Balancing Conservation and Commerce

A shadow value viability approach for handling bycatch in a multi-species fishery

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Abstract

The benefits from avoiding [irreversible] extinction events are often not well-known, which makes 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 acceptable level. Here I extend a recently developed shadow value viability approach for solving conservation problems with dynamic programming. As a social planner problem, the method involves identifying the loss from extinction that drives enough conservation effort to ensure survival with a given confidence. In my numerical application, the Pacific leatherback turtle population co-mingles with the California drift gillnet swordfish fishery and the risk of bycatch threatens both turtle survival and swordfish revenues. Using the social [fishery] planner's shadow value of leatherback extinction, I set market-based instruments for managing turtle bycatch that incentivize socially-optimal fishing behavior among decentralized fishers. This approach translates the viability objective into economic terms so that conservation and commercial harvest can be rationally integrated.

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

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1 Why *viable* control?

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 are not well-known. This precludes management guided by maximizing expected net benefits.

A logical alternative is to avoid catastrophe with some margin of safety and minimal costs. Unlike expected net benefit maximization, viable control involves limiting disastrous tail events to some acceptable level.[1] Cropper (1976) and Reed (1979) are early examples of work that highlight the trade-off between the risks of future catastrophe and the costs of competing economic values. Montgomery et al. (1994) goes further, asserting that we ought to be *explicitly* choosing some minimum tolerable likelihood of success, specifically in terms of long-run endangered species preservation. This line of thinking—that attention to catastrophe is paramount—was initially expressed by Roy (1952), who first vouched for safety-driven strategies in portfolio theory the same year when Markowitz's Nobel-famous *Portfolio Selection* accomplished more or less the same thing:

> *"Theory should take account of the often close resemblance between economic life and navigation in poorly charted waters or manoeuvres in a hostile jungle. Decisions taken in practice are less concerned with whether a little more of this or of that will yield the largest net increase in satisfaction than with avoiding known rocks of uncertain position or with deploying forces so that, if there is an ambush round the next corner, total disaster is avoided." – A.D. Roy*

In this paper, I revisit the "viability"-centered approach. Until recently, techniques for efficient, ongoing avoidance of a disastrous threshold have lagged far behind standard net benefit maximization. The difficulty arises from the need for joint-chance constraints that concern outcomes over a number of periods. Such constraints undermine the Markov property essential to typical solution techniques. A new shadow valuation-based dynamic programming method in Donovan et al. (2019) presents the computational framework needed to solve this problem. This paper provides theoretical backbone for elements of Donovan et al. and then shows how the shadow value viability approach informs market-based instruments for a solution in a system of decentralized resource users. These ideas are illustrated in the context of sustainable multi-species fisheries management.

[1] Most things we would like to concern ourselves with are certainly unpredictable in part, but not necessarily in the Knightian sense where it is an insurmountable task to assign some likelihood to disastrous tail events. It is reasonable to think we can both assess risk and limit it to some acceptable level; in many cases our abilities appear to improve with time. This is a manageable world of *known unknowns* (Tarantino, 1994).

In my numerical example, I provide a practical policy solution for the integrated management of the California drift gillnet 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 are static boundaries that can force fishing effort into less bountiful waters and typically 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 incentivizes 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. I provide a framework for doing so that reflects the shadow value of changes in the risk of leatherback extinction.

Viable control allows a decision-maker to proceed in the absence of explicit information on the benefits of taking preemptive action. Instead the focus is on respecting a viability goal that implicitly values the consequences of extinction. This value emerges from solving a stochastic dynamic programming problem and represents a one-time loss from extinction that drives enough conservation effort to ensure survival with a given confidence. The expected present [extinction] loss, conditional on the current state, represents the implicit value of the system moving towards or away from extinction. I use this shadow value to provide guidance for market based policy instruments that balance the risk of vulnerable species extinction with the potential rents of a commercial fishery.

Next I'll outline a theoretical viable control model and some of the insights that come from it. In Section 3 I describe the integrated management problem apparent in the California drift gillnet swordfish fishery and set up the multi-species fishery problem in the viable control framework. I 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, or fossil fuels. 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 involves joint outcomes over an extended time horizon (e.g. continued avoidance of species extinction). Such viable control problems were intractable until recent advances presented a way forward (e.g. Donovan et al. (2019)). Here, I will explore the results of a simple viable control model for the population of a single vulnerable species and tee up several important, desirable features that the model can provide.

2.1 Thinking realistically about species viability

I seek to manage a vulnerable species to meet a conservation goal over an extended time horizon T. Since long-term viability is never guaranteed, this goal often manifests as a constraint on the likelihood of extinction over many periods.[2] We can compactly summarize this statement with a constraint on a survival function $S(t)$, which gives the probability that failure time T_f is greater than our threshold T. This *viability constraint* is

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

I would like to ensure that our vulnerable species makes it to year T with at least Δ-% likelihood. The pair $\{T, \Delta\}$ is informed by policy language given in population management goals. This 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 management action lowers this probability.

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

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

This constraint cannot be summarized by simply constraining the likelihood of survival to Δ-% *in each period* (i.e. linearization), because of the non-convexity of this mathematical

[2] In fact, very long-term viability is impossible. Since populations are ultimately capped above by the carrying capacity, and below by extinction, the result is that random variation in population dynamics will send us towards each of these bounds over time (Bulte and van Kooten, 2001). This prevents us from pursuing any modeling methods that take advantage of a steady-state distribution.

object. 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 point is that in this type of conservation problem we are continually-concerned with the next T periods into the future (even as we implement policy and actual periods pass). 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 conservation objectives.[3] This program, in respecting the viability goal, will endogenously place population levels in a zone safely above extinction; just "how far" will be set by the strength of the stochastic component of the population dynamics and the opportunity costs and constraints on management actions.

Even for the most charismatic megafauna, management efforts will be bounded by physical, biological, or political constraints. Introducing a bound $\overline{A}$ on management action leads to a new 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 state space in which satisfying the viability constraint is possible. The lowest population for which viability is feasible, $\min\{X\}_k = X_k$, will just bind the viability constraint, and any improved states from here will more than satisfy it. Outside of the viability kernel, there is *no* program that can satisfy the viability constraint.

We need a solution that incentivizes action when the situation looks bleak, but also when the population is far from extinction in order to maintain that safety.[4] Next, I'll devise a model that prescribes the cost-effective feedback policy to achieve viability. Stochasticity in the evolution of the vulnerable population will motivate a policy in any state, even in places outside of the kernel because of the risk of reaching a worse state in the future.

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

[3] A feasible but inappropriate approach would be to use simple backwards induction over the finite horizon T. But this approach leads to a time-inconsistent policy: current decisions would be predicated on future planned decisions which would not hold once that future period arrives.

[4] This is an extreme case of the "blocked interval" problem in open-loop control, in which we smooth the intensity of our action over multiple periods to make up for a restriction on our preferred time path.

$V(X_t)$ of the following Bellman equation,

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

with respect to net revenues $\pi(\cdot)$, 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, while in a resource extraction context it might capture profits net of opportunity costs. The population X_t is bounded below by extinction, and the management problem stops if extinction occurs. Action $A(X_t)$ can be cast as one that is favorable to profits or to conservation. The optimal policy is $A^*(X_t) = A^*$.

