Balancing conservation and commerce

A shadow value viability approach for governing bycatch

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Abstract

The losses from extinction events are not well-known, making an expected net benefits approach to conservation problems difficult to justify. A viable control strategy instead focuses on limiting the risk of extinction to some acceptably low level. Here we extend a recently developed shadow value viability approach for solving conservation problems with irreversible thresholds with dynamic programming. In a social planner context, the method involves identifying the loss from extinction that drives enough conservation effort to ensure survival with a given level of confidence. We demonstrate the method in a numerical application to the Pacific leatherback turtle population, which comingles with the Pacific swordfish fishery. We show how the efficient 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.

Keywords: viable control, dynamic programming methods, shadow valuation, catastrophes, thresholds, bioeconomics, conservation, bycatch, market-based instruments, multi-species fisheries management (JEL codes: C6, Q2, Q5)

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1 Estimating–and avoiding–a loss due to species extinction

Natural resource management in the presence of potential catastrophe presents particular challenges. While the costs of preemptive action are usually understood, 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. Knowing that individuals are willing to pay huge amounts of money to protect a species will not provide us with an answer to "how much?" conservation action is warranted as population levels change or, alternatively, what population abundances we should aim for (Eiswerth and van Kooten, 2009). When eliciting willingness to pay for protection, researchers often make two simplifying assumptions for tractability: (1) each marginal individual animal holds the exact same value or (2) the population value is given by its status classification (e.g., threatened, endangered, etc.) making some marginal animals worthless and others at the transition between classifications hugely valuable.

The non-use value of individuals in a population—tied to a change in the risk of extinction (e.g. Montgomery et al. (1994))—is more nuanced than this. Individuals provide significant extinction risk reduction benefits in small populations, while for large populations, the contribution is smaller. Yet willingness to pay estimates as a continuous function of the population are generally unavailable, and almost nothing is known about the form of the marginal preservation benefit function (Eiswerth and van Kooten, 2009; Ojea and Loureiro, 2010).

A logical alternative in the absence of measured benefits is to avoid extinction with some margin of safety and minimal costs. While the decision maker must choose a level of confidence with which the desired outcome is achieved, Lichtenberg and Zilberman (1988) argue that a margin of safety approach is 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 efficient, *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. Such constraints undermine the Markov property essential to 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. In this paper, we provide theoretical backbone for elements demonstrated numerically by Donovan et al. We then show for the first time how this approach informs market-based instruments that achieve an efficient solution in a system of decentralized resource users.

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 value, Ω, representing the one-time loss from extinction when the endangered species population goes extinct. In a stochastic dynamic programming problem, we solve for the level of Ω that is just large enough to drive sufficient conservation effort to ensure survival with a given level of confidence. This extinction loss informs an expected present loss, $\omega(X)$, i.e. a shadow value of the species population level, which turns out to be 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 Figure 1.

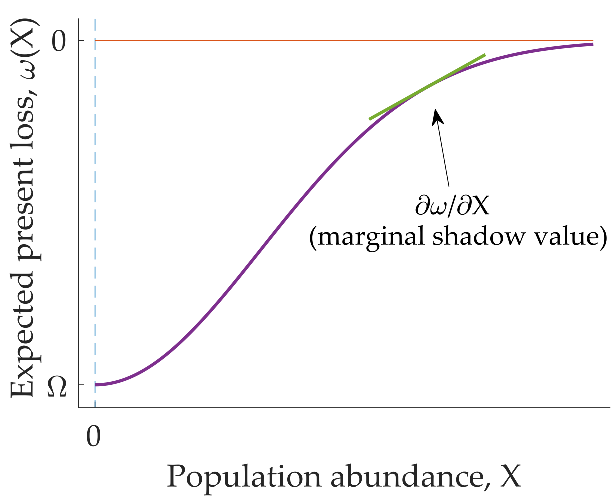

Figure 1: An illustration of the shadow value function, or the expected present loss due to extinction. At extinction ($X = 0$), a hypothetical loss of magnitude Ω is realized. As we move away from extinction and towards higher population abundances (to the right), this loss is discounted both in time and by the likelihood of transitioning closer to extinction at a later period. For ever-higher abundances, the expected present value of the loss, $\omega(X)$, decreases in magnitude.

The SVV structure is relatively simple but powerful. Once inserted into the planner's decision problem, the joint chance constraint barrier is dissolved and standard dynamic programming solution techniques can be used. Then, turning to decentralized management, the shadow value informs the setting of market-based instruments.

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 socially efficient trade-off with commercial fishery rents.

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, ideally at the smallest possible management cost. This probabilistic constraint requires simultaneous consideration of all periods over an extended time frame (e.g. species survival horizon) which undermines reliance on the Markov property on which dynamic programming depends. Such viable control problems were essentially intractable until recent advances presented a way forward (e.g. Donovan et al. (2019)). Here, we explore the results of a relatively simple viable control model for the population of a single vulnerable species and highlight the model's useful features.

