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Hawaii Permitted Deep-set Longline Fishery Estimated Anticipated Take Levels for Endangered Species Act Listed Species and Estimated Anticipated Dead or Serious Injury Levels for the Listed Marine Mammals [1]

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1 Introduction

In this report, prepared at the request of the NOAA Fisheries Pacific Islands Regional Office (PIRO), the Hawaii permitted deep-set longline (DSLL) fishery estimated anticipated take levels of nine protected species and four unidentified classifications are provided.

The nine species are

(1) loggerhead sea turtle
(2) leatherback sea turtle
(3) olive ridley sea turtle
(4) green sea turtle
(5) giant manta ray
(6) oceanic whitetip shark
(7) Indo-west Pacific (IWP) scalloped hammerhead shark
(8) sperm whale, and
(9) main Hawaiian Islands false killer whale stock (MHIFKW).

The four unidentified classifications are

(1) hardshell sea turtle
(2) unidentified ray
(3) manta/mobula (identified as a member of the Mobulidae family), and
(4) IWP unidentified hammerhead shark (an unidentified hammerhead shark caught within the IWP region).

Additionally, the anticipated dead or serious injury classification levels are provided for the two cetacean populations (sperm whale and MHIFKW). The data, methods, and assumptions used to estimate the anticipated take level and anticipated dead or serious injury level 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 Endangered Species Act (ESA) define “take” in slightly different ways; 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 DSLL fishery because an animal

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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 time period, 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 it is not feasible to monitor all aspects of a trip; thus, there is incomplete data available on such interactions.

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 observed to be caught twice during a Hawaii shallow-set longline 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, denote this random variable as T. The list of all possible outcomes and their corresponding probabilities is called a probability distribution. Since T 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 T observations. It is this discrete distribution that is interpreted as the ATL. Hereafter, T and ATL will refer to the annual take level and its distribution, unless otherwise stated. In other words, the ATL consists of the T outcomes that are anticipated from year-to-year. Estimating this distribution is the primary focus of this report.

To facilitate the calculation of ATLs, the ATL is interpreted as the anticipated probability distribution of T under the basic assumptions that (1) the underlying process that generates T does not change, and (2) the random values of T come up randomly, independently across years, and with a single fixed probability distribution. Herein, let T_{ATL} denote T under these assumptions.

The ATLs for the periods of 3 and 5 years are also derived and denoted as the 3-year ATL and 5-year ATL, respectively. That is, the distribution of T_{ATL} is derived for 3 periods of time: 1, 3, and 5 years. The 5-year ATL was only requested for marine mammals. For each time period, the mean and 95th percentile of the derived ATL are reported, as requested.

Next, let us consider takes that result in a classification of serious injury or mortality for marine mammals. Following the guidelines outlined by NMFS (2012), an observed marine mammal incidental take is classified as a death or into a relevant injury category (i.e., serious or non-serious). Herein, denote the classification of "death or serious injury" as DSI. Similar to T, it is assumed that the number of DSI classifications is a random variable. Define the DSI level as the number of DSI classifications over a specified period and denote this random variable as C_{DSI}. Additionally, let ADSIL denote the anticipated probability distribution of C_{DSI}. The ADSIL assumes the basic assumptions of the ATL listed above and that the process that generates a DSI classification does not change. Herein, let $C_{DSI,ATL}$ denote C_{DSI} under these assumptions. Unless otherwise stated, C_{DSI} and ADSIL refer to the annual DSI level. Similar to a take event, it is possible for the same animal to be involved in multiple DSI events.

The estimated ATLs are derived using a Bayesian inferential approach based on simplistic models that make a few critical assumptions. For some ATLs, these assumptions are unlikely to be true and steps are taken to try and mitigate the consequences of these violations. The necessity and usefulness of these simplistic models are discussed throughout this report. In the next section, the historical data sets are described. In Section 3 and 4, the methods and their assumptions and caveats are discussed. The results for each species classification of interest are provided in Section 5.

2 Historical Data

The Hawaii-permitted longline fishery is a limited-entry fishery with a maximum of 164 permits. In 2000, the Hawaii longline fishery was split into the two management components: deep-set (targeting primarily tunas, most commonly bigeye tuna) and shallow-set (targeting primarily swordfish). Since this split, an observer must be aboard monitoring bycatch on at least 20% of a year's DSLL trips. In this document, a Hawaii longline fishing trip is defined as any commercial fishing trip by a vessel that fishes using a Hawaii longline permit. Before departing on a fishing trip, a vessel's owner or operator are required to notify NOAA Fisheries Pacific Islands Regional Observer Program (PIROP) contractor at least 72 hours prior to their intended departure date. During this notification, they must declare if the trip will be a shallow-set trip. The DSLL fishery consists of all other trips and must comply with the regulations for this fishery, including the requirement of observer placement on a sample of vessels.

Although some of the DSLL regulations have changed since 2000, the only ones made with the intent to reduce bycatch of a protected species were those in the False Killer Whale Take Reduction Plan (FKWTRP) Final Ruling (see Code of Federal Regulations 50 *CFR*. § 229.37) that went into effect on December 31, 2012. Although the intent of the FKWTRP was to reduce the T outcomes of the false killer whale (FKW), it introduced several regulations that could affect the T outcomes of other species.

As shown in Table 2.1, the number of trips, fishing operations (sets), and hooks deployed have increased over the years, but from year-to-year this increase has not been steady. Additionally, the increase in the number of hooks deployed is more dramatic than the increases in the other two measures. Comparing 2002 to 2017, the number of trips increased by 25%, the number of sets increased by 37%, and the number of hooks deployed increased by 94%. How fishing operations are distributed over the fishing grounds changes seasonally and from year-to-year. Therefore, an increase in the number of trips, fishing operations, or hooks deployed does not necessarily increase a species' bycatch.

Sampling the DSLL fleet involves placing a NOAA Fisheries observer on a random sample of DSLL trips. 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, retained catch, and bycatch. This information is entered into a database called the Longline Observer Data System (LODS) (Pacific Islands Regional Office, 2019).

The observer manual (Pacific Islands Regional Observer Program, 2017) provides information on the program and the variables recorded.

As the estimator of the 2002–2017 annual take levels is based on the complex adaptive sample design used to select trips for observer placement, it is important to understand the design and the necessity for an adaptive design. An adaptive design is used to adapt to the availability of observers. Because a selected trip can only be sampled if an observer is available for deployment, observer availability must be considered. Observer availability and coverage levels vary throughout the year because of (1) fluctuation in the fleet's activity level, (2) demands of 100% coverage in the SSLL fishery, (3) an influx of observers after completion of NMFS observer training, (4) the departure of observers from the observer program, and (5) observers leaving and returning from leave. Because observers are not paid while waiting to be deployed, they must be assigned with minimal delay when available. The alternative of paying them while they are waiting to be deployed would increase the cost of the observer program. To adapt to the variability in observer availability and reach a balance between obtaining a probability sample and being cost effective, an adaptive sampling protocol that is based on two sampling schemes was developed.

