American Samoa Longline Fishery Estimated Anticipated Take Levels for Endangered Species Act Listed Species[1]

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18 June 2019

1 Introduction

In this report, prepared at the request of the NOAA Fisheries Pacific Islands Regional Office (PIRO), the American Samoa longline (ASLL) fishery estimated anticipated take levels of eight protected species and four unidentified classifications are provided.

The eight species are

(1) loggerhead sea turtle
(2) leatherback sea turtle
(3) olive ridley sea turtle
(4) green sea turtle
(5) hawksbill sea turtle
(6) giant manta ray
(7) oceanic whitetip shark, and
(8) Indo-west Pacific (IWP) scalloped hammerhead shark.

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).

The data, methods, and assumptions used to estimate the anticipated take levels are described within this report.

First, let us consider the definitions of "take" and "incidental take" and what is meant by the terms "bycatch" and "take level" in this report. Under the Endangered Species Act (ESA), "take" means to catch, kill, or harm a protected species in any way. An "incidental take" is a take that results from, but is not the purpose of, carrying out an otherwise lawful activity. Herein, "bycatch" refers to the total number of incidental take events in which an animal is hooked or entangled by the longline gear. Under this definition, bycatch is a component of the total incidental take in the ASLL 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 time period, such as the calendar year.

There are a few practical constraints on the definition of bycatch used herein. First, NOAA Fisheries 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

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[1] PIFSC Data Report DR-19-028
Issued on 06 June 2019

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, available data on such interactions are incomplete.

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 the variable take level is a random variable, one can talk about the probability of each possible value (outcome) of this variable. 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 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 years are also derived and denoted as the 3-year ATL. That is, the distribution of T_{ATL} is derived for 2 periods of time: 1 and 3 years. For each time period, the mean and 95th percentile of the estimated ATL are reported, as requested.

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 datasets are 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

Since 2006, NOAA Fisheries Pacific Islands Regional Observer Program (PIROP) has deployed observers on a sample of ASLL trips. They are 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, 2017). The American Samoa Observer Program Field Manual (Pacific Islands Regional Observer Program, 2017) provides information on the variables recorded.

Before departing on a fishing trip, the vessel's owner or operator is required to notify the American Samoa Observer Program (ASOP) at least 72 hours prior to their intended departure date. It is these notifications that are selected, and the trips associated with them designated to be sampled. In this document, an ASLL trip does not end until the crew lands their catch. If a vessel with an observer aboard comes into port and the catch is not landed, an observer is expected to be aboard when the vessel departs to continue fishing. Herein, a trip's effort and take are assigned to the year the trip ends. Table 2.1 gives the 2010–2017 annual number of trips by the ASLL fleet based on the notification records and the observed effort recorded in LODS. In 2018, based on the notification records, 60 trips landed, and 7 of these were observed. The data to compute the 2018 observed effort based on number of fishing operation or hooks deployed were unavailable at the time of this analysis. As shown in Table 2.1, the ASLL fishery has been on the decline in recent years. In 2017, there were approximately 14 active participants, a decline from approximately 24 participants in 2010, and 21 participants in 2014.

There are challenges with successfully designing and obtaining a probability sample of ASLL trips. One challenge is that the number of observers assigned to ASOP is limited to the available funding and the demand for observers in the Hawaii longline fisheries. Because a selected trip can only be sampled if an observer is available for deployment, observer availability must be considered when selecting notifications for observer placement. Observer availability and coverage levels vary throughout the year because of (1) fluctuations in the fleet's activity level, (2) an influx of observers assigned to American Samoa, and (3) observers leaving and returning from leave.

Another challenge is that a trip's departure date is unknown until the required notification is given, and the length of the trip is unknown until the trip ends. Furthermore, an ASLL trip's length based on the number of days at sea is highly variable. Between 2010 and 2017, the shortest trip was 3 days, the longest was 162 days, the first and third quartiles were 26 and 57 days, the median was 39 days, and the average was 43 days.