Despite substantial attention to joint chance-constrained problems like Equation 4 (e.g. Doyen and De Lara (2010); Ono et al. (2015); Alais et al. (2017)), to my knowledge, there is currently no exact solution method. Donovan et al. (2019) find a solution to a slightly modified problem using a shadow value approach,

$$
\begin{aligned}
V^{\Omega}(X_t) = \max_{A_t} \pi(A_t, X_t) + \beta \cdot \mathbb{E}_{\varepsilon}\left[V^{\Omega}(X_{t+1}) \mid A_t, X_t\right] \\
\text{s.t. } V^{\Omega}(0) = \Omega \ \ (\text{where } \Omega < 0),
\end{aligned}
\tag{5}
$$

with the same dynamics and viability constraint as before. I want to identify the smallest [hypothetical] extinction loss Ω that incentivizes enough management action to satisfy the viability constraint.[5] 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:

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

and,

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

[5] A straightforward description of the solution algorithm is available in Appendix A.1.

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 stream of perpetuity losses $(1-\beta)\cdot\Omega$ would kick in. The second definition of $V^{\Omega}(X_t)$ utilizes the fact that extinction is irreversible.

If the two policies A^* and A^{Ω} are identical, the the left term of Equation 7 is the same as Equation 6. The right term of Equation 7, which I'll define $\omega(X_t)$, can be reformed as

$$\begin{aligned}
\omega(X_t) &= \mathbb{E}_{T_f}\left[\sum_{s=t+T_f}^{\infty}\beta^{s-t}\cdot((1-\beta)\cdot\Omega)\,\middle|\,A^{\Omega},X_t\right] \\
&= \Omega\cdot\mathbb{E}_{T_f}\left[\beta^{T_f}\cdot\sum_{u=0}^{\infty}\beta^{u}\cdot(1-\beta)\,\middle|\,A^{\Omega},X_t\right]\ (\text{where } u=s-t-T_f) \\
&= \Omega\cdot\mathbb{E}_{T_f}\left[\beta^{T_f}\,\middle|\,A^{\Omega},X_t\right] \\
&= \Omega\cdot\sum_{s=t}^{\infty}\beta^{s-t}\cdot\Pr\left(T_f=s\mid A^{\Omega},X_t\right). \qquad (8)
\end{aligned}$$

$\omega(X_t)$ is a shadow value that represents the present expected loss from disaster, discounted by both time and the likelihood of extinction. The last line of Equation 8 uses the probability mass function that corresponds to the survival function in Equations 1 and 2.

The one-time loss Ω is incurred only at extinction. This propagates to all other states in present expected value form via $\omega(X_t)$. This function captures how value falls as X_t falls, especially as it nears extinction. Thus $\omega(X_t)$ provides the social planner an incentive to avoid degrading population levels regardless of the current population level. This insight was discovered numerically in Donovan et al. (2019) and first proven analytically here.

$\omega(X_t)$ is always negative, since Ω is a negative value and the summation in the last line of Equation 8 is bounded between 0 and 1. One last formulation of $\omega(X_t)$ (derived in Appendix A.2) provides us some additional insight about its shape,

$$\omega(X_t)=\Omega\cdot\left(1-(1-\beta)\cdot\sum_{s=t}^{\infty}\beta^{s-t}\cdot S\left(s\mid A^{\Omega},X_t\right)\right). \qquad (9)$$

The first two derivatives of Equation 9 with respect to X_t reveal that $\omega(X_t)$ is increasing and, under most conceivable dynamics $g(\cdot)$, concave.[6]

The derivative of $\omega(X_t)$ with respect to the current stock provides us with a shadow

[6] $S(s|X_t)$ can only be concave or 'S'-shaped with respect to X_t, for any s, depending on problem dynamics (e.g. an Allee effect after accounting for policy A^{Ω} can cause the 'S'-shape, but any policy will increasingly favor more protection at lower populations, so this is unlikely). If it is 'S'-shaped for some s there is a possibility for $\omega(X_t)$ to have a convex region for small X_t, but this disappears with heavier discounting.

value in the usual marginal sense, a marginal social cost of population change that derives from the change in the risk of extinction. A derivative of the other part of $V^{\Omega}(X_t)$, $V(X_t)$, 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 today's economic benefits. I will show in the next section how these pressures—that have motivated the optimal strategy A^{Ω}—can further motivate market-based instruments for a vulnerable bycatch stock that efficiently achieves a viability goal in a decentralized fisher-regulator setting.

3 Multi-species fisheries management

In recent years, academic guidance for fisheries management has become more holistic, incorporating many of the unregulated dimensions of fisheries management into rights-based schemes (Smith, 2012). Chiefly important to the present work 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 gathered by the implementation of market-based instruments.

Adjusting the scope of system components considered can generate different policy prescriptions. Economists and ecologists alike have just begun to understand the ways in which inter-species interactions affect the health and profitability of a whole fishery, and 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 I focus on the final case, specifically the presence of "choke stocks" that are highly vulnerable and thus, if of concern to managers, poised to introduce significant constraints to fisheries (Patrick and Benaka, 2013).

Bycatch is the unintended [but not unexpected] capture of 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, but common tactics like marine protected areas (MPAs) and mandatory gear requirements do not incentivize the avoidance of bycatch by fishers (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).[7] Gear that reduces bycatch is rarely a least-cost solution either, because the fleet is heterogeneous in ability to adapt (Wilen, 2002).

Market-based incentive schemes, on the other hand, are a significant refinement to bycatch management as they directly address undesirable fishing behavior (given sufficient observer coverage) (Arnason, 2012). They provide the opportunity for fishers to flexibly choose from a number of possible dimensions of bycatch avoidance, which then allows for protection for a bycatch species while minimizing the opportunity costs of bycatch avoidance efforts. This aligns with the requirements under the Magnuson-Stevens act.

This paper considers the case where bycatch is rare but very damaging. 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). 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, prices impose explicit costs of bycatch on the fishing fleet.[8] Each of these instruments will lead to a different organization of the fishing fleet's effort, which introduces an extension of the "prices versus quantities" discussion (Weitzman, 1974), couched within the integration of commercial and conservation objectives.

Most work concerning bycatch and market-bases instruments simply assumes that the level of the instrument (bycatch quota or price) is given,[9] 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, I detail how to set market-based instruments for bycatch linked to changes in the risk of extinction, instead of taking them as given.

3.1 Swordfish and Turtles

For two thousand years, swordfish off the coast of California and Oregon were fished with harpoons, a practice that took advantage of the short "basking" sessions swordfish tend to have after long periods at great depth (Davenport et al., 1993). Even the modern commercial fishery was largely committed to harpooning until the 1970's when California

[7] 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).

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

[9] This of course makes good sense when devising a *descriptive* model, e.g. Abbott and Wilen (2009).

began allowing the use of drift nets. While significantly cheaper and less labor-intensive, these large nets (on average around 500 meters) capture non-targeted species, and as much as 60% of catch may be discarded at sea (NMFS, 2010). These nets are set in shallow pelagic waters overnight, a time when many species spend time near the surface.[10]

The most salient bycatch species is the critically endangered leatherback turtle. These large (up to 500 kg) creatures regularly endure 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 in order to forage on plentiful populations of jellyfish. This feast is necessary for keeping jellyfish populations in check, which themselves feed on the larval stages of several commercially-valuable fish species (NMFS and FWS, 2013).

Leatherback turtle bycatch avoidance focuses on take of females since their numbers are the key limiting factor in reproduction. The incidental take of a mature female during this feeding period can have devastating 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). The time spent off the coast of California is a crucial stage in a mother's life cycle.

