https://doi.org/10.25923/9qy7-wz62

Hawaii Permitted Shallow-set Longline Fishery Estimated Anticipated Take Level for Endangered Species Act Listed Species[1]

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18 May 2018

1 Introduction

In this report, prepared at the request of the NOAA Fisheries Pacific Islands Regional Office (PIRO), the Hawaii permitted shallow-set longline (SSLL) fishery estimated annual anticipated take level distributions of seven Endangered Species Act (ESA) listed species and three related unidentified classifications are provided. The seven species are (1) loggerhead sea turtle, (2) leatherback sea turtle, (3) olive ridley sea turtle, (4) green sea turtle, (5) Guadalupe fur seal, (6) giant manta ray, and (7) oceanic whitetip shark. The three unidentified classifications are (1) unidentified pinniped, (2) unidentified Otariidae, and (3) manta/mobula (identified as a member of the Mobulidae family). The data, methods, and assumptions used to estimate the annual anticipated take level distributions are described within this report.

First, let us consider the definition of “take” and what is meant by the terms “bycatch” and “take level” in this report. The Marine Mammal Protection Act (MMPA) and the ESA define “take” in slightly different ways, but basically “take” means to catch, kill, or harm a marine mammal or protected species in any way. An “incidental take” is a take that results from, but is not the purpose of, the carrying out of an otherwise lawful activity. Herein, “bycatch” refers to the total number of incidental take events in which an animal is hooked or entangled in the longline gear. Under this definition, bycatch is a component of the total incidental take in the SSLL fishery because an animal may interact in other ways with the longline fishery besides hooking or entanglement. The term “take level” in this report refers to the bycatch over a specified period of time, such as the calendar year.

There are a few practical constraints on the definition of bycatch used herein. First, observers are instructed to record all observed hooked or entangled animals during haul back of the longline gear (Pacific Islands Regional Observer Program, 2017). Animals observed hooked or entangled that are freed before being landed on deck are included in this definition. However, hooked or entangled animals that are removed (e.g., by predators) or freed (e.g., by escape or drop-off) from the longline prior to the longline becoming visible on the haul back would not be observable and therefore could not be recorded unless warranted by convincing circumstantial evidence of their capture. These “missed” animals are not included in the bycatch as there is no practical way to quantify them. Nor does bycatch include animals that are not hooked or entangled but are in some other unobserved way caught, killed, or harmed by the activity of deep-set fishing. Such events are not included because there is incomplete data available on such interactions as it is not feasible to monitor all aspects of a trip.

Second, bycatch refers to the total number of bycatch events, which may exceed the number of individual animals that are caught. It is possible for an animal to be observed caught, then freed or released, and subsequently caught again during the same year. For example, a loggerhead sea turtle was

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[1] PIFSC Data Report DR-18-014.
Issued 16 October 2018.

observed to be caught twice during a shallow-set trip in 2012. These two events are considered separate bycatch events.

Next, let us consider how the term "anticipated take level" (ATL) is interpreted within this report. Under the assumption that take level is a random variable, one can talk about the probability of each possible value of the take level (outcome). Hereafter, this random variable is denoted as TL. The list of all possible outcomes and their corresponding probabilities is called a probability distribution. Since TL is a count, all outcomes will be nonnegative integers; hence, the probability distribution is a discrete distribution. This discrete distribution can be thought of as the relative frequency (probability) of each possible outcome from a long-run of random TL observations.

For this report, the ATL is interpreted as the anticipated probability distribution of TL under the basic assumptions that (1) the underlying process that generates TL does not change, and (2) the random values of TL must come up randomly, independently across years, and with a single fixed probability distribution. Furthermore, it is assumed that there are no annual take limits or limits on effort, and the SSLL fishery will remain open throughout the year. These assumptions are discussed further in Section 3.

The annual ATL consists of the take levels that are anticipated from year-to-year, and estimating this distribution is the primary focus of this report. The ATLs for the periods of 2 and 3 years are also derived in addition to the annual ATL. That is, the ATL is derived for three periods of time, denoted as annual ATL, 2-year ATL, and 3-year ATL. For each time period, the mean and 80th and 95th percentiles of the derived ATL are reported, as requested.

The estimated ATLs are derived using a statistically naïve Bayesian inferential approach, where naïve in the statistical setting generally refers to using a simplistic model that makes critical assumptions that are unlikely to be true (see Section 3.4 for details). The necessity and usefulness of such a simplistic model are discussed throughout this report. In the next section, the historical data set of take levels is described. In Section 3, the methods and their assumptions and caveats are discussed. The results for each species classification of interest are provided in Section 4.

2 Historical Data

The SSLL fishery re-opened in mid-2004 as a separately managed fishery. When the fishery re-opened, regulations were put into place to reduce the bycatch of sea turtles from historical levels. These regulations required (1) large circle hooks with a maximum of 10 degrees offset and mackerel-type bait, (2) a set certificate program to ensure that the fleet, as a whole, did not make more than 2,120 shallow-sets per year, and (3) annual take limits of 17 loggerhead sea turtles and 16 leatherback sea turtles. If the fishery reached one of the take limits, it was closed for the remainder of the calendar year and reopened the next calendar year.