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 many periods. We can compactly summarize this statement with a constraint on a survival function $S(t) \in [0,1]$, which gives the probability that failure time T_f is greater than our viability horizon T. This *viability constraint* is

$$S(T) = \Pr\{T_f > T\} \geq \Delta, \tag{1}$$

which requires that our vulnerable species will make it through year T with at least Δ-% likelihood. The pair $\{T, \Delta\}$ reflects a social preference, e.g. as often found in policy language in population management plans. The survival function implicitly relies on the dynamics of the population of vulnerable species X and management policy $A(X)$. In general, an increase in population or a conservation action increases $S(T)$.

Considering many periods complicates the assessment of viability because we are now concerned with limiting the distribution of many (T) joint outcomes. To make this explicit, the viability constraint can be written as a function of the state,

$$S(T) \equiv \Pr\left\{\bigcap_{\tau=t}^{t+T}(X_\tau > 0)\right\} = \Pr\left\{\left(\min_{t\leq\tau\leq t+T} X_\tau\right) > 0\right\} \geq \Delta. \tag{2}$$

This constraint cannot be summarized by simply constraining the likelihood of survival to Δ-% *in each period* (i.e. linearization), because extinction is irreversible. Joint-ness is central to the problem—what happens in some future period only matters if the population survives every earlier period.

A subtle but crucial element of this type of conservation problem is that we are continuallyconcerned with the next T periods into the future on a rolling basis as depicted in Figure 2. If instead the viability horizon did not roll forward with time, by $t + T - 1$ 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.

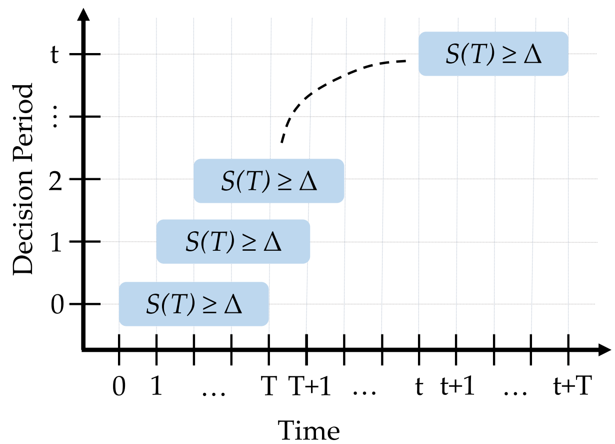

Figure 2: A viability program naturally features a rolling time horizon: at time 0 survivorship is sought for the next T periods (bottom-left shaded box) while knowing that at time 1 survivorship will be sought for time 1 through $T + 1$ (the next shaded box to the northeast), and so on.

Even for the most charismatic megafauna, conservation management efforts will typically be limited by physical, biological, or political constraints. Introducing a bound $\overline{A}$ on management action leads to an object central to viable control: the *viability kernel* (Doyen and De Lara, 2010),

$$\{X\}_k \text{ s.t. } S\left(T \mid \overline{A}, \{X\}_k\right) \geq \Delta. \tag{3}$$

This defines the subset of the state space $\{X\}_k$ in which satisfying the viability constraint is possible (i.e. with maximum effort). The lowest population for which viability is feasible 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* program that can satisfy the viability constraint.

We seek a solution with 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, the opportunity costs and constraints on actions and the preferences given by the viability horizon and confidence.

2.2 Long-term management for viable populations

A meaningful policy in a stochastic world is one that is sensitive to the current state of the world; it is a contingency plan for every possible future we can find ourselves in rather than a pre-determined time-path. State feedback is crucial when the future state cannot be perfectly predicted. A cost-effective solution to the long-run management of viable populations amid competing profit motives can be represented by the fixed-point $V(X_t)$ of the following Bellman equation,

$$
\begin{aligned}
V(X_t) = \max_{A_t} \pi(A_t, X_t) + \beta \cdot \mathbb{E}_\varepsilon \left[V(X_{t+1}) \mid A_t, X_t \right], \quad (4) \\
\text{s.t. } X_{t+1} = G(A_t, X_t, \varepsilon_t) \\
S\left(T \mid A_t, \{X\}_k\right) \geq \Delta,
\end{aligned}
$$

with profits $\pi(\cdot)$, discount factor β, stochastic (ε) population dynamics $G(\cdot)$, and the viability constraint. In a strictly conservation problem $\pi(\cdot)$ might capture management costs in the field (e.g. Donovan et al. (2019)), while in the resource extraction context in this paper it captures profits net of 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 $A(X_t)$ raises $\pi(\cdot)$ at the expense of conservation, though the opposite approach can easily be taken. The optimal policy is denoted $A^*(X_t) = A^*$.