Between 2006 and 2009, ASOP was developing its program and resolving issues concerning placing observers on vessels in the ASLL fleet. At this time, observer coverage was below 10%. Furthermore, ASOP will not place an observer on a vessel that does not have the United States Coast Guard (USCG) safety inspection decal which many vessels did not have. If a vessel is selected for observer placement and does not have the decal, it must obtain the decal or receive USCG clearance before it can depart (sometimes it is not feasible for the USCG to conduct this inspection within a reasonable amount of time). To ensure each vessel obtained this decal and resolved other issues with deploying observers, there was an effort to select each vessel for observer deployment at least once until all vessels were selected. It was during this process that ASOP identified one vessel as unsafe for observer placement; consequently, this vessel was excluded from observer placement until it became inactive at the end of 2015. Because of the low coverage and concern that the sample is not representative of the fleet's effort, observer data from 2006 to 2009 are not used to estimate the ATLs.

In 2010 and 2011, annual observer coverage (based on trip departures) was approximately 24% and 31%, respectively. Between 2012 and 2017, annual observer coverage ranged from approximately

15% to 19%. Even at these coverage levels, the number of observers assigned to ASOP was typically small. Between August 2010 and October 2011, there was a period of higher coverage where, on any given day, an average of approximately 5 observers and a maximum of 10 observer were deployed. Between 2014–2017, on any given day, typically 1 to 2 observers were deployed, but there were periods with 0 or more than 2 deployed. The periods with more than 2 observers deployed tended to be later in the year.

Basically, the sample is a convenient sample as trips are selected when an observer is ready to be deployed. Often, when an observer is ready to be deployed, one or no vessels may be available for observer deployment. If there is only one vessel departing on a trip, the observer will be placed on this vessel. If there are no vessels, then the observer will be placed on the next departing trip, unless more than one vessel is departing within a reasonable time frame, then the trip (vessel) is to be randomly (equal probability) drawn. When multiple notifications (trips) are available for observer deployment, instructions are to select the trip randomly (equal probability) from the multiple notifications. Furthermore, there is an effort not to have a vessel under or overrepresented in the database, but even this goal can be difficult to obtain with just a couple observers assigned to ASOP and an unstable fishery.

To estimate the ATLs in this report, only 2010–2018 observer data were considered, and 2018 data were only used when estimating the ATLs for three sea turtle species classifications: hawksbill, loggerhead, and unidentified hardshell sea turtles. The 2018 data were not used for the other species because the estimated ATLs were required before the needed data fields were available.

Another source of information is the American Samoa Longline Logbook database (Pacific Islands Fisheries Science Center, 2019). This database should contain the effort information concerning the number of fishing operations (sets) and hooks deployed per set, as recorded by the vessel's captain, for every ASLL trip. However, when computing the 2014–2015 bycatch estimates (see Section 3.1), it was noted that not all trips were represented in the database. Although the problem has been addressed, this database was not used for the 2014–2017 bycatch estimates. As there was no evidence of under reporting when 2010–2013 bycatch estimates were computed, the database was used. Another complication with using this database is that what constitutes a trip is not always consistent between it and LODS. For example, some trips in LODS are listed as two or more trips in the logbook database or vice-versa.

Table 2.1. The ASLL fleet's annual effort as recorded in the notification records and the amount of ASLL effort observed by ASOP (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.

Year	ASLL Effort	Observed Effort		
	Trips	Trips	Sets	Hooks
2010	135	25	785	2,315,496
2011	136	41	1,269	3,803,759
2012	126	18	628	1,826,190
2013	112	18	615	1,749,948
2014	99	19	565	1,490,524
2015	81	16	490	1,401,112
2016	64	12	424	1,179,209
2017	66	12	447	1,271,803

Next, let us consider any regulatory changes that could affect the T outcomes. On 23 September 2011, the Western Pacific Pelagic Fisheries; American Samoa Longline Gear Modifications to Reduce Turtle Interactions Final Rule (76 *FR* 52888) went into effect. Herein, this final rule is abbreviated as GMRTI. Although the intent of this rule was to reduce the *T* outcomes of the green sea turtle, it could also affect the *T* outcomes of other species.

