Bayesian Prediction of Fishery Biological Impacts from Limited Data: A Deep-Set Buoy Gear Case Study

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Highlights

- We developed a Bayesian procedure to predict the biological impacts of a developing fishery.

- We applied the method to data from deep-set buoy gear (DSBG) experimental trials.

- We evaluated several potential models of catch rates for three representative species.

- Our method addresses uncertainty inherent to limited data and rare event bycatch contexts.

- Our approach allows analysts to evaluate potential impacts of a new or expanding fishery with limited data.

Abstract

Predicting the biological impacts of new or expanding fisheries presents challenges due to limited data, high variability in catch rates, and the often low frequency of bycatch events. These issues arose in the case of the West Coast deep-set buoy gear (DSBG) fleet, which the Pacific Fisheries Management Council recommended in 2019 for authorization as a legal gear type. DSBG selectively targets swordfish (*Xiphias gladius*) with infrequent bycatch of other species. Limited effort and incomplete observer coverage result in a data-limited context for estimating the impacts of a fully authorized and expanded fishery. Recently, data analysts have explored Bayesian estimation for modeling rare-event bycatch in a manner that incorporates uncertainty and enables updating as more data become available. Here, we apply a Bayesian methodology to an integrated dataset of DSBG observer and logbook records to estimate bycatch rates under several plausible scenarios of DSBG authorization. We estimate posterior distributions of catch rates for three species caught in DSBG Exempted Fishing Permit (EFP) trials, and incorporate bootstrap samples of vessel-level effort to calculate posterior predictive distributions of catch counts under alternative management regimes. We discuss how our results can inform policy decisions about a new fishery with limited data, and how to extend this approach to other federal environmental actions. This approach allows policymakers to compare biological impacts of management alternatives while considering the uncertainty inherent in the predictions, and to determine whether the range of potential impacts is likely to significantly alter the affected environment.

Keywords: Bycatch, Bayesian methods, Impact analysis, Management thresholds, Limited data

1. Introduction

1.1. Estimating biological impacts with limited data

Assessing the impacts of fishing activity on biological resources is a routine and often statutorily required component of fisheries management. However, challenges arise when these impacts stem from rare events, are difficult to measure, or otherwise suffer from limited data. For example, when the target of conservation is an endangered species, interaction events may occur very rarely in the data, yet a single event can be of significant concern. Analysis is often hampered by low sample sizes (Martin et al. 2015, Amande et al. 2012, Dixon et al. 2005), or by a high frequency of zeros in the sample resulting in overdispersion and violation of model assumptions (Webley et al. 2011, O'Neill and Faddy 2003). This can result in high uncertainty in parameter estimates using traditional analytical methods (Martin et al. 2015, Webley et al. 2011, Cunningham and Lindenmayer 2005). Natural resource managers, policymakers, and fishery participants are often obligated to make decisions in spite of these issues (Komoroske and Lewison 2015, Granek et al. 2008). Up to 70 percent of annual catch limits in the United States are determined despite moderate or poor data availability, requiring the use of modeling approaches that can accommodate limited data (Newman et al. 2015).

In the United States, statutes including the National Environmental Policy Act (NEPA), the Endangered Species Act (ESA), the Marine Mammal Protection Act (MMPA), and the Magnuson-Stevens Fisheries Conservation and Management Act (MSA) require assessment of fishery impacts, including bycatch impacts, when taking significant federal fishery management actions. The primary data source for fisheries bycatch is onboard fisheries observers; however, observer coverage in many fisheries is incomplete (Carretta et al. 2020, Martin et al. 2015), requiring estimation of the total bycatch impacts of a given fishery. For example, the California drift gillnet (DGN) fishery had 19 percent observer coverage from 2000 through 2015 (Carretta 2020), meaning that the true bycatch impacts of four-fifths of all the effort in this fishery is unknown and must be estimated in order to draw conclusions about the fishery's compliance with environmental laws and regulations. Ratio estimates of total bycatch in incompletely observed fisheries are volatile in rare-event or small-sample contexts (Stock et al. 2019, Martin et al.

2015, Moore and Carretta 2014) and may not accurately predict bycatch over the long term, or at higher levels of effort. At the same time, estimates of total bycatch can have major impacts on fishery management and implementation of conservation statutes (Komoroske and Lewison 2015).

Rare events and limited data also pose challenges to making predictions about the future impacts of proposed actions. In some contexts, it may be important for managers to make inferences about potential catch of target species, which would occur more frequently in observed samples, in addition to endangered and protected species interactions, which occur rarely. When new gears or fishing permits are considered for authorization, questions arise about the economic viability of the new fishing activity (i.e., how many of the target species can a vessel expect to catch in one trip, and will this return enough of a profit to cover the cost of fishing?). Impacts to stocks of target species may raise further concerns, even when these stocks are not currently overfished. In these situations, ratio estimates are again volatile when predicting the impact of a new fishing activity, or an activity occurring at a substantially larger scale than that which contributes to the available data. This is true for fisheries as well as other contexts where managers authorize use of a newly developed technology or authorize the expansion of an activity with an expected impact on the biological and/or socioeconomic environment.

1.2. The Bayesian approach

Various methods exist for assessing rare-event or data-limited biological impacts such as those occurring in marine fisheries. For the aforementioned California DGN fishery, researchers have applied regression trees as one method for producing less volatile total bycatch estimates than ratio estimates or pooled means (Carretta 2020, Carretta and Moore 2014). Other model-based approaches commonly used to estimate fisheries bycatch include zero-inflated GLM models (Campbell 2015, Cambie 2011, Webley et al. 2011, Winter et al. 2011), ensemble random forest and other machine learning based approaches (Siders et al. 2020, Stock et al. 2020), and generalized additive models (GAMs; Stock et al. 2019, Hahlbeck et al. 2017, Campbell 2015). Incorporating covariates and ancillary datasets informing similar processes can improve precision in some data-limited cases (Stock et al. 2020, Martin et al. 2015).

Bayesian methods have emerged as a well-suited method to these problems, and have been applied in many contexts to assess fisheries bycatch (Parsa et al. 2020, Punt et al. 2020, Martin et al. 2015, Gardner et al. 2008, Hoyle and Maunder 2004, Pauly et al. 2000) and population dynamics for data-limited species (Winker et al. 2018, Juliette et al. 2017, Muradian et al. 2017, Moore and Barlow 2011). Bayesian models can identify the impact of multiple covariates on the impact of interest (Cosandy-Godin et al. 2015), and communicate the probability of impacts crossing regulatory thresholds (Martin et al. 2015). Bayesian analysis involves probabilistic inference based on data as well as prior knowledge, and often focuses on the posterior distribution of a variable of interest, from which the analyst can derive parameter estimates and credible intervals (i.e., a range that contains the true parameter value with a specified probability). These methods readily communicate the degree of uncertainty about the "true" value being explored, and can be updated with new data as more information becomes available.

Scientists have applied Bayesian methods in a number of biological and ecological contexts apart from fisheries bycatch. These include evaluation of the impact of a river restoration project on endangered steelhead (Conner et al. 2016), assessment of impacts of rainforest logging on birds and small mammals, (Crome et al. 1996), estimating forest cover over a given geographic area (Finley et al. 2008), and estimation of fishing trip behavior and future fishing effort (Vermard 2010).

Here, we propose a Bayesian procedure for predicting the biological impacts of a fishery under consideration for expansion, with known environmental impacts but limited data on these impacts. Our procedure uses data from experimental trials with a novel fishing method to infer a probability distribution of potential impacts under multiple scenarios of fishery expansion. We compare a variety of count data models to reflect the nature of the observer data used in our analysis (Gelman et al., Congdon). Our procedure incorporates multiple dimensions of uncertainty and allows the analyst to infer the probability of rare-event negative impacts crossing management thresholds, as well as the probability of desirable impacts meeting targets for economic viability of the action. This approach facilitates comparative scenario analysis and can readily inform managers both of what to expect and how certain

they can be of the expectations. To illustrate this approach we present a case study of the West Coast deep-set buoy gear (DSBG) fishery.

1.3. The case of the West Coast deep-set buoy gear fleet

Researchers first explored the use of DSBG on the West Coast beginning in the early 2010s. Their goal was to develop the gear as a method for selectively targeting swordfish with lower bycatch rates than DGN, the primary gear type used at the time in the West Coast swordfish fishery. DSBG employs a hook-and-buoy system to catch swordfish during the daytime, while they are feeding, with hooks commonly set at depths below 250 meters. This is in contrast to other gears such as DGN and shallow-set longline, which target swordfish near the surface at night, and are associated with higher rates of market species catch, bycatch, and protected species interactions per day of fishing. DSBG configurations include "standard" buoy gear (SBG) and "linked" buoy gear (LBG).

In 2015, the Pacific Fisheries Management Council (PFMC) recommended the issuance of exempted fishing permits (EFPs) for fishermen to test both the gear's potential bycatch impacts as well as its economic viability. The National Marine Fisheries Service (NMFS) has issued DSBG EFPs for the gear in both standard (SBG) and linked (LBG) configurations annually since 2015, with the most recently issued EFPs valid through December 31, 2021. Participation in DSBG EFP trials grew from five vessels in 2015 to a high of 26 vessels in 2019.

