-t} \cdot \pi(A^{\Omega}, X_\tau) \mid X_t \right] - \mathbb{E}_{T_f} \left[\sum_{\tau=t+T_f}^{\infty} \beta^{\tau-t} \cdot ((1-\beta) \cdot \Omega) \mid A^{\Omega}, X_t \right]. \tag{8}$$

In the final line the expectation of interest is over the distribution of possible failure (extinction) times ($T_f \in [1, 2, \dots, \infty]$) upon which the one-time loss Ω would be realized or, equivalently, the perpetual stream of losses $(1-\beta) \cdot \Omega$ would kick in. This second definition of $V^{\Omega}(X_t)$ uses the fact that extinction is irreversible.

Once the proper value of Ω is selected to meet the viability constraint, both policies A^{Ω} and A^* achieve the viability target, by construction. Despite a lack of theory to formally assess a proposed solution (like A^{Ω}) we argue the approximation is likely to be close. In the true problem (Eq. (4)), the joint chance constraint's only *explicit* imperative for the state variable is to keep it from crossing the threshold. This explicit imperative certainly generates an *implicit* incentive to keep the state variable from nearing the threshold, with an intensity growing with nearness. The SVV approach parallels these two features. The *explicit* condition imposed is a penalty incurred upon crossing the threshold. This explicit feature generates an *implicit* incentive which intensifies with nearness to the threshold (as illustrated in our application by the shadow value function $\omega(X_t)$ in Fig. 4). Furthermore, it turns out that it does so (again, implicitly rather than by explicit construction) in an economically logical way: it scales with the time-discounted expected risk of crossing the threshold (see Eq. (8)).

If one assumes that A^{Ω} is a sufficiently-close approximation of A^*, we can link Eqs. (7) and (8),

$$V^{\Omega}(X_t) \approx V(X_t) + \omega(X_t), \tag{9}$$

where the second summand in Eq. (8) is labeled $\omega(X_t)$.[7] It is helpful to re-write $\omega(X_t)$,

$$\omega(X_t) \equiv -\mathbb{E}_{T_f} \left[\sum_{\tau=t+T_f}^{\infty} \beta^{\tau-t} \cdot ((1-\beta) \cdot \Omega) \mid A^{\Omega}, X_t \right]$$

$$= -\Omega \cdot \mathbb{E}_{T_f} \left[\beta^{T_f} \cdot \sum_{u=0}^{\infty} \beta^u \cdot (1-\beta) \mid A^{\Omega}, X_t \right] \quad \text{(where } u = \tau - t - T_f \text{)}$$

$$= -\Omega \cdot \mathbb{E}_{T_f} \left[\beta^{T_f} \mid A^{\Omega}, X_t \right]$$

$$= -\Omega \cdot \sum_{\tau=t}^{\infty} \beta^{\tau-t} \cdot \Pr \left(T_f = \tau \mid A^{\Omega}, X_t \right), \tag{10}$$

where the last line of Eq. (10) uses the probability mass function that corresponds to the survival function in Eq. (1).

$\omega(X_t)$ is an incentive to avoid degrading population levels—one which is sensitive to changes in the current population level.[8] The one-time loss Ω is incurred only at extinction. This propagates to all other state levels in expected present value form via $\omega(X_t)$, which discounts Ω by both the time to and likelihood of extinction (as illustrated in Fig. 1). This captures how the opportunity cost of protection rises due to increased risk of extinction as X_t falls, especially as it nears the threshold for continued viability.

There are several properties of $\omega(X_t)$ worth noting. We know that $-\Omega \leq \omega(X_t) \leq 0$ since the summation in the last line of Eq. (10) is bounded between 0 and 1. Second, for any time-consistent policy, the derivative of $\Pr \left(T_f = \tau \mid A^{\Omega}, X_t \right)$ with respect to X_t is

---

[6] The latter two are affixed an Ω to differentiate from the original problem. We explain why the viability problem in Eq. (6) still results in a fixed-point after detailing the solution algorithm in Appendix A.1.

[7] This relation is exact when $A^{\Omega} = A^*$ since V is the presented expected value of profit under A^*, while V^{Ω} is defined as the presented expected value of profit under A^{Ω}, plus ω.

[8] This insight was discovered numerically in Donovan et al. (2019) and first derived analytically here.

decreasing and thus $\omega(X_t)$ is increasing. Further, as $\omega(X_t)$ approaches 0 from below it will be concave, and as X approaches 0, there is increasing potential for a convex region depending on the dynamics of the system. For example, if net growth in the stock becomes negative at low population levels (i.e., $\mathbb{E}[G(\cdot)] < 0$, consistent with an Allee effect) this will result in a minimum viable population (Stephens et al., 1999). The stronger the correlation between population abundance and the growth rate below this critical threshold, the more likely a convex region in the $\omega(X_t)$ curve, since marginally-improved abundances will create negligible improvements in viability.[9]

$\partial\omega(X_t)/\partial X_t$ provides us with a shadow value reflecting the marginal social cost of population change stemming from the change in the risk of extinction. The first term of $V^{\Omega}(X_t)$ is the present value of net returns, $V(X_t)$, which provides an additional opportunity cost incentive: as populations degrade, we will expect increased regulatory restrictions which hinder future profits. Both of these effects provide incentives that weigh against unfettered pursuit of immediate profits (at the expense of conservation). We will show in the next section how these pressures – that have motivated the optimal strategy A^{Ω} – can inform market-based instruments for a vulnerable bycatch stock that efficiently achieves a viability goal in a decentralized fisher-regulator setting.

3. Managing bycatch in multi-species fisheries

Academic guidance for fisheries management has become increasingly holistic over time, incorporating many of the unregulated dimensions of fisheries management into rights-based schemes (Smith, 2012). Most relevant to our problem are the margins of multi-species management and ecosystem health, which have values that are not by default part of the "texture" (Wilen, 2002) of rents acknowledged by market-based instruments for solely commercial species. Policy prescriptions will almost certainly shift as the number of species considered is expanded.

While economists and ecologists have begun to unpack the ways in which inter-species interactions affect the health and profitability of a whole fishery, additional applied theory for ecosystem-based management is needed (Smith, 2012). Interactions between commercially-relevant species and "nuisance" species hinder the profitability of the former through competition, predation, or bycatch constraints (Kasperski, 2016). Here we focus on the final case, specifically the presence of "choke stocks" that are highly vulnerable and, if sufficiently degraded, can lead managers to choke off access to co-mingling fished species (Patrick and Benaka, 2013).

Bycatch is the unintended (but not unexpected) capture of non-targeted animals in fishing gear. As fishers switched to drift netting and long-lines during the industrialization of the world's fisheries, this unnecessary waste became a highly visible problem (Lent and Squires, 2017; Northridge, 2018). Infamous examples include the now-extinct baiji (Chinese river dolphin) and the Gulf of California's near-extinct vaquita porpoise, which have both experienced heavy mortality as bycatch (Northridge, 2018).

Some fishery managers employ command-and-control-style solutions to prevent bycatch. While common tactics like marine protected areas (MPAs) and mandatory gear requirements can reduce bycatch, they do not provide incentives to continuously avoid bycatch (Lent and Squires, 2017). Further, MPAs have to be incredibly large to cover ranging pelagic species, imposing large costs on fishers (Hyrenbach et al., 2000).[10] Gear that reduces bycatch is rarely a least-cost solution either, because the fleet is heterogeneous in ability to adapt (Wilen, 2002) and efficient avoidance likely involves adjustment on multiple additional margins, e.g., fishing location or set timing.

Market-based incentive schemes, on the other hand, are a significant refinement to bycatch management as they provide an opportunity for fishers to flexibly choose from a number of possible dimensions of bycatch avoidance (Arnason, 2012). This flexibility enables protection of a bycatch species while minimizing the opportunity costs of avoidance efforts. This aligns with the requirements under the Magnuson–Stevens act.

We consider the case where bycatch is rare but very damaging. This creates the potential for fishery closures and thus forgone fishery rents, so a price instrument may be an appealing management alternative. But while closures squander rents, bycatch prices impose explicit costs of bycatch on the fishing fleet.[11] Each of these instruments will lead to a different organization of the fishing fleet's effort.

There has been extensive analysis of the relative merits of price versus quantity instruments in fisheries (e.g. Weitzman (2002) regarding commercial species and Pascoe et al. (2010) and Segerson (2011) for application to bycatch and discard management). We do not aim to identify a preferred instrument here but rather demonstrate the usefulness of shadow value viability in a decentralized setting by providing a population-dependent recommendation for the *level* of two simple instruments.

Most work concerning bycatch and market-based instruments simply assumes that the level of the instrument (bycatch quota or price) is given,[12] perhaps by biologists or simply arbitrarily (Boyce, 1996). But ideally such levels would be set to achieve a specified goal and account for economic and biological factors, like properly weighing species viability against potential commercial fishery rents. The shadow value viability approach of Section 2 provides guidance for considering these two competing incentives together, and provides meaningful guidance for realistic policy implementation in a stochastic world. In this section, we first solve for the optimal social planner bycatch avoidance then detail how to achieve this outcome in a decentralized setting using market-based instruments linked to changes in the risk of extinction, instead of taking them as given.

---

[9] In our application $\omega(X_t)$ is concave everywhere because we do not incorporate an Allee effect into the biological dynamics; as a result the discounting pattern dominates.

[10] Future climate variability will also change the effectiveness of these static boundaries. As ecosystems change, the habitat preferences of protected species will tend to take them elsewhere (Hazen et al., 2018).

[11] Additionally, prices introduce variability in the escapement of a vulnerable species, which may not be socially acceptable for species with extremely low populations.

[12] A sensible approach when devising a *descriptive* model, e.g. Abbott and Wilen (2009).

3.1. Swordfish and turtles

One of the most charismatic bycatch species is the critically endangered leatherback turtle. The Western Pacific stock of these large (up to 500 kg) creatures regularly endures one of the most incredible migrations of any species, traveling nearly 7000 miles from their Southeast Asia breeding grounds to the west coast of the United States to forage on plentiful populations of jellyfish (NMFS and FWS, 2013). Along this journey, they are subject to numerous collisions with the swordfishing fleets of several nations. Although the Western and Central North Pacific stock of swordfish – which co-mingles with the Western leatherback population – is not considered overfished or subject to overfishing (ISC Billfish Working Group, 2018), regulatory measures prompted by fisher interactions with leatherback turtles and other vulnerable species pose large costs to this valuable fishery.