Regulatory measures motivated by fisher interactions with leatherback turtles and other vulnerable species pose large costs to the valuable swordfish fishery. In 2001, 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 first 4 months of the August-January fishing season (NOAA, 2001).[11] Before the PLCA was put into place, the fishery is estimated to have taken up to 25 or so adult female turtles in a season (Carretta et al., 2019). There are an estimated 2600 adult females that are feeding off the coast of California and Oregon each year; thus the closure is currently only directly improving their numbers by at most 1% per year (Jones et al., 2012). In protecting so few leatherbacks, a potentially valuable fishery has been almost entirely eliminated.

The PLCA is thought to be the main reason for an exodus of fishing vessels, effort, and harvest.[12] Most of the potential value from the swordfish fishery is left unexploited in the

[10] A 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 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). Such a ban imposes additional unnecessary fishing costs if drift net usage can be used to selectively target swordfish.

[11] Additionally, swordfish longlining is prohibited, acoustic pingers are required on all drift nets to deter bycatch, and a loggerhead turtle closure area activates during El Niño years (NMFS, 2010; Hazen et al., 2018).

[12] In the last 30 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).

ocean, and its stock is thought to be healthy and under-exploited (NMFS, 2010). In fact, even at its peak, the small drift gillnet fishery did not appear to have a substantial effect on the swordfish stock, catching only 2000 fish, or around 1000 metric tons with an ex-vessel value of $7 million in 1993 (PacFIN, 2019). Figure 1 provides a map of the fishery that shows the shift in fishing locations and decrease in activity as a result of the PLCA.

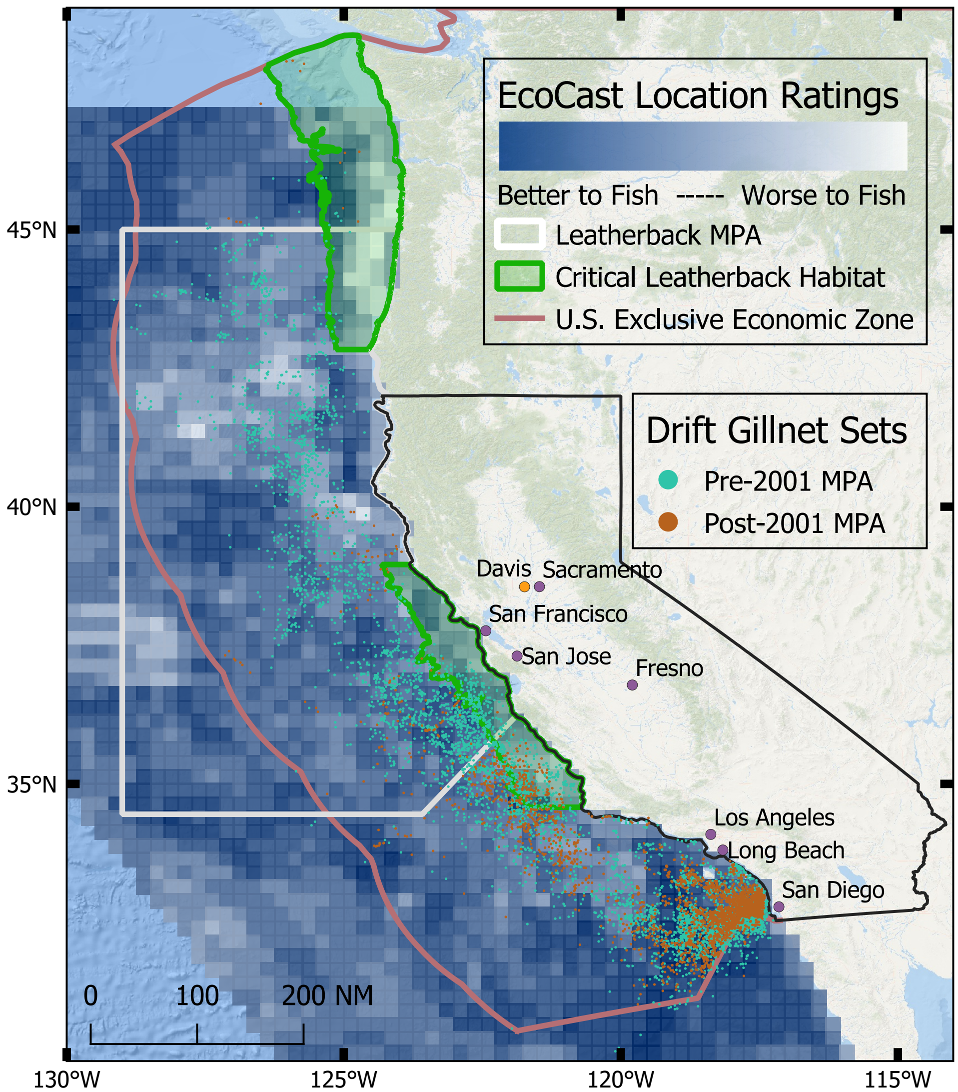

Figure 1: Map of the swordfish drift gillnet fishery. The 2001 Pacific Leatherback Conservation Area (PLCA) is outlined in white. Coastal areas designated critical for the migration and foraging of turtles are given by the two green sections NOAA (2012). Drift net sets targeting swordfish are given by 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 operationalized by the blue-to-white pixels, which designate favorable-to-unfavorable fishing locations. Notably, only a small region of the PLCA is unfavorable with respect to turtle bycatch in a given day.

Scientists have called for a more dynamic management strategy that allows for fisher adjustments in space and time as new biological data becomes available, in order to ensure the protection of ranging pelagic species (Hyrenbach et al., 2000; Hazen et al., 2018). A new resource being shared with fishers called EcoCast provides predictions of where commercial and protected populations are most likely to be, using the correlations between remote sensing data (e.g. temperature, currents, light penetration, productivity, and food availability) and tracking information for swordfish and leatherback turtles (Hazen et al., 2018). The output produced is a map designating areas that are worse (low swordfish or high bycatch) or better (high swordfish, low bycatch) for fishing (see Figure 1 for an example of this index). Hazen et al. (2018) estimate that if their recommended 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.

The availability of new, valuable informational products like EcoCast provide additional motivation for implementing market-based instruments. Under the current regulatory regime there is little incentive to adopt it. Alternatively, when facing a price or hard cap for bycatch, fishers would have a compelling reason to use such a product as a low-cost way of avoiding the leatherbacks. A market-based bycatch management policy is a plausible way of opening up the PLCA while incentivizing avoidance of bycatch through adjustments on many margins, including the use of innovations like EcoCast.[13]

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 rationalize the management of the multi-species drift gillnet fishery. The focus below is on showing how the each instrument can be determined endogenously.

3.2 Fisher incentives

Each season, fishers must decide how much effort to put into fishing for swordfish and how much effort to put into avoiding leatherback turtle bycatch. A simple, stylized way to capture both of these choices is to assume fishers will fish a fixed number of days and have captains choose their average daily swordfish catch (Abbott and Wilen, 2009).[14] Importantly, fishing is assumed to be monitored to avoid the potential for discards. For a given level of fishing effort (A_t), female turtle stock (X_t) and share of the stock not nesting

[13] 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.

[14] Swordfish fishers have historically opted to fish a small number of days and then shift to some outside option (NMFS, 2010). This outside option will determine the opportunity cost of an additional day of fishing, but this dimension of behavior is not immediately necessary to demonstrate the model.