The historical data are not collected over a random selection of years but consist of data collected over 8 consecutive years (2010–2017). This short time series of estimated *T* outcomes is unlikely to provide sufficient information to determine a pattern of dependency between 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 ATL are also explained. Because estimates of the *T* outcomes for years 2010–2017 are used to derive some of the ATLs, the methods used to estimate these values for the ASLL fishery are first explained.

3.1 Estimation of *T* outcomes for years 2010–2017

To begin, let t_{yr} denote the unknown *T* outcome for years $yr = 2010, \ldots, 2017$ and $\hat{t}_{yr}$ denote the estimate of the outcome for year *yr*. As observer coverage fluctuates during the year, the first step to computing $\hat{t}_{yr}$ is to examine the notification records and identify time periods when the number of observers being deployed and the level of fishing activity are relatively constant. To facilitate estimation, these periods are assumed to be strata, and within each stratum, it is assumed a simple random sample without replacement is drawn. A stratum is defined by a beginning and ending date, and trips are assigned to a stratum based on their departure date. The strata do not overlap and constitute the whole population so that each trip belongs to exactly one stratum. A sample drawn by this assumed design is often referred to as a stratified random sample (STR). The 2010–2015 t_{yr}s were estimated previously, and 2016–2017 t_{yr}s were estimated for this project. The $\hat{t}_{yr}$s were computed when requested and essentially categorized in three groups: 2010–2013, 2014–2015, and 2016–2017. For each group, the strata expanded over the time period of the grouping, and a stratum could overlap a year. Based on these assumptions, an appropriate sample-based estimator for the assumed sample design is used to estimate the take levels. As the actual sample is essentially a convenient sample, it is not appropriate to assume these estimators have the same statistical properties as when a STR is drawn. Time and resources did not permit modelling these data to predict the finite population estimand t_{yr}. Modelling to predict t_{yr} requires taking into account the data collection method. For species where observing a bycatch event has been extremely rare, using a simple model that assumes a constant take rate throughout the year can provide a good approximating model. When it is not reasonable to assume a constant take rate throughout the year, developing a good approximating model is not straightforward and could require making some questionable assumptions. Thus, a sample-based estimator is used to estimate t_{yr}. As a consequence of changes within the ASLL fishery and ASOP throughout the years, the estimator used to estimate the t_{yr}s is different between 2010–2013 and 2014–2017.

Estimators for finite population totals, such as t_{yr}, that are appropriate for a STR are the common unbiased STR estimator (STRE) and estimators that incorporate the idea of the ratio estimator but assume a STR, such as the combined ratio estimator (CRE) and the separate ratio estimator (SRE). Short descriptions of these three estimators follow; see Lohr (2010) for more detail.

First, let *i* denote the sampling unit, *h* denote the stratum, N_h denote the number of sampling units in strata *h* (population size of stratum), and n_h denote the number of sampling units in strata *h* that are sampled. Additionally, let *Y* denote the variable of interest where *y* represents a realized outcome of *Y*, and let ω_h denote the realized sample of sampling units in stratum *h*. The common unbiased estimator of the population total τ for a STR is

$$\hat{\tau}_{STR} = \sum_{h=1}^{H} N_h \bar{y}_h ,$$

where $\bar{y}_h = \frac{1}{n_h} \sum_{i \in \omega_h} y_{hi}$.