The requirement concerning the hook type and bait are still in place. The set certificate program and the limit of 2,120 shallow-sets per year were removed on 11 January 2010. The annual take limits have changed through the years because of Biological Opinion re-initiations and court orders. The loggerhead take limit was increased to 46 on 11 January 2010, and then decreased back to 17 by a court order on 31 January 2011. On 5 November 2012, the loggerhead take limit was increased to 34 and the leatherback take limit was increased to 26.

The fishery has been closed twice as a consequence of reaching one of the two annual take limits. On 20 March 2006, the fishery closed after reaching the loggerhead sea turtle limit of 17, and on 18 November 2011, the fishery closed after reaching the leatherback sea turtle limit of 16.

In addition to these regulations, a NOAA Fisheries observer has been placed on every SSLL trip since the fishery reopened in 2004. This person is instructed to observe the entire haul back of every fishing operation (set) and record all observed interactions with protected species and marine mammals, as well as a suite of variables concerning the trip, fishing operation, catch, and bycatch. This information is entered into a database called the Longline Observer Data System (LODS) (Pacific Islands Regional Office, 2017). The observer manual (Pacific Islands Regional Observer Program, 2017) provides information on the program and the variables recorded.

The historical take levels used in this report are derived from LODS. Before using these values to derive the ATL, we must consider the data structure and conditions that generated the historical data. For this report, the ATL assumes the gear and bait regulations are the same as the historical data and that there is no limit on the number of annual fishing operations by this fishery. Furthermore, the ATL assumes there are no annual take limits, whereas, the historical data were generated under leatherback and loggerhead annual take limits.

Although the fishery had limits on the number of sets prior to 2010, the limit was never reached. Table 2.1 gives the annual number of sets for 2004-2016. Year 2010 had the most recorded sets, but after that, the annual effort was generally lower, excluding the years the fishery closed. Since the limit in effort prior to 2010 was never reached and the effort did not increase after the limit was removed, it seems reasonable to include 2005-2009 take levels in a model that assumes no limit on effort.

Table 2.1. Annual number of sets, based on the date of haul back, in the SSLL fishery for years 2004-2016. Years 2004, 2006, and 2011 are years when the fishery was not open throughout the year. Year 2017's effort was not available at the time of the analyses for this report.

Year haul back began	Number of sets	Period fishery open
2004	135	19 June-31 December
2005	1,646	1 January-31 December
2006	850	1 January-20 March
2007	1,569	1 January-31 December
2008	1,597	1 January-31 December
2009	1,762	1 January-31 December
2010	1,872	1 January-31 December
2011	1,474	1 January-18 November
2012	1,364	1 January-31 December
2013	962	1 January-31 December
2014	1,338	1 January-31 December
2015	1,156	1 January-31 December
2016	727	1 January-31 December

For loggerheads and leatherbacks, the historical probability distributions of annual TL would have been truncated at the species' relevant take limit. The annual take limit in the historical data for loggerheads and leatherbacks means that the probability distribution of annual TL was truncated at the species' relevant take limit, assuming the take limit was a possible outcome. As the take limits changed over the period of the historical data, the probability distribution would have also changed. The annual take levels of the other species would also have been affected since the fishery closed when one of the limits was reached. How these annual take limits influenced fishing behavior and what would have happened in 2006 and 2011 if the fishery remained open is unknown.

Now let us consider the data structure. The historical annual take levels represent a short time series of 13 consecutive years (2005-2017). Thus, we expect to have dependent observations; that is, the historical annual take levels are likely correlated. This short time series is unlikely to provide sufficient information to determine a pattern of dependency across years or the right tail (higher take levels) of the ATL. The ATLs are likely asymmetrical, with a long right tail (the distribution is bounded on the left by 0). In summary, the historical take levels are unlikely to have come up independently across years and under the same probability distribution.

Next, let us consider the available data used in the analyses described herein. Except for the loggerhead sea turtle, oceanic whitetip shark, and rays, the recorded annual take levels from 2005 through the end of 2017 were considered when estimating the annual ATL. In 2004, there were only 135 SSLL sets (6 trips), and most of these occurred in October and November. As this sparse effort is unrepresentative of the fishery, 2004 take levels were not used.

For the loggerhead sea turtle, there were 27 takes observed during January 2018. As this is the highest observed take level since the fishery reopened in 2004, they were considered when estimating the loggerhead sea turtle's annual ATL. For the other species, the observed take levels in January 2018 were not unusual.

Whereas the observer is required to call NMFS protected species hotline as soon as possible and report an interaction with a sea turtle or marine mammal, there is not a similar requirement for the rays and oceanic whitetip shark, which were only recently listed/undergoing listing under ESA. At the time of these analyses, catch information was available for all sets through 18 November 2017. Thus, for the rays and oceanic whitetip shark, the recorded annual take levels from 2005 through 2016 were used, as well as the take level between 1 January 2017 and 18 November 2017. For these species, the historical annual take levels were computed using the catch (retained or discarded catch) as bycatch.

3 Methods

In this section, the general approach taken to estimate the annual ATL and the underlying assumptions behind this approach are described. The computation of the mean and percentiles of an ATL and the derivation of the 2-year and 3-year ATL are also explained. First, how the calendar year is split into segments to accommodate the years the fishery was closed is described.