$(1-\sigma)$, the expected amount of [daily, female] bycatch by the fleet is modeled as

$$\mathbb{E}\left[B_t|A_t, X_t\right] = \alpha \cdot A_t^{\rho} \cdot \left((1-\sigma)\cdot X_t\right)^{\theta}. \tag{10}$$

I estimate Equation 10 using a Poisson regression of bycatch events on the number of drift gillnet sets deployed per vessel-day and estimates of leatherback abundances proximate to the fishery, during years before the PLCA closure. Estimation yields $\rho > 1$, so marginal bycatch is increasing with increasing fishing effort. Appendix A.3 provides parameter descriptions, values, sources, and estimation details.

The fishery is small and takes the ex-vessel landings price for swordfish as given. I simplify the fleet's activity with a single representative fisher that fishes each vessel-day. At the beginning of the season, the fisher chooses the average number of sets to deploy per day throughout the season. Expected seasonal revenues given set pressure A_t are

$$\mu(A_t) = p_S \cdot \phi \cdot N_d \cdot A_t, \tag{11}$$

where p_S is the price of swordfish, ϕ is the expected catch of swordfish per set in metric tons, and N_d is the number of vessel-days when fishing takes place. 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). There is no limit on swordfish harvest, and fishers do not have a significant effect on the abundance of swordfish, thus swordfish levels are not explicitly modeled for simplicity.[15]

In the beginning of each period, the regulator sets a bycatch price or a total allowable catch for bycatch; each instrument will have a different impact on the fisher's expected revenues. These instruments are set with respect to anticipated fishing activity and a current stock estimate. I will first discuss the population dynamics informing the latter.

3.3 Leatherback turtle dynamics

While the fishers concern themselves with one season at a time, the leatherback population dynamics tie these decisions together. The change in the population of adult female leatherbacks is determined by a series of stochastic shocks,

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

[15] I do expect that some of these assumptions would need to be relaxed over a longer period of time, because if the PLCA was actually removed, it is possible that a large number of vessels of differing capacity would enter the fishery.

where M_t, B_t, R_t are Poisson-distributed shocks regarding outside-fishery mortality, bycatch in the swordfish fishery, and recruitment from younger age-classes, respectively. Their distributions depend on the population X_t, and the harvest shock is additionally affected by fishing effort A_t, as seen at the beginning of this section.

These dynamics incorporate the idea of *demographic stochasticity*, which captures the variability in growth due to the sampling from a distribution of possible 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). Demographic stochasticity is often ignored in the bioeconomics literature in favor of *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). A full explanation and derivation of the leatherback dynamics along with some additional background and insight is found in Appendix A.4.

3.4 Regulating fisher behavior for viability

A social planner wants to maximize the expected revenues 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} that they would like to see in the fishery since in this model changing commercial harvesting effort is also the sole lever for influencing bycatch. The desire for fishing revenues will compete against the social planner's 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,

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

while meeting the shadow extinction value, viability, and state variable constraints below.

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

The regulator, in attempting to manage a number of 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.

3.4.1 Setting a bycatch price

When facing a price on bycatch, expected seasonal revenues of the fishing fleet as a function of fishing effort (sets/vessel-day) is given by

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

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

The resulting first order condition tells us about the relationship between the bycatch price and optimal fishing effort given that price, $A(X_t|P_t)$,

$$P(X_t) = \frac{\partial \mu(A_t)}{\partial A_t}\Big|_{A(X_t|P_t)} \Big/ \left(N_d \cdot \frac{\partial \mathbb{E}[B_t|A_t, X_t]}{\partial A_t}\Big|_{A(X_t|P_t)}\right). \tag{15}$$

The fleet will fish until the marginal revenue per expected turtle caught is equal to the landings price. Using our particular functional form, we can write effort as

$$A(X_t|P_t) = \left(\frac{p_S \cdot \phi}{\alpha \cdot \rho} \cdot \frac{1}{P(X_t) \cdot ((1-\sigma) \cdot X_t)^{\theta}}\right)^{\frac{1}{\rho-1}}, \tag{16}$$

and by inspection, this has all of the predictable comparative statics we may expect, e.g. decreasing in bycatch price and bycatch stock, all else equal.

The regulator is interesting in making sure $A(X_t|P_t) = A^{\Omega}$. Inverting Equation 16 provides a formula for this instrument that reflects the social planner's shadow value of leatherback extinction via the optimal policy function A^{Ω}.

3.4.2 Setting a quota on bycatch

If the regulator instead chooses to implement a total allowable catch for the bycatch species, fishers will now consider how their actions affect the expected season length over which they are allowed to fish. Because bycatch events are Poisson-distributed, the time to Q_t events is Erlang-distributed with mean

$$\mathbb{E}\left[N|A_t, X_t, Q_t\right] = \frac{Q(X_t)}{\mathbb{E}\left[B_t|A_t, X_t\right]}. \tag{17}$$

Equation 17 gives us the expected number of days spent fishing in the season as a function of a given total allowable catch Q_t and the expected amount of bycatch per day.

This provides us with a different revenue function than Equation 14,

$$\mathbb{E}\left[\pi(A_t)|X_t,Q_t\right] = \frac{\mu(A)}{N_d}\cdot\mathbb{E}\left[N|A_t,X_t,Q_t\right]. \tag{18}$$

In our case, ever-decreasing fishing effort will always raise revenues through infinitely-long seasons with infinitesimal bycatch risk. Since the season is at most open for N_d vessel-days, a maximizer of expected revenues will choose to reduce their fishing effort to the point where $\mathbb{E}[N|A_t,X_t,Q_t] = N_d$. This edge case leads us to the simple condition that the regulator should set their quota equal to the social planner's expected seasonal bycatch,

$$Q(X_t) = \left\lfloor N_d\cdot\mathbb{E}\left[B_t|A^{\Omega},X_t\right]\right\rfloor. \tag{19}$$

In the case of a non-integer expected harvest, which is likely, violating a non-integer total allowable catch is no different than harvesting beyond the greatest integer below the expectation. In my application the quota will be set after applying the floor function to the social planner's expected harvest.

In our particular case, we can write effort conditional on this quota as

$$A(X_t|Q_t) = \left(\frac{Q(X_t)}{\alpha\cdot N_d\cdot((1-\sigma)\cdot X_t)^{\theta}}\right)^{\frac{1}{\rho}}, \tag{20}$$

which will be more conservative than A^{Ω} because of the rounding above. Rounding also introduces another quirk, effort actually *decreases* with increasing populations for a given cap, this is because leatherback interactions become more likely with higher numbers.

3.4.3 Prices vs. quantities

The stochastic nature of bycatch in this setting interacts with prices and quotas in an interesting way. Both promote caution; prices directly encourage the avoidance of turtles, and quotas directly encourage the avoidance of fishery closures. Without discussion, it isn't all that obvious which management regime is more cautious (or more profitable).

In a bad year for bycatch, a closure cuts off revenues in favor of a better future state for the leatherbacks, while a higher bycatch bill under the price instrument enables more degradation (and fishing revenues). In a good year with no closure, the quantity instrument encourages lower fishing effort than a bycatch price (due to the rounding above) and therefore brings in less fishing revenue, but these revenues might be higher once we account for any bycatch fees incurred with the price instrument.