When *Y* has an approximate proportional relationship with an auxiliary variable *X*, an estimator that is based on the concept of the ratio estimator but takes into account the stratified design can be more efficient (smaller mean square error) than the STR estimator. For the ratio estimator 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. In the CRE, first the strata are combined to estimate τ_x and τ_y using the STR estimator ($\hat{\tau}_{y,STR} = \sum_{h=1}^{H} N_h \bar{y}_h$ and $\hat{\tau}_{x,STR} = \sum_{h=1}^{H} N_h \bar{x}$), then the ratio estimation is applied. The combined ratio estimator is

$$\hat{\tau}_{CRE} = \hat{R}\tau_x ,$$

where $\hat{R} = \hat{\tau}_{y,STR} / \hat{\tau}_{x,STR}$.

For the SRE, the ratio estimator is applied first, then the strata are combined. Using this estimator requires knowing the population totals of the *x*-values within each stratum, denoted as τ_{xh}. The separate ratio estimator is

$$\hat{\tau}_{SRE} = \sum_{h=1}^{H} \hat{\tau}_{yh,RAT} ,$$

where $\hat{\tau}_{yh,RAT} = \tau_{xh} \frac{\hat{\tau}_{yh}}{\hat{\tau}_{xh}}$, $\hat{\tau}_{yh} = N_h \bar{y}_h$, and $\hat{\tau}_{xh} = N_h \bar{x}_h$. The SRE can improve efficiency if $\hat{\tau}_{yh} / \hat{\tau}_{xh}$ varies between stratum, but should not be used when the n_hs are small because the ratio is biased and the bias can propagate through the strata. When n_h is small for some strata, the CRE has less bias.

When estimating t_{yr} for $yr = 2010, \ldots, 2017,$ the trips are the sampling unit, the variable of interest (*Y*) is a trip's bycatch, and y_i is the i^{th} trip's realized bycatch. Trips that begin and end in different years have bycatch assigned to the year that the trip ended; that is, trips that begin in year *yr* and end the following year will have a *y*-value of 0 for year *yr*. Since *Y* is often perceived to be proportional to fishing effort, the CRE and SRE are of interest since effort can be incorporate into the estimator as the auxiliary variable *X*.

Now, let us consider how t_{yr} is estimated for the different groupings of years. When estimating t_{yr} for $yr = 2010, \ldots, 2013,$ the number of fishing operations (sets) and the number of hooks deployed are considered as auxiliary variables. Denote these auxiliary variables as X_{sets} and X_{hooks}, respectively. Similar to a trip's bycatch, trips that begin and end in different years have their effort assigned to the year the trip ended. To incorporate effort as expressed by the number of trips that could potentially have positive *y*-values in the year of interest, let X_{trip} denote a variable where the outcome for the i^{th} trip is $x_{trip,i} = 1$ if the trip ended in the year of interest and $x_{trip,i} = 0$ if no hooks were deployed or the trip ended in a different year. Similarly, the outcome of X_{sets} and X_{hooks} for the i^{th} trip is 0 if $x_{trip,i} = 0$ and the trip's number of sets and hooks deployed if $x_{trip,i} = 1$. For 2010–2013, the total number of trips that could have positive bycatch $(x_{trip,i} \neq 0)$ is derived from the notification records. Except for the oceanic whitetip shark, in some stratum there are no observed takes (all observed y-values equal 0) , and time did not permit determining how best to estimate variance and evaluate the efficiency of the different estimators in this circumstance. As the SRE can introduce unwanted bias and be inefficient if there is not a near proportional relationship, the auxiliary variables X_{sets} and X_{hooks} are not considered. Excluding the oceanic whitetip shark, the point estimates based on the STRE and SRE are equivalent, except for the 2010 green sea turtle take estimates where the estimate using STRE is 51 and SRE is 50. For the oceanic whitetip shark, the SRE with X_{sets} is used as this estimator appeared to be the most efficient.