Despite substantial attention to joint chance-constrained problems like Equation 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. Donovan et al. (2019) find a solution to a slightly modified problem using a shadow value approach,

$$
V^{\Omega}(X_t) = \max_{A_t} \left\{ \pi(A_t, X_t) + \beta \cdot \mathbb{E}_\varepsilon \left[V^{\Omega}(X_{t+1}) \mid A_t, X_t \right] \right\}, \quad (5)
$$

$$
\begin{aligned}
\text{s.t. } & X_{t+1} = G(A_t, X_t, \varepsilon_t) && \text{(stochastic dynamics)} \\
& S\left(T \mid A_t, \{X\}_k, \Omega\right) \geq \Delta && \text{(viability)} \\
& V^{\Omega}(0) = \Omega < 0 && \text{(extinction loss)} \\
& \max\{\Omega\} && \text{(minimal motivating loss).}
\end{aligned}
$$

We want to identify the smallest [hypothetical] extinction loss Ω that incentivizes enough management action to satisfy the viability constraint.[1] The new policy $A^{\Omega}(X_t) = A^{\Omega}$ and fixed point $V^{\Omega}(X_t)$ are affixed an Ω to differentiate from the original problem. To inspect how the additional constraint $V^{\Omega}(0) = \Omega$ modifies the value function, we can write out both values explicitly:

$$V(X_t) = \mathbb{E}_{T_f}\left[\sum_{\tau=t}^{t+T_f-1} \beta^{\tau-t} \cdot \pi(A^*, X_\tau) \,\middle|\, X_t\right] \tag{6}$$

and,

$$\begin{aligned} V^{\Omega}(X_t) &= \mathbb{E}_{\varepsilon}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \cdot \left(\pi(A^{\Omega}, X_\tau) \cdot \mathbb{1}(X_\tau > 0) + ((1-\beta)\cdot\Omega)\cdot \mathbb{1}(X_\tau = 0)\right) \,\middle|\, X_t\right] \\ &= \mathbb{E}_{T_f}\left[\sum_{\tau=t}^{t+T_f-1} \beta^{\tau-t} \cdot \pi(A^{\Omega}, X_\tau) \,\middle|\, X_t\right] + \mathbb{E}_{T_f}\left[\sum_{\tau=t+T_f}^{\infty} \beta^{\tau-t} \cdot ((1-\beta)\cdot\Omega) \,\middle|\, A^{\Omega}, X_t\right]. \end{aligned} \tag{7}$$

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

If the two policies A^* and A^{Ω} are identical, we can link Equations 6 and 7,

$$A^{\Omega} = A^* \implies V^{\Omega}(X_t) = V(X_t) + \omega(X_t), \tag{8}$$

where the second summand in the last line of Equation 7 is labeled $\omega(X_t)$. It is helpful to re-write $\omega(X_t)$,

$$\begin{aligned} \omega(X_t) &\equiv \mathbb{E}_{T_f}\left[\sum_{\tau=t+T_f}^{\infty} \beta^{\tau-t} \cdot ((1-\beta)\cdot\Omega) \,\middle|\, A^{\Omega}, X_t\right] \\ &= \Omega \cdot \mathbb{E}_{T_f}\left[\beta^{T_f} \cdot \sum_{u=0}^{\infty} \beta^{u} \cdot (1-\beta) \,\middle|\, A^{\Omega}, X_t\right] \text{ (where } u = \tau - t - T_f) \\ &= \Omega \cdot \mathbb{E}_{T_f}\left[\beta^{T_f} \,\middle|\, A^{\Omega}, X_t\right] \\ &= \Omega \cdot \sum_{\tau=t}^{\infty} \beta^{\tau-t} \cdot \Pr\left(T_f = \tau \mid A^{\Omega}, X_t\right), \end{aligned} \tag{9}$$

where the last line of Equation 9 uses the probability mass function that corresponds to the survival function in Equation 1.

[1] The solution algorithm is described in detail in Appendix A.1.

$\omega(X_t)$ provides the social planner an incentive to avoid degrading population levels, which is sensitive to changes in the current population level.[2] The one-time loss Ω is incurred only at extinction. This propagates to all other states in expected present value form via $\omega(X_t)$, which discounts Ω by both the time to and likelihood of extinction (Figure 1 provides an illustration). This captures how value falls—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 Ω is a negative value and the summation in the last line of Equation 9 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 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 (e.g. if there is some tendency for stocks to decrease ($\mathbb{E}[G(\cdot)] < 0$) at low levels due to critical depensation).

$\partial\omega(X_t)/\partial X_t$ provides us with a shadow value in the usual marginal sense, a marginal social cost of population change that derives from the change in the risk of extinction. The second part 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. 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-

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

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 thus, if of concern to managers, poised to motivate significant constraints on fisheries (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 fisheries 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).[3] 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 wasted 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.[4] 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); Segerson (2011) for application to bycatch and discard management). We do not aim to identify a preferred instrument here but rather demonstrate the usefulness

[3]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).

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

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,[5] 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 forces 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.

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 7,000 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 caused an exodus of fishing vessels, effort, and harvest.[6] 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.[7]

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

[6]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).