A highly-visible example occurred in 2001, when NOAA created the Pacific Leatherback Conservation Area (PLCA), a massive 250,000 square mile region off the coast of California that is off-limits to fishing vessels during the most productive months of the August–January fishing season of the bycatch-prone drift gillnet swordfish fishery (NOAA, 2001). This led to an exodus of fishing vessels, effort, and harvest.[13] Based on turtle population and bycatch estimates, the closure likely improves leatherback numbers by at most 1% per year (Jones et al., 2012; Carretta et al., 2019), while almost entirely eliminating the fishery.[14]

In fact, even at its peak, the small drift gillnet fishery had little impact on swordfish stock health, but returned an ex-vessel value of $12.6 million (2020 USD) (PacFIN, 2019). Fig. 3 provides a map of the fishery that shows the stark shift in fishing location and decrease in overall activity as a result of the PLCA. Notably, only a small region of the PLCA is unfavorable with respect to turtle bycatch in a given day.

Scientists have called for more dynamic management strategies to ensure the protection of ranging pelagic species (Hyrenbach et al., 2000; Hazen et al., 2018). To continue our illustration within the drift gillnet fishery, a new resource provides predictions of where commercial and protected populations are most likely to be, using correlations between remote sensing data (e.g. temperature, currents, light penetration, and food availability) and tracking information for swordfish and leatherback turtles (Hazen et al., 2018). The output produced is a heatmap designating areas that are worse (low swordfish or high bycatch) or better (high swordfish, low bycatch) for fishing (Fig. 3 contains an example of this index). Hazen et al. (2018) estimate that if this dynamic closure was implemented in the drift net fishery, about 50%–90% of the PLCA could be exploited each day with the same near-zero expected take of leatherback turtles observed currently.

Under the area closure regulation, there is little incentive to adopt newly available (and valuable) informational products. But when facing a price or cap for bycatch, fishers have a compelling reason to use such a product as a low-cost option for avoiding leatherbacks. A market-based bycatch management policy is a plausible way of opening up the PLCA while incentivizing avoidance of bycatch through adjustments on cheaper margins.[15,16]

The rest of this section proceeds with mapping the insights from the shadow value viability model in Section 2 to bycatch price and quantity instruments that can improve the management of the pacific swordfish and leatherback turtle stocks. The focus below is on showing how each instrument can be determined endogenously.

3.2. Modeling the Pacific swordfish fishery

As pelagic species, swordfish and leatherback turtles range widely across several regions from California to Hawaii, Japan, Korea, and Taiwan (Tagami et al., 2014). Since a pragmatic solution for leatherback conservation will require a concerted effort across the Pacific (Hazen et al. (2018); see Abrego et al. (2020) for the Eastern Pacific population) we consider a bycatch mitigation policy that spans these regions, i.e., as established by an international agreement. For the present analysis we set aside regional heterogeneity since we aim to illustrate the key ideas in as simple a model as possible. We parameterize a fishery that is consistent with the statistics of the Hawaiian fishery but scaled to capture the global scope of these species. Hawaii has much more detailed data available than regions outside the U.S., the fleet is much larger than California's and its gear reflects what is most commonly used in our regions of interest. Nearly all of the Hawaiian fishery is committed to longlining rather than drift nets (ISC Billfish Working Group, 2018). For simplicity we assume that longlines would be available to Californian fishers under a unified policy.

Because our baseline (unregulated) fishery model operates without significant incentives to avoid bycatch, we calibrate to the Hawaiian swordfish fleet in the late-90's, just before the first major leatherback avoidance efforts began.[17] This period (1994–1999) was stable in terms of swordfish catch, fleet size and effort, and bycatch (WPRFMC, 2004; Bartram and Kaneko, 2004). Appendix A.2 provides parameter descriptions, values, sources, and estimation details.

---

[13] In the last 25 years, the number of vessels participating has decreased by 86% from 141 to 20 per season (PacFIN, 2019). Effort in terms of sets per vessel is down 37% (40 to 25) and vessels fish 71% fewer days (45 to 10) (PacFIN, 2019). Harvests have decreased by 85% (800 to 100 metric tons) due to fishing in less productive waters, as the swordfish are abundant but not evenly distributed (Carretta et al., 2019; PacFIN, 2019).

[14] Similarly, a future ban on drift nets will come into effect in 2023, effecting a closure of sea surface (Hazen et al., 2018). The replacement deepset buoy gear will be used during the day, targeting swordfish around 1200 ft below the surface at a time of day where they are more or less swimming amongst themselves, while turtles and other vulnerable species swim at much shallower depths (NMFS and FWS, 2013). A ban imposes additional unnecessary fishing costs if drift net usage can be used while selectively target swordfish.

[15] The lifting of the PLCA in concert with corrected fisher incentives would also allow more of the U.S. swordfish demand to be met with sustainable domestic harvest, replacing imported harvest under much less scrutiny. This may potentially reduce leatherback interactions in other frenzied fisheries internationally.

[16] Parallel arguments on incentives for technology adoption and change created by market based instruments have been made in the more well-known context of pollution control (Stavins, 2003).

[17] The two American fisheries were the first to implement significant bycatch regulations in the year 2000 (NOAA, 2004; Swimmer et al., 2017).
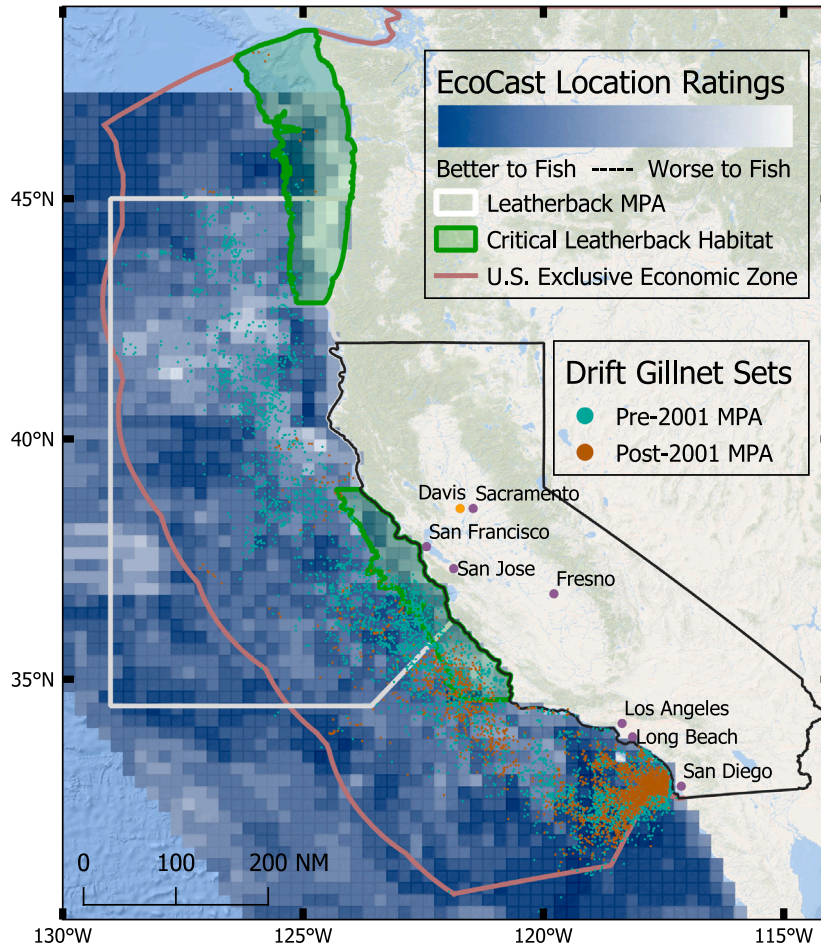
Fig. 3. Map of the drift gillnet swordfish fishery. The 2001 PLCA is outlined in white. Coastal areas designated critical for the migration and foraging of turtles are given by the two green sections (NOAA, 2012). Drift net sets targeting swordfish are given by the aquamarine (1990–2000) and burnt orange (2001–2017) scatterplots (Carretta et al., 2019). An index representing swordfish and turtle abundance predictions from the EcoCast project (Hazen et al., 2018) for a sample day in October 2019 are depicted by the blue-to-white pixels, which designate better (high swordfish, low bycatch) versus worse (low swordfish or high bycatch) fishing locations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Each season, N (international) fishers must decide how much effort to put into fishing for swordfish and how much effort to put into avoiding leatherback turtle bycatch. For simplicity, we do not explicitly model other margins of adjustment for bycatch abatement other than limiting swordfish fishing effort. Fishers typically only set one line per night (when swordfish come near the surface) and longlining for swordfish requires long soak times (the length of time a set is active); thus we consider a representative fisher who chooses the number of days they will exert this effort. Importantly, fishing is assumed to be monitored to ensure accuracy of reported landings of swordfish and turtles. For a given level of fishing effort A_t (days/season), female[18] leatherback bycatch by a representative fishing vessel is modeled as

$$\mathbb{E}\left[B_t | A_t\right] = \theta \cdot \sigma \cdot A_t, \tag{11}$$

where θ captures the expected bycatch per unit effort (BPUE) and σ is the female share of the vulnerable adult population. There is no reliable estimate of the mortality rate of turtle bycatch (immediate or delayed), but it is likely to be very high, as hooks cannot often be retrieved (Bartram and Kaneko, 2004; Swimmer et al., 2017). We pessimistically set this value to 1 and note that any improvements to behavior or gear that improve this statistic could be captured through changing the θ parameter. It is not evident that there is a strong population-dependent component driving bycatch rates (Bartram and Kaneko, 2004; Swimmer et al., 2017)

---

[18] Leatherback turtle bycatch avoidance focuses on take of adult females since their numbers are the key limiting factor in reproduction. The incidental take of a mature female during this feeding period can have stark consequences for population growth because it takes 16 years for a leatherback to mature (and begin laying eggs) and less than 1% of turtles make it to this age (Jones et al., 2012).

especially within the policy-relevant range at or above the population level at which the social planner pauses fishing as illustrated in Section 4.1.