When estimating tl_{yr} for $yr = 2014, \ldots, 2017,$ X_{sets} and X_{hooks} are not considered because the population totals are unknown (see Section 2); instead, days away from the port (days at sea) obtained from the notification records is considered as an auxiliary variable. Denote this auxiliary variable as X_{out}. Additionally, due to less effort in the fishery, small values of n_h are common; therefore, using the CRE was considered when calculating estimates. Because there are strata that have trips ending in two different years but have few or no observed trips ending in one of these years, a synthetic adaption of the CRE is used. Basically, the synthetic CRE has the same form as the CRE, but a trip's ending date is ignored when estimating *R*. For year's *yr* estimate, let y_i* and x_i* denote the i^{th} trip's bycatch and effort regardless if the trip ended in *yr*. The synthetic estimator of *R* is $\hat{R}* = \hat{\tau}_{STR,y*} / \hat{\tau}_{STR,x*}$ and $\hat{\tau}_{CRE} = \hat{R} * \tau_x$, where τ_x is defined as before (the total of *x*-values for trips ending in *yr*). For example, if using X_{trip}, the ratio being estimated is the bycatch rate per trip and it is estimated using a trip's *y**-value (bycatch) and *x**-value (equals 1 unless the trip did not deploy any hooks) for all observed trips in the strata that have at least one trip ending in *yr*. To derive the point estimate, this ratio is then multiplied by the number of trips that ended in the year of interest. For the bycatch of all species, this synthetic CRE with X_{trip} is used. The STR estimator is not used because of the problem of having so few observations in some stratum, and X_{out} did not appear to have a near proportional relationship to *Y* for any of the species of interest.

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.

With the ASLL fishery, only a subset of t_{yr}s might be regarded as realizations of T_{ATL}; that is generated from the ATL. Because the degree of impact GMRTI (see Section 2) had on *T* is unclear, two estimated ATLs are derived for each species. The first assumes that *T* outcomes from 2010–2017 are realizations of T_{ATL}, and the second assumes that *T* outcomes from 2012–2017 are realizations of T_{ATL}. Herein, let ATL_{10} and ATL_{12} denote these two ATLs, respectively.

Since T_{ATL} is a count, the distribution must 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. If overdispersion or underdispersion arise in count data, it is generally 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 assuming the data are collected using a stratified random design. Because a finite population of ASLL 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 assumed STR (for more detail, see Chapter 7 of Gelman et al., 2004). If a species' number of observed takes between 2010 and 2017 is 5 or less, one of two data distributions is specified. Hereafter, bycatch events are referred to as "extremely rare" if 5 or fewer 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

If an observed bycatch event has been extremely rare for a certain species, 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 $yr = 2010,\ldots,2018$ ($yr = 2012,\ldots,2018$ for ATL_{12}), 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 ASLL 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 2010–2018 ($yr = 2012,\ldots,2018$ for ATL_{12}), denote this average as $\overline{N}_{yrs}$. 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}.

For species that are extremely rarely taken, the *y*-values for 2018 are known and considered as realizations from the ATL assumed iid $\text{Poisson}(\lambda_{trip})$ data distribution. Therefore, ATL_{10} and ATL_{12} refer to the 2010–2018 or 2012–2018 *y*-values being used.

3.2.2 COM-Poisson data distribution for rare bycatch events

For species where an observed bycatch event has been rare, the number is well above 5 (see tables in Section 4). For these species, it is not assumed that *y*-values are iid random variables; consequently, the assumed stratified design needs to be taken into account.

As the time available to conduct these analyses did not permit developing a probability model that accounted for the stratified design, for $yr = 2010, \ldots, 2017,$ 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 estimate 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 8 estimated realizations of T_{ATL} ($\hat{t}_{yr}$ for $yr = 2010, \ldots, 2017$), the posterior distribution can 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. The 2010–2011 data are available to create an informative prior. Although most of these data were generated prior to the GMRTI, they capture 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 GMRTI. Although 2012–2017 data are related to what is being used as our realizations of T_{ATL} ($\hat{t}_{yr}$ for $yr = 2012, \ldots, 2017$ when deriving ATL_{12} and $yr = 2010, \ldots, 2017$ when deriving ATL_{10}), incorporating it into the priors helps to account for some of the uncertainty around $\hat{t}_{yr}$. Hence, 2010–2017 data are 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 followed by the specific steps.