Table 2.1. The DSLL fleet's annual effort as recorded by the vessels (Pacific Islands Fisheries Science Center, 2019) and the amount of DSLL effort observed by PIROP (Pacific Islands Regional Office, 2019). A trip is assigned to the calendar year its retained catch was landed. Effort is expressed as the number of trips, number of fishing operations (sets), and the number of hooks deployed.

	DSLL Effort			Observed Effort		
Year	trips	sets	hooks	trips	sets	hooks
2002	1,180	14,248	27,441,631	284	3,536	6,806,822
2003	1,216	14,733	29,657,401	259	3,207	6,450,221
2004	1,332	15,888	31,890,476	324	3,928	7,841,804
2005	1,398	16,506	33,549,695	364	4,602	9,360,671
2006	1,341	16,372	34,414,412	281	3,605	7,542,491
2007	1,381	17,781	38,735,969	270	3,508	7,627,296
2008	1,333	17,875	40,063,212	288	3,917	8,785,395
2009	1,225	17,001	38,177,005	250	3,520	7,879,685
2010	1,179	16,077	37,244,654	256	3,567	8,152,319
2011	1,246	16,888	40,022,132	253	3,540	8,260,092
2012	1,305	18,152	44,163,002	263	3,659	8,768,728
2013	1,328	18,750	46,769,514	272	3,830	9,278,133
2014	1,302	17,873	45,963,197	274	3,831	9,608,237
2015	1,385	18,409	47,331,741	283	3,725	9,393,436
2016	1,419	19,315	50,873,134	283	3,880	9,872,439
2017	1,478	19,578	53,258,093	297	3,832	10,148,196

As mentioned previously, longline vessels are required to notify the PIROP contractor prior to their intended departure date. To enable sample selection, the PIROP contractor numbers the notifications sequentially in the order in which they are received. Herein, this assigned number is referred to as the notification number. It is these notification numbers that are selected, and the trips associated with them designated to be sampled.

The first stage of the sampling protocol is a systematic sample. The systematic sample requires having an observer available to be deployed whenever a selected trip is ready to depart. Achieving this requirement under full targeted coverage, typically 20% coverage, throughout the year requires having enough observers on contract to accommodate higher levels of fleet activity and paying them when they are not deployed on a vessel. These requirements cannot be met under the current level of funding; therefore, the sample selected under the systematic design is slightly smaller than the targeted coverage, typically 5% less. Drawing the systematic sample at this level seems to provide the maximal percent coverage by the systematic sample in which few selected trips are missed. Since 2011, a 15% systematic sample is drawn unless PIROP does not have enough observers. In this situation, the coverage level of the systematic sample is adjusted. For example, in 2014, it was necessary to reduce the systematic sample down to 10% at the beginning of the year, and when there were enough observers, a new systematic sample for the remainder of the year was drawn at 17% coverage. Prior to 2011, the first quarter (January–March) systematic sample was drawn at 10% coverage and the other quarters at 15% coverage.

Now let us consider drawing the additional samples required to achieve the targeted coverage level. Only after all upcoming notifications selected by the systematic sample are assigned an observer and there are still observers ready to be deployed should additional samples be drawn. The method for drawing these samples needs to be straight forward, as they are needed quickly and with little forewarning. Drawing the additional notifications using simple random sampling without replacement (SRSWOR) from the list of notifications still eligible for observer placement is straightforward and the method that the observer program is instructed to use. Hereafter, this complex adaptive sample design is called a “systematic-plus” (SYSPLUS) design.

Because the occasions when secondary samples are drawn are not randomly selected but determined by the need to deploy observers, the probability a notification is selected by the secondary sample is unknown and needs to be approximated. To approximate these probabilities, the contractor's list of notifications is used. Examination of these records reveal time periods when coverage appears to have been greater or less than the full targeted coverage. Specifically, time periods for which the number of secondary samples is greater than expected are periods of higher coverage, and those for which the number of secondary samples are fewer than expected are periods of lower coverage. Before computing the inclusion probabilities (the probability a sampling unit is included in the sample), periods of comparable coverage are identified. The inclusion probabilities are computed by enumerating the number of notifications during consecutive time periods of comparable coverage and assuming that the secondary samples are selected with equal probability from those trips that have not been selected as part of the systematic sample. An outcome of the secondary sample is that notifications are selected with unequal probability. For example, notifications that are included in the sampling frame of the secondary sample will have a greater probability of being selected than those excluded.

The SYSPLUS has been used to select DSLL trips since 2002. For this reason, only 2002–2017 observer data are used to derive anticipated takes, except for the IWP scalloped and unidentified hammerhead sharks. For these species, 2004–2017 observer data are used, as requested by PIRO.

The historical data are not collected over a random selection of years but consist of data collected over 16 consecutive years (2002–2017). This short time series of estimated T outcomes is unlikely to provide sufficient information to determine a pattern of dependency across years or the extent of an ATL's right tail (higher take levels). The ATLs are likely asymmetrical, with a long right tail (the distribution is bounded on the left by 0).

3 Methods for estimating ATL

In this section, the general approach taken to estimate the ATL is described, including the underlying assumptions behind the approaches. The computation of the mean and 95th percentile of an ATL and the derivation of the 3-year and 5-year ATL are also explained. Because estimates of the *T* outcomes for years 2002–2017 are used to derive some of the ATLs, the methods used to estimate these values for the DSLL fishery are first explained.

3.1 Estimation of *T* outcomes for years 2002–2017

To begin, assign a trip's bycatch to the year its retained catch was landed, and let t_{yr} denote the unknown *T* outcome for years $yr = 2002,\ldots,2017$ and $\hat{t}_{yr}$ denote the sample-based estimate of the outcome for year *yr*. For an unequal probability sample without replacement, the Horvitz-Thompson estimator (HTE) and generalized ratio estimator (GRE) are appropriate estimators of finite population totals, such as t_{yr}. Short descriptions of both estimators follow; see Thompson (1992) for more detail.

Let *i* denote the sampling unit, π_i denote the inclusion probability of sampling unit *i*, *Y* denote the variable of interest where *y* represents a realized outcome of *Y*, and ω denote the realized sample of unique sampling units. The unbiased HTE of the population total τ is

$$\hat{\tau}_{HTE} = \sum_{i \in \omega} \frac{y_i}{\pi_i}.$$

The variance of the HTE is small when the *y*-values are approximately proportional to the inclusion probabilities; when there is no such relationship, the variance can be very large (Thompson, 1992).

When *Y* has an approximate proportional relationship with an auxiliary variable *X*, the GRE can be more efficient (smaller mean square error) than the HTE. For the GRE to apply, the two quantities *y* and *x* (realized outcome of *X*) must be measured on each sample unit and the population total of the *x*-values exactly known. Let τ_x and τ_y denote the population totals of the *x*-values and *y*-values, respectively. The GRE is

$$\hat{\tau}_{GRE} = \frac{\hat{\tau}_x}{\hat{\tau}_y} \tau_x$$

where the components $\hat{\tau}_y$ and $\hat{\tau}_x$ are the Horvitz-Thompson estimates of τ_y and τ_x. Whereas the HTE is an unbiased estimator, the GRE is not. If there is no linear relationship between the *y*-values and either the inclusion probabilities or any auxiliary variable, using the GRE with $x_i = 1$ for all sample units (i.e. notifications) is recommended (Hajek, 1971, p. 236; and Thompson, 1992, p. 69–70).