3.1 Segmenting the year

Based on the dates the fishery was closed; 20 March 2006 and 18 November 2011, the calendar year was split into 3 segments: (1) 1 January - 20 March, (2) 21 March - 18 November, and (3) 20 November – 31 December. For each species, the take levels within each segment were examined across years, and a decision was made from four options:

- Option 1: Estimate the ATL for each period defined by the dates of the 3 segments.
- Option 2: Exclude year 2006 and estimate the ATL for two periods. The first period is defined by combining segments 1 and 2, and the second period is defined by segment 3.

- Option 3: Exclude year 2011 and estimate the ATL for two periods. The first period is defined by segment 1, and the second period is defined by combining segments 2 and 3.
- Option 4: Exclude years 2006 and 2011 and estimate the ATL using the annual take levels for the remaining years.

For the rays and oceanic whitetip shark, Options 3 and 4 were not considered as year 2017 would also need to be excluded since the take level for the third segment in 2017 was not available.

If the calendar year is broken into periods, the take levels for the different periods are treated as independent observations; that is, they are assumed to be uncorrelated with one another even for successive time periods. This is unlikely to be true since a trip can overlap successive time periods and bycatch events have shown a propensity to occur in clumps.

If years 2006 and 2011 are excluded, information is lost. These are the years with the largest take levels of loggerheads and leatherbacks. Although what would have happened if the fishery remained open is unknown, the take level would have been at least the value of the relevant take limit. In summary, there is a trade-off between breaking the year into periods and deriving each period's ATL at the cost of complexity and excluding years 2006 and 2011 and estimating the annual ATL at the cost of losing information.

As the fishery was closed in the first quarter of 2006, this year is only included if a species showed a propensity in the historical data (2005-2017) for relatively higher take levels in the first segment of the year, or if the first part of 2006 had an unusual number of takes (higher or lower than other years). In 2011, the fishery was closed near the end of the year. This year is only excluded if its take levels were within the interquartile range of the empirical distribution of 2005-2017 take levels for the period defined by combining segments 1 and 2 (1 January - 18 November) and bycatch events had historically occurred in the later part of the year.

3.2 Estimation of the ATL

In principal, we can use different strategies to estimate the distribution of our hypothetical TL outcomes, the ATL. A straightforward nonparametric approach uses a large random sample of independent observed TL-values, and the relative frequency that an outcome happens is tallied for all observed outcomes. This empirical probability distribution is our estimated ATL. This approach is not appropriate for our small data set of 13 dependent observations. Alternatively, a parametric model that we think is a good approximation of the underlying process that generates our hypothetical TL-values can be used. With this strategy, the model's parameters need to be estimated before the ATL can be estimated. Although this strategy still has its limitations when applied to a small data set, it is generally preferred when estimating a probability distribution based on a small data set.

As estimates of the ATL are needed, it is natural to consider Bayesian inference which is based on the posterior probability distribution (or simply posterior distribution), including prediction of hypothetical data. The posterior predictive distribution refers to the posterior distribution of hypothetical replicates of the data generated under the same conditions which produced the data. In our case, the data are the historical take levels, and the posterior distribution of hypothetical replicates of the data is the ATL.

A Bayesian approach to inference starts with the formulation of a model that we think is adequate to describe the situation of interest. Specifically, the model provides a joint probability distribution of the variable of interest, TL, and the unknown parameters of the data distribution (probability distribution function assumed to have generated the data). This joint density can be written as a product of two distributions that are commonly referred to as the prior distribution and the data distribution. The intent of the prior distribution is to capture our knowledge or beliefs about these parameters without reference to the data.

3.3 Data distributions and priors

In this subsection, the probability distribution functions that were used to model the data distribution and their corresponding prior distributions are presented. Since TL is a count, the distribution needs to be appropriate for counts; that is, only nonnegative integer values are possible outcomes. The Poisson distribution is a standard distribution to consider when modeling count data. A limiting characteristic of this distribution is that the variance equals the mean (equidispersion). When the mean and variance differ significantly, the counts are referred to as being dispersed. Overdispersion refers to the phenomenon of the variance exceeding the mean, and underdispersion refers to the phenomenon of the variance being less than the mean. A frequent reason why dispersion arises in count data is the failure of some basic assumption of the Poisson model.

One would expect the phenomena of dispersion to arise in TL-values. Some of the reasons for this expectation are the lack of independent observations, a small sample size, and heterogeneity (the failure of the assumption of a single fixed probability distribution).

An increasingly popular model that allows for both overdispersed and underdispersed counts is a two-parameter generalization of the Poisson distribution known as the COM-Poisson (Conway-Maxwell-Poisson or CMP) distribution (Conway and Maxwell, 1962). Using the parameterization introduced by Guikema and Coffelt (2005), the probability distribution function for a COM-Poisson random variable Y with parameters $\mu > 1$ and $\upsilon \geq 1$ is

$$P(Y = y \mid \mu, \upsilon) = \left(\frac{\mu^y}{y!}\right)^{\upsilon} \frac{1}{Z(\mu,\upsilon)} \quad y = 0, 1, 2, \ldots$$

where $Z(\mu,\upsilon) = \sum_{j=0}^{\infty} \left(\frac{\mu^j}{j!}\right)^{\upsilon}$ is the normalizing constant. As $Z(\mu,\upsilon)$ is intractable, an asymptotic approximation can be used (Minke et al. 2003 and Shmueli et al. 2005). This distribution's mean and variance can be approximated by

$$E[Y] \approx \mu + \frac{1}{2\upsilon} - \frac{1}{2}, \qquad V[Y] \approx \frac{\mu}{\upsilon}.$$

These approximations help us see that the parameter υ controls the amount of dispersion through its inverse relationship with variance. When $\upsilon = 1$, the probability distribution function reduces to the Poisson distribution, whereas $\upsilon < 1$ corresponds to overdispersion and $\upsilon > 1$ corresponds to underdispersion. Unless, μ, υ, or both are small, μ closely approximates the mean.