The PFMC initially adopted a range of alternatives (ROA) for recommending federally authorized DSBG fishing off the U.S. West Coast in June 2018. This ROA includes various scenarios for different amounts of authorized DSBG effort under a range of associated management regimes. In September 2019, the PFMC adopted its final preferred alternative (FPA) and NMFS began moving to authorize DSBG as a legal gear type for targeting swordfish off the West Coast. A preliminary iteration of the analysis presented in this paper as a case study informed the PFMC's selection of an FPA for authorization. The PFMC's Scientific and Statistical Committee also reviewed this preliminary methodology in 2019.

The majority of swordfish currently supplied to the West Coast is from foreign imports. Stakeholders in the West Coast swordfish fishery, including fishermen and the environmental community, generally supported authorization, in the hopes that DSBG would prove an economically viable domestic source of swordfish with lower conservation impacts than DGN or longline. However, the amount of effort during EFP trials was much lower than the levels proposed under the PFMC's authorization scenarios. This issue of limited data, combined with the rare-event nature of bycatch events, meant that simply scaling up the catch rates of the EFP trials was insufficient for predicting the biological impacts of an expanded, fully authorized fleet, or for comparing the various authorization scenarios.

In this paper, use an integrated dataset of DSBG EFP observer and logbook data to model catch rates of species caught in DSBG EFP trials from 2015 through 2019. We then use these models to predict a range of potential catch counts for an expanded fishery, using sampled estimates of effort under each of the Council's authorization scenarios. Our approach allows for a comparison of potential target species catch, and rare-event bycatch, between various scenarios for expansion of the fleet, while communicating the degree of uncertainty in the estimates.

2. Materials and Methods

2.1. Overview

The goal of our analysis is to (1) estimate the posterior distribution of the catch rate parameter for each examined species, and then to (2) estimate a range of potential impacts of DSBG authorization at higher scales than have occurred previously. For our case study we analyze three representative species caught in DSBG fishing to date: (1) swordfish (*Xiphias gladius*), the target species of the fishery; (2) bigeye thresher shark (*Alopias superciliosus*), a non-target species frequently caught as bycatch; and (3) loggerhead sea turtle (*Caretta caretta*), a protected species with only one interaction in DSBG EFP trials.

2.2. Data sources and integration

Data on DSBG EFP trials come from observer records and fishermen's logbooks from January 2015 through December 2019. Our data include both SBG and LBG configurations. Data managers produced a combined dataset that prioritizes observer records and integrates logbook data for trips where an observer was not present. Observer coverage was 77% on average during this period, though NMFS reduced observer coverage requirements in 2018 and 2019. Table 1 displays total days fished and observer coverage for the period reflected in our analysis.

Table 1: Summary of DSBG Effort and Observer Coverage by Calendar Year

Year	Days Fished	Days Observed	Observer Coverage
2015	132	132	100%
2016	286	286	100%
2017	324	324	100%
2018	616	520	84%
2019	671	302	45%
TOTAL	2029	1564	77%

DSBG, in both its SBG and LBG configurations, selectively targets swordfish. No other species are a target for this fishery, though fishermen may land some incidentally caught species, such as opah (*Lampris guttatus*) and escolar (*Lepidocybium flavobrunneum*). Of the species caught in DSBG trials and appearing in our dataset, the majority are rare-event bycatch. Of non-target species only escolar, bigeye thresher shark, and blue shark occurred more than once per hundred days fished. However, some species

occurring rarely in the data are of significant conservation concern. In particular, loggerhead sea turtles (*Caretta caretta*) have an endangered species listing under the ESA and are the subject of stringent regulations on other U.S. Pacific fisheries. The MMPA protects the northern elephant seal (*Mirounga angustirostris*), though it is not listed as a strategic stock. The National Marine Fisheries Service declared Yelloweye rockfish (*Sebastes ruberrimus*) overfished in 2002, and a 2017 assessment showed the stock remained overfished at 28 percent of its unexploited level (Gertseva and Cope 2017).

Our complete integrated dataset includes the catch count of each species at the day fished level (i.e., each observation in our dataset corresponds to one day of DSBG fishing[1]). Some DSBG trips are single day trips, while others include multiple consecutive days fished, which might be in the same location or spread over various fishing sites. Due to the rare event nature of the data and sparse information on fishing locations, we assume that days fished are independent, even if multiple days are undertaken by the same vessel or on the same trip. We also include data on soak hours, estimated based on the number of pieces of DSBG gear used on each day and the total soak time reported in observer records or logbooks. This allows us to control for variation in effective fishing effort from day to day. We also include a binary variable on the gear configuration used on each day, as preliminary evidence suggests there may be differences in catch rates for some species between SBG and LBG configurations. LBG caught many SBG-caught species less frequently or not at all; however, this may be due to the rare-event nature of these species and the relatively low LBG effort in our dataset (of 2029 total days fished, only 79 or 3.9% were LBG days). Table 2 summarizes the variables used in our models.

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[1] DSBG EFP effort is restricted to daytime hours. Gear must be set after sunrise and hauled before sunset. Up to ten pieces of gear may be deployed at a given time. A "day fished" refers to all fishing conducted on a single calendar day, regardless of time spent fishing or how many times each piece of gear is set and hauled.

Table 2: Descriptive Statistics for Variables Used in Modeling

Variable	Description	Mean	Median	Mode
Swordfish	Swordfish catch per day	1.36964	1	0
Thresher	Bigeye thresher shark catch per day	0.11286	0	0
Loggerhead	Loggerhead sea turtle catch per day	0.00049	0	0
Soak Hours	Total soak hours (pieces of gear × soak time)	71.62668	70	80
Gear Type	Indicator where 1 = LBG and 0 = SBG	0.03894	0	0

2.2. Model specification

Previous studies have used the Poisson distribution to model catch (Martin et al. 2015). The Poisson distribution is especially well-suited to data in which observations have a high probability of a zero count, a smaller probability of a count of one, and a near-zero probability of higher counts. However, the Poisson is less appropriate for more commonly caught species, where the data may violate the assumption of a mean at least roughly equal to the variance. Model specifications in the literature sometimes include zero-inflated models for situations where some effort is assumed to take place in times or areas with zero bycatch risk (i.e., observations must cross a "hurdle" that there is a nonzero probability of catching a given species before the Poisson likelihood is estimated).

We explored several count data models with specifications accounting for variation in both soak hours and gear type. These included (1) standard Poisson models, with and without covariates for soak hours and gear configuration; (2) a negative binomial model; (3) a zero-inflated Poisson model; and (4) a zero-inflated negative binomial model.

Our Poisson model of catch per day has the following functional form:

$$f(y \mid \lambda) = Poisson(x, \lambda)$$
$$\text{where } \ln(\lambda) = \beta_1 + \beta_2 g$$

In this model, y is the number of takes, λ is the per-buoy-hour take rate parameter, and x is the number of buoy-hours of fishing effort. The per-buoy-hour take rate parameter, λ, includes a base level parameter β_1 to model the standard buoy gear per-buoy-hour take rate plus an offset β_2 multiplied by an indicator variable for linked buoy gear ($g = 0$ for SBG, $= 1$ for LBG), to model the difference between LBG and SBG take rates. Simplifications of this model in our analysis omit the buoy hour component β_1 and/or the gear type indicator β_2, and instead consider λ as a per-day-fished take rate parameter. The observed data for loggerhead sea turtle satisfy the Poisson assumption that the mean is equal to the variance.

The negative binomial model used in our analysis has the following functional form:

$$h\,(y \mid \mu,\, \phi) = Neg\text{-}bin(x\,\mu,\, \phi)$$
$$\text{where } \ln(\mu) = \beta_1 + \beta_2 g$$

This likelihood function is a generalization of the Poisson likelihood, with mean μ and variance $\mu + \mu^2/\phi$. This specification relaxes the Poisson assumption that the mean is equal to the variance by including an overdispersion parameter, $\phi > 0$; for sufficiently large values of ϕ, the right term in the expression for the variance approaches 0, and the model effectively reduces to Poisson. Two frequently caught species in our analysis, swordfish and bigeye thresher shark, violate the Poisson assumption due to overdispersed catch counts (i.e., having a catch variance higher than their mean catch rates).

In addition to the Poisson model (with and without covariates) and the negative binomial model, we explored zero-inflated formulations of the Poisson and negative binomial. However, these specifications did not improve model fit for any species (see Table 3 below) and raised concerns about identification issues, which we explored in more detail and found such models may be inappropriate for the data we analyze in this study (see Appendix).

We used GLM estimation as an initial step in model assessment, using the Akaike information criterion (AIC) for preliminary model ranking. Following Markov Chain Monte Carlo (MCMC) estimation of our models (described in detail in the following section), we applied a posterior predictive checking

procedure that compares simulated data drawn from the posterior distribution to the observed data. This procedure simulates 50 datasets by drawing from the posterior distribution estimated by each model, and then compares the proportion of zeros in the simulated data with the proportion of zeros in the source data for each species. The model returning a value closest to 1 from this check produces simulated data that most closely resembles the source data in terms of the number of days with zero catch of the species under analysis.

Table 3 summarizes the models explored for this study, their likelihood functions, and diagnostics for each species, including AIC from GLM fitting and the proportion-of-zeros comparison from Bayesian posterior predictive checking. The following subsection describes our simulation procedure for calculating the posterior distribution of each model in more detail.