When estimating t_{yr}, the notifications are the sampling unit and y_i is the number of bycatch events linked to notification *i*. Hereafter, let the random variable *Y* represent the random number of bycatch events for a notification (trip). Because the inclusion probabilities are related to the number of observers actively employed and the level of activity in the fishery, a proportional relationship between the *y*-values and inclusion probabilities is not expected. Thus, the variance of the HTE can be very large when using observer data collected using the SYSPLUS design described in Section 2.

Because *Y* is often perceived to be proportional to fishing effort, the GRE is of interest since effort can be incorporate into the estimator as the auxiliary variable *X*. First consider expressing effort as the number of fishing operations or as the number of hooks deployed. For the species whose ATLs are being estimated, the relationship between the *y*-values and these two metrics of effort have been explored, and an approximate proportional relationship has not been found.

To incorporate effort as expressed by the number of trips that could potentially have positive *y*-values in the year of interest, let $x_i = 1$ if the i^{th} notification is linked to a trip that landed its retained catch in the year of interest and $x_i = 0$ if no hooks were deployed or the retained catch is landed in a different year. Defining the auxiliary variable this way should have similar benefits to using the GRE with $x_i = 1$ for each sampling unit (notification), but has the advantage of naturally correcting for selected notifications that did not link to a trip whose *y*-value could potentially be positive. Here, we use this definition of x_i as the effort metric with the GRE to estimate t_{yr}.

3.2 Bayesian data analysis to estimate ATL

To estimate the distribution of hypothetical T_{ATL} outcomes, the ATL, it is natural to consider using Bayesian inference as it involves deriving the posterior probability distribution (or simply posterior distribution) of the variable of interest. That is, the posterior probability distribution of T_{ATL} is an estimate of ATL.

A Bayesian approach to inference starts with the formulation of a model that is presumed to adequately describe the situation of interest. Specifically, the model provides a joint probability distribution of the variable of interest and the unknown parameters of the data distribution (probability distribution function assumed to generate 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.

Since T_{ATL} is a count, the distribution needs to be appropriate for counts. 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 the *T* outcomes. 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).

In our situation, the t_{yr}s are estimated using data collected under the SYSPLUS design, and only a subset of t_{yr}s might be considered relevant; that is, produced under similar conditions as the ATL assumes. Because a finite population of DSLL trips is being sampled, inferences concerning these values should be conditional on the observed data and the pattern of observed and unobserved trips resulting from the SYSPLUS sample (for more detail, see Chapter 7 of Gelman et al. 2004). Depending on if a species' number of observed takes between 2002 and 2017 (2004–2017 for IWP scalloped and unidentified hammerhead sharks) is 5 or less, one of two data distributions is specified as the data distribution. Hereafter, bycatch events are referred to as being extremely rare if 5 or less events were observed over the historical time series and rare if greater than 5 events were observed. First, the Bayesian data analysis for extremely rare bycatch events is outlined, then the data analysis for rare bycatch events is outlined.

3.2.1 Poisson data distribution for extremely rare bycatch events

For the species where an observed bycatch event has been extremely rare, a simple model that assumes the *y*-values (a trip's bycatch) are independent, identically distributed (iid) Poisson(λ_{trips}) random variables is likely to be a good approximating model for the data distribution. Under this distributional assumption, the missing data pattern supplies no information on λ_{trip} (the bycatch rate) and can be ignored. To build this model, for year *yr*, let $t_{obs,yr}$ denote the total observed takes and $t_{mis,yr}$ denote the total takes on unobserved (missed) trips where $t_{yr} = t_{obs,yr} + t_{mis,yr}$. Under the modeling framework, these three values are considered outcomes of the random variables $T_{obs,yr}$, $T_{mis,yr}$, and T_{yr}, respectively. Now, assume the iid Poisson assumption over the years $yr = 2002,\ldots,2017$ ($yr = 2002,\ldots,2017$ for IWP hammerheads), and let $t_{yrs} = \sum_{yr} t_{yr}$, $t_{obs,yrs} = \sum_{yr} t_{obs,yr}$, $t_{mis,yrs} = \sum_{yr} t_{mis,yr}$, and p_{yrs} denote the coverage level of trips over these years (the number of observed trips divided by the total number of DSLL trips by the fleet). Under properties of the Poisson distribution, $T_{yrs} \sim \text{Poisson}(\lambda_{yrs})$ where $\lambda_{yrs} = N_{yrs}\lambda_{trip}$ and $T_{obs,yrs} \sim \text{binomial}(T_{yrs}, p_{yrs})$. Although the outcomes t_{yrs} and $t_{mis,yrs}$ are both unknown, they are potentially observable quantities and can be estimated using an appropriate sample-based estimator (see Section 3.1) or predicted using a suitable approximating model. To distinguish between a sample-based estimate and a model-based prediction of a *T* outcome, let $\hat{t}$ denote a sample-based estimate and $\tilde{t}$ denote a model-based prediction. Assuming the iid Poisson model, the posterior predictive distribution of $\tilde{t}_{yrs}$ given $t_{obs,yrs}$ is estimated as

$$P(\tilde{t}_{yrs} \mid t_{obs,yrs}, p_{yrs}) = \frac{P(t_{obs,yrs} \mid \tilde{t}_{yrs}, p_{yrs}) P(\tilde{t}_{yrs})}{\sum_{\tilde{t}_{yrs}} P(t_{obs,yrs} \mid \tilde{t}_{yrs}, p_{yrs}) P(\tilde{t}_{yrs})},$$

where $T_{obs,yrs} \sim \text{binomial}(\tilde{t}_{yrs}, p_{yrs})$. When deriving the posterior distribution of $\tilde{t}_{yrs}$ in this report, the prior distribution of $\tilde{t}_{yrs}$ is specified as $p(\tilde{t}_{yrs} = t_{yrs}) \propto \sqrt{t_{yrs}+1} - \sqrt{t_{yrs}}$, which is the objective integrated reference prior (a noninformative prior) for a binomial index (Berger et al., 2012). The prior is truncated at the smallest value of t_{yrs} such that $P(\tilde{t}_{obs,yrs} \le t_{obs,yrs} \mid \tilde{t}_{yrs} = t_{yrs}) < 0.0001$.

When estimating $\tilde{t}_{yrs}$, we are estimating the total takes over the specified historical period. Under the iid Poisson assumption, $\tilde{t}_{yrs} \sim \text{Poisson}(\lambda_{yrs})$ where $\lambda_{yrs} = N_{yrs}\lambda_{trip}$. To estimate the ATL, let T_{ATL} denote the anticipated annual take levels which would occur in years with effort equal to the average number of annual trips for years 2002–2017, denote this average as $\bar{N}_{yrs}$. To estimate the ATL, we begin with estimating λ where $T_{ATL} \sim \text{Poisson}(\lambda)$. The posterior distribution of λ_{yrs} is expressed as

$$P(\lambda_{yrs} \mid t_{obs,yrs}, p_{yrs}) = \frac{P(t_{obs,yrs} \mid \lambda_{yrs}, p_{yrs}) P(\lambda_{yrs})}{\int P(t_{obs,yrs} \mid \lambda_{yrs}, p_{yrs}) P(\lambda_{yrs}) d\lambda_{yrs}},$$

where $T_{obs,yrs} \mid (\lambda_{yrs}, p_{yrs}) \sim \text{binomial}(\tilde{t}_{yrs}, p_{yrs})$ and $P(\lambda_{yrs}) \propto 1/\sqrt{(\lambda_{yrs})}$ (the noninformative Jeffreys prior for the Poisson parameter). The estimated λ is then defined to be the posterior distribution of $\lambda_{yrs} \mid (t_{obs,yrs}, p_{yrs})$ rescaled so that λ is the posterior distribution when effort equals $\bar{N}_{yrs}$.