[7]Similarly, a future ban on drift nets will come into effect in 2023, effecting a closure of sea surface (Hazen

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). Figure 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

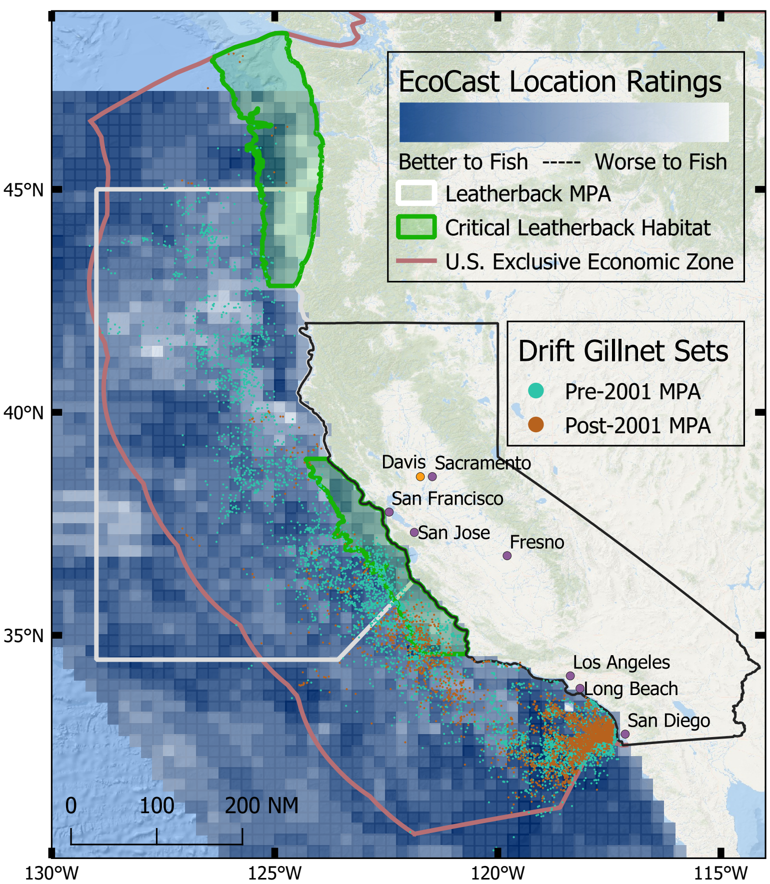

Figure 3: Map of the drift gillnet swordfish fishery. The 2001 PLCA is outlined in white. Coastal areas designated critical for the migration and foraging of turtles are given by the two green sections NOAA (2012). Drift net sets targeting swordfish are given by the aquamarine (1990-2000) and burnt orange (2001-2017) scatters (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.

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et al., 2018). The replacement deepset buoy gear will be used during the day, targeting swordfish around 1200 feet 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.

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 (Figure 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.[8]

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 Hawaiia, 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 Ábrego 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.

[8]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.

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.[9] 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.

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. Fishers 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[10] leatherback bycatch by a representative fishing vessel is modeled as

$$\mathbb{E}\left[B_t | A_t\right] = \theta \cdot \sigma \cdot A_t, \tag{10}$$

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).

The fishery has a limited number of vessel permits and the stock of swordfish is large enough that the representative fisher returns positive rents.[11] The fisher takes the ex-vessel landings price for swordfish as given. Expected seasonal profits per vessel are

$$\pi(A_t) = p \cdot \phi \cdot A_t - \frac{c}{2} \cdot A_t^2, \tag{11}$$

[9] The two American fisheries were the first to implement significant bycatch regulations in the year 2000 (NOAA, 2004; Swimmer et al., 2017).

[10] 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).

[11] 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.

where p is the price of swordfish, ϕ is the expected catch per unit effort (CPUE) of swordfish (mT/day), and c captures the costs of additional 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,

$$X_{t+1} = X_t - M_t - B_t + R_t, \tag{12}$$

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 in Equation 12 embody *demographic* stochasticity, which captures the variability in growth due to a random sampling of potential births and deaths (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). 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 optimal 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. The social planner considers the tradeoff between fishing profits and the valuation of a change in the risk of extinction. The equivalent program to Equation 5 is to solve for the fixed point of the following Bellman equation,

$$V^{\Omega}(X_t) = \max_{A_t} \left\{ N \cdot \pi(A_t) + \beta \cdot \mathbb{E}_{\{M_t, B_t, R_t\}} \left[V^{\Omega}(X_{t+1}) \mid A_t, X_t \right] \right\}, \tag{13}$$

while meeting the shadow extinction loss, viability, and state variable constraints below:

$$\begin{aligned} &X_{t+1} = X_t - M_t - B_t + R_t && \text{(stochastic dynamics)} \\ &S\left(T \mid A_t, \{X\}_k, \Omega\right) \geq \Delta && \text{(viability)} \\ &V^{\Omega}(0) = \Omega < 0 && \text{(extinction loss)} \\ &\max\{\Omega\} && \text{(minimal motivating loss).} \end{aligned}$$

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 outcomes of Problem 13. 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

$$\pi(A_t | P_t) = \pi(A_t) - P(X_t) \cdot \mathbb{E}\left[B_t | A_t\right], \tag{14}$$

where $P(X_t)$ is the dynamic bycatch pricing function set by the regulator.