The fishery has a limited number of vessel permits and the stock of swordfish is large enough that the representative fisher returns positive rents. There is no limit on swordfish harvest, as fishers have not had an overwhelming effect on the abundance of swordfish (ISC Billfish Working Group, 2018), thus swordfish levels are not modeled for simplicity. The fisher takes the ex-vessel landings price for swordfish as given. Expected seasonal profits per vessel are

$$\pi(A_t) = p \cdot \phi \cdot A_t - \frac{c}{2} \cdot A_t^2, \tag{12}$$

where p is unit the price of swordfish, ϕ is the expected catch per unit effort (CPUE) of swordfish (mT/day), and c parameterizes the costs of fishing effort. Other input costs are not relevant with respect to the swordfish/bycatch trade-off and do not need to be modeled if fishers are committed to fishing at least part of the season (Abbott and Wilen, 2009).

3.3. Leatherback turtle dynamics

While the fishers concern themselves with one season at a time, the leatherback population dynamics tie these decisions together. We model adult female leatherback population dynamics as determined by a combination of stochastic shocks,

$$X_{t+1} = X_t - M_t - B_t + R_t, \tag{13}$$

where M_t, B_t, and R_t are negative binomial random variables capturing natural mortality, bycatch-induced mortality, and recruitment from younger age-classes, respectively. Their distributions depend on the population X_t. The bycatch shock is additionally affected by fishing effort A_t, as seen at the beginning of this section.

The bioeconomics literature typically favors *environmental* stochasticity, which affects the entire population as a group, e.g. in the form of a multiplicative shock on logistic growth (Lande et al., 2003). However, the dynamics that make up Eq. (13) (see Appendix A.3) embody *demographic* stochasticity and heterogeneity, which captures the variability in growth, death, and fecundity among individuals in the population (Lande et al., 2003; Melbourne and Hastings, 2008). This is especially important for modeling endangered species because low numbers are more sensitive to random birth or death events. Indeed, adult leatherbacks may produce few viable offspring even over long periods of time due to an unlucky chain of deleterious idiosyncratic shocks; each hatchling has less than a 1% chance of making it to maturity[!] (Jones et al., 2012). The risk of bycatch shortens the effective lifespan of adult females dramatically and thus the number of viable offspring-making it paramount that fishing pressure is reduced so prospective mothers live long enough to lay multiple clutches of hundreds of eggs over their lifetime. We discuss and derive leatherback dynamics in further detail in Appendix A.3.

3.4. Regulating fisher behavior for viability

We model a social planner focused on maximizing expected profits of the commercial fishery while accepting at most some small likelihood of extinction. This amounts to choosing the cost-effective amount of fishing effort A^Ω of a representative fisher since, in this model, changing commercial harvesting effort is also the sole lever for influencing bycatch. In other words, the set of management actions is simply $A \geq 0$, with $\overline{A}(X) = 0$ being the maximally-conservationist action in Eq. (2). The social planner considers the trade-off between fishing profits and the valuation of a change in the risk of extinction. The equivalent program to Eqs. (5) and (6) is to solve the following system:

$$\min \{\Omega\} \ \text{s.t.} \ S\left(T \mid X_t, A^\Omega\right) \geq \Delta \ \text{and} \ X_t \in \{X\}_k, \tag{14}$$

$$\text{and} \ V^\Omega(X_t) = \max_{A_t} \left\{ N \cdot \pi(A_t) + \beta \cdot \mathbb{E}_{\{M_t, B_t, R_t\}} \left[V^\Omega(X_{t+1}) \mid A_t, X_t \right] \right\}, \tag{15}$$

$$\text{s.t.} \ V^\Omega(0) = -\Omega \qquad \text{(extinction loss, } \Omega > 0)$$

$$X_{t+1} = X_t - M_t - B_t + R_t \qquad \text{(stochastic dynamics)}.$$

The regulator, in attempting to manage N decentralized fishers, aims to solve a slightly different problem (below), choosing the strength of market instruments rather than the optimal fishing effort directly, in order to match the outcome from solving Eqs. (14) and (15). In the beginning of each period (fishing season), the regulator sets a bycatch price or a total allowable catch for bycatch given a current stock estimate and an anticipated fisher response; we now show how each instrument impacts the representative fisher's expected profit and optimal choice of fishing effort.

3.4.1. Setting a bycatch price

When facing a price $P_t = P(X_t)$ on bycatch, expected seasonal profits of the representative fisher as a function of fishing effort is given by

$$\pi(A_t | P_t) = \pi(A_t) - P(X_t) \cdot \mathbb{E}\left[B_t | A_t\right], \tag{16}$$

where $P(X_t)$ is the dynamic bycatch pricing function set by the regulator. The representative fisher ignores the impact of this year's effort on next year's price, given that their impact is small relative to that of the overall fishery (their optimization problem is static).

The dynamic price – which captures the marginal user cost of bycatch – assures that the static optimization result falls in-line with the social planner's goal.

The resulting first-order condition for the representative fisher's profit-maximization problem tells us about the relationship between the bycatch price and optimal fishing effort given that price, $A^P(X_t)$. Fishers will fish until the marginal profit per expected turtle caught is equal to the landings price. Substituting functional forms for profits and expected bycatch, the optimal policy anticipating fisher behavior is

$$P(X_t) = \frac{p \cdot \phi - c \cdot A^P(X_t)}{\theta \cdot \sigma}. \tag{17}$$

The regulator is interested in harmonizing choices under the price instrument and the cost-effective outcome: $A^P(X_t) = A^\Omega(X_t)$. Substituting the social planner's cost-effective fisher effort function A^Ω provides a formula for this instrument that reflects the planner's shadow value for leatherback population levels.

3.4.2. Setting a total allowable catch

If the regulator instead implements a total allowable catch for the bycatch species $Q_t = Q(X_t)$, fishers now consider how their actions affect the expected season length over which they are allowed to fish. In this case, a total allowable catch for vulnerable species can be extremely low, and it will not be politically feasible to divide it into a set of individual quotas (Holland and Jannot, 2012; Kauer et al., 2018). The optimal quota is given by

$$Q(X_t) = N \cdot \mathbb{E}[B_t | A^Q(X_t)] = N \cdot \theta \cdot \sigma \cdot A^Q(X_t), \tag{18}$$

and since we aim to dramatically drop the amount of bycatch in the fishery, the quota constraint will typically bind: $B_t \leq Q(X_t)$. As for the price instrument, the regulator substitutes the cost-effective fisher effort function, $A^Q(X_t) = A^\Omega(X_t)$.

In the real fishery, the shared nature of the total allowable turtle catch incentivizes a race to fish. For simplicity, we do not include this feature in our model (nor the mitigative risk-pooling cooperatives fishers may choose to form). While derby conditions would change the expected profits of fishers, they would not change this general approach of mapping the social planner's effort to a regulator's quota function above.

While Eq. (18) typically returns a non-integer value, a quota must be an integer. Systematically rounding down the total allowable catch introduces an arbitrarily more conservative regulator (than the one setting a price). In our application, the regulator stochastically rounds expected harvest to an integer value so that the expected total allowable catch is equal to the expected bycatch of the social planner; in the long run, the effects of over- and under-shooting the ideal bycatch will be more comparable to the outcomes under the price instrument.[19]

Next we turn to a numerical illustration of the solution to the social planner's problem and how it can be achieved using market based instruments in a decentralized fishery.

4. A shadow value viability solution for bycatch

4.1. The social planner's cost-effective policy for avoiding extinction

We consider a social planner concerned with avoiding leatherback extinction ($X = 0$) with $\Delta = 95\%$ confidence over a $T = 100$ year rolling viability horizon. These values for Δ and T match the ecological objectives mentioned in Hazen et al. (2018) and Abrego et al. (2020) (for the Eastern Pacific population). The SVV approach estimates the smallest loss Ω upon extinction that induces sufficient bycatch avoidance effort to meet this goal, thus minimizing cost to the swordfish fishery. The model yields a Ω estimate of \$49 billion, which is equivalent to an annual perpetuity loss of \$1.5 billion using a 3% discount rate.

The value of Ω propagates to neighboring population states via the shadow value function $\omega(X_t)$, reflecting stochastic dynamics under the optimal policy and discounting by the time to – and likelihood of – hitting the extinction threshold (see Section 2). Losing an additional adult female turtle embodies non-negligible long-run risk even at moderate population levels, e.g., with a marginal shadow value of \$27 thousand at an abundance of 1500. Table 1 provides illustrative values of key variables for low, mid and high population abundances.

While these marginal turtle values may seem high, this partly reflects our choice to model the problem as simply as possible, particularly the available margins of adjustment to reduce bycatch. The only margin of adjustment for avoiding bycatch is to avoid fishing altogether; this comes with a high cost because swordfish are lucrative. Including additional margins of adjustment that are less costly than fishing effort – like changing the time of harvest, place of harvest, or the depth of fishing gear – would reduce the marginal value of an additional turtle since the opportunity cost of protection would be cheaper. Lowering the catchability of leatherbacks from the estimated baseline decreases the magnitude of $\omega(X)$, increases $V(X)$, and permits more intense fishing at lower turtle levels without pushing turtle populations closer towards extinction. By observing how $V(X)$ changes, the SVV method can provide estimates of the value of these new technologies.

---

[19] Additionally, as the expected bycatch function may not map an integer quota back to an integer amount of effort (days/fisher), we allow the fisher the same level of sophistication (stochastic rounding) when choosing their level of effort, conditional on the quota imposed. These stochastic rounding steps ensure that the expected amount of effort under the quota matches that under the (now-equivalent) price instrument.

Table 1

Key variables under the social planner's cost-effective policy at various population levels.