Random draws of T_{ATL} are simulated in three steps: (1) Simulate draws of $\tilde{t}_{yrs}$ from its posterior distribution. (2) Simulate draws of λ from its posterior distribution conditional on the draws of $\tilde{t}_{yrs}$. (3) Simulate draws of T_{ATL} from a $\text{Poisson}(\lambda)$ distribution conditional on the draws of λ. The open source code in Evidence of Absence (Dalthorp, Huso, and Dail, 2017) is used to generate draws from the posterior distribution of T_{ATL}.

3.2.2 COM-Poisson data distribution for rare bycatch events

For species where an observed bycatch event has been rare, the number of observed bycatch events are well above 5 (see tables in Section 5). For these species, it is not assumed that *y*-values are iid random variables; consequently, the SYSPLUS design needs to be taken into account. Additionally, because the FKWTRP went into effect on 31 December 2012, only the unknown values of the *T* outcomes for $yr = 2013, \ldots, 2017$ are assumed to be generated under the conditions assumed for the ATL.

As the time available to conduct these analyses did not permit developing a probability model that accounted for the SYSPLUS design, for $yr = 2013, \ldots, 2017$, the value of $\hat{t}_{yr}$ is used as if it is the true value of t_{yr}. One of the consequences of assuming the estimated value is the true value of a finite population estimand is that the uncertainty around the estimated value is not incorporated into the posterior distribution.

To estimate the ATL, T_{ATL} outcomes are assumed to be iid COM-Poisson (Conway-Maxwell-Poisson or CMP) random variables (Conway and Maxwell, 1962). The COM-Poisson distribution is a two-parameter generalization of the Poisson distribution that allows for both overdispersed and underdispersed counts. Using the parameterization introduced by Guikema and Coffelt (2008), 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.

The method, algorithm, and code by Chanialidis et al. (2018) are used to fit the Bayesian COM-Poisson model. Thus, the parameters μ and υ are not estimated directly but derived from estimates of β and δ where

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

3.2.2.1 Priors for β and δ

After specifying the COM-Poisson distribution as the data distribution, the next step is to specify priors for the unknown parameters β and δ. With only 5 estimated realizations of T_{ATL} ($\hat{t}_{yr}$ for $yr=2013,\ldots,2017$), 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 *T* outcomes that are unlikely to be realized because of the pressure to protect ESA listed species. Regarding data that is available to create an informative prior, there is the 2002–2012 data. Although this data was generated prior to the implementation of the FKWTRP, it captures a range of possible conditions that could affect the *T* outcomes. For example, changes in the spatial and temporal distribution of effort, fishing behavior, and environment conditions could have a greater impact on *T* outcomes than any possible changes associated with the FKWTRP. Although 2013–2017 data is related to what is being used as our relevant historical data ($\hat{t}_{yr}$ for $yr=2013,\ldots,2017$), incorporating it into the priors helps to account for some of the uncertainty around $\hat{t}_{yr}$. Hence, 2002–2017 data is used to derive the priors for the unknown parameters β and δ.

To begin, β and δ are both assigned a Gaussian prior. The mean and variance of the Gaussian priors are derived using simulations based on the historical data. Next, the basic steps of the simulations are discussed then specifics are given.

The basic steps of the simulations are as follows: (1) Create a dataset of *K* hypothetical T_{ATL} outcomes, (2) Using this data set, compute the posterior distribution of β and δ assuming the COM-Poisson data distribution and specifying flat Gaussian priors (noninformative priors) for both parameters, (3) The mean and variance of each posterior distribution is recorded. The value of *K* is large enough that the priors of β and δ have little influence on the posterior distribution. These 3 steps are replicated *R* times. Let $\mu^*_{(\beta)r}$, $\sigma^{2*}_{(\beta)r}$, $\mu^*_{(\delta)r}$, and $\sigma^{2*}_{(\delta)r}$ denote the mean and variance of the posterior distribution of β and δ, respectively, for the r^{th} replicate . The averages of these recorded values are used as their corresponding values for the Gaussian priors. That is, the prior for β is Gaussian($\mu_\beta, \sigma^2_\beta$) where $\mu_\beta = \sum_{r=1}^{R} \mu^*_{(\beta)r} / R$ and $\sigma^2_\beta = \sum_{r=1}^{R} \sigma^{2*}_{(\beta)r} / R$. Similarly, the prior for δ is Gaussian($\mu_\delta, \sigma^2_\delta$) where $\mu_\delta = \sum_{r=1}^{R} \mu^*_{(\delta)r} / R$ and $\sigma^2_\delta = \sum_{r=1}^{R} \sigma^{2\,*}_{(\delta)r} / R$.

Now, let us consider how the hypothetical T_{ATL} data sets are generated. The purpose of the hypothetical data sets is to generate different datasets of what the future might look like based on the historical data. The following are the steps taken to generate the hypothetical T_{ATL} data sets.

1. For $yr = 2002, \ldots, 2017$, the posterior distribution of $\tilde{t}_{yr}$ or the bootstrap distribution of $\hat{t}_{yr}$ is obtained. If the year had fewer than 10 observed trips with positive *y*-values then the posterior distribution of $\tilde{t}_{yr}$ is derived. The posterior distribution is obtained using the same binomial data distribution in the Bayesian model for iid Poisson(λ_{trip}) random variables described in Section 3.2.1, but with $\tilde{t}_{yr}$, $t_{obs,yr}$, and $\tilde{t}_{mis,yr}$ replacing $\tilde{t}_{yrs}$, $t_{obs,yrs}$, and $\tilde{t}_{mis,yrs}$, respectively. Similarly, the coverage level of trips for year *yr*, p_{yr}, replaces p_{yrs}. When more than 10 observed trips had positive *y*-values, the model that assumes the *y*-values are iid Poisson(λ_{trip}) variates is less likely to be a good approximating model. Therefore, the bootstrap distribution of $\hat{t}_{yr}$ was generated using a bootstrap algorithm that mimics the SYSPLUS sample. The bootstrap distribution makes no distributional assumptions concerning the *y*-values. The bootstrap algorithm does not work well when less than 10 trips have positive *y*-values. Because the posterior distribution of $\tilde{t}_{yr}$ or the bootstrap distribution of $\hat{t}_{yr}$ is derived depending on how many trips had positive *y*-values, there is an inconsistency in the type of distribution being estimated. Time did not permit a resolution to this discrepancy.
2. This step uses the posterior and bootstrap distributions derived in the first step to create three probability distributions of hypothetical *T* outcomes. The three distributions are defined by the three historical time periods (1) 2002–2008, (2) 2009–2012, and (3) 2013–2017. The probability distributions assume similar conditions to those influencing take levels in their respective historical time period. Years 2009–2012 were prior to the FKWTRP final ruling but the annual quota of bigeye tuna was consistently reached, closing part of the fishing grounds for the remainder of the year. Years 2002–2008 took place prior to the FKWTRP final ruling and the fisheries annual quota on bigeye tuna being consistently reached. To derive each of these distributions, for the relevant years (2002–2008, 2009–2012, and 2013–2017), 1,000 outcomes are drawn from each year's posterior or bootstrap distribution. These draws are then combined and their empirical probability distribution computed. The resulting three empirical probability distributions are used in the next step.