The deviations under the bycatch quota from outcomes under the price instrument lead to socially-inefficient levels of commercial harvest and bycatch avoidance effort. This is because the price instrument affords more within-season flexibility between good and bad seasons and is able to track the social planner's expected outcomes exactly. Prices do introduce more uncertainty in total bycatch relative to a hard cap, but this increased variance is precisely the amount tolerated in the socially optimal case. Especially when the regulator seeks low limits on stochastic outcomes, prices would be expected to trump quantities in achieving the desired level of viability with less opportunity cost in terms of forgone commercial revenues.[16]

Next I 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 solution for the California drift gillnet fishery

4.1 Avoiding extinction

The social planner wishes to avoid extinction, an irreversible threshold at $X = 0$, with 90% likelihood over the next 20 years. These latter values are arbitrary, but reflect a typical planning horizon and confidence seen in listings under the Endangered Species Act. The shadow value viability approach estimates the smallest loss Ω upon extinction such that this goal can be met at minimal cost to the California drift gillnet swordfish fishery.

The model yields an estimated Ω of \$2.26 billion. A discount factor of $\beta = 0.97$ implies an equivalent perpetuity of \$67.8 million per year, which is far above the maximum annual ex-vessel revenues from the fishery (\$9.2 million). This loss propagates to neighboring population states via stochastic dynamics under the optimal policy, providing a function $\omega(X)$ that discounts Ω in both time to and likelihood of hitting the extinction threshold. Figure 2 illustrates this by decomposing the value function into its two components, $V^{\Omega}(X) = \omega(X) + V(X)$, the present "shadow value" function and present expected revenues, respectively.

For large leatherback populations, the risk of extinction is very low and the value function hugs present expected revenues, $V^{\Omega}(X) \approx V(X)$. At low populations, extinction is very salient and the present shadow value of extinction dominates the value function,

[16] Additionally, a quota can create additional behavioral problems within the fishery. For example, if we move away from the abstraction of a single representative fisher, it becomes evident that an indivisible, common-property bycatch quota induces a race to fish regardless of how swordfish are managed. Even those holding guaranteed swordfish quota will race to exercise them before the fishery closes, ignoring the full effect of their behavior on the length of the fishing season.

$V^{\Omega}(X) \approx \omega(X)$. The domain of Figure 2 is focused in on low levels of leatherback turtles in order to observe this transition.

What are the implications of a shadow value that only becomes substantial at population levels close to extinction? Under the optimal policy, populations will be driven down to near extinction, due perhaps to a misperception of safety. The current biological opinion used to inform the dynamics in this paper assumes an ability for the leatherbacks to recover from very low populations.

Absent turtle bycatch in the swordfish fishery, leatherback dynamics lead to an expected population of around 2700 (near the low end of estimates today (NMFS and FWS, 2013)). But the optimal policy consistent with the model specified above is for the fishery to operate at maximum fishing effort (or no effort to avoid bycatch) over much of the X-domain, down to 120 leatherbacks. This level of activity is expected to take the population from 2700 to 2050 turtles in just 20 years, which shows just how tremendous an effect just one of the many fisheries that interact with the leatherbacks can have on the population.

The model described in Section 3.3 (and detailed in Appendices A.3 and A.4) is consis-

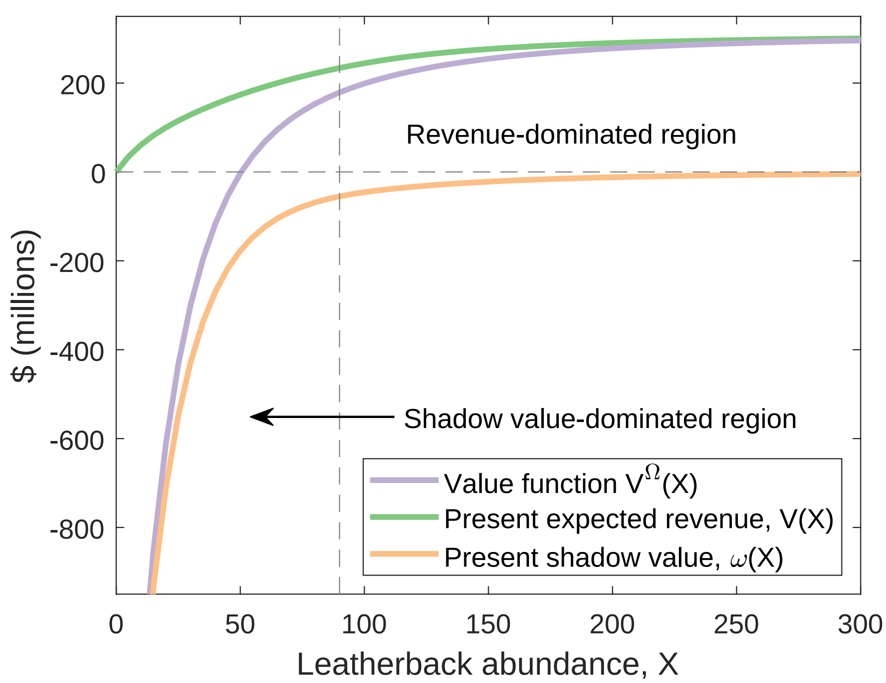

Figure 2: Decomposition of the value function $V^{\Omega}(X)$ (violet) into its constituent parts, the present expected fishing revenues $V(X)$ (green) and the present shadow value $\omega(X)$ (orange). Only for very low populations does the shadow value begin to bite. The vertical line delineates the region where the change in extinction risk becomes a more salient motivator (via $\omega'(X)$) for reducing fishing effort than the prospect of decreased revenues from reducing effort in the future (via $V'(X)$).

tent with historical observations and recent scientific study of leatherback turtles. However, results from this baseline model do not appear to be concordant with the management concerns of biologists. The optimal policy allows turtle numbers to decline precipitously, albeit not all the way to extinction, while still maintaining viability. The reason for this is that, under the model, the leatherback population is still relatively stable even at very low levels of a couple hundred turtles.

Allowing for such low numbers would be disastrous in the estimation of biologists. One explanation for this apparent contradiction is the need for modeling "out of sample" turtle dynamics that explain how the population is likely to behave at levels far below current observations. Though the model incorporates population dynamics believed to be important at low population levels (e.g. demographic stochasticity), it is possible that the model is too optimistic about population viability at low levels.

The long run solution to this contradiction is deeper examination of low-population dynamics in such species, for example the potential for Allee effects and evolving non-bycatch mortality risk due to climate and environmental change. Many modeling options exist for incorporating uncertainty in the parameterization of dynamic systems,[17] but most require more biological information than is presently known.

For the present analysis I will consider a simple alternative that respects a potential for less-favorable survival conditions by setting a higher population threshold, specifically at the bottom limit for which ecologists are comfortable extrapolating the current understanding of leatherback dynamics.

4.2 An alternative threshold

Here I consider a manager concerned with falling below a higher threshold, $\overline{X} = 2000$. This will be incentivized in the solution by a new level for Ω, that again is incurred at $X = 0$. Below $\overline{X}$, we are in violation of our viability constraint. Unlike a quasi-extinction threshold (see Donovan et al. (2019)) this new threshold can be crossed without implying extinction. This threshold is about 20% lower than the most pessimistic current population estimate (NMFS and FWS, 2013; Hazen et al., 2018).

Despite the reversibility of crossing $\overline{X}$, the shadow value from the new solution makes this prohibitively costly. Under the optimal policy, the likelihood of being below the

[17] For example, provided a credible distribution for an uncertain parameter, the shadow value viability algorithm can be adjusted to accommodate expectations of future values over this distribution (e.g. Donovan et al. (2019) consider a manager that receives new ecological information over time). Another solution would be to use the maximin approach from robust optimization, which focuses on maximizing revenues conditional on the worst plausible set of dynamic equations.