The basic steps of the simulations are: (1) Create a dataset of *K* hypothetical TL_{ATL} outcomes. (2) Using this dataset, 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 are 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 $\mathrm{Gaussian}(\mu_\beta, \sigma^2_\beta)$ 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 $\mathrm{Gaussian}(\mu_\delta, \sigma^2_\delta)$ 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} datasets are generated. The purpose of the hypothetical datasets is to generate different datasets for possible futures based on the historical data. The following steps are taken to generate the hypothetical T_{ATL} datasets.

1. Except for the oceanic whitetip shark, the posterior distribution of $\tilde{t}_{yr}$ is derived for $yr = 2010,\ldots,2017$. The posterior distribution is obtained using the same binomial data distribution in the Bayesian model for iid $\text{Poisson}(\lambda_{trip})$ random variables described in Section 3.2.13.2.1, 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}. Because there are so few observed takes of these species in a given year, there is often insufficient information to reliably fit a model that allows for dispersed counts of a trip's take; therefore, the binomial data distribution often provides a better approximating model. Oceanic whitetip sharks are caught more frequently, and there is likely enough information to fit a model that allows for dispersed counts. However, time did not permit developing a Bayesian model that accounted for the assumed STR sample. Instead, based on the finite population central limit theorem (see Thompson, 1992 and Lohr, 2010 for more information), it was assumed that $\hat{t}_{yr}$ is a Student's *t* variate whose degrees of freedom is computed using Satterthwaite's approximation (see Thompson, 1992 for more information).
2. This step uses the posterior and Student's *t*-distributions derived in the first step to create two probability distributions of hypothetical *T* outcomes. The two distributions are defined by the two historical time periods (1) 2010–2011 and (2) 2012–2017. The probability distributions assume similar conditions to those influencing take levels in their respective historical time period. The two periods were decided upon based on when the GMRTI went into effect, 23 September 2011. To derive each of these distributions for the relevant years (2010–2011, and 2012–2017), 1,000 outcomes are drawn from each year's posterior distribution (Student's t-distribution for oceanic whitetip sharks). These draws are then combined, and their empirical probability distribution computed. The resulting two 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, and k_2 represent the number of draws from each of the two empirical probability distributions, respectively, and let $\mathbf{K} = (k_1, k_2)$, the vector of these two variables. It is assumed that $\mathbf{K}$ has a binomial distribution with sample size $K = \sum_{i=1}^{2} k_i$ and respective probabilities 0.10 and 0.90. For each of the *R* replications, a draw of $\mathbf{K}$ is simulated. Let $\mathbf{K}_r^* = (k_{1r}^*, k_{2r}^*)$ denote the r^{th} draw for $r = 1,\ldots,R$. After $\mathbf{K}_r^*$ is drawn, k_{1r}^*, and k_{2r}^* values are drawn from their respective empirical distributions. These values are pooled to create the r^{th} dataset 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 account for the uncertainty around $\hat{t}_{yr}$, a more rigorous approach would likely result in more accurate ATL estimates. As mentioned previously, the data distribution should be for the data and the data collection method (assumed STR). Even if a more rigorous approach were conducted, the current ASLL regulations have only been in place since 2012, 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 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 3.1 where there are only 5 possible outcomes. The 95^{th} 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 3.1. 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	0.60	0.60
1	0.23	0.83
2	0.10	0.93
3	0.06	0.99
4	0.01	1.00

3.4 Estimation of the 3-year ATL

To derive the estimated 3-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 3-year ATL. If these sums are interpreted to occur over consecutive years, the reported 95^{th} percentile 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 3.2.2 is used to estimate the ATLs of interest. This includes (1) using the $\hat{t}_{yr}$s as the unknown true t_{yr}-values, (2) assuming the t_{yr}s for $yr = 2010, \ldots, 2017$ (ATL_{10}) or $yr = 2012, \ldots, 2017$ (ATL_{12}) are realizations of T_{ATL}, and (3) generating 100 datasets of 500 hypothetical *T* outcomes for determining the parameter values of the Gaussian priors.