Table 3: Summary of Exploratory Model Diagnostics

Model	Specification	Likelihood $f(y_i \mid \lambda_i)$	Swordfish AIC	Prop. 0	Bigeye Thresher AIC	Prop. 0	Loggerhead Turtle AIC	Prop. 0
M 1.0	Poisson, No Covariates	$Poisson(x_i\,\lambda_i)$	6912	0.6854	1554	0.9778	19	1.0000
M 1.1	Poisson, Soak Hours Covariate	$Poisson(x_i\,\lambda_i)$ where $(\lambda_i) = \beta_1$	6811	0.7882	1556	0.9765	20	1.0001
M 1.2	Poisson, Soak Hours & Gear Covariates	$Poisson(x_i\,\lambda_i)$ where $ln(\lambda_i) = \beta_1 + \beta_2 g_i$	6678	0.7516	1545	0.9744	22	0.9999
M 2.0	Negative Binomial	$Neg\text{-}bin(x_i\,\mu_i,\ \phi)$ where $ln(\mu_i) = \beta_1 + \beta_2 g_i$	6363	0.9908	1436	1.0001	24	*N/A*
M 3.0	Zero-Inflated Poisson	$p{\times}Poisson(x_i\,\lambda_i) + (1\text{-}p){\times}0$ where $ln(\lambda_i) = \beta_1 + \beta_2 g_i$	6495	0.5855	1442	0.6314	23	*N/A*
M 4.0	Zero-Inflated Negative Binomial	$p{\times}Neg\text{-}bin(x_i\,\mu_i,\ \phi) + (1\text{-}p){\times}0$ where $ln(\mu_i) = \beta_1 + \beta_2 g_i$	6364	0.9473	1438	0.6368	25	*N/A*

We suspect the reason why some models do not converge for infrequently caught species (i.e., loggerhead sea turtle), is due to an identification problem that arises in estimating a richly parameterized model from data with insufficient features to distinguish between different model specifications. Our data implicitly reflect the range of environmental variation in the locations and times where fishing was tested, but only control for method (SBG or LBG) and effort, reflecting the need to predict future fishing impacts in the absence of controls on other determinants of catch variation. For a species where the majority of the observed catch counts are 0s, with a limited number of isolated observed catch events (1s) and few if any observations with more than one catch event, the posterior density which results for a richly parametrized model may be unidentified, resulting in a continuous range of parameter values with the highest posterior density. In this case, Bayesian simulation will fail to converge, instead producing cyclical behavior that trades off parameter levels that jointly maximize the posterior. The appendix provides an example of how this problem can arise in the case of a zero-inflated Poisson model.

The Poisson model provided the best fit for loggerhead sea turtle, whereas the negative binomial provided the best fit for the more commonly caught species (swordfish and bigeye thresher shark). Including soak hours and gear type as a covariate improved model fit for swordfish and bigeye thresher shark, but not for loggerhead sea turtle, likely because there is insufficient variation in the dataset for the covariates to contribute meaningfully to the models' predictive power.

Including zero-inflation did not improve goodness of fit for either the Poisson or negative binomial model. Additionally, we note that zero-inflated models are identified weakly for count data with a range spanning 0 and 1 only, due to insufficient information in the data to identify separately the zero inflation probability and the Poisson parameter (see Appendix).

Based on our model evaluations we proceed to fit a simple Poisson likelihood model for loggerhead sea turtle, and a negative binomial likelihood model (with covariates for gear type and soak hours) for swordfish and bigeye thresher shark.

2.3. Posterior estimation and prediction

We apply a standard Bayesian simulation methodology for estimation and prediction of our models. A Bayesian analysis proceeds by specifying a prior $p(\theta)$ and a likelihood function $f(y|\theta)$ which models the probability of observing data y for given levels of the parameters θ. Bayes' rule gives the posterior probability of observing the data as $p(\theta|y) = \frac{f(y|\theta)p(\theta)}{\int f(y|\theta)p(\theta)d\theta}$. With the advent of simulation-based Bayesian methodologies such as MCMC and Hamiltonian Monte Carlo (HMC), calculation of the integral in the denominator is unnecessary[2], and estimation proceeds by sampling in proportion to the numerator of the posterior, $p(\theta|y) \propto f(y|\theta)p(\theta)$. Once a likelihood and prior are specified, Bayesian simulation can proceed.

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[2] An alternative to simulation-based methods for evaluating Bayesian statistical models is the integrated nested Laplace approximations algorithm (INLA) (Rue and Martino 2009). The method uses a second-order Taylor approximation to the posterior distribution in a neighborhood of interest, with exact integration of the approximating function. The INLA method is particularly suited to estimation contexts involving big datasets characterized by high spatial and temporal resolution as well as data from multiple sources (Blangiardo and Cameletti, 2015), conditions that do not pertain to our application.

Following inference of the posterior distribution, the posterior predictive distribution is calculated as

$f(\tilde{y}|y) = \int f(\tilde{y}|\theta)p(\theta|y)\,d\theta$. In a Bayesian simulation context, the integral on the right is estimated

iteratively by drawing a value of the parameters θ on each simulation pass, then drawing a value of $\tilde{y}$

from the likelihood function for the current value of θ. Under suitable regularity conditions, the simulated

frequency of draws of $\tilde{y}$ will converge to the posterior predictive distribution.

When simulating the posterior distribution we used a weakly informative prior[3] on the catch rate

parameter and the gear configuration parameter. This allows the posterior distribution to assume a wide

range of potential values, while providing some prior information that we do not expect substantial

overdispersion in the estimates of the posterior distribution. This is desirable as we aim to quantify the

degree of uncertainty about the predictions given the available data, and relatively uninformative priors

allow the posterior distribution to take shape with stronger influence from the observed data than

specified prior knowledge.

We used the R statistical package and STAN to implement Bayesian MCMC methods for model

estimation (see Betancourt 2017 for theoretical and technical background on this procedure and

programming software). We used the HMC procedure in *rstan* to fit the models, and the *bayesplot*

package to conduct posterior predictive checks. All 2029 days fished in our dataset were included in the

estimation process. Our HMC runs consisted of 40,000 iterations, including 20,000 burn-in iterations, and

four chains. Diagnostic statistics confirmed convergence of the four chains onto stable estimates. From

the estimated posterior distributions we can infer both point and range estimates for the catch rate

parameter of each species, conditional on effort as measured in daily soak hours as well as the gear

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[3] For our negative binomial models of swordfish and bigeye thresher shark catch, we use a normal(0,10) prior on the catch rate and gear configuration parameters. Although the normal distribution typically allows negative values, which would be inappropriate for these data, our specification of a logged catch rate parameter allows us to assume normality (i.e., exponentiation during the simulation step results in positive values only). For our simple Poisson model (without covariates) of loggerhead sea turtle catch, we use a gamma prior with hyperparameters phi(0,1), which also represents a weakly informative prior while restraining the catch rate parameter to positive values.

specification used. This modeling procedure incorporates uncertainty both in the process error in catch rates and in observation error in daily catch counts.

After estimating the posterior distribution of the catch rate for each species, we turn to predicting the range of possible catch counts and corresponding probabilities under two different scenarios for expanding the DSBG fleet. To do we must make assumptions about the level of expected effort as the fleet is expanded. Table 3 shows the timing and maximum amount of permit issuance under each alternative.

Table 4: Maximum Annual Permit Issuance under the Proposed Action Alternatives

Alternative	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12
Open Access	500	500	500	500	500	500	500	500	500	500	500	500
Limited Entry	50	75	100	125	150	175	200	225	250	275	300	300

The limited entry (LE) alternative refers to a scheme of issuing permits to specific qualifying applicants based on swordfish fishing experience and other factors, with a maximum limit of 300 permits. This scenario corresponds to the PFMC's final preferred alternative (FPA) for authorization, adopted in September of 2019. Under the Open Access alternative, we assume 500 permits would be available in every year based on a recommendation from the PFMC's Highly Migratory Species Management Team (HMSMT). For the purpose of this analysis, we assume one unique vessel will fish each permit.

For each alternative, we estimate a posterior predictive distribution (PPD) for total catch in each year after issuance of the maximum number of permits. We also estimate PPDs for the entirety of the twelve-year period when numbers of permits under the LE alternative are "ramped up." This facilitates a comparison of impacts between the Open Access scenario where 500 permits are available immediately, and the LE scenario where fewer permits are available initially, with more made available each year up to a maximum of 300. We explored several methods for estimating the total effort under each alternative and initially derived PPDs using a point estimate for the total expected soak hours. In 2018 and 2019, the two

years with comparatively high participation in DSBG EFP trials, fishermen acquired and fished

approximately 42% of the total available EFPs. Also in 2018 and 2019, each participating vessel fished an

average of 25.74 days per year. The average soak hours per day fished were 71.6. We calculated a point

estimate of effort for each alternative based on the following formula:

$$X_{pred} = TotalPermits \times Utilization \times AvgDays \times AvgHours$$

For example, the Open Access alternative consists of 500 permits per year, so multiplying by an assumed

42% utilization level, 25.74 days fished per permit per year, and 71.6 average soak hours per day results

in an estimated 5,405 days fished or 387,027 soak hours per year.