3. This step draws K hypothetical T outcomes for each of the R replicates. To begin, let k_1, k_2, and k_3 represent the number of draws from each of the three empirical probability distributions, respectively, and let $\mathbf{K} = (k_1, k_2, k_3)$, the vector of these three variables. It is assumed that $\mathbf{K}$ has a multinomial distribution with sample size $K = \sum_{i=1}^{3} k_i$ and respective probabilities 1/6, 2/6, and 3/6. For each of the R replications, a draw of $\mathbf{K}$ is simulated. Let $\mathbf{K}_r^* = (k_{1r}^*, k_{2r}^*, k_{2r}^*)$ denote the r^{th} draw for $r = 1, \ldots, R$. After $\mathbf{K}_r^*$ is drawn, k_{1r}^*, k_{2r}^*, and k_{3r}^* values are drawn from their respective empirical distributions. These values are pooled to create the r^{th} data set of K hypothetical T outcomes. This step assumes that the conditions that influenced the take levels in the more recent years are more likely to occur in the future.

Although the priors computed by this approach helped to account for the uncertainty around $\hat{t}_{yr}$, a more rigorous approach would likely result in estimates of the ATL that are more accurate. As mentioned previously, the data distribution should be for the data and the data collection method (SYSPLUS). Additionally, priors based on the 2002–2012 data could be developed using a Bayesian model with a similar data distribution but with a noninformative prior. As a complex adaptive design has been used to select trips for observer placement, for many species, developing a good approximating data distribution is challenging and may not be possible for all species.

Even if a more rigorous approach was conducted, the current DSLL regulations have only been in place since 2013 and it is not realistic to presume that one can analyze so few years of data and obtain a suitable understanding of the patterns in T outcomes across years. Although the effect of priors on Bayesian inference can be evaluated by trying several different priors, time did not permit trying different informative priors and an exhaustive sensitivity analysis.

3.3 Model for Estimation of ATL of MHIFKW

To estimate the ATL of MHIFKW, the first step is to estimate the ATL of FKW within Hawaii's EEZ (EEZFKW) following methods outlined in Section 3.2.2. After this step, the process used to estimate the T of MHIFKW in the most current annual stock assessment report (Carretta et al., 2018, pp. 96–108) is followed. This process multiplies the estimated T outcome of EEZFKW by the proportion of DSLL sets within the EEZ that were within the overlap zone of the pelagic and MHI stock of FKW open to longline fishing. The resulting number is considered to be the estimated T outcome of FKW within this overlap zone. This number is then multiplied by the quotient of the current estimated density of MHIFKW in this zone divided by the current estimate of FKW density in this zone. This quotient is interpreted as the proportion of FKWs in this zone that are anticipated to be MHIFKWs. The current estimate of this quotient is 0.6040.

The species classification referred to as a blackfish (BF) also needs to be considered when estimating the ATL of EEZFKW. The BF classification results when an observed take is determined to be either a FKW or short-finned pilot whale. Using the methods outlined in McCracken (2010), all BF bycaught within Hawaii's EEZ are estimated to have a probability greater than 0.90 of being a FKW. As there are no observed BF during the 2013–2017 period and only 9 during the 2002–2012 period, for simplicity, the BFs are considered FKWs when deriving the ATL of MHIFKW.

When estimating the ATL of MHIFKW, the number 0.0604 is fixed and the annual proportion of sets within the EEZ that are within the overlap zone is considered random. Denote this random variable as *Z*. Table 3.1 provides the annual DSLL fleet's effort within Hawaii's EEZ and the overlap zone along with the percentage of sets within the EEZ that are in the overlap zone. Since the overlap zone is small compared to the area of the EEZ that is opened to DSLL fishing, this proportion is small and expected to stay small. To derive the ATL of MHIFKW, the predictive posterior distribution of Z needs to be derived. The method used to derive the posterior distribution of *Z* is discussed next.

Starting with the data distribution, *Z* is assumed to have a $\text{beta}(a,b)$ distribution. Since the FKWTRP did not impose any regulations within the overlap zone, the 2002–2017 proportions are assumed to have been generated under the same conditions as those assumed for the ATL. Next, let us consider the priors for *a* and *b*. The beta distribution's expected value is $a/(a+b)$. The priors of the beta distribution can be thought of as the number of successes (*a*, sets within the overlap zone) and the number of failures (*b*, sets outside of the overlap zone) anticipated. A large value of $a+b$ reflects greater confidence in our expectations of potential *Z* outcomes. As we are fairly confident that *Z* will remain small, it seems reasonable to have priors that result in a large value for $a+b$. Hence, a uniform distribution with a lower bound of 2 and an upper bound of 3 is specified as the prior for *a*, and a uniform distribution with lower and upper bounds of 450 and 550, respectively, is specified as the prior for *b*. To estimate the posterior distribution of *Z*, first, 10,000 draws from the posterior distribution of *a* and *b* are simulated. Then, conditional on *a* and *b*, 10,000 draws of *Z* from the beta distribution are simulated.

At this juncture, draws from the ATL of MHIFKW are ready to be simulated. For draws $d=1,\ldots,10{,}000,$ the product of the d^{th} draw from *Z,* the d^{th} draw from the ATL of EEZFKW, and 0.0604 represents the d^{th} draw from the ATL of MHIFKW.

Table 3. 1. The annual number of DSLL sets within Hawaii's EEZ and the overlap zone of the pelagic and MHI stock of FKW that is open to DSLL fishing. The percentage of DSLL sets within Hawaii's EEZ is provided in the last column.

Year	Hawaii's EEZ	Overlap Zone	Percent (%) in Overlap Zone
2002	6,265	22	0.35
2003	7,264	60	0.83
2004	6,865	70	1.02
2005	8,713	46	0.53
2006	7,688	17	0.22
2007	6,762	31	0.46
2008	7,426	13	0.18
2009	6,089	27	0.44
2010	3,750	10	0.27
2011	6,016	20	0.33
2012	6,119	15	0.25
2013	5,602	6	0.11
2014	4,560	13	0.29

Year	Hawaii's EEZ	Overlap Zone	Percent (%) in Overlap Zone
2015	6,053	22	0.36
2016	5,353	20	0.37
2017	5,159	60	1.16

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

Since the ATL is a discrete distribution, the mean (expected value) of T_{ATL} 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 with a small range of values, the cumulative probability may not equal $p/100$. For example, consider the probability distribution in Table 3.2 where there are only 5 possible outcomes. The 95th percentile of this distribution is 3 (because the next lower outcome has a probability less than 0.95), and the cumulative probability for this percentile is 0.99. If one drew a large sample from this probability distribution, one would expect approximately 99% of the outcomes to be 3 or less.