When a Bayesian COM-Poisson model was used to model a hypothetical data distribution of TL, the method, algorithm, and code by Chanialidis et al. (2018) were used. Thus, the parameters μ and υ were not estimated directly but derived from estimates of β and δ where

$$\mu = exp(\beta) \quad \text{and} \quad \upsilon = exp(-\delta).$$

After specifying the COM-Poisson distribution as the data distribution, the next step is to specify priors for the unknown parameters β and δ. Given our small sample size, the posterior distribution will be sensitive to one's choice of priors; however, specifying uninformative priors can be unhelpful. This is because noninformative priors can result in excessively large TL-values. Regarding an informative prior, beyond the data, we have scant knowledge concerning TL. However, one would expect that excessive annual take levels, relative to historical levels, would likely not be permitted, or at least strongly discouraged. Therefore, the ATL ought to cover the spread of annual take levels that are perceived to be potential outcomes given the historical take levels. For the ATL estimated herein, take levels far beyond the historical levels were not perceived as potential outcomes and priors are thus chosen accordingly.

As the historical data consist of a small sample of non-independent observations, it is likely that the upper percentiles have not been realized, and the spread (variation) in the ATL is greater than observed. Based on these insights, when determining the priors for the Bayesian COM-Poisson models used herein, the COM-Poisson distribution was first fitted to the historical data based on frequentist methods (Sellers and Shmueli, 2010) using the R package COMPoissonReg (Sellers, Lotze, and Raim, 2017). Then, the parameters β and δ were estimated using the appropriate transformations (Chanialidis et al. 2018), denoted as $\hat{\beta}_f$ and $\hat{\delta}_f$, and the parameters of the Gaussian priors were specified as follows: (1) the Gaussian prior for β had a mean of $\hat{\beta}_f$ and variance of 0.25, and (2) the Gaussian prior for δ had a mean of $\hat{\delta}_f - log(1/3)$ and variance of 0.25. That is, the β prior was centered on the frequentist estimate of β, and the δ prior was centered at $\hat{\delta}_f - log(1/3)$ resulting in approximately three times the frequentist estimate of variance.

Heuristics were used to derive a multiplier to the observed estimate of variance that would be consistent from species-to-species and provide a suitable fit to the data. Basically, different values were tried, and the value of 1/3 was decided upon. The variance of Gaussian priors was also determined heuristically. Again, different values were tried until a value that provided a suitable fit across species was determined. Because the parameters of the Gaussian priors were derived using the data, our priors would change if a different sample (hypothetical years) was drawn.

The frequentist model did not converge for all species. In these situations, a few observations from the early years of the SSLL fishery were dropped when computing the parameters of the Gaussian priors (see Section 4 for species-specific details). These dropped observations had the value of 0; consequently, the average TL would be increased using remaining data. As the early years had small annual take limits and a limit on effort, they could be considered less representative of the conditions assumed for the ATL. By dropping some of the earlier years, the more recent years would have greater influence on the posterior ATL. If this strategy did not work, a quasi-Poisson model based on the quasi-likelihood function (McCullagh and Nelder, 1989) was fitted. Then, $\hat{\beta}_f$ was specified as the estimate of the Poisson parameter, and $\hat{\delta}_f$ was specified as the natural logarithm of the estimate of the quasi-likelihood dispersion parameter. If one of these two strategies was used, it is specified in the results for the relevant species in Section 4.

Although the effect of priors on Bayesian inference can easily be evaluated by trying several different priors, time did not permit trying different informative priors or an exhaustive sensitivity analysis.

When deriving the ATL for the period defined by the third segment of the calendar year, there were a few species with no observed positive take levels. In this situation, a different data distribution needs to be specified. The binomial distribution with an unknown index parameter n and known p was specified as the data distribution in these situations.

The binomial distribution follows under the assumption that the historical and hypothetical TLs are independently, identically distributed Poisson random variables. Let τ_{obs} represent the sum of take levels in the data set, m denote the size of the data set (number of observed take levels), and y denote one additional draw from this Poisson distribution. Under properties of the Poisson distribution, it is known that the distribution of $\tau = \tau_{obs} + y$ conditional on τ_{obs} is the binomial distribution

$$\binom{\tau_{obs}+y}{y}\left(\frac{1}{m+1}\right)^{y}\left(\frac{m}{m+1}\right)^{\tau_{obs}}.$$

Under this reformulation, $\tau = \tau_{obs} + y$ is the unknown parameter in the binomial distribution and the posterior distribution of $y = \tau - \tau_{obs}$ is the posterior ATL. The prior distribution was specified as the integrated reference prior for a binomial index (Berger et al. 2012), and the open source code in Evidence of Absence (Dalthorp, Huso, and Dail, 2017) was used to generate the posterior distribution.