The resulting first-order condition for the representative fisher's (static) 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

$$P(X_t) = \frac{p \cdot \phi - c \cdot A^P(X_t)}{\theta \cdot \sigma}, \tag{15}$$

The regulator is interested in harmonizing choices under the price instrument and the social optimum: $A^P(X_t) = A^{\Omega}(X_t)$. Substituting the social planner's optimal 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 chooses to implement a total allowable catch for the bycatch species $Q_t = Q(X_t)$, fishers will 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 won't be politically feasible to divide it into a set of individual quotas (Holland and Jannot, 2012; Kauer et al., 2018). Since we aim to dramatically drop the amount of bycatch in the fishery, the following constraint will bind:

$$Q(X_t) = N \cdot \mathbb{E}[B_t | A^Q(X_t)] = N \cdot \theta \cdot \sigma \cdot A^Q(X_t). \tag{16}$$

As for the price instrument, the regulator substitutes the social planner's optimal fisher effort function, $A^Q(X_t) = A^{\Omega}(X_t)$.

While Equation 16 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.[12]

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 An SVV solution for the bycatch problem

4.1 The social planner's optimal 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 Ábrego et al. (2020) (for the eastern pacific population). The SVV approach estimates the smallest loss

[12] 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.

Ω upon extinction that induces sufficient bycatch avoidance effort to meet this goal while minimizing cost to the swordfish fishery. The model yields a Ω estimate of \$118 billion, which is equivalent to an annual perpetuity loss of \$3.5 billion using a 3% discount rate.

The value of Ω propagates to neighboring population states via the shadow value, $\omega(X_t)$, encapsulating stochastic dynamics under the optimal policy and discounting by the time to—and likelihood of—hitting the extinction threshold (Section 2). Losing an additional adult female turtle embodies non-negligible long-run risk even at moderate population levels, with a marginal value of \$40 thousand at an abundance of 1,500. Table 1 provides illustrative values of key variables for low, mid and high population abundances.

Table 1: Key variables under the optimal policy at various population abundances.

Variable	Symbol	X=500	1500	2500
fishing effort (vessel-days)	$A^{\Omega}(X)$	0	9	17
expected bycatch	$\mathbb{E}[B_t \vert A^{\Omega}(X)]$	0	57	108
seasonal profits (\$M)	$\pi(A^{\Omega}(X))$	0	22.5	37.1
shadow value (\$M)	$\omega(X)$	-1100	-68	-47
expected present profits (\$M)	$V(X)$	27	267	522
Present values of an additional turtle				
marginal shadow value [of reduced extinction risk] (\$K)	$\partial\omega(X)/\partial X$	6500	40	14
marginal profit [of relaxed bycatch constraint] (\$K)	$\partial V(X)/\partial X$	99	300	216

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. Including additional margins of adjustment that are less costly than fishing effort—like changing the time 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 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.

Figure 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 Figure 4 is focused on the region where this transition occurs.

The shadow value clearly has an impact on the optimal fishing policy. Imposed on Figure 4 is the permissible level of fishing by the social planner, in vessel-days per fisher.

Approaching the lower extent of the viability kernel (588 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 1,137 leatherbacks.

The bottom sub-figure displays the resultant 100-year probability mass function for leatherbacks, 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 this threshold in the intermediate future. This trade-off between safety and fishing profits leaves the stock largely between 650 and 1,270 turtles, representing two standard deviations centered on the mean.[13] 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 kernel, the likelihood of "dipping below" the lower bound of the viability kernel (at least temporarily) is still quite high; after 100 years, 10% of the probability mass is below this boundary (538 turtles). In this region, the planner imposes a moratorium on fishing, though this is true for higher levels as well.