Table 3. 2. 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

3.5 Estimation of the 3-year and 5-year ATL

To derive the estimated 3-year and 5-year ATL, for each year, a large number of random outcomes are generated from the posterior annual ATL. For each corresponding replicate, the outcomes are then summed over the years. For example, to estimate the 3-year ATL, draws representing the first, second, and third year T_{ATL} outcomes are generated from the posterior annual ATL, and then these three T_{ATL} outcomes are summed to derive an outcome from the 3-year ATL. This process is replicated 10,000 times, generating a data set of 10,000 random values from the 3-year ATL. The empirical probability distribution of the generated data set is used as an approximation of the posterior n-year ATL, for $n = 3, 5$. If these sums are interpreted to occur over consecutive years, the reported 95th percentile would be expected to underestimate these sums if annual take levels are non-independent.

4 Methods for estimating ADSIL

For the marine mammal species, the ADSIL also needs to be estimated and this involves estimating the probability a bycatch event results in a DSI. As only animals bycaught from 2007 to present have had their injury classified under the current policy directive for classification (NMFS 2012), injury classifications prior to 2007 are not considered when estimating this probability. Additionally, since the FKWTRP regulated the hooks used, for those species that tend to depredate catch or bait and get hooked, its implementation may have affected this probability. As the FKW and BF tend to get hooked, only 2013–2017 injury classifications are used when estimating this probability for the FKW. The large whales (sperm, humpback, and Bryde's whale) are not known to depredate catch or bait, and their observed interactions have been entanglements. Therefore, their 2007–2017 injury classifications are used, and because there are so few classifications of large whales bycaught in the DSLL and SSLL fisheries, these classifications are pooled when estimating this probability.

This section provides a general explanation of the estimation of ADSIL. After estimating ADSIL as the posterior distribution of $C_{DSI,ATL}$, the mean and percentiles of the estimated ADSIL are computed in the same manner as these statistics for the estimated ATL. Similarly, the estimated 3-year and 5-year ADSILs are computed in the same manner as for the ATLs. The estimation of ADSIL is first explained for the sperm whale and then for the FKW.

4.1 Estimating the sperm whale's ADSIL

For the large whales, the three injury classifications of interest for estimating ADSIL are (1) death or serious injury (DSI), (2) non-serious injury (NSI), and (3) a prorated (PR) category where under the current policy (NMFS 2012) an injury is assumed to have a probability of 0.75 of being a DSI. The Bayesian model for ADSIL assumes that bycatch events (past and future) have common probabilities θ_1, θ_2, and θ_3 of being classified in these three categories, respectively. Let m_1, m_2, and m_3 represent the observed count in each category, respectively, and $M = (m_1, m_2, m_3)$ the vector of these three counts. The model used to estimate ADSIL begins with assuming that the data distribution of M is the multinomial distribution with sample size $m_+ = \sum_{i=1}^{3} m_i$ and respective probabilities θ_1, θ_2, and θ_3, where $\sum_{i=1}^{3} \theta_i = 1$. The vector $\theta = (\theta_1, \theta_2, \theta_3)$ is then assigned the uniform prior distribution (assigns equal probability to any vector θ satisfying $\sum_{i=1}^{3} \theta_i = 1$). The resulting posterior density of θ is proportional to

$$g(\theta) = \theta_1^{m_1} \theta_2^{m_2} \theta_3^{m_3}$$

(Gelman et. al., 2004), which is known as the Dirichlet distribution with parameters $(m_1 + 1, m_2 + 1, m_3 + 1)$. To simulate draws from this Dirichlet distribution the R function *rdirichlet* in the package LearnBayes (Albert, 2009) is used.

At this juncture, draws from the posterior distribution of M conditional on T_{ATL} and θ are simulated from the multinomial distribution conditional on the simulated draws of T_{ATL} and θ. This step assumes that T_{ATL} and θ are independent. The next step is to generate the number of PR classifications that are DSI. For this step, it is assumed that this number is a binomial variate conditional on the number of PR classifications (m_3) and the probability 0.75 that a PR take is a DSI. Adding a simulated draw from this binomial distribution to a simulated draw of m_1 represents a simulated draw from the

ADSIL. To estimate the sperm whale's ADSIL, 10,000 draws were simulated from each distribution involved in the process.

4.2 Estimating the ADSIL of MHIFKW

Now consider formulating the ADSIL of MHIFKW. It is assumed that all FKW stocks have the same probability distribution of a take being classified as DSI. For the FKW the third injury category (PR) does not apply, thus the injury classifications can be collapsed into the 2 categories (1) DSI and (2) NSI. ADSIL is formulated in a similar manner as for the sperm whale but without the third category. The assumed data distribution of M is the binomial distribution with sample size $m_+ = \sum_{i=1}^{2} m_i$ and probability of a DSI θ.

As the BFs bycaught within the EEZ are considered FKWs when estimating the ATL of EEZFKW, the injury classifications of observed BFs and unidentified cetaceans, excluding the unidentified large whales, can be considered additional information and used to develop a prior density. As recommended by the Pacific Scientific Review Group for marine mammals, the BF and unidentified cetacean injury classifications are both pooled when estimating θ for these two species. The prior density of θ is the $\text{beta}(s+1, f+1)$ distribution, where *s* is the number of BF and unidentified cetacean classified as DSI and *f* is the number classified as NSI. Based on this formulation of the prior, the posterior density of θ is the $\text{beta}(s+m_1+1, f+m_2+1)$ distribution. Under the assumption that MHIFKW's T_{ATL} and θ are independent, draws from the ADSIL are simulated from the binomial distribution conditional on the simulated draws of MHIFKW's T_{ATL} and θ.

5 Results

Unless specified, the Bayesian COM-Poisson model described in Section 3.2.2 is used to estimate the ATLs of interest. This includes (1) using $\hat{t}_{yr}$, $yr = 2013, \ldots, 2017$, as the true t_{yr}-values and assuming these values are generated under similar conditions as T_{ATL} and (2) generating 100 datasets of 500 hypothetical *T* outcomes for determining the parameter values of the Gaussian priors.

5.1 Sea Turtles

Table 5.1 presents the observed takes $(t_{obs,yr})$ and $\hat{t}_{yr}$s for the sea turtles. Although these values appear to have increased in recent years (2013–2017), there are some high values prior to 2013.

Table 5. 1. The observed takes (obs) and $\hat{t}_{yr}$s (est) for the four sea turtle species and the classification of unidentified hardshell sea turtle.