Table 1: Outcomes under the optimal policy with the modified threshold $\overline{X}$, conditional on a starting population of 2700 leatherbacks (the expected population under the PLCA). The population distribution stabilizes after 100 years. The last column provides comparative values at $\overline{X}$.

System Outcomes		$t = 0$	20	100	$X_t = \overline{X}$
expected population	$\mathbb{E}[X_t]$	2700	2420	2280	2000
standard deviation	$\sigma[X_t]$	-	90	130	-
sets/vessel-day	$A(X_t)$	1.62	1.20	0.87	0.18
expected bycatch	$\mathbb{E}[B_t \mid A_t, X_t]$	23.3	8.5	3.0	0.02
seasonal revenue ($M)	$\mu(A_t)$	7.5	5.5	4.0	0.8
value function ($M)	$V^{\Omega}(X_t)$	166	127	86	-780
present expected revenue ($M)	$V(X_t)$	180	150	127	60
present shadow value ($M)	$\omega(X_t)$	-14	-23	-41	-840

threshold after $T = 20$ years is a rare tail event ($S(T) \geq 90\%$) for initial states in the viability kernel ($X \geq X_k = 2100$). While $\overline{X}$ can be breached temporarily, this entails a stark increase in shadow value for the social planner; $\omega(\overline{X}) = -\$840$ million, a whole 14 times greater than present expected revenues at the same population (see Table 1).

Table 1 provides information on key outcomes at different time horizons under the optimal policy. Assuming a starting population of 2700 leatherbacks (the expected population with current dynamics under the near-moratorium caused by the PLCA), the population approaches a distribution centered on 2280 individuals, 15% higher than $\overline{X}$ (and in significantly better shape than under the extinction threshold). Optimal fishing effort at this level resembles the state of the fishery at its peak just before the PLCA. Expected bycatch, however, is much lower than in the past due to declines in leatherback numbers over the past 20 years. These bycatch levels are [reassuringly] similar to the hard-caps considered (but ultimately rejected) by NOAA (2016). Expected seasonal ex-vessel revenues are \$4 million, nearly 5 times greater than the present post-PLCA level (PacFIN, 2019). This produces a revenue stream with present expected value of \$127 million. At 2280 turtles, the present shadow value sits at about one-third of this valuation.

Figure 3 provides a decomposition of the value function with respect to the modified threshold. Below approximately 2300 leatherbacks, the shadow value has more bite relative to the prospect of decreased revenues in the future from constrained fishing effort. Above this value, the prospect of future lost revenues from further constraints on fishing increasingly necessary at lower leatherback populations motivates conservation more strongly than the the viability shadow value.

The shadow value clearly has an impact on the policy function. Imposed on Figure 3

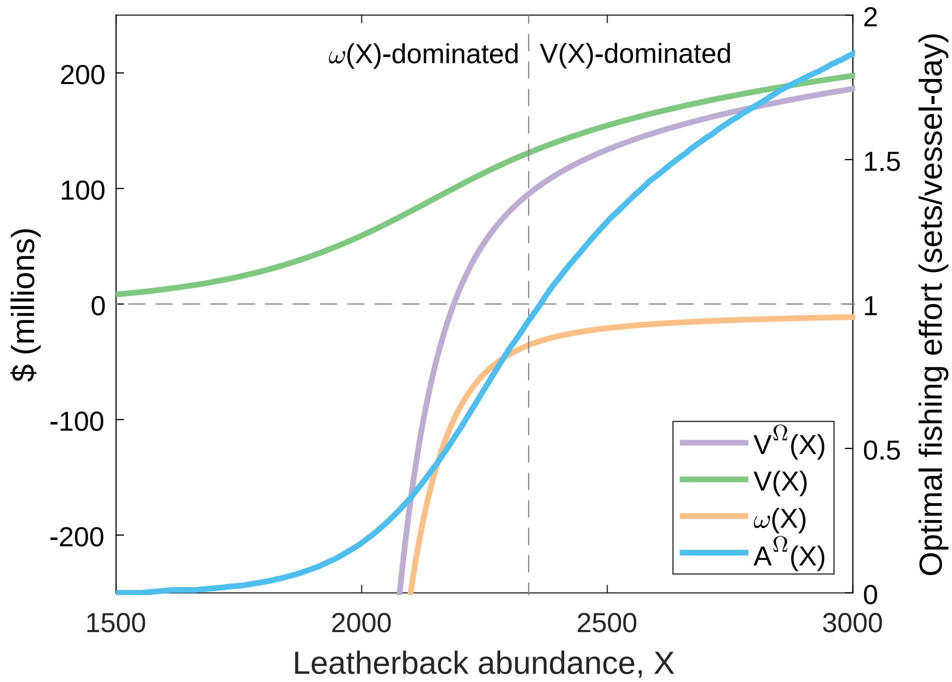

Figure 3: Like before, the value function $V^{\Omega}(X)$ (violet) is decomposed into present expected fishing revenues $V(X)$ (green) and present shadow value $\omega(X)$ (orange). Superimposed is the optimal fishing effort $A^{\Omega}(X)$ (blue) prescribed by the shadow value viability program.

is the optimal policy function of the social planner, in sets per vessel-day. Approaching the threshold from above leads to a larger shadow value in concert with steep decline in fishery exploitation. Very little effort is being exerted below the threshold in the interest of building up leatherback stocks to an expected abundance of 2280 (standard deviation of 130). The social planner opts for an outright fishing moratorium below 1500 leatherbacks.

The next section explores how the social planner's actions numerically map into the regulation of decentralized fishers.

4.3 From shadow values to market-based instruments

Table 2 provides some important comparisons of key outcomes under each of the policy instruments. First, note that higher populations are preferred under the quantity instrument. This is due to the regulator implementing a moratorium when the social planner's expected bycatch falls below 1 turtle (at a population of roughly 2200 leatherbacks). The right panel of Figure 4 further illustrates how the risk of falling to degraded levels and requiring a moratorium affects the present expected revenues under the quantity instrument. Another consequence of the setting of integer quota is that fishing effort will

Table 2: Comparison of key outcomes under each of the two instruments.

Price Instrument		$t = 0$	20	100	$X_t = \overline{X}$
expected population	$\mathbb{E}[X_t]$	2700	2420	2280	2000
price ($K)	$P(X_t)$	107	218	440	8600
sets/vessel-day	$A(X_t\|P_t)$	1.62	1.20	0.87	0.18
expected bycatch	$\mathbb{E}[B_t\|A_t, X_t]$	23.3	8.5	3.0	0.02
seasonal revenue ($M)	$\mu(A_t)$	7.5	5.5	4.0	0.8
seasonal bycatch costs ($M)	$P(X_t) \cdot \mathbb{E}[B_t\|A_t, X_t]$	2.5	1.9	1.3	0.2
present expected revenue ($M)	$V(X_t\|P_t)$	180	150	127	60
present bycatch costs ($M)	$C(X_t\|P_t)$	60	52	45	22

Quantity Instrument		$t = 0$	20	100	$X_t = \overline{X}$
expected population	$\mathbb{E}[X_t]$	2700	2460	2325	2000
quota (equals expected bycatch)	$Q(X_t)$	23	8	3	0
sets/vessel-day	$A(X_t\|Q_t)$	1.61	1.26	0.95	0
seasonal revenue ($M)	$\mu(A_t)$	7.2	5.2	4.3	0
present expected revenue ($M)	$V(X_t\|Q_t)$	173	144	118	31

be weakly lower for a given population and therefore bring in less revenues within season. The regulator mitigates these effects by maintaining healthier populations in order to more safely harvest swordfish without closure.