While simple proportional extrapolation from the effort characteristics of DSBG EFP trials to make

predictions about effort in an expanded fishery is theoretically and computationally simple, it does not

incorporate uncertainty about future effort levels into the prediction process. In reality, effort and

participation in any fishery is a random variable influenced by factors such as perceived profitability,

opportunity costs of fishing, availability of other sources of fishing and non-fishing revenue, fishery

regulations, and other factors, many of which are difficult or impossible to measure. In order to capture

some of the uncertainty about how much participants will fish in the expanded fishery, we utilize a

bootstrapping procedure that samples from the empirical distribution of annual days fished per vessel in

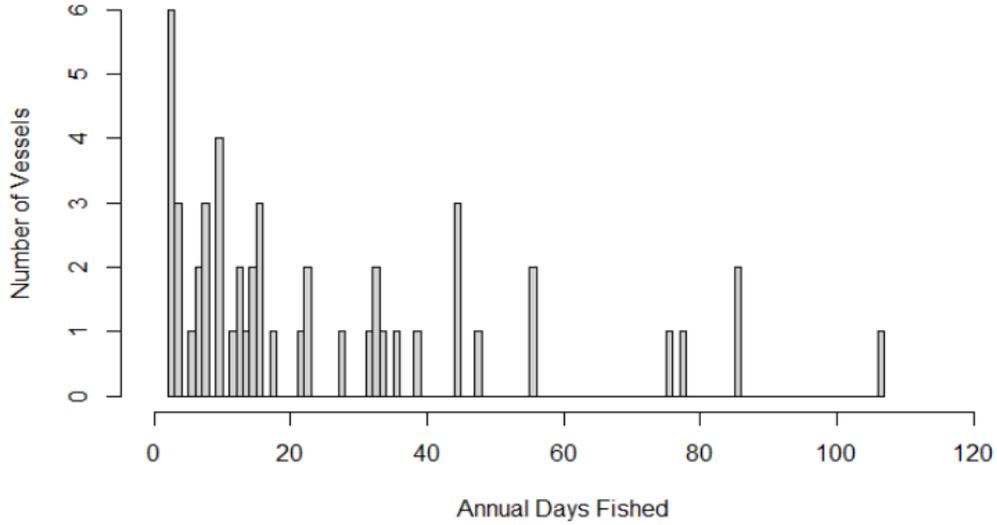DSBG EFP fishing. Figure 1 displays this distribution.

Figure 1: Histogram of Days Fished per Vessel per Year

For each simulated draw from the posterior distribution of the catch rate parameter, we estimate effort by sampling with replacement from the empirical distribution of annual days fished per vessel, with the number of samples equal to the number of expected active permits. That is, after determining how many active permits we expect under a given alternative, we draw a random sample for each permit to estimate how many days it will fish. Summing this vector of days fished per active vessel and multiplying by average soak hours generates a sample of potential effort in soak-hours for a given number of active permits. This incorporates another dimension of uncertainty (variation in levels of effort) into the predictions.

To calculate the PPDs for predicting the impacts of our DSBG expansion scenarios, we simulate draws from the posterior distribution of the catch rate parameter using our sample of effort described above. For the negative binomial models which include covariates (i.e., for swordfish and bigeye thresher shark), we derive the PPD as follows:

1. Use HMC to simulate a large number of draws from the posterior distribution, $p(\mu, \phi|y)$.
2. Iteratively simulate the PPD by plugging in simulated draws of the values μ and ϕ from the posterior sample into the likelihood $h(y|\mu, \phi)$, then drawing a predicted value of $\tilde{y}$.

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For the Poisson model without covariates (i.e., for loggerhead sea turtle), we employ the same procedure, except we draw from the Poisson posterior distribution $p(\lambda|y)$ and plug a simulated draw of λ into the Poisson likelihood $h(y|\lambda)$ to draw a predicted value of $\tilde{y}$.

Each draw incorporates a unique sample from the empirical distribution of effort, corresponding to a simulated predicted level of total effort over the period. We use the *rpois* and *rnbinom* functions in R to simulate 20,000 draws from the posterior distribution of the Poisson and negative binomial models, respectively. To incorporate the gear type parameter β_2, we draw from the posterior separately for the SBG portion of effort (where $g_i = 0$) and the LBG portion (where $g_i = 1$), apportioning the estimated effort to each in the same proportion seen in DSBG EFP trials. That is, we draw from the posterior distribution for 3.9% of the total sampled effort (the proportion of LBG effort in the observed data) with the β_2 gear shift offset parameter "turned on" to simulate LBG effort. For the remaining 96.1% of effort, we draw from the posterior distribution with the β_2 gear shift offset parameter "turned off" to simulate SBG effort. Summing the two resulting catch counts yields one observation of the PPD for that species.

For the Poisson models without covariates (i.e., for loggerhead sea turtle), we simply simulate draws from the posterior distribution of the catch rate parameter and multiply by a sample of effort at each draw.

In summary, our Bayesian predictive procedure for estimating potential catch under a given scenario of DSBG fleet expansion follows the following steps:

1) Identify the species and expansion scenario to be analyzed.

2) Determine the likelihood model and covariate specification that best fits the observed data.

3) Use Hamiltonian Monte Carlo methods to simulate the posterior distribution of the catch rate parameter.

4) Draw a sample from the empirical distribution of days fished per vessel per year, with a sample size equal to the number of active permits anticipated under the selected scenario.

5) Sum the vector of vessel-level effort and multiply by the average soak hours per day to arrive at an estimate for total soak hours under the selected scenario.

6) Multiply the effort estimate by the proportion of anticipated SBG effort and simulate a draw from the posterior distribution of the catch rate parameter with the gear shift parameter excluded.

7) Multiply the effort estimate by the proportion of anticipated LBG effort and simulate a draw from the posterior distribution of the catch rate parameter with the gear shift parameter included.

8) Sum the draws from steps 6 and 7 to arrive at an estimate for the total anticipated catch.

9) Repeat steps 4 through 8 10,000 times to construct the PPD for the selected scenario.

10) Repeat steps 1 through 9 for each additional scenario.

11) Repeat steps 1 through 10 for each additional species.