Year	Leatherback		Loggerhead		Olive Ridley		Green		Unidentified Hardshell	
	obs	est	obs	est	obs	est	obs	est	obs	est
2002	2	6	4	19	7	31	1	3	0	0
2003	1	4	0	0	3	15	0	0	0	0
2004	3	14	0	0	13	45	1	4	0	0
2005	1	3	0	0	2	17	0	0	0	0
2006	2	9	0	0	11	55	2	6	0	0
2007	2	4	1	6	7	26	0	0	0	0
2008	1	11	0	0	3	17	0	0	0	0
2009	1	3	0	0	4	17	0	0	0	0
2010	1	6	1	6	3	10	0	1	0	0
2011	3	14	0	0	7	36	1	5	0	0
2012	1	6	0	0	6	34	0	0	0	0
2013	3	15	2	11	9	42	1	5	0	0
2014	7	38	0	0	8	50	3	16	0	0
2015	4	18	2	9	13	69	1	4	0	0
2016	3	15	2	7	31	160	1	5	1	5
2017	0	0	3	12	26	118	3	18	0	0

5.1.1 Leatherback sea turtle

The leatherback sea turtle's estimated ATLs reflect the higher 2013–2016 values of $\hat{t}_{yr}$ and the uncertainty around these estimates. Table 5.2 reports the requested statistics for the different requested ATLs: annual and 3-year.

Table 5. 2. The mean and 95th percentile of the specified leatherback sea turtle's posterior ATLs.

Period of ATL	Mean	95th Percentile
annual	17.1	43
3-year	51.4	95

5.1.2 Loggerhead sea turtle

In the recent years, the $t_{obs,yr}$s and $\hat{t}_{yr}$s for the loggerhead sea turtle show a possible increase in *T* outcomes. However, the year with the highest values for these variables is 2002. The values from 2002 are down-weighted when deriving the ATL. This is likely justified as there were changes in the regulations to ensure that fishing operations were set deep after there was evidence not all fishing operations were being set deep in early 2002. Table 5.3 reports the requested statistics.

Table 5. 3. ***The mean and 95th percentile of the specified loggerhead sea turtle's posterior ATLs.***

Period of ATL	Mean	95th Percentile
annual	9.1	27
3-year	27.3	57

5.1.3 Olive ridley sea turtle

The olive ridley sea turtle's estimated ATLs reflect the higher 2013–2017 values of $\hat{t}_{yr}$. Table 5.4 gives the requested statistics.

Table 5. 4. ***The mean and 95th percentile of the specified olive ridley sea turtle's posterior ATLs.***

Period of ATL	Mean	95th Percentile
annual	70.7	171
3-year	212.1	373

5.1.4 Green sea turtle

The green sea turtle's estimated ATLs reflect the higher 2013-2017 values of $\hat{t}_{yr}$. Table 5.5 shows the requested statistics.

Table 5. 5. The mean and 95th percentile of the specified green sea turtle's posterior ATLs.

Period of ATL	Mean	95th Percentile
annual	13.0	39
3-year	38.7	81

5.1.5 Unidentified hardshell sea turtle

Although there is only 1 observed take of an unidentified hardshell sea turtle, its estimated ATLs are derived using the Bayesian COM-Poisson model. This decision is based on the observation that the 2013–2017 $\hat{t}_{yr}$s for the hardshell turtles (loggerhead, olive ridley, and green) tend to be higher than previous years and that the 1 observed take of an unidentified hardshell turtle occurred in 2016. Using the COM-Poisson model is consistent with what is used for the hardshell turtles. Table 5.6 shows the requested statistics. If the model for extremely rare events is used, the results would be similar to those for the sperm whale since there was only 1 observed take of a sperm whale (see Table 5.16).

Table 5. 6. ***The mean and 95th percentile of the specified unidentified hardshell sea turtle's posterior ATLs.***

Period of ATL	Mean	95th Percentile
annual	2.8	9
3-year	8.2	18

5.2 Giant manta ray and other related classification

This section concerns the giant manta ray and two other species classifications that may contain a giant manta ray: manta/mobula and unidentified ray. Table 5.7 shows the observed takes $(t_{obs,yr})$ and $\hat{t}_{yr}$s for the rays of interest.

Table 5. 7. The observed takes (obs) and $\hat{t}_{yr}$ (est) for the giant manta ray and the two other ray classifications of concern.

	Giant Manta Ray		Manta/Mobula		Unidentified Ray	
Year	obs	est	obs	est	obs	Est
2002	0	0	19	104	3	11
2003	0	0	4	19	1	6
2004	1	3	8	39	0	0
2005	2	7	0	0	0	0
2006	2	11	2	21	0	0
2007	2	5	6	31	1	1
2008	2	10	2	10	1	5
2009	4	23	3	19	3	20
2010	17	95	1	6	2	5
2011	1	5	2	9	0	0
2012	2	11	1	6	2	12
2013	1	5	0	0	4	21
2014	3	11	4	16	0	0
2015	2	10	5	25	4	21
2016	4	22	3	16	1	4
2017	0	0	5	26	1	7

5.2.1 Giant manta ray

The highest $\hat{t}_{yr}$ of the giant manta ray is in 2010, where the $t_{obs,yr}$ and $\hat{t}_{yr}$ are over four times higher than any other year. Expect for 2010, the $t_{obs,yr}$s range from 0 to 4. Although 2010 is not included in the relevant historical years, it is incorporated into the prior and thus incorporated into the estimated ATLs. Table 5.8 shows the requested statistics.

Table 5. 8. The mean and 95th percentile of the specified giant manta ray's posterior ATLs.

Period of ATL	Mean	95th Percentile
annual	20.0	60
3-year	59.9	126

5.2.2 Manta/Mobula ray

The highest $\hat{t}_{yr}$ of the manta/mobula ray is in 2002, where $t_{obs,yr}$ and $\hat{t}_{yr}$ are over two times higher than the other years. Expect for 2002, the $t_{obs,yr}$s range from 0 to 8. Although 2002 is not included in the relevant historical years, it is incorporated into the prior and thus incorporated into the posterior ATLs. Years 2002–2008 having less influence in determining the parameter values of the prior is reflected by the smaller mean and upper 95th percentile than would be expected if years 2002–2017 had equal influence. Table 5.9 shows the requested statistics.

Table 5. 9. The mean and 95th percentile of the specified manta/mobula's posterior ATLs.

Period of ATL	Mean	95th Percentile
annual	19.0	53
3-year	59.9	115

5.2.3 Unidentified ray

There is not a clear pattern of $t_{obs,yr}$ and $\hat{t}_{yr}$ increasing or decreasing over the years. Table 5.10 shows the requested statistics.

Table 5. 10. The mean and 95th percentile of the specified unidentified ray's posterior ATLs.

Period of ATL	Mean	95th Percentile
annual	14.0	39
3-year	41.6	83

5.3 Sharks

This section concerns two species of sharks, oceanic whitetip shark and IWP scalloped hammerhead shark, and the related IWP unidentified hammerhead shark. Because these sharks could be kept after being caught (retained) until recently, the T_{ATL} and ATLs are based on the historical catch, which includes bycatch and retained catch. Table 5.11 shows the observed catches ($t_{obs,yr}$) and $\hat{t}_{yr}$s for the sharks of interest.

Table 5. 11. The observed catch (obs), includes bycatch and retained catch, and $\hat{t}_{yr}$s (est) for the sharks of concern.