Under the bycatch pricing instrument, very large prices on bycatch act as a deterrent to depleting stocks much below 2300 turtles. The direct pecuniary costs of bycatch total one-third of revenues, which is expected given the shadow value/revenue ratio of the social planner seen previously. The bycatch price of a turtle may seem surprisingly high, but this is because the shadow value is estimated relative to the opportunity costs of fishing, which is lucrative.[18] Here, fishing effort is the only margin of adjustment the fisher has to reduce bycatch, a point of departure of the model from the real-world application. If there are truly many margins available that affect bycatch avoidance, some cheaper than others, than the shadow value and thus the bycatch price will certainly be adjusted downward.

The right panel of Figure 4 shows that the two instruments promote similar fishing effort at higher abundances, but diverge once the social planner is expected to catch less than one turtle per year. This is the primary reason present expected revenues are driven apart near the threshold. The jagged pattern in the fishing effort under the quota reflects the stock effect on the likelihood of turtle bycatch.

Prices are markedly worse than quotas for the fisher once present expected bycatch

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

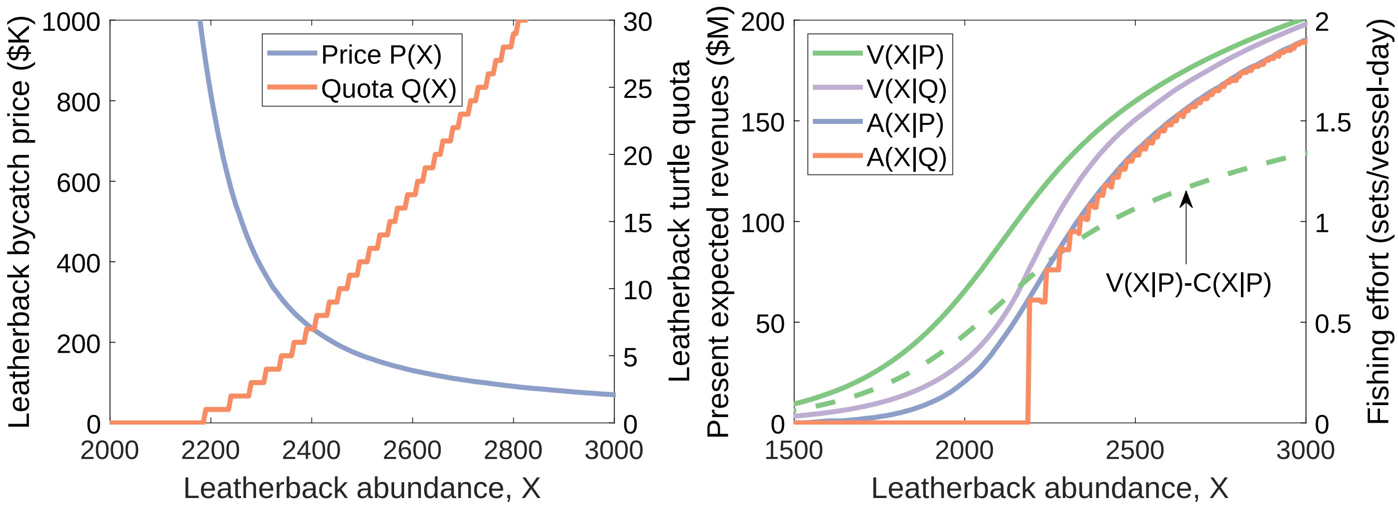

Figure 4: The left panel displays the price and quantity instruments implied by the social planner's optimal policy. The right panel shows how these two instruments influence fishing effort (A) from a representative fisher as well as present expected revenues (V) under each case.

costs are considered, chiefly because the common-pool quota is free. In the long-run expectation (Table 2), we see that the quantity instrument out-performs the price instrument profit-wise by 30%. The point where this relationship flips, around 2200 turtles, is in the tail of the population distribution in response to the quota instrument, i.e. where management rarely takes the system.

While prices do provide flexibility where a moratorium certainly wouldn't, this flexibility comes at too high a cost to be the preferred management choice of the *fisher* without the return of [some of] the landings fees. In considering the benefits from a *social* perspective, the price instrument is still the preferred choice because it provides higher present expected revenues at any population level.

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 an emerging shadow value viability approach. Beyond revealing the ideal social policy, the approach also informs the setting of market-based instruments for attaining the desired result among decentralized resource users.

The use of shadow value viability suggests potential for increased welfare beyond the benefits of species conservation. In the case of integrated management of commercial and conservation objectives in multi-species fisheries, 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.

When are market-based instruments 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. In cases of species with sub-critical populations, like the vaquita porpoise, it may not be politically feasible to use prices or quotas to regulate private actors. On the other hand, "weakened" species, those threatened but not immediately at risk of extinction, could stand to benefit. With sufficient resources and proper management, many of these species would have strong chances of recovery to stable levels that support long-run viability.

Valuation of the benefit in question (avoidance of extinction) is not feasible with stated or 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, which is clearly not constant. While it is certainly feasible to elicit stated preferences 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 marginal shadow value of the vulnerable species population can shift dramatically and non-linearly as the population falls.

Shadow value viability is also a departure from the typical approach that directly values benefits and costs (like the social cost of carbon, for example). Some bycatch species certainly provide additional value beyond that of their existence. They can play essential roles in their ecosystem, serving as predator or prey for other species, or provide greater environmental benefits (Crocker and Tschirhart, 1992; Brock et al., 2009). However, there are two reasons to believe that this route towards valuation is less fruitful than the one suggested presently. First, the vulnerable bycatch species of interest for this type of research are often very low in number, thus the sum total of ecosystem services provided by such a small population is also likely to be small. Second, the valuing of ecosystem services requires significantly more knowledge than is often available (Brock et al., 2009).

The method illustrated here is thus most suitable when explicit benefits of species preservation are difficult to measure. In my numerical application, the implied 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.

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 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, which enables all of these urgent issues to be investigated through an economic lens.

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Appendices for "Balancing Conservation and Commerce"

A.1 Chance-constrained dynamic programming algorithm

Here, I'll go through how to computationally 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) (here). Some of the more technical details can be found there. The code (in Matlab) for this project can be found on my website, here.

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 all of these things.

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 (5) given this value. Mechanically, 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 with this value. If it does, decrease the value and look for a "cheaper" solution. The choice of algorithm is not terribly important as the problem is well-behaved and will pick a single lowest value Ω that satisfies program 5.

A.2 Alternate formulation of the expected present shadow value

Equation 8 does not offer an obvious visualization of $\omega(X_t)$, and we might want to know if it has some properties that are favorable for optimization. Rewriting $\omega(X_t)$ in terms of the survival function $S(t)$ can help us here.

Starting with the form of our desired result (and suppressing A^{Ω}, X_t for simplicity),[1]

$$\begin{aligned}
\sum_{s=0}^{\infty} \beta^i \cdot S(i) &= \sum_{i=0}^{\infty} \beta^i \cdot \Pr(T_f > i) \\
&= \sum_{i=0}^{\infty} \beta^i \cdot \sum_{j=i+1}^{\infty} \Pr(T_f = j) \\
&= \sum_{j=1}^{\infty} \Pr(T_f = j) \cdot \sum_{i=0}^{j-1} \beta^i \\
&= \sum_{j=1}^{\infty} \Pr(T_f = j) \cdot \frac{1-\beta^j}{1-\beta},
\end{aligned}$$

and we can re-write the lower index of the sum to $j = 0$ if $X_t > 0$ because $\Pr(T_f = t) = 0$. Otherwise we know $\omega(X_t) = \Omega$. Rearranging the last line gives us

$$\sum_{j=0}^{\infty} \beta^j \cdot \Pr(T_f = j) = 1 - (1-\beta) \cdot \sum_{j=0}^{\infty} \beta^j \cdot S(j),$$

which is used and discussed in Section 2.2, Equation 9.