3. Results

Below are the results of our posterior predictions for three species. Posterior predictive checking indicated all models provide a good fit to the source data. We report summary statistics (mean, median, and mode) for our PPDs as well as a 95% credible interval. As an example of how to visualize these predictions, we also display a figure for each species that illustrates the PPD of predicted annual catch once the PFMC's final preferred alternative for DSBG expansion specifies the maximum number of permits. We present results for the initial 12-year "ramp up" period for each alternative, and for annual catch on an ongoing basis, assuming issuance of the maximum number of permits under the LE alternative.
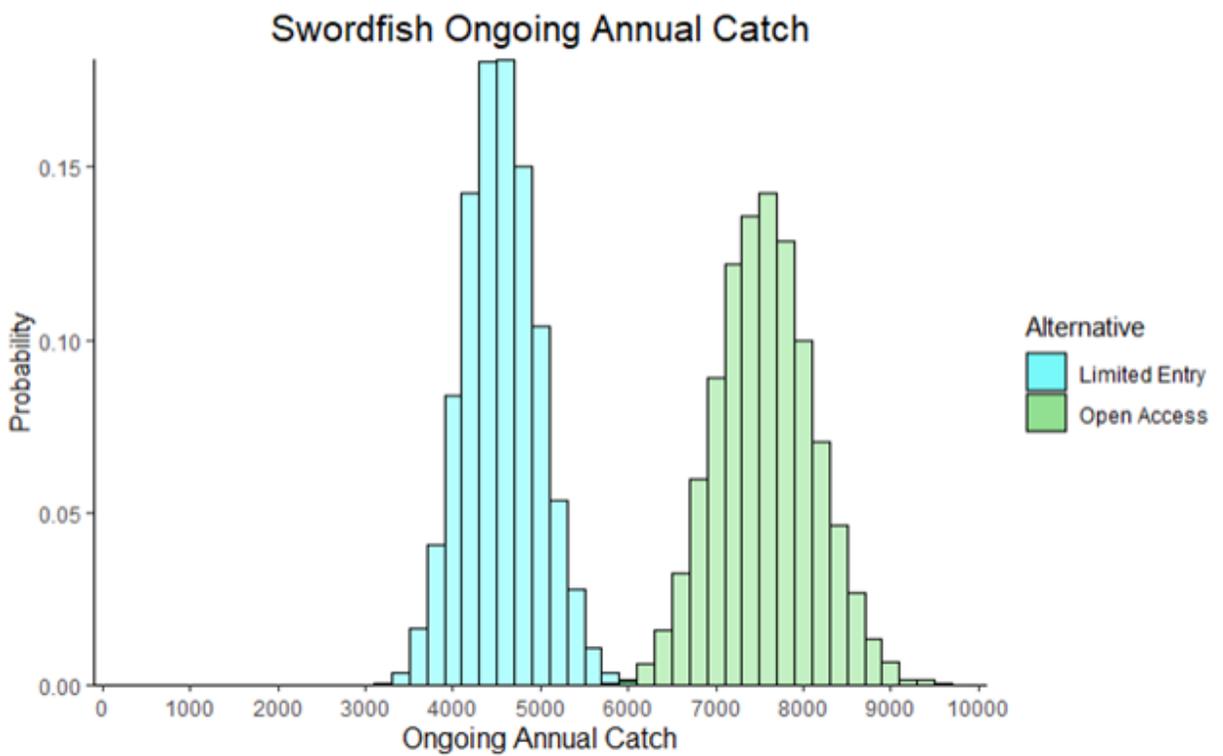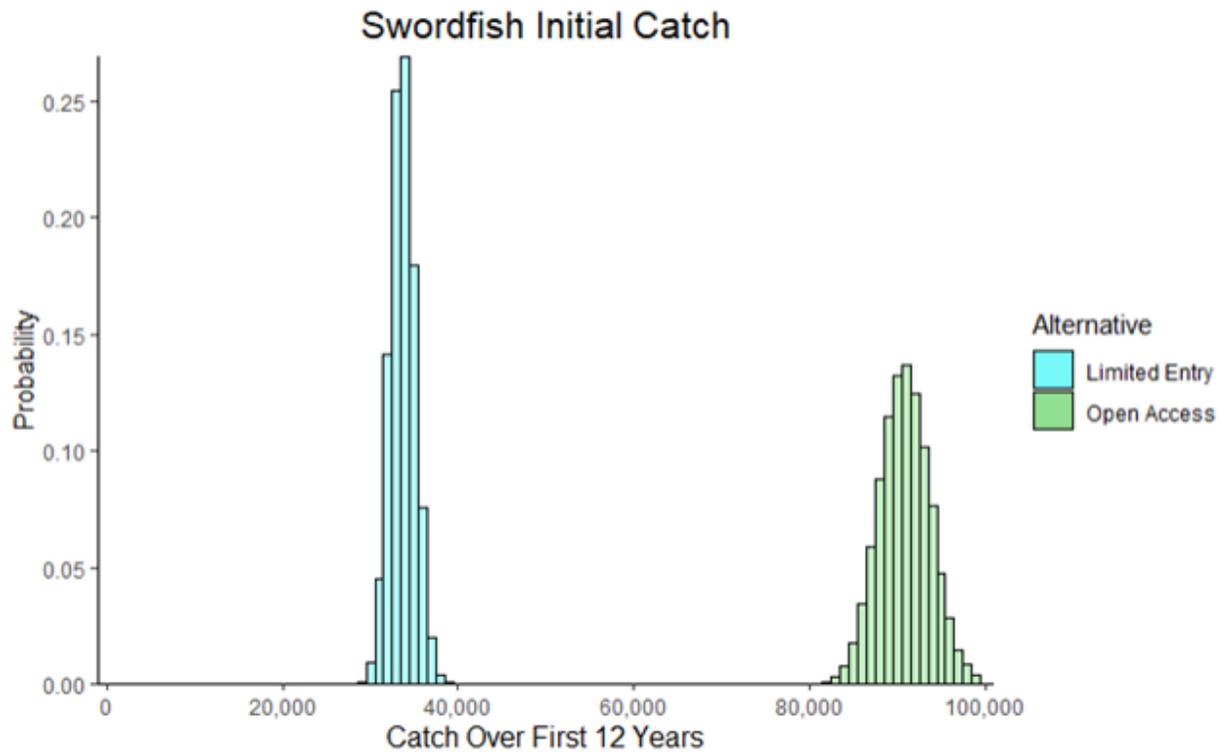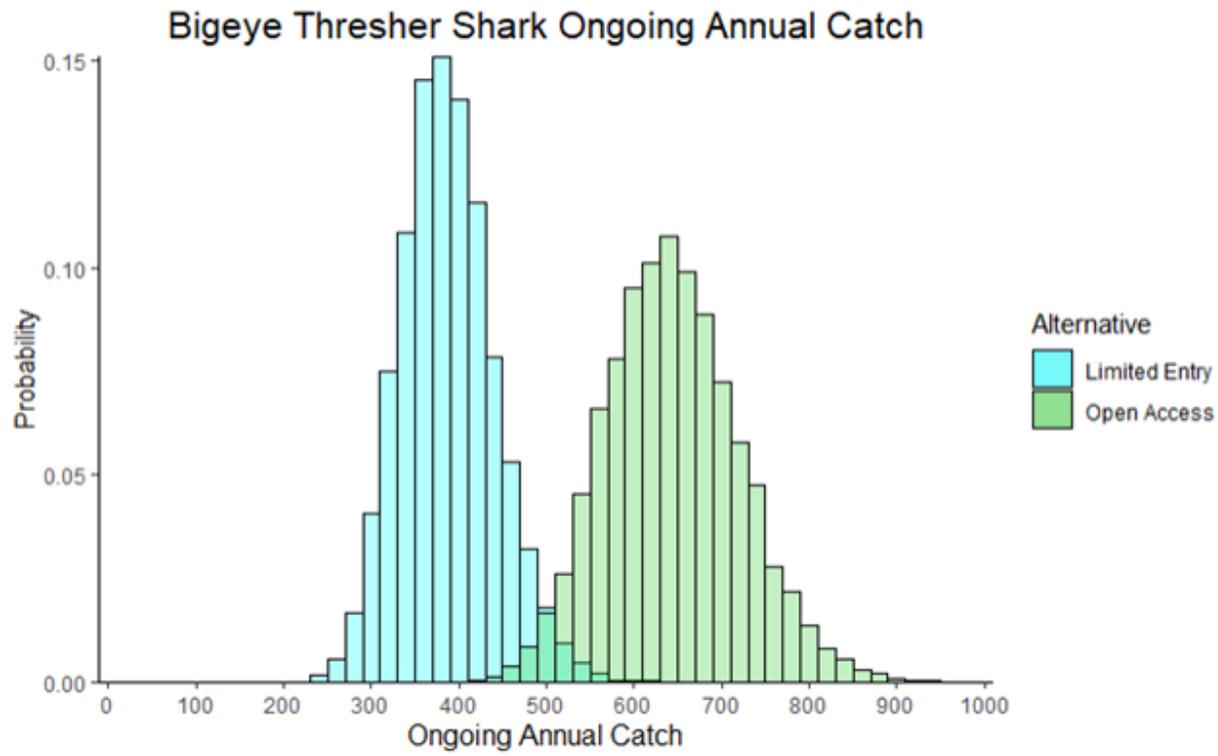
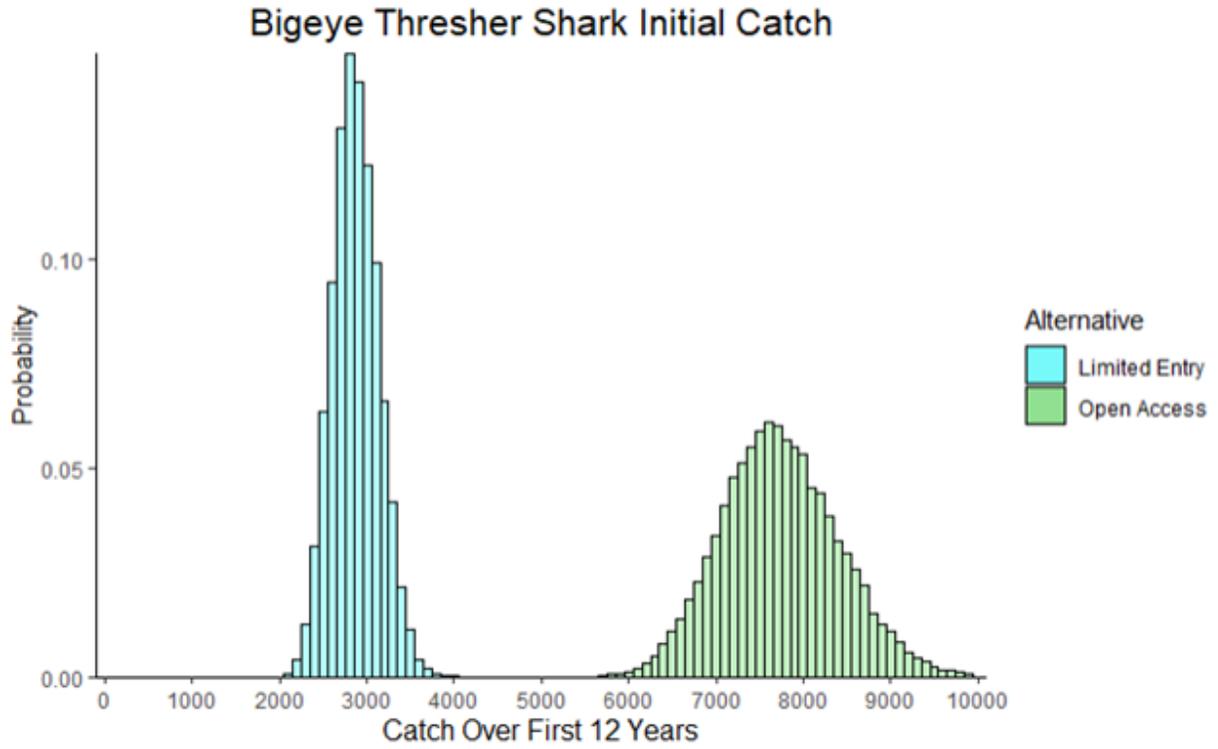**Figure 2:** Posterior Predictions for Swordfish