One can check the adequacy of a proposed model by inspecting the posterior ATL. This can be done by locating the observed data values in the posterior distribution. If very few of the observed values are in the tails of the posterior distribution, then the model seems reasonable. On the other hand, an observed value in the extreme tail portion of the posterior distribution, upper 1%, casts doubt on the adequacy of the model because extreme values in a small data set are unexpected. Particular attention was paid to the fit in the right tail (higher values) of the distribution as this is where the requested 80^{th} and 95^{th} percentiles are located.

A few other potential Bayesian models were quickly investigated before deciding upon this set of methods. A Bayesian negative binomial model and uninformative priors for the Bayesian COM-Poisson models were both explored; however, diagnostics indicted problems with convergence, instability concerning the estimation of the variance parameter, or unreasonably long right tails. Based on these limited exploratory analyses, the Bayesian models used herein seemed to be the most suitable among those considered given the nature of the historical data and time constraints.

3.4 Naïve Bayesian inference

This section explains why inferences in this report are considered naïve. A simplistic Bayesian model is used to approximate a process of data generation that is likely complex and very difficult to accurately capture. At least three of the underlying assumptions of the simplistic Bayesian model are violated. First, the historical data from 13 consecutive observations are treated as if independent but they are not. With just 13 data points, it is not realistic to presume that one can analyze the data and obtain a suitable understanding of the patterns in TL from year to year. Second, as discussed in Section 2, the conditions that produced our 13 consecutive observations are different from the conditions assumed for the hypothetical data. The hypothetical data assumes no take limits or restrictions on effort, whereas the historical data were generated under these conditions (only years 2005-2009 had effort restrictions throughout the year). How these conditions influenced fishing behavior and the process that generates TL is unknown. Third, as explained in Section 3.3, the priors were derived using the historical data. The assumptions that the prior makes no reference to the data and the underlying process that generates TL does not change are core assumptions of Bayesian inference.

Inferring patterns and additional information from so few observations is very challenging, and all methods of statistical inference will have shortcomings. Nevertheless, estimates of ATLs are required. When contemplating the appropriateness of the methods used to estimate the ATLs in this report, one needs to consider (1) the complexity of the problem, (2) the limitations of the historical data and our knowledge, (3) the limited time to develop methods and derive the ATLs, and (4) if the reported Bayesian inferences seem reasonable, appropriate, and useful for their intended purpose.

3.5 Inference: derivation of the mean and percentiles of the posterior ATL distribution

Since the posterior ATL is a discrete distribution, the mean (expected value) of TL is the sum over all possible outcomes of the product of the value of the outcome and its posterior probability of occurring.

The p^{th} percentile of a posterior ATL is the smallest outcome satisfying the condition that the sum of probabilities (cumulative probability) over all possible outcomes up to the percentile is at least $p/100$. For a discrete distribution, the cumulative probability may not equal $p/100$. That is, for a large number of observations, one would expect approximately p percent of the outcomes not to exceed the value of the p^{th} percentile. For example, consider the probability distribution in Table 3.1 where there are only 5 possible outcomes. The 80th and 95th percentiles of this distribution are 1 and 3, respectively, and the cumulative probability for these percentiles are .83 and .99. If one drew a large sample from this probability distribution, one would expect approximately 83% of the outcomes to be 1 or 0 and 99% of the outcomes to be 3 or less.

Table 3.1. A hypothetical example of a probability distribution with 5 possible outcomes. The probability of each outcome and its cumulative probability is given.

Outcome	Probability	Cumulative probability
0	.60	.60
1	.23	.83
2	.10	.93
3	.06	.99
4	.01	1.00

3.6 Estimation of the 2-year and 3-year ATL

To derive the estimated 2-year and 3-year ATL, for each year, a large number of random outcomes were generated from the posterior annual ATL. For each corresponding replicate, the outcomes were then summed over the years. For example, to estimate the 2-year ATL, outcomes representing the first and second year TL-values were generated from the posterior annual ATL, and then these two TL-values were added to derive an outcome from the 2-year ATL. This process was replicated 10,000 times, generating a data set of 10,000 random values from the 2-year ATL. The empirical probability distribution of the generated data set was used as an approximation of the posterior m-year ATL, for $m = 2,3$. With time permitting, the posterior m-year ATL can be computed mathematically by computing the probability of each possible outcome of a m-year ATL using the posterior annual ATL under the assumption that annual take levels arise independently. If these sums are interpreted to occur over consecutive years, the reported 80th and 95th percentiles would be expected to underestimate these sums if annual take levels are non-independent.

4 Results

Unless specified, the Bayesian COM-Poisson model described in Section 3.3 was used to derive the posterior ATLs of interest. The mean of the posterior annual ATL is expected to be greater than the average annual take level for the historical data since the ATL assumes that the fishery does not close during the year, as happened in 2006 and 2011.

4.1 Sea Turtles

Table 4.1 presents the annual take levels for each species of sea turtle when the ATL was requested. Because all unidentified hardshell sea turtle takes were counted as a loggerhead sea turtle take when monitoring the fisheries take levels against the loggerhead take limit, the take levels for loggerhead sea turtles includes the unidentified hardshell sea turtle takes.

Table 4.1. The annual take levels for the sea turtle species of concern. The annual take levels for 2006 and 2011 are for a partial year of fishing as the fishery closed on 20 March 2006 and 18 November 2011.