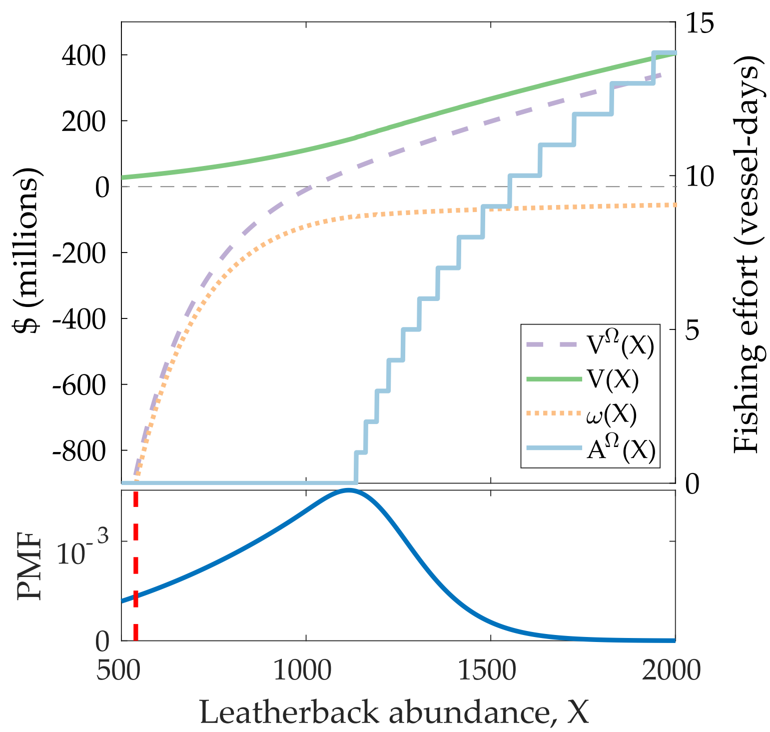

Figure 4: Decomposition of the value function $V^{\Omega}(X)$ (dashed line) into expected present profits $V(X)$ (solid line) and shadow value $\omega(X)$ (dotted line). Optimal fishing effort, $A^{\Omega}(X)$, is plotted using the right axis (step function). The sub-figure shows the resulting probability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

[13] 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 4,000.

This 100-year distribution would call for moratoriums around 60% of the time in the future. This result is a symptom of wanting to extract swordfish rents earlier rather than later, as well as aiming for the "least safe" distribution correspondent to our viability constraint. If it was suddenly easier to avoid bycatch along some other margin, the resulting distribution would hardly improve, while the fishing effort and value function curves would all shift to the left. Intermittent closures are also consistent with the situation in the Hawaiian fishery. Closures occur every year after only 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 (Swimmer et al., 2017).

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 Figure 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. Figure 5 provides an illustration of the two instruments.

The bycatch price of a turtle is high, as it is tethered to the opportunity costs of fishing, which is lucrative.[14] Similar to the discussion in Section 4.1, if additional, cheaper

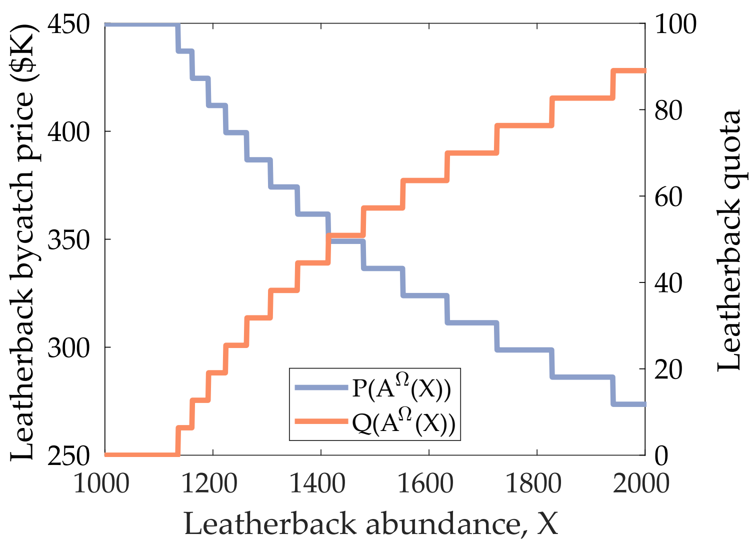

Figure 5: Price (P) and quota (Q) instruments implied by the social planner's optimal policy.

[14]Needless to say, a risk pool would be necessary in order to convince any fisher to participate.

margins for bycatch avoidance are available, then the bycatch price will certainly be adjusted downward. However, considering the amount of effort we see in protecting turtles (Swimmer et al., 2017), high prices are not surprising.

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.

Figure 6 presents a decomposition of the price instrument. We understand intuitively—and formally from Section 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 doesn't need to continue increasing bycatch prices once they're 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.

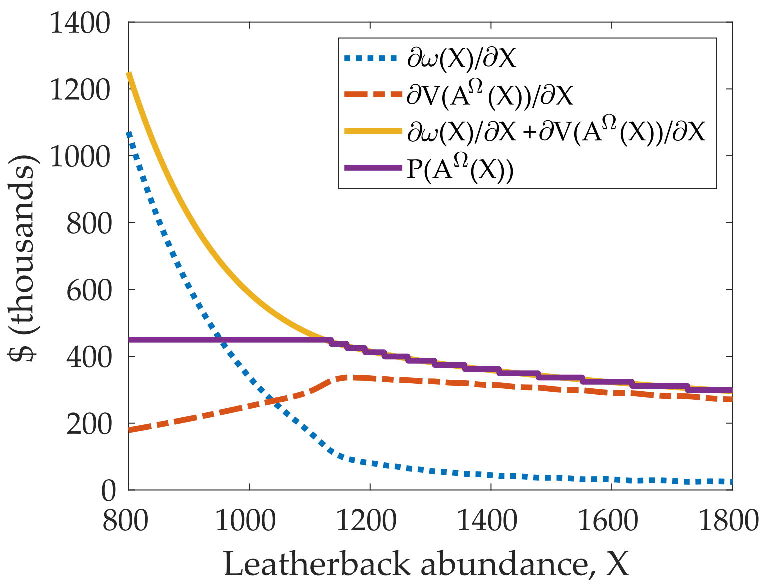

Figure 6: Decomposition of the leatherback bycatch price (step function). As long as the price does not prevent fishers from fishing entirely (below 1,137 leatherbacks), it captures the sum of two effects, the marginal benefit of relaxing regulation in the future (dot-dashed line) and the marginal shadow value [of reduced risk of extinction] (dotted line).