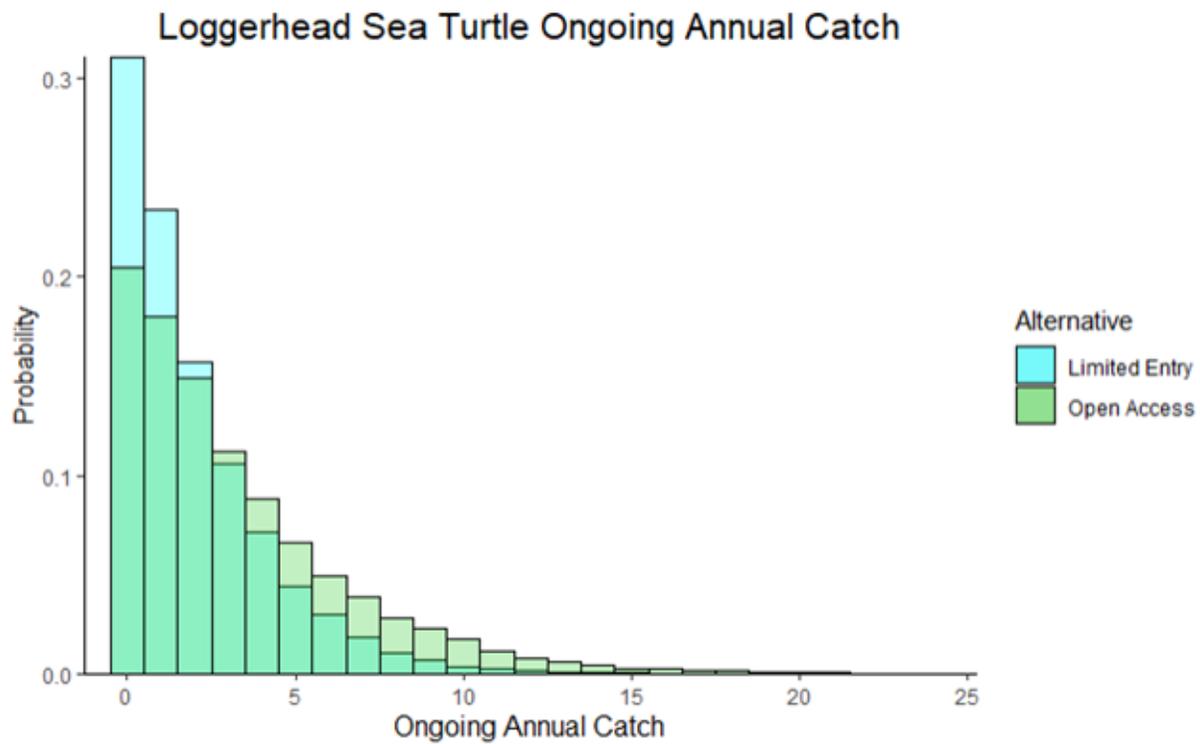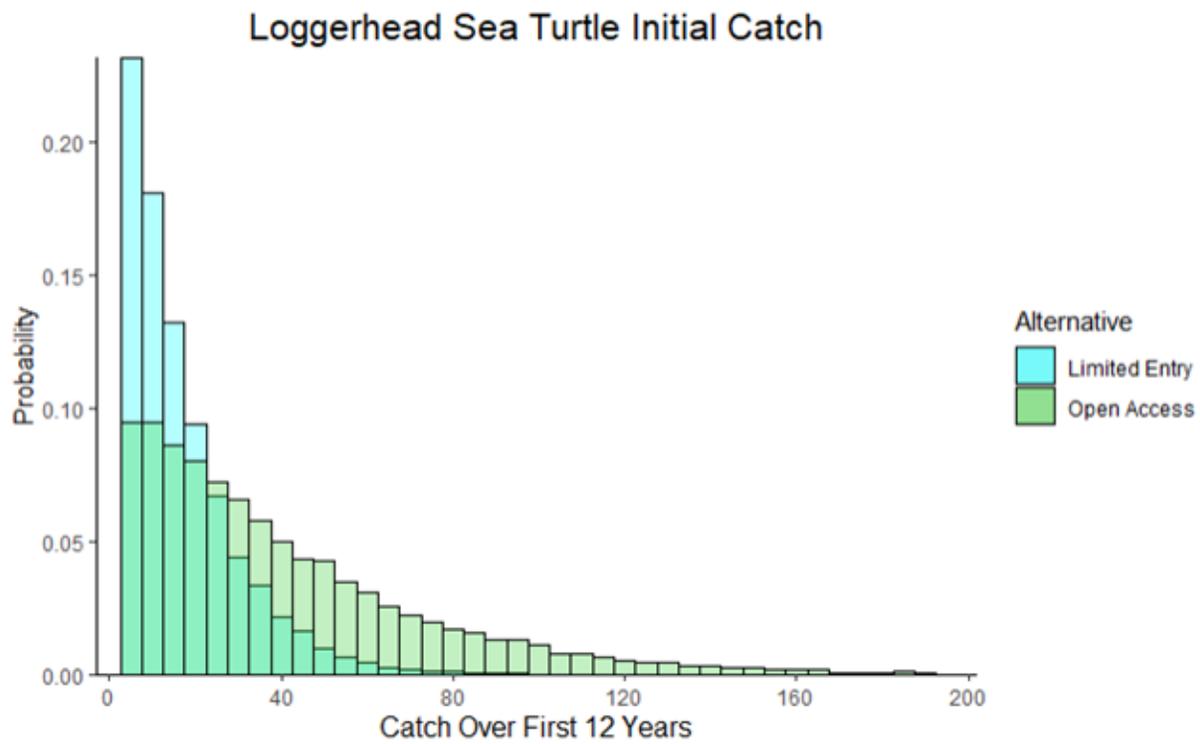**Figure 3:** Posterior Predictions for Bigeye Thresher Shark

Figure 4: Posterior Predictions for Loggerhead Sea Turtle

Table 5 below summarizes the results of our analysis for all three species and both alternatives (including both the initial 12-year period of fishery ramp-up and the predicted ongoing annual catch in subsequent years). Results presented include the mean of the PPD, as well as the median, upper, and lower bounds of the Bayesian 95% credible interval. The mode of each distribution is also included, and represents the most likely single value for total catch over the given time period, for each alternative.

Table 5: Results of Bayesian Estimation

Species	Timeframe	Alternative	Mean	CI 2.5%	Median	CI 97.5%	Mode
Swordfish	*Initial 12 Years*	Open Access	90,840	85,277	90,782	96,668	91,536
		Limited Entry	33,684	31,022	33,666	36,445	33,068
Swordfish	*Ongoing Annual*	Open Access	7,561	6,495	7,547	8,675	7,292
		Limited Entry	4,547	3,736	4,534	5,410	4,433
Bigeye Thresher Shark	*Initial 12 Years*	Open Access	7,740	6,483	7,707	9,139	7,860
		Limited Entry	2,871	2,381	2,859	3,418	2,886
Bigeye Thresher Shark	*Ongoing Annual*	Open Access	644	505	641	805	618
		Limited Entry	387	291	385	500	388
Loggerhead Sea Turtle	*Initial 12 Years*	Open Access	40	1	29	138	7
		Limited Entry	15	0	11	52	2
Loggerhead Sea Turtle	*Ongoing Annual*	Open Access	3	0	2	13	0
		Limited Entry	2	0	1	8	0

4. Discussion

4.1. Interpretations and policy implications

Our analysis calculates a distribution of predicted catch counts and their associated probabilities for three representative species, under two DSBG expansion alternatives considered by the PFMC. Our PPDs quantify the degree of uncertainty about the predictions and allow interpretation in terms of both point estimates and a range of probabilities. The credible intervals of each PPD can be compared to management thresholds and interpreted probabilistically. For example, the upper bound of the 95% credible interval for annual loggerhead sea turtle bycatch under the PFMC's preferred alternative is 8. This means our analysis indicates a 95% probability that the true number of interactions will be 8 or fewer. For context, in 2020 the annual hard cap on loggerhead interactions in the Hawaii longline fishery (which targets the same swordfish stock as the proposed DSBG fleet) was 17. That is, even with the limited data available from DSBG EFP trials, we can infer a 95% chance that the annual number of loggerhead sea turtle interactions with under the PFMC's preferred alternative will be less than half what is allowed for the Hawaii longline fishery.

We note that our predictions rely on the assumption that the conditions of a future fishery will resemble those at the time of EFP fishing. If the authorized DSBG fishery performs differently in terms of spatial distribution of fishing effort, experience level of fishermen, availability of productive fishing locations, price and profitability, abundance and distribution of species, or other factors, data from EFP fishing may not provide an optimal basis for predicting catch, bycatch, or protected species interactions. However, one advantage of our approach is that it can be readily updated as new or more appropriate data become available, reducing the level of uncertainty in our predictions.

These results can inform decision-making by allowing managers to compare the probable impacts of various alternative scenarios. PPDs allow straightforward evaluation of the probability of impacts exceeding a given regulatory or scientific threshold. As a hypothetical example, the upper bound on the 95% credible interval for bigeye thresher shark bycatch under the LE alternative is 499. The lower bound

on the credible interval for the Open Access alternative is 505. Studies suggest that bigeye thresher sharks are vulnerable to exploitation at low levels of fishing mortality (Fu et al. 2016; Young et al. 2015). Assuming enactment of a regulatory threshold of 500 takes per year for the proposed DSBG fleet, our analysis would indicate that the LE alternative is 95% likely to remain below this threshold on an annual basis, whereas the Open Access alternative is over 95% likely to exceed it.