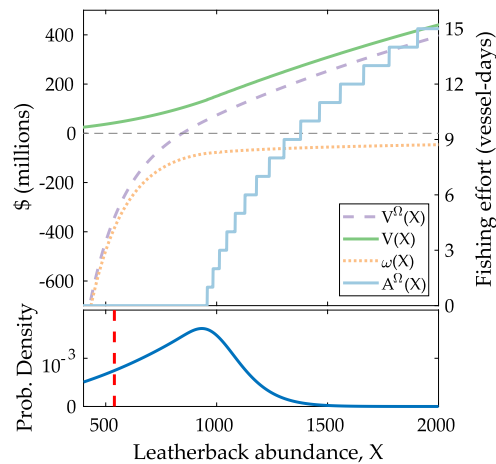| Variable	Symbol	X = 500	1500	2500
Fishing effort (vessel-days/vessel)	$A^{\Omega}(X)$	0	11	18
Expected fleet bycatch	$\mathbb{E}[B_t \mid A^{\Omega}(X)]$	0	70	114
Seasonal fleet profits ($M)	$\pi(A^{\Omega}(X))$	0	27	39
Shadow value ($M)	$\omega(X)$	477	56	40
Expected present fleet profits ($M)	$V(X)$	37	309	553
Present values of an additional turtle				
Marginal shadow value (of reduced extinction risk) ($K)	$\partial \omega(X)/\partial X$	2700	27	11
Marginal profit (of relaxed bycatch constraint) ($K)	$\partial V(X)/\partial X$	134	286	208

Fig. 4. Decomposition of the value function $V^{\Omega}(X)$ (dashed line) into expected present profits $V(X)$ (smooth solid line) and shadow value $\omega(X)$ (dotted line). Cost-effective fishing effort, $A^{\Omega}(X)$, is plotted using the right axis (step function). The lower sub-figure shows the resulting probability density function for turtle abundances (solid line) and the lower bound of the viability kernel (vertical dashed line).

Fig. 4 decomposes the value function into its two components, $V^{\Omega}(X) = \omega(X) + V(X)$, the shadow value function and expected present profits, respectively. For larger leatherback abundances, the risk of extinction is low and the value function hugs expected present profits, $V^{\Omega}(X) \approx V(X)$. At lower populations, extinction is more salient and the shadow value dominates the value function, $V^{\Omega}(X) \approx \omega(X)$. The domain of Fig. 4 is focused on the region where this transition occurs.

The shadow value clearly has an impact on the optimal fishing policy. Superimposed on Fig. 4 is the permissible level of fishing by the social planner, in vessel-days per fisher. Approaching the lower extent of the viability kernel (538 turtles) from above leads to a larger shadow value in concert with a steep decline in fishery exploitation. The social planner opts for an outright fishing moratorium below 957 leatherbacks.

The bottom sub-figure displays the resultant probability distribution of leatherbacks in year 100, conditional on the optimal policy. In attempting to prevent a partially-random dynamic process from hitting its lower bound, the social planner aims for populations to be far from extinction in the intermediate future. This trade-off between safety and fishing profits leaves the stock largely between 500 and 1070 turtles, representing one standard deviation centered on the mean.[20],[21] These populations are viable as defined by the $\{T, \Delta\}$ pair. While the risk of extinction within 100 years is less than 5% within the viability kernel, the likelihood of "dipping below" the lower bound of the viability kernel (at least temporarily) is still quite high; after 100 years, 19% of the probability density is below this boundary (538 turtles); even though net growth is positive in expectation, turtle dynamics are highly sensitive to poor recruitment years. In this region, the planner imposes a moratorium on fishing, though this is true for higher levels as well.

Under this policy, caps would generally be below 10 turtles and moratoriums with a cap of zero would not be uncommon.[22] This could have a significant effect on the viability of the fishery itself, although our model does not consider the additional costs

---

[20] Absent turtle bycatch in the swordfish fishery, the leatherback dynamics laid out in Appendix A.3 lead to an expected female adult population of around 4000.

[21] Our analysis lumps all sub-populations of adult female turtles together; if we were to require viability for each of these sub-populations, this range would likely be much higher.

[22] Intermittent closures are consistent with the situation in the Hawaiian fishery (Swimmer et al., 2017). Closures occur every year after a small number of turtle encounters, and the fishery was closed the entirety of the first three years of the post-90s regulation in favor of protecting leatherback and loggerhead turtles.
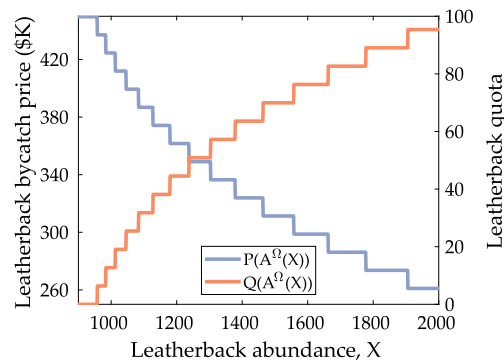
Fig. 5. Price and quota instruments implied by the social planner's optimal fishing policy. The step-behavior arises from the integer-nature of the choice variable in the social planner's problem.

that would follow from repeated shutdowns as this would depend on details of the new fishery, i.e., fixed costs of shutdowns and available income from fishers' next best option outside of this fishery. Generally, as these closure costs increase, the cost-effective level of seasonal fleet fishing effort will fall in favor of maintaining higher leatherback abundances, and thus more flexible and longer fishing seasons.

4.2. From shadow values to market-based instruments

Prices and quotas both promote bycatch avoidance; prices directly encourage the avoidance of turtles, and quotas do so indirectly by instead encouraging avoidance of fishery closures. In Section 3.4, we designed each of the two instruments to be equivalent, incentivizing the same amount of effort as the social planner and reproducing the same value function in Fig. 4. We do not pursue a comparison of instruments à la Weitzman (2002) or Segerson (2011), but rather a discussion of the mapping process of SVV output to decentralized governance. Fig. 5 provides an illustration of the two instruments.

The bycatch price of a turtle is very high, as it is tethered to the opportunity costs of fishing, which is lucrative.[23] Similar to the discussion in Section 4.1, if additional, cheaper margins for bycatch avoidance are available, then the bycatch price would adjust downward. However, considering the amount of effort put into protecting turtles (Swimmer et al., 2017), high prices are not surprising, and recent work suggests that social value for individual turtles implied by bycatch regulations in Hawaii's longline fishery is an order of magnitude higher (Sweeney, 2020).

The quota set by the regulator rises quickly with the leatherback stock. As the marginal benefits of ever-higher leatherback abundances decreases (discussed next) the regulator is increasingly more tolerant of additional bycatch events that have less of an impact on the viability of the species.

Fig. 6 presents a decomposition of the price instrument. We understand intuitively – and formally from Section 2.2 – that the level of our regulatory instruments should capture two values: the marginal shadow value of increased extinction risk, $\partial \omega(X)/\partial X$, as well as the marginal value of less regulatory-constrained profits in the future, $\partial V(X)/\partial X$. The price instrument precisely embodies the sum of these two marginal effects that weigh against contemporary marginal profits. Unlike the social planner that is increasingly concerned as stocks decline, the regulator does not need to continue increasing bycatch prices once they are high enough to preclude any fishing activity. At high numbers, neither are as concerned with viability and the price is only reflecting the opportunity cost of having more restrictive regulation in the future.

4.3. Sensitivity to parameters of the viable control objective

For the viability problem outlined in Section 2, the social planner must provide three preference parameters: the pair $\{T, \Delta\}$ reflects social preferences about risk often found in resource management plans and the discount factor (β) specifies intertemporal preferences. So far, we have taken these parameters to be exogenously given. However, there is certainly a trade-off between a more stringent viability target (higher levels of T and/or Δ) and the increased opportunity costs of the conservation effort necessary to get there. And even though the viability framework puts the biological target center stage, present values are a key feature, suggesting an important role for the choice of discount factor or, equivalently, discount rate $r = \beta^{-1} - 1$.[24] For insight into these model inputs, we re-solve the viability model while varying the discount rate r and the central risk parameter, namely the confidence level Δ, around the baseline levels used in the analysis above (3.1% and 95%, respectively). We end the section with a discussion of the viability (confidence) supply curve, which is notably non-monotonic but increasing on average.

---

[23] While the total bycatch costs are manageable at the fishery level, individuals could go bankrupt; a risk pool would be necessary in order to convince smaller fishers to participate. Alternatively, policy design could mitigate this risk by distributing taxes back to fishers in equal shares without removing the individual's incentive to avoid bycatch.

[24] Since damages to the turtle population are controlled by the joint chance constraint, and the actual, realized values that are discounted are private fishery profits, there is a case for using the market interest rate for the discount rate in our particular application.
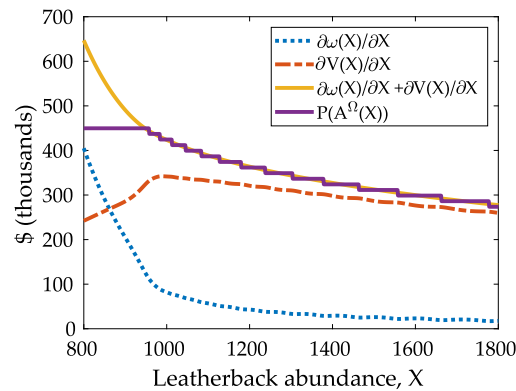
Fig. 6. Decomposition of the leatherback bycatch price (step function). As long as the price $P(\cdot)$ does not prevent fishers from fishing entirely (as it does below $X = 957$ leatherbacks), it captures the sum of two effects: the marginal benefit of relaxing regulation in the future (dot-dashed line) and the marginal shadow value [of reduced risk of extinction] (dotted line).

Sensitivity to the choice of discount rate

In Fig. 7 we show how key results change as we vary the discount rate. The top-left panel shows that, as expected, Ω increases with r since an increasing discount rate decreases the salience (in present value terms) of any given Ω (see Eq. (10)). Thus, as r increases, Ω must increase to maintain a shadow value (ω) sufficient to drive enough conservation effort to maintain achievement of the viability objective, i.e. a society with a higher discount rate would trigger conservation efforts only if it gives a larger value to the species, all else equal. Furthermore, a higher discount rate reduces the present value of loss from future closures; because of this shrinking present opportunity cost of fishing, Ω increases in order to ensure sufficient shadow value-driven motivation to moderate the impact of fishing.

The top-right panel of Fig. 7 shows that (for any given turtle abundance) the optimal fishing intensity increases with r. This effect also follows from impacts to the present loss of future fishing closures: a higher discount rate makes future closures less salient and thus increases contemporaneous fishing effort (for any given turtle abundance). This causes the resulting stationary distribution of turtle abundance levels (bottom-right panel) under the given policy to shift towards zero.

The bottom-left panel shows that expected seasonal profits fall as the discount rate increases. When r is high, more intensive harvest effort leads to lower expected turtle abundance, which in turn leads to lower seasonal effort and more frequent closures. A low r is therefore good on average for both the leatherbacks and the fishers. When turtle numbers are allowed to increase, seasons can remain open more frequently and for longer, increasing the prospective profits of future periods.