Year	Leatherback	Loggerhead	Olive Ridley	Green
2005	8	12	0	0
2006	2	17	0	0
2007	5	15	1	0
2008	2	0	2	1
2009	9	3	0	1
2010	8	7	0	0
2011	16	12	0	4
2012	7	6	0	0
2013	11	7	0	0
2014	16	15	1	1
2015	5	13	1	0
2016	5	15	0	0
2017	4	21	4	2

4.1.1 Leatherback sea turtle

The leatherback sea turtle's estimated annual ATL was derived using Option 1 (see Section 3.1). For the period defined by the third segment of the calendar year, the takes levels from the years prior to 2010 were excluded to achieve convergence of the frequentist COM-Poisson model when determining the parameters of the Gaussian priors. Only 4 years had positive take levels during this period, and these occurred after 2009. Table 4.2 reports the requested statistics for the different requested ATLs: annual, 2-year, and 3-year.

Table 4.2. The mean and requested percentiles of the specified leatherback sea turtle's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	10.0	14 (.805)	21 (.959)
2-year	20.0	26 (.805)	35 (.958)
3-year	30.0	38 (.814)	48 (.955)

4.1.2 Loggerhead sea turtle

The loggerhead sea turtle's estimated annual ATL was derived using Option 3. To account for the unseen high takes in the first part of year 2018, 27 takes in January and 2 in February, when deriving the parameters of the Gaussian priors, a data point of 34 takes was added to the 13 historical data points in the first segment of the year. Because of the 27 takes in January, there was pressure on the fishery to not exceed the annual take limit of 34 loggerheads. One does not know how the fishery would have behaved in February and March of 2018 if there was no annual limit on loggerhead takes. In 2016, there were 7 loggerhead takes between 1-20 March, but for the rest of the years, 0-3 takes were recorded during this period. To account for the pressure on the fishery and the historical take levels for 1-20 March, the added data point was assigned the value of 29+5=34. Table 4.3 reports the requested statistics. As the value of 34 is debatable, the posterior annual ATL was also derived for each of the added values of 29, 32, 36, and 39. Table 4.4 gives the different values of the mean and the percentiles for each of these posterior annual ATLs.

Table 4.3. The mean and requested percentiles of the specified loggerhead sea turtle's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	15.6	23 (.804)	36 (.950)
2-year	30.9	43 (.813)	59 (.952)
3-year	46.7	61 (.803)	81 (.954)

Table 4.4. The mean and requested percentiles of the loggerhead sea turtle's posterior annual ATLs for each of the different added data points to the data set used to determine the parameters of the Gaussian priors. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Added data point	Mean	80th percentile	95th percentile
29	15.1	22 (.804)	34 (.950)
32	15.2	23 (.816)	35 (.953)
36	15.7	24 (.819)	37 (.954)
39	16.1	24 (.805)	38 (.952)

4.1.3 Olive ridley sea turtle

The olive ridley sea turtle's estimated annual ATL was derived using Option 4. To achieve convergence of the frequentist COM-Poisson model when determining the parameters of the Gaussian priors, the take level of 0 from year 2005 was excluded. With the olive ridley sea turtle, 6 of the 9 takes have occurred since 2014; 4 occurred in 2017. Table 4.5 gives the requested statistics.

Table 4.5. The mean and requested percentiles of the specified olive ridley sea turtle's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	1.4	2 (.800)	5 (.958)
2-year	2.9	5 (.854)	8 (.960)
3-year	4.3	7 (.849)	11 (.963)

4.1.4 Green sea turtle

The green sea turtle's estimated annual ATL was derived using Option 2. Table 4.6 gives the requested statistics. To achieve convergence of the frequentist COM-Poisson model used to determine the parameters of the Gaussian priors, only takes after 2007 were used. There were no takes in the period defined by the third segment of the calendar year; therefore, the binomial distribution conditional on 0 takes was used to derive the posterior ATL distribution for this period. Table 4.6 gives the requested statistics.

Table 4.6. The mean and requested percentiles of the specified green sea turtle's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	1.4	2 (.808)	5 (.965)
2-year	2.8	4 (.806)	8 (.967)
3-year	4.1	6 (.818)	10 (.964)

4.2 Giant manta ray and other related classification

This section concerns the giant manta ray and another species classification that may contain a giant manta ray called manta/mobula. For the rays, the take levels for the 3rd segment of the calendar year were not available. Table 4.7 gives the historical annual take levels for the rays of interest.

Table 4.7. The annual takes for the giant manta ray and another ray classification of concern. The annual take levels for 2006 and 2011 are for a partial year of fishing as the fishery closed on 20 March 2006 and 18 November 2011, and the take levels given for 2017 are for the January 1-November 18 period.