One significant contribution of this paper is the identification of the negative binomial likelihood model in the Bayesian context for predicting impacts that occur frequently, such as target species catch in a fishery. Past studies (e.g., Parsa et al. 2020, Punt et al. 2020, Martin et al. 2015, Gardner et al. 2008, Hoyle and Maunder 2004, Pauly et al. 2000) have focused on estimation of rare-event bycatch, with less attention to the issue of predicting impacts on targeted or commonly caught species. Our model evaluations found the negative binomial to be a good fit for two species for which the data violate the Poisson assumption that the mean equals the variance. One of these, swordfish, is the target species of the DSBG fleet and the primary focus of the proposed expansion scenarios. The economic viability of the proposed DSBG fleet is a major concern of stakeholders, especially current and prospective swordfish fishery participants. Our analysis facilitates a side-by-side comparison of probable swordfish catch counts, which impact the economic viability of the fishery, against probable bycatch impacts. At a presentation of a preliminary version of this analysis to the PFMC before selection of a final preferred alternative, stakeholders and policymakers were able to use this probabilistic framework to reason that the LE alternative was acceptable in terms of likely swordfish harvest as well as the frequency of bycatch. We further used the results of this procedure to evaluate the potential socioeconomic impacts (e.g., swordfish landings, revenues, and price) of the proposed expanded fleet.

4.2. Other applications and methodological extensions

The Bayesian approach outlined in this paper need not be limited to the study of fisheries impacts.

Bayesian methods have been applied already in other ecological and environmental contexts (Conner et al. 2016, Vermard 2020, Finley et al. 2008, Crome et al. 1996), and the predictive procedures we present are more generally applicable to scenarios where an extractive or otherwise ecologically significant activity is being established or expanded. For example, analysts could apply this method to predict ecological impacts resulting from habitat removal from logging, landscape development, or other activities, based on existing data on these activities as well as prior knowledge about the response of the species in question. Aquaculture development on the U.S. West Coast is another arena where a relatively new and small-scale technology is under consideration for potential expansion. Our procedure could be adapted to evaluate various scenarios for the environmental impacts of aquaculture expansion, based on data collected from the relatively low number of existing facilities.

Our results incorporate several dimensions of uncertainty into the PPDs used for prediction. There are other assumptions in our calculations for which we could explicitly add predictive uncertainty. For example, rather than assuming the same percentage of active permits as was seen in DSBG EFP trials, we could incorporate a range of plausible proportions of permits actively fished into our effort sampling procedure. We could also sample from the empirical distribution of soak hours per day fished, in the same manner as our procedure for sampling vessel-level seasonal effort. Specifying more strongly informative priors, based on expert advice or some other source, could also affect the results by configuring the sampling procedure to rely less on the observed data and more on prior knowledge. While we do not utilize informative priors in this paper, they could become useful in the future if the conditions faced by an authorized fishery differ strongly from those experienced during EFP fishing.

4.3. Final considerations

Bayesian modeling is well-suited to the problem of estimating the biological impacts associated with the expansion or scaling-up of an ecologically significant activity or technology. We have demonstrated a method for generating a probability distribution of predicted fishery impacts that can provide valuable insights even for impacts that occur rarely or for which data are sparse. We applied this method to a multispecies analysis of an emerging fishing method to compare alternative scenarios of fishery expansion. Future efforts may focus on extending and generalizing this approach to evaluate and predict potential catch of other fisheries undergoing regulatory changes, along with other applicable contexts beyond fisheries management. This methodology might also help to relieve budgetary and time constraints on impact evaluations, such as those required under NEPA and ESA, by providing a versatile approach to comparing outcomes under various scenarios, and quantifying how certain one can truly be about those outcomes.

5. Acknowledgments

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Appendix: Weak Identification in the Zero-inflated Poisson Model with Rare Event Catch Data

An identification problem occurs when a probability density function $p(\theta^{(i)}|y)$ can assume the same value for different levels of the parameters (Cameron and Trivedi, 1998), $p(\theta^{(1)}|y) = p(\theta^{(2)}|y)$ for $\theta^{(1)} \neq \theta^{(2)}$, where $\theta^{(i)}, i = 1, 2$, is a parameter vector and y is a vector of observations.

We are interested in the problems that may arise in a Bayesian simulation context when the posterior is weakly identified: $h(\theta^{(1)}|y) \cong h(\theta^{(2)}|y)$ for $\theta^{(1)} \neq \theta^{(2)}$. We conjecture that this condition may lead to poor model performance, in terms of difficulty in achieving convergence in Bayesian simulations, and imprecise credible intervals for the parameters.

To demonstrate how the identification problem may arise in the case of fitting a richly parametrized model to observer data for rare-event bycatch, we evaluate a zero-inflated Poisson (ZIP) model fitted to count data with a very high proportion of 0s, a small proportion of 1s, and no larger values observed. This addresses a general problem we perceive in Bayesian estimation of rare-event bycatch, and the specific case of fitting Bayesian models to our data for loggerhead sea turtle (see Section 2.2 of the main body of this paper).

To illustrate our ZIP example, we assume the effort is the same for each catch observation in our hypothetical data set[4] (e.g. $x_i = 1$ unit of effort for all observations $i = 1, 2, \ldots, n$). We also assume a flat prior (e.g. $g(\theta) = a$), which is approximately true over a limited range of parameter values in the case of rare event interactions for the noninformative priors we employed. Thus the posterior may be written as $p(\theta|y) \propto \prod_{i=1}^{n} f(y_i|\theta)$, the likelihood of the exchangeable sample of observed catch counts, $y = (y_1, y_2, \ldots, y_{1000})$, allowing us to focus on identification of the parameters of the ZIP model from the data used to estimate it. We hypothesize a typical rare event bycatch data set of n exchangeable observed

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[4] This simplification abstracts from day-level observations with approximately equal numbers of hook-hours in the observer data used to produce our estimates.

units of fishing effort with 0 catch of a rare-event bycatch species observed on $n - 1$ observations, and a

single isolated catch event ($y_i = 1$ for some $i \in 1, 2, ..., n$, and $y_j = 0$ for $j \neq i$). This approximates the

actual, observed data for loggerhead sea turtle catch per day by DSBG in our study.

The ZIP likelihood function for an individual observation y_i has

$$f(y_i \,|\lambda, p) = p \frac{\lambda^{y_i} e^{-\lambda}}{y_i\,!} + (1 - p)\, I\{y_i = 0\},$$

with $\lambda > 0$ and $0 \leq p \leq 1$, and $I\{y_i = 0\}$ is the indicator function which assumes the value 1 if $y_i = 0$

and 0 otherwise.

When applied to data with a single observed catch count of 1 and $n - 1$ observed 0s, the posterior

probability density function is

$$h(\lambda, p|y, n) \propto \prod_{1}^{n} f(y_i \,|\lambda) = \left(pe^{-\lambda} + 1 - p \right)^{n-1} p\lambda e^{-\lambda},$$

or in log form,

$$\ln h(\lambda, p|y, n) \propto (n - 1) \ln\left(pe^{-\lambda} + 1 - p \right) + \ln(p) + \ln(\lambda) - \lambda.$$

Noting that $\ln(\cdot)$ is a monotonically increasing function, we can derive the first order conditions which

identify the posterior mode using the log posterior density:

$$\frac{\partial \ln h(\lambda, p|y, n)}{\partial \lambda} = -\frac{(n - 1)pe^{-\lambda}}{pe^{-\lambda} + 1 - p} + \frac{1}{\lambda} - 1 = 0,$$

And

$$\frac{\partial \ln h(\lambda, p|y, n)}{\partial p} = -\frac{(n - 1)\left(1 - e^{-\lambda}\right)}{pe^{-\lambda} + 1 - p} + \frac{1}{p} = 0.$$

Substituting $p = 1$ and $\lambda = \frac{1}{n}$ shows the first order condition for λ is satisfied and the first partial

derivative of $\ln h(\cdot)$ with respect to p is positive, meeting the Kuhn-Tucker conditions for a local

(constrained) maximum of the posterior density at these values. It is straightforward to show that $\lambda = \frac{1}{n}$ meets the second order condition for a maximum conditional on $p = 1$, in which case the model simplifies to the standard Poisson distribution without zero inflation.

However, each of the first order conditions implicitly defines p as a function of λ such that the corresponding first order condition is satisfied. Letting $p_{(u)}$ denote the formulas for p obtained from solving the first order conditions for $u = \lambda$ or p, we find

$$p_{(\lambda)}(\lambda, n) = \frac{1 - \lambda}{(n\lambda - 1)e^{-\lambda} + 1 - \lambda}$$

and

$$p_{(p)}(\lambda, n) = \frac{1}{n(1 - e^{-\lambda})} \; .$$

These values are nearly identical for given $\lambda \geq \frac{1}{n}$, suggesting a potential range of values of (λ, p) for which $h(\cdot)$ is near its maximum, given near attainment of both first order conditions for a maximum. However, subtraction of these expressions shows that

$$p_{(\lambda)}(\lambda, n) - p_{(p)}(\lambda, n) = o(\lambda) > 0.$$

Thus the FOCs are not exactly satisfied for any $\lambda > 0$.