Sensitivity to the choice of confidence level

In Fig. 8, we replicate the sensitivity analysis in Fig. 7 with respect to the confidence level Δ. As expected, requiring a higher confidence level in our viability constraint forces Ω to increase (top-left panel) in order to incentivize lower fishing intensity (higher conservation effort) at any given turtle abundance level (top-right panel). Because fishing intensity typically decreases as Δ increases (top-right panel), the resulting stationary distribution for the turtle population shifts to the right (bottom-right panel). Thus, as expected, a more-stringent viability target (higher Δ) is better for leatherback abundance.

Notably, a higher Δ is better on average for the fishers' expected seasonal profits (bottom-left panel, Fig. 8). As the stringency of the conservation goal increases, so do rents for fisherman, i.e., opportunity costs of stronger protection are *negative*. This occurs because – given the specified population dynamics – a higher confidence level necessitates a higher turtle population as a buffer, which in turn requires less constraint on fishing effort on average in the long-run. However, these are long-run average opportunity costs, which ignore differences in payoffs in the transition from any given starting state. We would expect this to matter: the stationary distribution of turtle abundance increases with Δ and thus over any given initial time frame the expected opportunity costs will also be higher.

A more comprehensive opportunity cost measure is given by the difference in the expected present value of profits from any given starting state ($V(X_t)$) for some change in Δ. Indeed, this metric generates the anticipated result that the expected present value of opportunity costs of achieving viability are, on average, increasing in the confidence level. For example, at $X_t = 1200$, this metric falls by \$32.6M as we increase Δ from 0.85 to 0.95, generating an average marginal cost of \$3.6M per confidence point (0.01). While this "viability supply curve" (marginal cost per confidence point) is increasing *on average* as Δ increases from 0.7 to 0.95, we find that this curve is not monotonic. For a small minority of step increases in confidence, the incremental unit of confidence is less costly to achieve than the previous one. The reason is that two things change as Δ increases. First, there is shrinkage in the state space over which the now more stringent viability constraint can be met, i.e., the viability kernel $\{X\}_k$ becomes smaller (see Eq. (2)). Second, there is the more obvious direct effect: conditional on $X_t \in \{X\}_k$, extinction is avoided with greater confidence. Thus, while the marginal cost (in present value terms) of achieving an additional confidence point *typically* increases, *a priori* it does not do so in a predictable fashion for any given step.
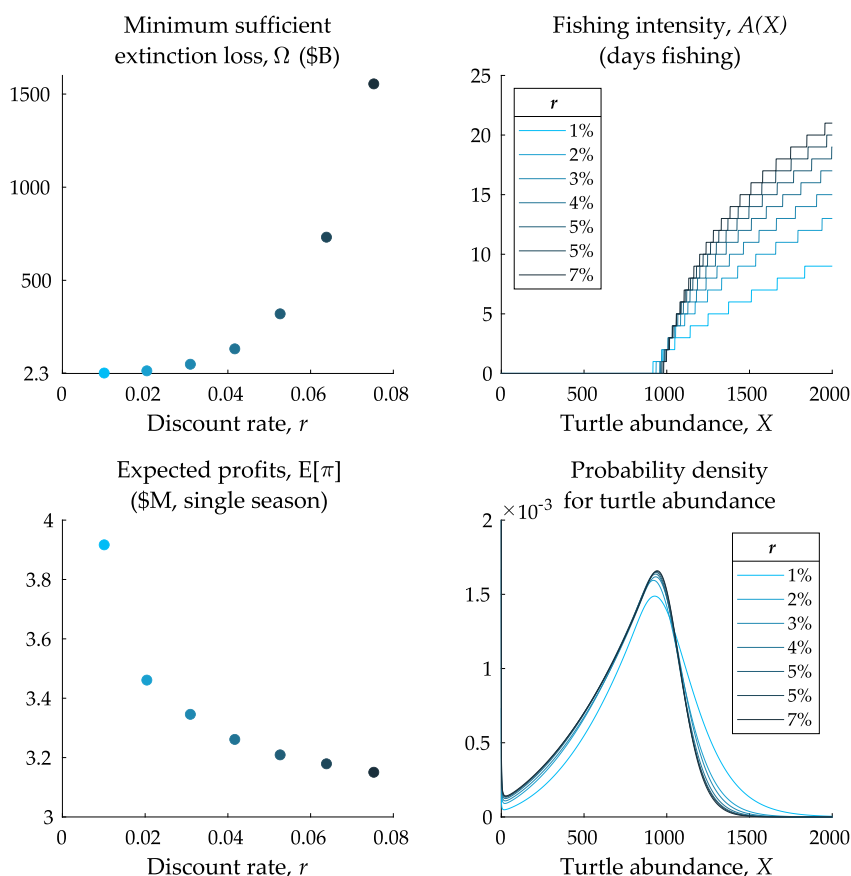
14

Fig. 7. Sensitivity of viability model results to the choice of discount rate.

This sensitivity analysis with respect to the confidence level can be coupled to other techniques from the greater viability theory literature. In the first column of Fig. 8, Δ appears on the horizontal axis, however one could also think of reversing the horizontal and vertical axes and considering the slope of the curve to gain a sense of *marginal viability* (De Lara and Martinet, 2009; Martinet et al., 2016)—with respect to Ω and expected profits. Maximizing viability – rather than seeking to minimize the costs of meeting a fixed, minimal level of Δ, as we do – is a compelling alternative in settings where there are multiple ecological and economic objectives, like the sustainable management of natural resources. In the absence of a simple social welfare function that maps viability and profits into a single metric, marginal viability can provide a way forward—De Lara and Martinet (2009) and Martinet et al. (2016) use this alternative metric in order to rank the sustainability of outcomes in a system with many constraints that represent various objectives and contribute to their definition of viability.

5. Discussion

While the real world involves overlapping commercial and conservation concerns, management models typically treat these problems independently. The framework in this paper identifies a policy that simultaneously balances conservation benefits of a vulnerable species with the opportunity costs incurred in commercial resource use. This integration is enabled by application of a shadow value viability approach. Beyond revealing the cost-effective conservation policy, the approach also informs the setting of market-based instruments for attaining this desired result among decentralized resource users.

SVV is a departure from the typical approach that maximizes the gap between expected benefits and costs. Our method is most suitable when the explicit benefits of species preservation are difficult to measure—in the case of bycatch, other routes like valuing ecosystem services provided by vulnerable species require more information than is often available (Crocker and Tschirhart, 1992; Brock et al., 2009). In our numerical application, a shadow value is derived with respect to biological concerns around leatherback turtle viability and the opportunity costs of conservation effort within a fishery. This shadow value motivates costly conservation action to avoid increasing prospects of extinction.

A population-dependent valuation of the avoidance of extinction is not feasible with revealed preference methods and impractical with stated preference techniques. Optimal management of vulnerable species is hampered by a lack of information about what value is lost at the margin as the population declines. While stated preference methods are used to elicit values for a status change, e.g.
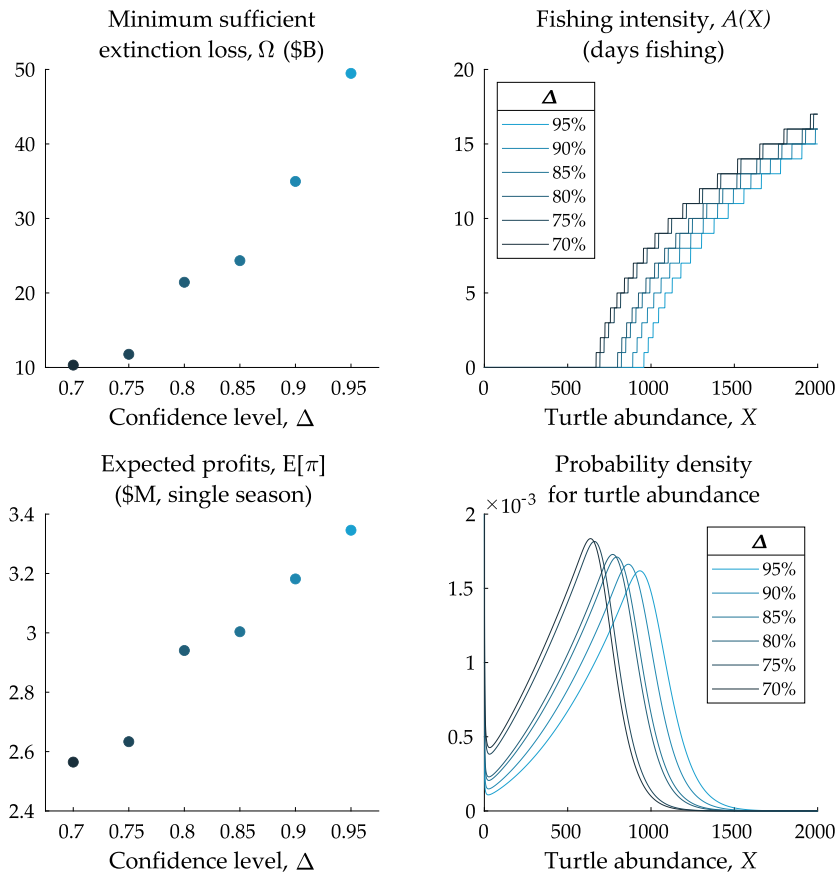
Fig. 8. Sensitivity of viability model results to the choice of confidence level.

from endangered to only threatened, this single point value is unsatisfactory for dynamic management; ideal management should respond to value gained or lost at any population level. And, as illustrated in Section 4, the shadow value of the vulnerable species population can shift dramatically and non-linearly as the population falls.

The SVV approach offers a way forward for relaxing inefficient command and control policies while still achieving conservation goals. The guidance suggested here opens up the possibility for the de-implementation of excessively costly management methods like large marine protected areas or restrictive gear standards. SVV grants this added flexibility in providing a way to set the level of market-based instruments.

When is SVV best-suited to achieve stewardship of non-targeted, ecologically-important species? There will always be species with little commercial value that are incidentally caught due to their proximity to commercially-relevant stocks. Weakened species – those threatened but within the viability kernel and less immediately at risk of extinction – stand to benefit the most from shadow valuation methods, as their populations are large enough that talk of the trade-offs between conservation and commercial objectives is still possible.