5 Discussion

While the real world involves overlapping commercial and conservation concerns, management models typically treat these problems independently. The framework in this paper is the first to identify 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 novel shadow value viability approach. Beyond revealing the socially ideal 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 (e.g. the social cost of carbon). 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 (empowered by the Endangered Species Act) and the opportunity costs of conservation effort within a fishery. This shadow value motivates costly conservation action to avoid increasing prospects of extinction. In contrast, direct valuation methods attempt to justify conservation by accumulating values not directly related to extinction risk.

A population-dependent valuation of the avoidance of extinction is not feasible with revealed preference methods and impractical with revealed 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. 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 to 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.

To build intuition for the SVV approach, in this paper we choose a simple model, pared to essential components. In future research, the setting of real world policy instrument levels (prices or quotas) should consider additional 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 that state variable. However, an evolving level of the target stock will be relevant in many fisheries.

The modeling of viability-style goals has broad applications. 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 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.

References

Abbott, J. K. and Wilen, J. E. (2009). Regulation of fisheries bycatch with common-pool output quotas. *Journal of Environmental Economics and Management*, 57(2):195–204.

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

Arnason, R. (2012). Property Rights in Fisheries: How Much Can Individual Transferable Quotas Accomplish? *Review of Environmental Economics and Policy*, 6(2):217–236.

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

Boyce, J. R. (1996). An Economic Analysis of the Fisheries Bycatch Problem. *Journal of Environmental Economics and Management*, 31(3):314–336.

Brock, W. A., Finnoff, D., Kinzig, A., Pascual, U., Perrings, C., Tschirhart, J., and 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. and van Kooten, G. C. (2001). Harvesting and conserving a species when numbers are low: population viability and gambler's ruin in bioeconomic models. *Ecological Economics*, 37(1):87–100.

Carretta, J. V., Moore, J. E., and 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*.

Connell, J. H. (1983). On the Prevalence and Relative Importance of Interspecific Competition: Evidence from Field Experiments. *The American Naturalist*, 122(5):661–696.

Crocker, T. D. and Tschirhart, J. (1992). Ecosystems, externalities, and economies. *Environmental and Resource Economics*, 2(6):551–567.

Donovan, P., Bair, L. S., Yackulic, C. B., and Springborn, M. R. (2019). Safety in Numbers: Cost-effective Endangered Species Management for Viable Populations. *Land Economics*, 95(3):435–453.

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

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

Haight, R. G. (1995). Comparing extinction risk and economic cost in wildlife conservation planning. *Ecological Applications*, 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., and Lewison, R. L. (2018). A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. *Science Advances*, 4(5):eaar3001.

Holland, D. S. and Jannot, J. E. (2012). Bycatch risk pools for the US West Coast Groundfish Fishery. *Ecological Economics*, 78:132–147.

Hyrenbach, K. D., Forney, K. A., and Dayton, P. K. (2000). Marine protected areas and ocean basin management. *Aquatic Conservation: Marine and Freshwater Ecosystems*, 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., and 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. *Marine Policy*, 64:55–63.

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

Lande, R., Engen, S., and SÆther, B.-E. (2003). *Demographic and environmental stochasticity*. Oxford University Press.

Lande, R., Sæther, B.-E., and Engen, S. (1997). Threshold Harvesting for Sustainability of Fluctuating Resources. *Ecology*, 78(5):1341–1350.

Lent, R. and Squires, D. (2017). Reducing marine mammal bycatch in global fisheries: An economics approach. *Deep Sea Research Part II: Topical Studies in Oceanography*, 140:268–277.

Lichtenberg, E. and Zilberman, D. (1988). Efficient Regulation of Environmental Health Risks. *The Quarterly Journal of Economics*, 103(1):167–178. Publisher: Oxford Academic.

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

Montgomery, C. A., Brown, Gardner M., J., and Adams, D. M. (1994). The Marginal Cost of Species Preservation: The Northern Spotted Owl. *Journal of Environmental Economics and Management*, 26(2):111–128.

Newbold, S. C. and Siikamäki, J. (2009). Prioritizing conservation activities using reserve site selection methods and population viability analysis. *Ecological Applications: A Publication of the Ecological Society of America*, 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., and Kovacs, K. M., editors, *Encyclopedia of Marine Mammals (Third Edition)*, pages 149–151. Academic Press.