Year	Giant Manta Ray	Manta/Mobula
2005	0	0
2006	0	0
2007	5	0
2008	0	1
2009	0	0
2010	6	1
2011	3	2
2012	0	0
2013	0	0
2014	1	1
2015	0	2
2016	0	3
2017	2	4

4.2.1 Giant manta ray

For the years 2005-2016, all takes of the giant manta ray occurred in the 2nd segment of the calendar year. The giant manta ray's estimated annual ATL was derived using Option 2. To achieve convergence with the frequentist COM-Poisson model used to derive the parameters of the Gaussian priors for the period defined by combining the 1st and 2nd segment of the calendar year, only takes from 2007 were used. As there were no observed takes in the 3rd segment of the year, the binomial distribution conditional on 0 takes was used to derive the posterior ATL for this period. Table 4.8 gives the requested statistics

Table 4.8. The mean and requested percentiles of the specified giant manta ray's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	2.5	4 (.815)	8 (.952)
2-year	5.1	8 (.827)	13 (.954)
3-year	7.6	11 (.811)	17 (.955)

4.2.2 Manta/Mobula ray

Like the giant manta ray, all takes of the manta/mobula classification occurred in the 2nd segment of the calendar year for 2005-2016. The manta/mobula ray estimated annual ATL was derived using Option 2. As there were no observed takes in the 3rd segment of the year, the binomial distribution conditional on 0 takes was used to derive the posterior ATL for this period. Table 4.9 gives the requested statistics.

Table 4.9. The mean and requested percentiles of the specified manta/mobula's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	1.7	3 (.846)	5 (.952)
2-year	3.5	5 (.801)	9 (.964)
3-year	5.2	8 (.848)	11 (.952)

4.3 Oceanic whitetip shark

Table 4.10 shows an extreme high take level of 348 in 2005, 2007-2011 take levels ranging from 48 to 98, and 2012-2017 take levels ranging from 24 to 32. All but 3 of the oceanic whitetip shark takes occurred between the 1st of January and the 18th of November, and the vast majority occurred in the 2nd segment of the calendar year. With little time to try and understand what variables could be associated with the high take level in 2005 and the shift to lower take levels since 2012, the decision was to include all years when estimating the ATL except for 2006 because of the early closure, low take level, and the historical trend of most takes occurring during the 2nd segment of the calendar year. To account for the 2005 high take level, a 2-component mixture model was used which assumed that TL was generated from one of two distributions. One distribution was assumed to generate the TL-values during a 'typical' year, and the other distribution was assumed to generate the TL-values during an 'unusual' year. The 'typical' year (first component) was interpreted as a year when the outcome is similar to the historical take levels observed in 2007-2017, ignoring the non-independent pattern in take levels (2007-2011 take levels higher than 2012-2012 take levels). The 'unusual' year (second component) was interpreted as a year when the outcome is an unusually high take level, such as in 2005. The mixing proportions were fixed at 0.925 for the first component and 0.075 for the second component. The mixing proportions can be interpreted as the probability that TL is generated from the first component and from the second component, respectively. These mixing proportions were based on 1 extreme value out of 12 years

(1/12≈0.083). As the extreme value happened in 2005 and takes levels have decreased in recent years, the second component was slightly down weighted to 0.075.

The first component was estimated in the same manner as the estimation of the ATL for the other species. Specifically, the distribution was estimated using Option 2 but only 2007-2017 take levels were used. For the period defined by the 3rd segment of the calendar year, the quasi-Poisson distribution was fitted to derive parameters of the Gaussian priors; however, since the estimated dispersion parameter (0.9) indicated slight underdispersion (the value of the dispersion parameter for equidispersion is 1), equidispersion was assumed when computing $\hat{\delta}_f$. Equidispersion was assumed because 9 data points are not expected to provide a good estimate of the dispersion parameter, and underdispersion is not expected since oceanic whitetip shark takes have the propensity of being clumped.

The second component was modeled as a discrete uniform distribution. One extreme value, 2005 take level, is not sufficient to fit a model and evaluate its fit; therefore, a discrete uniform distribution was decided upon as it is a flat distribution (all possible outcomes have equal probability). The lower bound was fixed at the 92.5th percentile of the posterior distribution of the first component, 124 takes. The upper bound was fixed at 400 takes to allow a take level greater than what has been observed.

With our mixing proportions, a long-run of 10,000 hypothetical TL observations would be expected to consist of roughly 9250 TL observations from the first component's distribution and 750 TL observations from the second component's distribution. Therefore, to estimate the annual ATL, 9250 TL outcomes were generated from the first component's distribution and 750 TL outcomes were generated from the second component. The empirical distribution of these 10,000 generated TL outcomes is the estimated annual ATL reported herein.

Inferences based on a mixture model normally take into account the uncertainty in the estimates of the mixing proportions and parameters of the components. The uncertainty in the mixing proportions and the second component's parameters (lower and upper bound of the discrete uniform distribution) are not taken into account in the algorithm described above. With just 12 data points and 1 extreme value, one cannot expect to derive reliable estimates of the mixing proportions or parameters of each component, check the fit of the mixture model, or check the mixture model's assumptions. Inferences reported herein are expected to be sensitive to the chosen mixing proportions and discrete uniform distribution.

Table 4.10. The annual takes for the oceanic whitetip shark. The annual take levels for 2006 and 2011 are for a partial year of fishing as the fishery closed on 20 March 2006 and 18 November 2011, and the take level given for 2017 is for the January 1-November 18 period.

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Take	348	1	98	48	53	90	78	24	27	21	22	32	29

Table 4.11. The mean and requested percentiles of the specified oceanic whitetip shark's posterior ATLs. In the percentile columns, the numbers in parenthesesare the cumulative probability at the percentile.