Our objective in this article was to build intuition for the SVV approach, using a simple model, pared to essential components. In future research, the setting of real world policy instrument levels (prices or quotas) should consider additional elements for more comprehensive representation of a system. This includes the set of relevant decision margins for bycatch avoidance (e.g., technology adoption, location choice, fishing time of day, gear setup, etc.). In our application, given a robust commercial stock, we set aside the need for incorporating that state variable. However, an evolving level of the target stock will be relevant in many fisheries. Finally, while we focus on the extinction-avoidance value of the vulnerable stock to be conserved, if other ecosystem service values are salient and available, those may also be incorporated.

The SVV approach requires specifying intertemporal preferences and risk preferences (often found in management plans). With an increase in the discount rate (r) or confidence (Δ), generally we see an increase in the minimum sufficient extinction loss (Ω). Further the increase in r leads to an increase in fishing intensity, accompanied by a shift down in the density of the vulnerable stock (turtle abundance) while the increase in Δ leads to the opposite. Notably, expected annual profits in a season increase as Δ increases, exhibiting a *negative* annual opportunity cost to maintain a more stringent confidence level. However, when accounting for transitions from a given starting state, the opportunity cost is positive (the expected present value of long-run profit is lower) as expected, on average \$3.6M per confidence point in the neighborhood of our baseline parameterization. However, this viability

supply curve is not monotonic/well-behaved across each individual point since both the viability kernel and Ω shift as Δ is varied. This marginal cost curve will also shift downward as fishers move beyond the single type of conservation action modeled here (reducing fishing effort) to take advantage of a broader set of conservation actions (e.g., adjusting fishing time, place, depth and gear).

Shifting focus from the notion of marginal value to total value of a species, if this latter value was known, we could simply plug that in for Ω and find the economically efficient level of viability (instead of the other way around). However, eliciting the value of an entire species from people is arguably problematic (as discussed in the introduction). In the VSL context, the elicitation and interpretation of value is from small changes in the risk of death. Analogously, in our setting, researchers could elicit the marginal value of a change in the stock level at some given population level. However, we fully expect this marginal value to be quite sensitive to the level of the stock, in particular as a population declines. Indeed in our framework, we capture this feature with the function $\omega(X)$, which is distinctly concave. (Note that the marginal value is given by $\partial\omega/\partial X$.) Thus, eliciting the marginal value in a WTP/WTA framework would be extremely costly given that it is far from constant over the relevant range of stock levels and eliciting the value of a species in its entirety is arguably fraught.

The SVV approach does offer a potentially simplified way forward for WTP/WTA studies. Recall that in the SVV solution, Ω represents the minimum sufficient extinction loss that would trigger enough conservation action to meet the viability objective (with the given confidence over the given time horizon). Thus, Ω provides a benchmark, which enables posing a simpler question to respondents: is preservation of the species worth at least Ω? If so, then the viability objective as stated is worth pursuing. While this approach has the benefit of relying on a binary question instead of an open-ended one (arguably easier to answer reliably), this does not necessarily resolve moral concerns associated with considering the extinction of a species.

The conclusion to the above comparison relies not only on preferences for species preservation but *also* on time preferences. As seen in Section 4.3, the larger the discount rate, the larger the preservation value needed to justify sufficient conservation to meet the viability objective.

The modeling of viability-style goals has a broad set applications beyond conservation settings. Management objectives that aim to stay above (or below) a particular threshold over time with some margin of safety are abundant in natural resource management and elsewhere. Notable examples include maintaining viable populations for endangered species (illustrated here), global temperatures below a maximum increase, and zoonotic disease prevalence away from outbreak levels. Each of these cases center on avoiding a threshold with dire but inestimable consequences. Shadow value viability translates the implied value of avoiding these thresholds to the benefits of reducing risk on the margin, enabling all of these urgent issues to be investigated with an intuitive economic approach.

Appendix. Appendices for "Balancing conservation and commerce"

A.1. A joint-chance constrained dynamic programming algorithm

Here, we discuss how to solve the dynamic programming problem with a joint-chance constraint, assuming some previous knowledge of dynamic programming. The code for this project can be found at piercedonovan.github.io.

1. Setup

    (a) Define all program parameters (biological, economic, political), functions (cost, harvest responses given a particular policy instrument, and state equations), and state/control sets. Initialize the Markov transition matrix, which will depend on several of these.
    (b) Document the state space where it is possible to satisfy the viability constraint, because we only look for an optimal policy where it is feasible. Identify this viability kernel by finding the likelihood of extinction over the designated horizon, conditional on starting state, given the strongest possible conservation action.
    (c) Provide sufficiently wide range of values for $\Omega > 0$. Let the first guess of Ω be the midpoint between the upper and lower bounds.

2. Solve the dynamic program in Eq. (6) conditional on a value for Ω.

    (a) Initialize the value function as desired, e.g., $V^{\Omega}(X_t) = 0$, except impose $V^{\Omega}(X_t = 0) = -\Omega$. Note that since $X_t = 0$ is irreversible, this value will be maintained throughout.
    (b) Solve using value function iteration (VFI) (Judd, 1998) by repeating these steps until convergence: (i) find $A(X_t)$, the optimal (candidate) policy action (A) for every state (X_t); and (ii) update the value function (V^{Ω}) using $A(X_t)$.

3. Check viability constraint and update Ω.

    (a) Check if each state in the viability kernel satisfies the viability constraint given the optimal policy $A(X_t)$ under Ω. If no (yes), increase the lower (decrease the upper) bound on Ω to the current guess. Set the new level of Ω to the midpoint between bounds. Repeat Step 2, except end the search if the most recent two iterations over Ω are sufficiently close (with the lower guess not being sufficient for viability and the upper one satisfying the constraint). The exact choice of search algorithm over Ω is not consequential [in our case].

Table A.1
Parameter definitions with values, descriptions, and sources.

Parameter	Value	Description and source[a]
Viability		
T	100	Rolling window horizon (chosen)
Δ	0.95	Viability confidence level (chosen)
Economic		
β	0.97	Discrete discount factor (chosen)
p	$6500	Ex vessel price of swordfish per metric ton (2020 dollars) (WPRFMC, 2004)
ϕ	0.88	CPUE (mT/day) (WPRFMC, 2004; Bartram and Kaneko, 2004)
θ	0.024	BPUE (turtles/day) (WPRFMC, 2004; Bartram and Kaneko, 2004)
N	500	Number of vessel permits for swordfish (WPRFMC, 2004; Tagami et al., 2014)
c	160	Estimated cost parameter ($/day^2) (WPRFMC, 2004)
Biological		
σ	0.53	% of bycatch that are adult females (NMFS and FWS, 2013)
ρ	0.3	% of turtles nesting (Jones et al., 2012; NMFS and FWS, 2013)
γ	80	Mean [female] 2-day hatchling survivors (Jones et al., 2012)
η_R	0.03	Demographic heterogeneity in recruitment (Abrego et al., 2020)
η_M	0.03	Demographic heterogeneity in mortality (assumed same as recruitment)
m_1	0.75	1st-year natural mortality (Jones et al., 2012)
m	0.20	>1st-year natural mortality (Jones et al., 2012)
a	15	Years to maturity (after 1st) (Jones et al., 2012)
K	75 000	Intraspecific competition parameter (NMFS and FWS, 2013)

[a]Some values have been transformed from other units used in the source material.

To be assured of a fixed point for V^{Ω} we require the state space X to be compact, the discount factor β to be less than one, and the reward π to be bounded above and below (Judd, 1998). These conditions hold for the problem specified in Eq. (6). There are two features of this viability problem that are atypical in dynamic programming problems, however neither involves or disturbs the contraction mapping required for the fixed point. First, we impose the constraint that $V^{\Omega}(0) = -\Omega$. However, to achieve this we simply include this in the initial guess for the value function before solving with VFI. Since $X_t = 0$ is irreversible, the value is maintained throughout the VFI solution process. Second, in Step 3 in the algorithm above, we check if the viability constraint is satisfied and (if needed) update Ω before resolving. However, this only occurs once the fixed point V^{Ω} has already been identified for a given level of Ω.

A.2. Parameter values, descriptions, and sources

Table A.1 provides all model parameter definitions with values, descriptions, and sources. Economic parameters are derived from averages over 1994–1999 in the Hawaiian longline fishery. The cost parameter c is estimated by using the profit-maximizing condition of the representative fisher corresponding to Eq. (12), using an average effort of 35 days/vessel. This ensures seasonal catch per vessel (30 mT), fleet catch (3000 mT) and ex-vessel revenue ($19M (2020 dollars)) match the unregulated case in our model (WPRFMC, 2004). This puts bycatch at a maximum of around 220 adult female leatherbacks, which is within the bounds of the best estimates for the unregulated fishery (and similar in scale to other unregulated longline fisheries) (Bartram and Kaneko, 2004). N scales average Hawaiian vessel landings by weight to the total fishing activity seen over the same seven-year period (we assume that the other fleets have similar structure).

We calibrate turtle dynamics to the energetics experiments in Jones et al. (2012). Our model tracks the evolution of adult female turtles since evidence suggests the number of mature females is the limiting factor in the production of new recruits (Jones et al., 2012). Only a portion of the population $1 - \rho$ is vulnerable to bycatch as they range from the warmer spawning waters. For every nesting female, 80 female hatchlings survive the first two days (variation in recruitment, η_R, is calibrated to nesting sites in Abrego et al. (2020)), and 25% of those make it through the year. An estimated 0.7 females make it to maturity from each adult-nesting year. As the half-life of an adult is only 3–4 years, the expected production of mature females is 1.4–2.1 per adult female today.

A.3. Vulnerable species dynamics

Valuable insight about the response to risk can of course come from deterministic models (e.g. Reed (1979), more in Nøstbakken and Conrad (2007)). Policy guidance, however, may be fairly limited without a model that reflects a stochastic economic and ecological reality (Lande et al., 1997; Bulte and van Kooten, 2001). Bulte and van Kooten (2001) assert that the extinction of a species will likely be caused by stochastic perturbations, rather than predictable or controllable systematic pressures like hunting or habitat degradation. Deterministic modeling can lead to a "safe" solution where a vulnerable population is left to sit just above some minimum viable threshold, but if this is done in a stochastic world, the prescription is akin to an environmental "gambler's ruin".

A focus on species viability requires careful modeling of dynamics at low population levels that differs from standard approaches suitable for large populations. Vulnerable species may produce few viable offspring even over long periods of time due to an unlucky chain of deleterious, idiosyncratic shocks. For small aggregations of a species, population dynamics become much more sensitive

Table A.2
Timeline of stylized seasonal events.