A.3 Parameter values, descriptions, and sources

Harvest parameters were determined using Poisson regression of estimated counts of leatherback turtle bycatch from Carretta et al. (2019) on *fleet* effort[2] in pursuing swordfish (in sets/vessel-day) from NMFS (2010) and PacFIN (2019), conditional on an estimate of the leatherback population feeding on jellyfish near California and Oregon, pre-PLCA closure (derived from NMFS and FWS (2013)). The estimating equation is

$$\mathbb{E}[B_t | A_t] = \alpha \cdot \frac{N_d}{\nu} \cdot A_t^{\rho} \cdot \hat{X}^{\theta},$$

where N_d/ν adjusts α to only female catch on a vessel-day scale, and $\hat{X} = 4000$ is an estimate of the number of adult female turtles in the California current ecosystem in the years just before the PLCA. θ is not estimated due to a lack of turtle population data, and is assumed to be 1. The share of non-nesting females, $(1-\sigma) \cdot X_t$, will take the place of $\hat{X}$.

I calibrate turtle dynamic parameters to the energetics experiments in Jones et al. (2012).

[1] A continuous version of this proof can be done using integration by parts or Fubini's theorem.

[2] The expected bycatch harvest function is currently derived from publicly-available data, but estimation can be improved with the help of more granular logbook data in the future.

Table A.3: Parameter definitions with values and sources.

Parameter	Value	Description and Source
Viability		
T	20	rolling window horizon (chosen)
Δ	0.90	viability confidence (chosen)
Economic		
β	0.97	discrete discount factor (chosen)
p_S	\$7700	ex vessel price of swordfish per metric ton (PacFIN, 2019)
ϕ	0.2	average metric tons of swordfish per set (PacFIN, 2019)
N_d	3000	number of vessel-days per season pre-PLCA (NMFS, 2010)
Biological		
ν	0.75	female population share (Jones et al., 2012; NMFS and FWS, 2013)
σ	0.295	share of nesting females (Jones et al., 2012; NMFS and FWS, 2013)
γ	80	mean [female] 2-day hatchling survival (Jones et al., 2012)
m_1	0.75	1^{st}-year mortality (Jones et al., 2012)
m	0.20	> 1^{st}-year mortality (Jones et al., 2012)
a	15	years to maturity (after 1^{st}) (Jones et al., 2012)
K	75000	adult female carrying capacity (NMFS and FWS, 2013)
Harvest*		
α	$9.6 \cdot 10^{-7}$	base bycatch harvest parameter
ρ	3.0	effort effect bycatch harvest parameter (sets per day)
θ	1.0	density effect bycatch harvest parameter (number of CA turtles)

*Data sources: NMFS (2010); Hazen et al. (2018); Carretta et al. (2019); PacFIN (2019)

There are currently an estimated 3700 adult female turtles in the population (of 5000), and 1100 of them nest in a given year. The other 2600 are vulnerable to bycatch in California. For every nesting female, 80 female hatchlings survive the first two days, and 25% of those make it through the year. An estimated 0.65 females make it to maturity from each adult-nesting year. As the half-life of an adult is only 3-4 years (or two nesting years per female), the expected number of mature females (in 16 years) is only 1.3 per adult female today.

A.4 Vulnerable species dynamics

Valuable insight about the behavioral response to disaster 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 an unsafe solution where a vulnerable species is allowed 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, which differs notably 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, localized aggregations of a species, population dynamics become much more sensitive to [random] birth or death events. This is called *demographic stochasticity*, which captures the variability in growth due to the sampling from a distribution of possible births and deaths (Lande et al., 2003; Melbourne and Hastings, 2008).[3] 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.

Table A.4: Timeline of stylized seasonal events.

start of year t	share σ of X_t observed in Southeast Asia, hatchlings appear
start of season	$(1-\sigma) \cdot X_t$ observed in California, instrument set by the regulator
fisher response	effort A_t and expected bycatch harvest $\mathbb{E}[B_t \vert A_t, X_t]$ 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

I will expand on the examples found in the supplementary materials of Melbourne and Hastings (2008). Throughout this section, I will only model the female population, since evidence suggests the number of females is the limiting factor in the production of new recruits (Jones et al., 2012).

I start by letting the number of [female] hatchlings born to adult i at time t be described

[3] A related 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).

by a Poisson distribution with average 2-day hatchling survival γ per adult female:

$$J_{i,t} \sim Poisson(\gamma).$$

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 rate of 1st-year mortality, m is the yearly expected mortality beyond the first year, which needs to be survived $a = 15$ years until maturity (for low populations, this is about 1%), X_t is the current number of adult females, and K is the carrying capacity before adult mortality. This density-dependence captures the fact that intraspecific competition competition for common resources will affect juvenile survivorship (Schoener, 1973; Connell, 1983).[4]

An age class model, for example including juveniles, early adults and adults of reproductive age would be most realistic, however this would require 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 the approach in as simple a setting as possible, I will use a stylized population model of representative adult female turtles. This implicitly assumes that the relative shares of the different age classes are fixed over time; most notably, I 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 expected survival, the number of juveniles J that survive to maturity from adult i at time t is given by

$$R_{i,t} \sim Binomial\left(J_{i,t}, s(X_t)\right) \equiv Poisson\left(\gamma \cdot s(X_t)\right),$$

where the equivalence comes from the law of total probability.

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

$$R_t = \sum_{i}^{\sigma \cdot X_t} R_{i,t} \sim Poisson\left(\gamma \cdot \sigma \cdot X_t \cdot s(X_t)\right),$$

since the sum of independent Poisson random variables is also Poisson-distributed. This

[4] 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.

equation captures the full role of demographic stochasticity in recruitment.

Similarly, the seasonal natural mortality and bycatch of turtles can be represented by two additional Poisson variables,

$$
\begin{aligned}
M_t &\sim Poisson\left(m \cdot X_t\right), \text{ and,} \\
B_t &\sim Poisson\left(\alpha \cdot N_d \cdot A_t^{\rho} \cdot ((1-\sigma) \cdot X_t)^{\theta}\right),
\end{aligned}
$$

where m is the expected individual adult mortality rate, and the likelihood of bycatch harvest is related to the current density of the stock and the intensity of daily fleet fishing effort A_t within the fishery as described in Appendix A.3.

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

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

We can write the distribution of the change in the population between seasons using the convolution of the three Poissons, which yields a Skellam distribution,

$$X_{t+1} - X_t \sim Skellam\left(\gamma \cdot \sigma \cdot X_t \cdot s(X_t),\ m \cdot X_t + \alpha \cdot N_d \cdot A_t^{\rho} \cdot ((1-\sigma) \cdot X_t)^{\theta}\right).$$

To get a sense of where the population will tend to concentrate in the absence of human impacts, I 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

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

which gives about 2700 adult females in the western pacific stock, about 70% of the currently estimated level of female leatherbacks (NMFS and FWS, 2013). This seems plausible given current conditions (NMFS and FWS, 2013). 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 0.22, and the expected mortality is 0.2. While there is no 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 a bad series of coin flips.