Nøstbakken, L. and Conrad, J. M. (2007). Uncertainty in Bioeconomic Modelling. In Weintraub, A., Romero, C., Bjørndal, T., Epstein, R., and Miranda, J., editors, *Handbook Of Operations Research In Natural Resources*, International Series In Operations Research amp; Mana, pages 217–235. Springer US, Boston, MA.

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

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

PacFIN (2019). Swordfish Landings Data.

Pascoe, S., Innes, J., Holland, D., Fina, M., Thébaud, O., Townsend, R., Sanchirico, J., Arnason, R., Wilcox, C., and Hutton, T. (2010). Use of Incentive-Based Management Systems to Limit Bycatch and Discarding. *International Review of Environmental and Resource Economics*, 4(2):123–161. Publisher: Now Publishers, Inc.

Patrick, W. S. and Benaka, L. R. (2013). Estimating the economic impacts of bycatch in U.S. commercial fisheries. *Marine Policy*, 38:470–475.

Reed, W. J. (1979). Optimal escapement levels in stochastic and deterministic harvesting models. *Journal of Environmental Economics and Management*, 6(4):350–363.

Schoener, T. W. (1973). Population growth regulated by intraspecific competition for energy or time: Some simple representations. *Theoretical Population Biology*, 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.

Smith, M. D. (2012). The New Fisheries Economics: Incentives Across Many Margins. *Annual Review of Resource Economics*, 4(1):379–402.

Stephens, P. A., Sutherland, W. J., and Freckleton, R. P. (1999). What Is the Allee Effect? *Oikos*, 87(1):185–190.

Swimmer, Y., Gutierrez, A., Bigelow, K., Barceló, C., Schroeder, B., Keene, K., Shattenkirk, K., and Foster, D. G. (2017). Sea Turtle Bycatch Mitigation in U.S. Longline Fisheries. *Frontiers in Marine Science*, 4. Publisher: Frontiers.

Tagami, D., Wang, H., and 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.

Weitzman, M. L. (2002). Landing Fees vs Harvest Quotas with Uncertain Fish Stocks. *Journal of Environmental Economics and Management*, 43(2):325–338.

Wilen, J. (2002). Property Rights and the Texture of Rents in Fisheries. In *Evolving Property Rights in Marine Fisheries*, pages 1–29, Big Sky, Montana.

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

Ábrego, 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., and The Laúd OPO Network (2020). Enhanced, coordinated conservation efforts required to avoid extinction of critically endangered Eastern Pacific leatherback turtles. *Scientific Reports*, 10(1):4772. Number: 1 Publisher: Nature Publishing Group.

Appendices for "Balancing conservation and commerce"

A.1 A joint-chance constrained dynamic programming algorithm

Here, we'll go through how to solve the dynamic programming problem with a joint-chance constraint, assuming some previous knowledge of dynamic programming. This is partially derived from a more formal algorithm that can be found in the appendix of Donovan et al. (2019). The code for this project can be found at `piercedonovan.github.io`.

1. Define all program parameters (biological, economic, political), functions (cost, harvest responses given a particular policy instrument, state equations), and state/control sets. Initialize the Markov transition matrix, which will depend on several of these.

2. We need to document the state space where it is possible to satisfy the viability constraint, because we will only look for an optimal policy when it is feasible. Identify the viability kernel by finding the likelihood of extinction over the designated horizon, conditional on starting state, given the maximum possible management action.

3. Guess a value for Ω, and solve the dynamic program (Equation 5) given this value. During value function iteration (Judd, 1998), "refresh" the value $V(X = 0) = \Omega$ after each application of the Bellman equation. This allows the loss to propagate from the extinction state to neighboring states.

4. Check if each state in the viability kernel satisfies the viability constraint given the optimal policy under Ω. If this is not the case, increase Ω and retry (otherwise, decrease Ω and look for a "cheaper" solution). The choice of search algorithm is not consequential [in our case].

A.2 Parameter 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 Equation 11, using an average effort of 35 days/vessel. This ensures seasonal catch per vessel ($30mT$), fleet catch ($3,000mT$) 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 Ábrego 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.

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

Parameter	Value	Description and Source*
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 survival (Jones et al., 2012)
η_R	0.03	demographic heterogeneity in recruitment (Ábrego et al., 2020)
η_M	0.03	demographic heterogeneity in mortality (assumed same as recruitment)
m_1	0.75	1^{st}-year natural mortality (Jones et al., 2012)
m	0.20	> 1^{st}-year natural mortality (Jones et al., 2012)
a	15	years to maturity (after 1^{st}) (Jones et al., 2012)
K	75000	intraspecific competition parameter (NMFS and FWS, 2013)

*Some values have been transformed from other units used in the source material.

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 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).[1] 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: 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 $\mathbb{E}[B_t \mid A_t]$ 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

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:

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

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

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 1$^{\text{st}}$-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).[2]

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. $\mathbb{E}[R_{t+a}|X_t] \approx \mathbb{E}[R_t]$. 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-

[2]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.

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.

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 (Equation 10) 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

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

which gives around 4,000 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, 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 4,000 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%.