The figures below apply these derivations to the dataset described above. Figure 5 shows the values of $p_{(\lambda)}(\lambda, 1000)$ and $p_{(p)}(\lambda, 1000)$ for a range of values of $\lambda \geq \frac{1}{1000}$. Although the values given for the two formulas differ slightly, they appear in the figure to coincide, suggesting weak identification of the posterior mode over a wide range of values that nearly attain the FOCs simultaneously.

Figure 6 shows the percentage of the maximum value of the posterior attained for a range of values of (λ, p) with $p = p_{(\lambda)}(\lambda, 1000)$. Comparison with Figure 5 shows that the posterior density remains at a high level for values of $\lambda \in [1 \times 10^{-3}, 1000 \times 10^{-3}]$ and even larger, and for $p \in [0, 1]$.

Figure 7 displays the posterior density for the ZIP model in a 3-dimensional figure, clearly showing the ridge of (λ, p) values with relatively high posterior density. We believe this reflects a tradeoff between a higher value of the Poisson mean parameter, λ, against a lower probability of being in the Poisson regime, p, to keep the unconditional probability of observing a zero, $pe^{-\lambda} + (1 - p) \cdot 1$, roughly constant along the ridge $(\lambda, p_{(\lambda)})$. The discussion may be irrelevant, given the challenge of clearly defining the difference between fishing conditions where the chance of catching a species is truly 0 from that with a low catch probability. Given the inability of the ZIP model in this case to separately identify λ or p with a reasonable level of precision, and that the objective of our method is prediction, not inference, we believe this discussion further supports using the more parsimonious standard Poisson model for the data in question.

We believe a similar issue arises for the case of the ZINB model with overdispersion, but few positive catch events. In this case, there is even more ambiguity in the model, as both the zero-inflation feature and the overdispersion parameter model a departure from the standard Poisson to capture the degree of overdispersion. We hence expect an even greater difficulty with separately identifying the mean of the negative binomial process, the overdispersion parameter, and the zero-inflation parameter for data with a preponderance of zero observations.
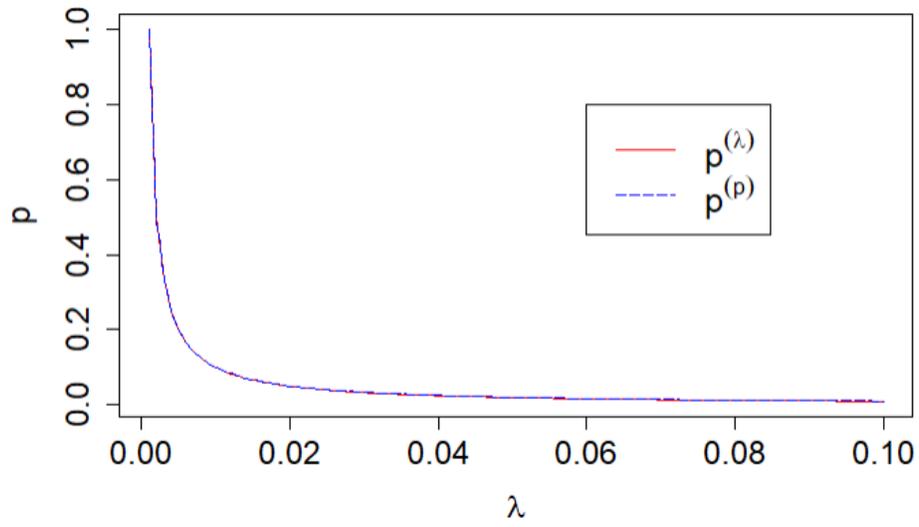
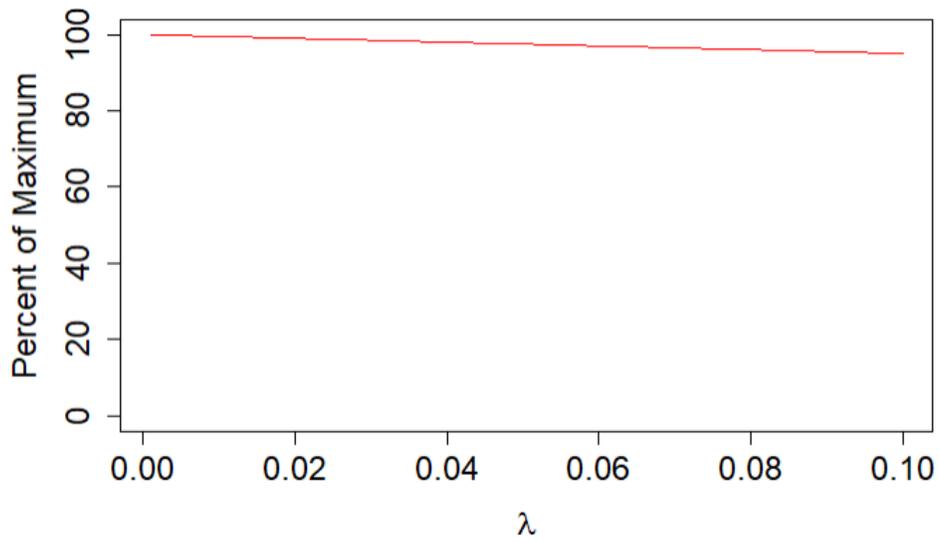**Figure 5:** Values of p which satisfy the first order conditions with respect to λ and p

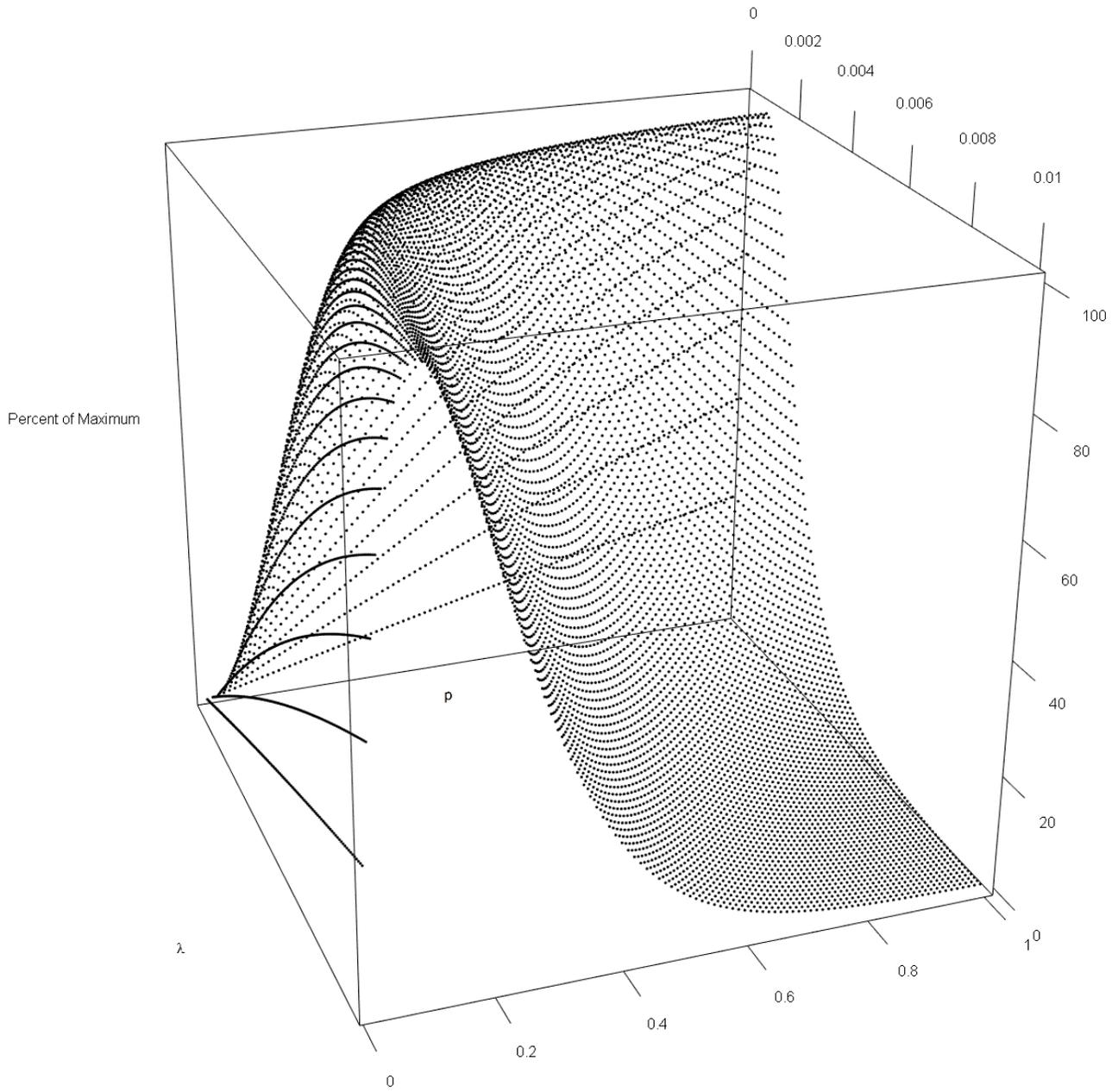**Figure 6:** Percent of maximum posterior attained for (λ, p) with $p = p^{(\lambda)}(\lambda, 1000)$

Figure 7: Posterior density surface over a range of λ and p