Number of years	Mean	80th percentile	95th percentile
1	71.6	102 (80.1)	227 (95.0)
2	144.5	205 (80.2)	371 (95.3)
3	216.4	307 (80.2)	464 (95.0)

4.4 Guadalupe fur seal and related species classifications

This section concerns the Guadalupe fur seal and other species classifications that may contain a guadalupe fur seal called unidentified pinniped and unidentified Otariidae. As shown in Table 4.12, there were no takes in the three species classifications of interest until 2014. In recent years, the fishery has increased activity off the West Coast of the Continental United States. As the takes have occurred off the West Coast, positive take levels should continue if this effort continues. If take levels from 2005-2017 are used to derive the annual ATLs, the annual ATLs would underestimate TL if the increased effort off the West Coast continues. For this reason, the estimated ATLs were based on the take levels from 2012-2017. Year 2012 was selected as the cut-off date because fur seal takes are still a rare event, and using year 2014 as the cut-off date would not include years with takes levels of 0. Additionally, 2012 was the first year of lower oceanic whitetip shark take levels (see Section 4.3), possibly signaling a significant shift in effort outside the range of the oceanic whitetip shark and inside the range of the Guadalupe fur seal. Time did not permit further analyses of the distribution of effort. For all three species classifications of interest, the annual ATP was estimated modeling the annual take levels (Option 4 applied only to 2012-2017 take levels).

Table 4.12. The annual takes for the Guadalupe fur seal and other species classification of interest. The annual take levels for 2006 and 2011 are for a partial year of fishing as the fishery closed on 20 March 2006 and 18 November 2011.

Year	Guadalupe Fur Seal	Unidentified Pinniped	Unidentified Otariidae
2005	0	0	0
2006	0	0	0
2007	0	0	0
2008	0	0	0
2009	0	0	0
2010	0	0	0
2011	0	0	0
2012	0	0	0
2013	0	0	0
2014	0	0	1
2015	1	3	2
2016	0	0	0
2017	3	0	0

4.4.1 Guadalupe Fur Seal

The quasi-Poisson distribution was fitted to the 2012-2017 annual Guadalupe fur seal take levels to derive the parameters of the Gaussian priors. Table 4.13 gives the requested statistics.

Table 4.13. The mean and requested percentiles of the specified guadalupe fur seal's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	1.7	3 (.848)	6 (.967)
2-year	3.5	5 (.800)	9 (.959)
3-year	5.2	8 (.844)	12 (.963)

4.4.2 Unidentified Pinniped

The quasi-Poisson distribution was fitted to the 2012-2017 annual unidentified pinniped take levels to derive the parameters of the Gaussian priors. Table 4.14 gives the requested statistics.

Table 4.14. The mean and requested percentiles of the specified unidentified pinniped's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	1.5	3 (.884)	5 (.964)
2-year	2.9	5 (.855)	8 (.964)
3-year	4.4	7 (.852)	10 (.953)

4.4.3 Unidentified Otariidae

The frequentist COM-Poisson distribution was fitted to the 2012-2017 annual unidentified Otariidae take levels to derive the parameters of the Gaussian priors. Table 4.15 gives the requested statistics.

Table 4.15. The mean and requested percentiles of the specified unidentified Otariidae's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probability at the percentile.

Period of ATL	Mean	80th percentile	95th percentile
annual	1.1	2 (.864)	4 (.965)
2-year	2.2	4 (.872)	6 (.956)
3-year	3.3	5 (.833)	8 (.954)

5 Discussion

With 100% observer coverage in the SSLL fishery since the fishery reopened in 2004, there are many bycatch observations for a SSLL set. These set-level observations are not independent observations as one would expect correlation between sets within a trip, trips by the same crew (particularly captain), sets close in time and space, and potentially other variables. One could consider a nonparametric resampling method of these observations to generate a large sample of TL-values and then use the empirical distribution of this large sample to estimate the ATL. Most resampling methods, however, assume that the independent unit of observation is being resampled. Although there are methods to resample dependent data, it is not clear how to apply these methods to the SSLL data set. Furthermore, a resampling method assumes the SSLL data set is representative of the anticipated data set as defined previously. Because the annual ATL is needed, it is the year-to-year variation in the take levels that needs to be captured, and the historical SSLL data set only contains 13 non-independent observations of annual take levels. Since this data set is too small to use its empirical distribution or a nonparametric resampling method for independent or dependent observations to estimate the annual ATL, a simplistic Bayesian model was used.

Bayesian modeling is convenient and useful when estimating the ATL; however, the knowledge and information on the process generating TL in the SSLLL fishery is insufficient to accurately model what is likely a complex process. Thus, the estimated annual ATLs were based on simplistic Bayesian models that made several critical assumptions. Some of these assumptions may not be true, and others are known not to be true. When evaluating the simplistic Bayesian models used to estimate annual ATL, one needs to ask if the inferences appear to be reasonable. Larger take levels than observed since 2004 are anticipated; however, takes levels markedly greater than the highest observed take levels are not anticipated. Using parametric models under the Bayesian framework allowed the structure to model the right tail of the ATL under these expectations. Among the few models that were considered, the chosen COM-Poisson Bayesian model appeared to be the most suitable for modeling ATL, except when there were no positive observed take levels and the Bayesian binomial model was utilized.

Although all estimators of ATL based on the small historical data set will have shortcomings, the simplistic Bayesian models used herein could be improved. Exploratory studies followed up with different simulations that address some of the uncertainties in the methods applied herein would be informative.

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