Start of year t ····	Share ρ of X_t observed nesting in Southeast Asia, hatchlings appear
Start of season ····	$(1 - \rho) \cdot X_t$ northern exploitable population, instrument $\{P_t, Q_t\}$ set by the regulator
Fisher response ····	Effort A_t and expected bycatch harvest $\mathbb{E}[B_t \vert A_t]$ chosen by fisher
During season ····	Stochastic harvest B_t and natural mortality M_t affect adult turtles
End of season ····	New recruits R_t added to population

to [random] birth or death events. This is called *demographic stochasticity*, which captures variability in growth due to the sampling from a distribution of possible births and deaths (Lande et al., 2003; Melbourne and Hastings, 2008).[25] This concept is particularly important for the modeling of a vulnerable species, but is largely ignored in the bioeconomics literature (Lande et al., 2003). This appendix details a simple way to take demographic stochasticity into account by expanding on the examples found in the supplementary materials of Melbourne and Hastings (2008). Table A.2 presents the order of events implied by our model.

We start by letting the number of [female] hatchlings born to adult i at time t be described by a Poisson distribution with mean 2-day hatchling survival γ_i:

$$FH_{i,t} \sim Poisson(\gamma_i).$$

Fecundity differs for each adult—*demographic heterogeneity*—as some individuals produce more or less offspring than others. Following Melbourne and Hastings (2008), we assume γ_i is gamma-distributed with mean γ and heterogeneity (shape) parameter η_R. From the law of total probability, $FH_{i,t}$ thus has a negative binomial (NB) distribution:

$$FH_{i,t} \sim NB(\gamma, \eta_R).$$

The likelihood of each hatchling surviving to maturity is given by

$$s(X_t) = (1 - m_1) \cdot (1 - m)^a \cdot \left(1 - \frac{X_t}{K}\right),$$

where m_1 is the expected 1st-year mortality rate and m is the expected yearly mortality beyond year one, which needs to be survived $a = 15$ years until maturity. For low populations, $s(\cdot)$ is about 0.9%. X_t is the current number of adult females and K captures the effect of intraspecific competition for common resources (Schoener, 1973; Connell, 1983).[26]

An age class model including yearlings, juveniles and adults of reproductive age would be most realistic, however this requires three state variables to capture the turtle population at any point in time. Since this paper is intended to concretely illustrate the essential elements of SVV in as simple a setting as possible, we use a stylized model of representative adult female turtles. This assumes the relative shares of different age classes are fixed over time; notably, we assume that the expected number of recruits R to the adult population at the end of a season is what we may expect of today's hatchlings several years in the future, i.e. $\mathbb{E}[R_{t+a} \vert X_t] \approx \mathbb{E}[R_t]$. Given this relation, the number of hatchlings that survive to maturity (recruitment) from adult i at time t is given by

$$R_{i,t} \sim Binomial\left(FH_{i,t}, s(X_t)\right) \equiv NB\left(\gamma \cdot s(X_t), \eta_R\right),$$

where the equivalence again takes advantage of the law of total probability.

Summing survived offspring from all nesting females ($\rho \cdot X_t$) gives us

$$R_t = \sum_i^{\rho \cdot X_t} R_{i,t} \sim NB\left(\gamma \cdot \rho \cdot X_t \cdot s(X_t), \eta_R \cdot \rho \cdot X_t\right),$$

since the sum of independent NB random variables with the same shape parameter is also NB-distributed (using the mean-shape parameterization). The mean and variance are

$$\mathbb{E}[R_t] = \gamma \cdot \rho \cdot X_t \cdot s(X_t),$$

$$\mathbb{V}[R_t] = \mathbb{E}[R_t] + \frac{\mathbb{E}[R_t]^2}{\eta_R \cdot \rho \cdot X_t}.$$

The importance of demographic heterogeneity becomes evident at low abundances. The variance-to-mean ratio approaches $1 + \gamma/\eta_R$ as the population declines, and at very large abundances it reaches the Poisson limit of one.

---

[25] A relevant but distinct concept is the *Allee effect*, which yields a positive correlation between the per capita growth rate and population size below a critical threshold (Stephens et al., 1999).

[26] Density-dependence is typically thought to be a stronger factor in *juvenile* mortality if individual fitness increases with age or size, or if there are hierarchies in the population that create an uneven distribution of resources (Schoener, 1973; Connell, 1983). This feature only needs to be modeled once; the fecundity (γ) of adults can decrease with increasing population density as well, capturing the same effect.

The above captures the full role of demographic stochasticity and heterogeneity in recruitment. Similarly, the seasonal natural mortality and bycatch of turtles can be represented by two additional NB-distributed variables,

$$M_t \sim NB\left(m \cdot X_t, \eta_M \cdot X_t\right)$$
$$\text{and, } B_t \sim NB\left(N \cdot \theta \cdot \sigma \cdot A_t, \eta_M \cdot X_t\right),$$

where m is the expected individual mortality rate, the expected bycatch harvest by the representative fisher (Eq. (11)) is scaled up by the size of the fishery N, and η_M is the heterogeneity parameter related to variation in the mortality rate from turtle to turtle.

In sum, the dynamics of the leatherbacks is given by a series of stochastic shocks of natural mortality, bycatch, and recruitment,

$$X_{t+1} = X_t - M_t - B_t + R_t.$$

To get a sense of where the population will tend to concentrate in the absence of human impacts, We consider the case where $\mathbb{E}[X_{t+1}] = X_t \equiv X^*$, which simplifies to the condition $\mathbb{E}[M_t] = \mathbb{E}[R_t]$. The *stable*, non-zero equilibrium is

$$X^* = K \cdot \left(1 - \frac{m}{\gamma \cdot \rho \cdot (1 - m_1) \cdot (1 - m)^a}\right),$$

which gives around 4000 adult females in the western pacific stock, which corresponds to a total population around 100,000 (Jones et al., 2012). Above X^*, the *expected* change will be a decrease in population, and below, an increase, if there is no bycatch harvested.

For very low populations, the expected recruitment per adult female is roughly 0.21, and the expected mortality is 0.2. While there is no evident Allee effect that triggers below a threshold and dooms the species (where we would impose a quasi-extinction threshold), demographic stochasticity still presents an extreme risk. The expected change in the population is indeed positive, but variance can sentence an unexpected number of the last few individuals to death from an unlucky series of coin flips. At 4000 adult females, the standard deviation of the change in population is 2.5% of the current abundance, while at a population of 400, this increases to nearly 10%.

References

Abbott, J.K., Wilen, J.E., 2009. Regulation of fisheries bycatch with common-pool output quotas. J. Environ. Econ. Manage. 57 (2), 195–204.

Abrego, M.E., Acuña Perales, N., Alfaro-Shigueto, J., Azócar, J., Barragán Rocha, A.R., Baquero, A., Cotto, A., Darquea, J., de Paz, N., Donoso, M., Dutton, P.H., Fonseca, L., Gadea, V., García, D., Genovart, M., Jimenez, A., del Rosario Juárez, M., López Sánchez, K.C., Mangel, J.C., Martínez Suzano, M.L., Miranda, C., Ocampo, E., Ordaz Becerra, A., Ortiz-Alvarez, C., Paladino, F.V., Pasara-Polack, A., Pingo, S., Piedra Chacón, R., Quiñones, J., Rguez-Baron, J.M., Salas Jiménez, J.C., Salazar, H., Santidrián Tomillo, P., Sarti Martínez, A.L., Spotila, J.R., Tavera, A., Urteaga, J., Vallejo, F., Velez, E., Wallace, B.P., Williard, A.S., Zárate, P.M., The Laúd OPO Network, 2020. Enhanced, coordinated conservation efforts required to avoid extinction of critically endangered Eastern Pacific leatherback turtles. Sci. Rep. 10 (1), 4772.

Alais, J.-C., Carpentier, P., De Lara, M., 2017. Multi-usage hydropower single dam management: chance-constrained optimization and stochastic viability. Energy Syst. 8 (1), 7–30.

Arnason, R., 2012. Property rights in Fisheries: How much can individual transferable quotas accomplish? Rev. Environ. Econ. Policy 6 (2), 217–236.

Bartram, P.K., Kaneko, J.J., 2004. Catch to Bycatch Ratios: Comparing Hawaii's Longline Fisheries with Others. Technical Report, JIMAR and NOAA, Honolulu, Hawaii, USA.

Baumgärtner, S., Quaas, M.F., 2009. Ecological-economic viability as a criterion of strong sustainability under uncertainty. Ecol. Econom. 68 (7), 2008–2020.

Boyce, J.R., 1996. An economic analysis of the Fisheries bycatch problem. J. Environ. Econ. Manage. 31 (3), 314–336.

Brock, W.A., Finnoff, D., Kinzig, A., Pascual, U., Perrings, C., Tschirhart, J., Xepapadeas, A., 2009. Modelling biodiversity and ecosystem services in coupled ecological-economic systems. In: Biodiversity, Ecosystem Functioning, and Human Wellbeing: an Ecological and Economic Perspective. Oxford Scholarship.

Bulte, E.H., van Kooten, G.C., 2001. Harvesting and conserving a species when numbers are low: population viability and gambler's ruin in bioeconomic models. Ecol. Econom. 37 (1), 87–100.

Carretta, J.V., Moore, J.E., Forney, K.A., 2019. Estimates of Marine Mammal, Sea Turtle, and Seabird Bycatch from the California Large-Mesh Drift Gillnet Fishery: 1990–2017. NOAA Technical Memorandum, NOAA-TM-NMFS-SWFSC-619, In: NOAA technical memorandum NMFS.

Connell, J.H., 1983. On the prevalence and relative importance of interspecific competition: Evidence from field experiments. Amer. Nat. 122 (5), 661–696.

Crocker, T.D., Tschirhart, J., 1992. Ecosystems, externalities, and economies. Environ. Resour. Econ. 2 (6), 551–567.

De Lara, M., Martinet, V., 2009. Multi-criteria dynamic decision under uncertainty: A stochastic viability analysis and an application to sustainable fishery management. Math. Biosci. 217 (2), 118–124.

Donovan, P., 2021. An alternative climate policy tool that reflects the scientific consensus. Working Paper, piercedonovan.github.io/files/research/donovan_alternative_climate_policy.pdf.