Year	Oceanic Whitetip		IWP Scalloped Hammerhead		IWP Unidentified Hammerhead	
	obs	est	obs	est	obs	Est
2002	840	3,574	0	0	0	0
2003	524	2,515	0	0	0	0
2004	718	2,938	2	6	2	7
2005	341	1,282	0	0	0	0
2006	331	1,346	0	0	0	0
2007	262	1,341	1	7	0	0
2008	144	741	0	0	0	0
2009	244	1,236	0	0	0	0
2010	252	1,198	0	0	0	0
2011	225	1,176	0	0	0	0
2012	172	878	0	0	0	0
2013	196	973	0	0	0	0
2014	370	1,670	0	0	0	0
2015	531	2,654	0	0	0	0
2016	423	2,188	0	0	0	0
2017	242	1,257	0	0	0	0

5.3.1 Oceanic whitetip shark

The oceanic whitetip shark is caught much more frequently than the other species considered in this report. For this reason, there is greater precision around the $\hat{t}_{yr}$s. When computing the parameter values of the Gaussian prior, generating data sets of 500 *T* outcomes conveyed too much confidence in the prior distribution, whereas, data sets of 20 *T* outcomes appeared to capture a more realistic level of uncertainty. Hence, datasets of 20 *T* outcomes are generated. Table 5.12 provides the requested statistics.

Table 5. 12. The mean and 95th percentile of the specified oceanic whitetip shark's posterior ATLs.

Number of years	Mean	95th Percentile
annual	1,708.2	3,185
3-year	5,103.1	7,632

5.3.2 IWP scalloped hammerhead shark

The IWP scalloped hammerhead shark estimated ATLs are derived using the Bayesian model for extremely rare events introduced in Section 3.2.1 and specifying 2004–2017 as the historical relevant years. Table 5.13 gives the requested statistics. Because the $P(T_{ATL} \le \tilde{t}_{(0.95)}) > 0.95$ ($\tilde{t}_{(0.95)}$ is the 95^{th} percentile of the ATL) for the ATLs, these probabilities are provided.

Table 5. 13. The mean and 95th percentile of the specified IWP scalloped hammerhead shark's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Number of years	Mean	95th Percentile
annual	1.2	4 (0.978)
3-year	3.7	9 (0.963)

5.3.3 IWP unidentified hammerhead sharks

The IWP unidentified hammerhead shark estimated ATLs are derived using the Bayesian model for extremely rare events introduced in Section 3.2.1 and specifying 2004–2017 as the historical relevant years. Table 5.14 shows the requested statistics. As one of the ATLs has $P(T_{ATL} \leq \tilde{t}_{(0.95)}) > 0.95$, these probabilities are provided.

Table 5. 14. The mean and 95th percentile of the specified IWP unidentified hammerhead shark's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Number of years	Mean	95th percentile
1	0.9	3 (0.970)
3	2.6	7 (0.954)

5.4 Marine mammals

Table 5.15 presents the observed takes $(t_{obs,yr})$ and $\hat{t}_{yr}$s for the marine mammals. A BF caught within Hawaii's EEZ is considered a FKW when estimating the ATL of MHIFKW. For marine mammals, the requested estimated ADSIL are also provided.

Table 5. 15. The observed catches (obs) for the sperm whale and the FKW and BF bycaught within Hawaii's EEZ (HIEEZ). The $\hat{t}_{yr}$s (est) are provided for the sperm whale. The FKW and BF combined $\hat{t}_{yr}$s (est FKW+BF) are provided.

Year	Sperm Whale		FKW and BF Within HIEEZ		
	obs	est	obs(FKW)	obs(BF)	est FKW+BF
2002	0	0	0	0	0
2003	0	0	2	1	12
2004	0	0	3	0	14
2005	0	0	1	1	4
2006	0	0	2	2	24
2007	0	0	2	0	10
2008	0	0	3	3	20
2009	0	0	3	0	13
2010	0	0	3	1	16
2011	1	6	3	1	14
2012	0	0	3	0	15
2013	0	0	1	0	4

Year	Sperm Whale		FKW and BF Within HIEEZ		
	obs	est	obs(FKW)	obs(BF)	est FKW+BF
2014	0	0	2	0	9
2015	0	0	0	0	0
2016	0	0	1	0	5
2017	0	0	2	0	11

5.4.1 Sperm whale

The sperm whale's estimated ATLs are derived using the Bayesian model for extremely rare events introduced in Section 3.2.1. Table 5.16 gives the requested statistics. As $P(T_{ATL} \leq \tilde{t}_{(0.95)}) > 0.95$ for the ATLs, these probabilities are provided.

Table 5. 16. The mean and 95th percentile of the specified sperm whale's posterior ATLs. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; that is, $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th Percentile
annual	0.6	3 (0.984)
3-year	1.9	6 (0.964)
5-year	3.1	9 (0.957)

The 2007–2017 injury classifications for large whales results in 1 DSI, 2 NSI, and 2 PR. Table 5.17 shows the requested statistics based on the estimated ADSIL.

Table 5. 17. The mean and 95th percentile of the specified sperm whale's posterior ADSILs. In the percentile columns, the numbers in parentheses are the estimated cumulative probabilities at the percentile; that is, $P(C_{DSI,ATL} \leq \tilde{c}_{DSI,(0.95)})$.

Period of ALDSI	Mean	95th percentile
annual	0.3	2 (0.987)
3-year	1.0	4 (0.975)
5-year	1.7	5 (0.952)

5.4.2 MHI false killer whale

The ATL of EEZFKW are derived using the Bayesian COM-Poisson model. Simulated draws from this distribution are used in the process described in Section 3.3 to generate simulated draws from the ATL of MHIFKW. Because the process in the most current annual stock review report is used to estimate the T_{ATL} outcomes of MHIFKW, T_{ATL} and $C_{DSI,ATL}$ outcomes are real numbers, as opposed to integers. Table 5.18 shows the requested statistics.

Table 5.18. The mean and 95th percentile of the MHIFKW's posterior ATLs.

Period of ATL	Mean	95th Percentile
annual	0.043	0.130
3-year	0.125	0.282
5-year	0.214	0.414

The 2013–2017 injury classifications of BF and unidentified cetaceans (excluding large whales) result in 4 DSI and 1 NSI. These classifications are used to determine the parameter values of the prior distributions as described in Section 4.2. The 2013–2017 injury classifications of FKW result in 26 DSI and 7 NSI. Using these classifications, simulated draws from the ADSIL of MHIFKW are obtained following the process outlined in Section 4.2. Table 5.19 shows the requested statistics.

Table 5.19. The mean and 95th percentile of the specified MHIFKW posterior ADSILs.

Period of ALDSI	Mean	95th Percentile
annual	0.033	0.102
3-year	0.099	0.222
5-year	0.166	0.329

6 Discussion

Bayesian modeling is convenient and useful when estimating the ATL; however, the knowledge and information on the process generating *T* outcomes in the DSLL fishery is insufficient to accurately model what is likely a complex process, and all methods of statistical inference will have shortcomings. For the marine mammals, estimating the ADSIL required assuming that bycatch events (past and future) have common probabilities of being classified in the relevant injury categories. With so few bycatch events annually, it is not feasible to make a reliable evaluation of this assumption. Nevertheless, estimates of ATLs and ADSILs are required.

When contemplating the appropriateness of the methods used to estimate the ATLs and ADSILs 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 ADSILs, and (4) if the reported Bayesian inferences seem reasonable, appropriate, and useful for their intended purpose.

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