Donovan, P., Bair, L.S., Yackulic, C.B., Springborn, M.R., 2019. Safety in numbers: Cost-effective endangered species management for viable populations. Land Econom. 95 (3), 435–453.

Doyen, L., De Lara, M., 2010. Stochastic viability and dynamic programming. Systems Control Lett. 59 (10), 629–634.

Doyen, L., Thébaud, O., Béné, C., Martinet, V., Gourguet, S., Bertignac, M., Fifas, S., Blanchard, F., 2012. A stochastic viability approach to ecosystem-based fisheries management. Ecol. Econom. 75, 32–42.

Eisworth, M.E., van Kooten, G.C., 2009. The ghost of extinction: Preservation values and minimum viable population in wildlife models. Ecol. Econom. 68 (7), 2129–2136.

Fitzpatrick, L.G., Kelly, D.L., 2017. Probabilistic stabilization targets. J. Assoc. Environ. Resour. Econ. 4 (2), 611–657.

Haight, R.G., 1995. Comparing extinction risk and economic cost in wildlife conservation planning. Ecol. Appl. 5 (3), 767–775.

Hazen, E.L., Scales, K.L., Maxwell, S.M., Briscoe, D.K., Welch, H., Bograd, S.J., Bailey, H., Benson, S.R., Eguchi, T., Dewar, H., Kohin, S., Costa, D.P., Crowder, L.B., Lewison, R.L., 2018. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. Sci. Adv. 4 (5), eaar3001.

Holland, D.S., Jannot, J.E., 2012. Bycatch risk pools for the US west coast groundfish Fishery. Ecol. Econom. 78, 132–147.

Hyrenbach, K.D., Forney, K.A., Dayton, P.K., 2000. Marine protected areas and ocean basin management. Aquat. Conserv. Mar. Freshw. Ecosyst. 10 (6), 437–458.

ISC Billfish Working Group, 2018. Stock Assessment for Swordfish (Xiphias gladius) in the Western and Central North Pacific Ocean through 2016. Technical Report ISC/18/ANNEX/16, ISC, Yeosu, Republic of Korea.

Jones, T.T., Bostrom, B.L., Hastings, M.D., Houtan, K.S.V., Pauly, D., Jones, D.R., 2012. Resource requirements of the Pacific leatherback turtle population. PLoS One 7 (10), e45447.

Judd, K.L., 1998. Numerical Methods in Economics. MIT Press.

Kasperski, S., 2016. Optimal multispecies harvesting in the presence of a nuisance species. Mar. Policy 64, 55–63.

Kauer, K., Bellquist, L., Gleason, M., Rubinstein, A., Sullivan, J., Oberhoff, D., Damrosch, L., Norvell, M., Bell, M., 2018. Reducing bycatch through a risk pool: A case study of the U.S. West Coast groundfish fishery. Mar. Policy 96, 90–99.

Lande, R., Engen, S., Sther, B.-E., 2003. Demographic and Environmental Stochasticity. Oxford University Press.

Lande, R., Sther, B.-E., Engen, S., 1997. Threshold harvesting for sustainability of fluctuating resources. Ecology 78 (5), 1341–1350.

Lent, R., Squires, D., 2017. Reducing marine mammal bycatch in global fisheries: An economics approach. Deep Sea Res. II 140, 268–277.

Lichtenberg, E., Zilberman, D., 1988. Efficient regulation of environmental health risks. Q. J. Econ. 103 (1), 167–178.

Lichtenberg, E., Zilberman, D., Bogen, K.T., 1989. Regulating environmental health risks under uncertainty: Groundwater contamination in California. J. Environ. Econ. Manage. 17 (1), 22–34.

Martinet, V., Peña Torres, J., De Lara, M., Ramírez C., H., 2016. Risk and sustainability: Assessing Fishery management strategies. Environ. Resour. Econ. 64 (4), 683–707.

Melbourne, B.A., Hastings, A., 2008. Extinction risk depends strongly on factors contributing to stochasticity. Nature 454 (7200), 100–103.

Montgomery, C.A., Brown, J., Adams, D.M., 1994. The marginal cost of species preservation: The northern spotted owl. J. Environ. Econ. Manage. 26 (2), 111–128.

Newbold, S.C., Siikamäki, J., 2009. Prioritizing conservation activities using reserve site selection methods and population viability analysis. Ecol. Appl.: Publ. Ecol. Soc. Amer. 19 (7), 1774–1790.

NMFS and FWS, 2013. Leatherback Sea Turtle (Dermochelys Coriacea) 5-Year Review : Summary and Evaluation. White Paper, NOAA, Commerce and Interior.

NOAA, 2001. Endangered and Threatened Wildlife; Sea Turtle Conservation Requirements; Taking of Threatened or Endangered Species Incidental to Commercial Fishing Operations, Vol. 66. FR 44549.

NOAA, 2004. Fisheries Off West Coast States and in the Western Pacific; Western Pacific Pelagic Fisheries; Pelagic Longline Fishing Restrictions, Seasonal Area Closure, Limit on Swordfish Fishing Effort, Gear Restrictions, and Other Sea Turtle Take Mitigation Measures, Vol. 69. FR 17329.

NOAA, 2012. Endangered and Threatened Species: Final Rule to Revise the Critical Habitat Designation for the Endangered Leatherback Sea Turtle, Vol. 77. FR 4169.

Northridge, S., 2018. Bycatch. In: Würsig, B., Thewissen, J.G.M., Kovacs, K.M. (Eds.), Encyclopedia of Marine Mammals, third ed. Academic Press, pp. 149–151.

Nøstbakken, L., Conrad, J.M., 2007. Uncertainty in bioeconomic modelling. In: Weintraub, A., Romero, C., Bjrndal, T., Epstein, R., Miranda, J. (Eds.), Handbook of Operations Research in Natural Resources. In: International Series In Operations Research, Springer US, Boston, MA, pp. 217–235.

Ojea, E., Loureiro, M.L., 2010. Valuing the recovery of overexploited fish stocks in the context of existence and option values. Mar. Policy 34 (3), 514–521.

Ono, M., Pavone, M., Kuwata, Y., Balaram, J., 2015. Chance-constrained dynamic programming with application to risk-aware robotic space exploration. Auton. Robots 39 (4), 555–571.

Oubraham, A.c., Zaccour, G., 2018. A survey of applications of viability theory to the sustainable exploitation of renewable resources. Ecol. Econom. 145, 346–367.

2019. Swordfish Landings Data. Technical report, Pacific Fisheries Information Network, URL: https://reports.psmfc.org/pacfin/f?p=501:1000:.

Pascoe, S., Innes, J., Holland, D., Fina, M., Thébaud, O., Townsend, R., Sanchirico, J., Arnason, R., Wilcox, C., Hutton, T., 2010. Use of incentive-based management systems to limit bycatch and discarding. Int. Rev. Environ. Resour. Econ. 4 (2), 123–161.

Patrick, W.S., Benaka, L.R., 2013. Estimating the economic impacts of bycatch in U.S. commercial fisheries. Mar. Policy 38, 470–475.

Reed, W.J., 1979. Optimal escapement levels in stochastic and deterministic harvesting models. J. Environ. Econ. Manage. 6 (4), 350–363.

Rougé, C., Mathias, J.-D., Deffuant, G., 2013. Extending the viability theory framework of resilience to uncertain dynamics, and application to lake eutrophication. Ecol. Indic. 29, 420–433.

Schoener, T.W., 1973. Population growth regulated by intraspecific competition for energy or time: Some simple representations. Theor. Popul. Biol. 4 (1), 56–84.

Segerson, K., 2011. Policies to reduce stochastic sea turtle bycatch: An economic efficiency analysis. In: Conservation of Pacific Sea Turtles. University of Hawai'i Press, Honolulu.

Shiferaw, M.L., Doty, J.B., Maghlakelidze, G., Morgan, J., Khmaladze, E., Parkadze, O., Donduashvili, M., Wemakoy, E.O., Muyembe, J.-J., Mulumba, L., Malekani, J., Kabamba, J., Kanter, T., Boulanger, L.L., Haile, A., Bekele, A., Bekele, M., Tafese, K., McCollum, A.M., Reynolds, M.G., 2017. Frameworks for preventing, detecting, and controlling zoonotic diseases. Emerg. Infect. Diseases 23 (13).

Smith, M.D., 2012. The new Fisheries economics: Incentives across many margins. Annu. Rev. Resour. Econ. 4 (1), 379–402.

Stavins, R.N., 2003. Experience with market-based environmental policy instruments. In: Mäler, K.-G., Vincent, J.R. (Eds.), Handbook of Environmental Economics. In: Environmental Degradation and Institutional Responses, vol. 1, Elsevier, pp. 355–435.

Stephens, P.A., Sutherland, W.J., Freckleton, R.P., 1999. What is the allee effect? Oikos 87 (1), 185–190.

Sweeney, J.R., 2020. Balancing Goods and Bads: Uncovering the Implicit Price of Fishery Bycatch Using Bayesian Decision Analysis. Working Paper.

Swimmer, Y., Gutierrez, A., Bigelow, K., Barceló, C., Schroeder, B., Keene, K., Shattenkirk, K., Foster, D.G., 2017. Sea turtle bycatch mitigation in U.S. longline Fisheries. Front. Mar. Sci. 4.

Tagami, D., Wang, H., Chang, Y.-J., 2014. Spatial Distribution of Swordfish Catches for longline fisheries in the Western and Central North Pacific and Eastern Ocean. Technical Report ISC/14/BILLWG-1/03, ISC Billfish Working Group, Honolulu, Hawaii, USA..

Viscusi, W.K., Aldy, J.E., 2003. The value of a statistical life: A critical review of market estimates throughout the world. J. Risk Uncertain. 27 (1), 5–76.

Weitzman, M.L., 2002. Landing fees vs harvest quotas with uncertain fish stocks. J. Environ. Econ. Manage. 43 (2), 325–338.

Wilen, J., 2002. Property rights and the texture of rents in Fisheries. In: Evolving Property Rights in Marine Fisheries. Big Sky, Montana, pp. 1–29.

Western Pacific Regional Fishery Management Council, 2004. Pelagic Fisheries of the Western Pacific Region: 2002 Annual Report. Technical Report, Western Pacific Regional Fishery Management Council, Honolulu, Hawaii, USA.