The reported statistics (mean and 95th percentile) from an estimated ATL are point estimates that have a measure of uncertainty around them. Although these reported statistics may differ between ATL_{10} and ATL_{12}, it is inappropriate to conclude that the probability distribution generating *T* changed after 2011. To make such inference requires an analysis designed to evaluate this question and is not the purpose of this report.

For those species classifications where a bycatch event is extremely rare (hawksbill, loggerhead, and unidentified hardshell sea turtles), the ATL assumes that the *y*-values are iid $\text{Poisson}(\lambda_{trip})$ random variables, and it is the observed *y*-values from 2010 and 2011 that are being included or excluded. Excluding the y-values from 2010 and 2011 results in the exclusion of 66 observer data points, or approximately 40% of the sampled trips. Furthermore, these 66 observations all have the value of 0. Because of the smaller sample size and exclusion of so many values of 0, we expect ATL_{12} to have a longer right tail but still be bounded by 0 on the left.

The results are provided first for the sea turtles, then the rays, and finally the sharks. For each of these groups, a table provides the observed takes and $\hat{t}_{yr}$ for $yr = 2010, \ldots, 2017$. It is important to note that there are no observed takes for some species, but a positive estimated total in some years. This occurs because a stratum can have trips ending in two different years. For 2014–2017 estimates, the estimator uses all observations from the relevant strata (strata with trips ending in the year of interest) to estimate the take rate per trip (see Section 3.1). Consequently, a year can have no observed takes but a positive value for the estimated take rate and $\hat{t}_{yr}$.

Although the 2012–2017 $\hat{t}_{yr}$s may generally be smaller or larger than the 2010–2011 $\hat{t}_{yr}$s or some other characteristic in the $\hat{t}_{yr}$s observed, it is inappropriate to draw conclusions about the effectiveness of the GMRTI or any other changes in the t_{yr}s as there is uncertainty around these estimates. While it is possible to estimate a standard error using the common variance estimator for the assumed STR design, this estimator does not capture the added uncertainty, including the added bias, introduced when creating strata based on the notification logs and after the samples are drawn. Furthermore, it is not clear how to approximate a confidence interval around these sample-based estimates as assuming an approximate Gaussian distribution or Student's *t*-distribution is inappropriate for most species given the rarity of a bycatch event.

4.1 Sea Turtles

Table 4.1 presents the observed takes ($t_{obs,yr}$) and $\hat{t}_{yr}$s for the sea turtles. There has been a significant decline in effort since 2011 (Table 2.1), and for some species, the 2012–2017 estimated takes are not generally smaller than those for 2010–2011, as explained previously, it is inappropriate to conclude that the gear modifications in the GMRTI are not effective. There are likely other variables, such as the spatial and temporal distributions of effort, that may influence the take rate. To draw inference on the effectiveness of the GMRTI requires an analysis designed to evaluate this question and is not the purpose of this report.

Table 4.1. The observed takes (obs) and $\hat{t}_{yr}$s (est) for the five sea turtle species and the classification of unidentified hardshell sea turtle.

Year	Leatherback		Loggerhead		Olive Ridley		Green		Hawksbill		Unidentified Hardshell	
	obs	est	obs	est	obs	est	obs	est	obs	est	obs	est
2010	0	0	0	0	0	0	6	50	0	0	0	0
2011	2	4	0	0	1	4	11	32	0	0	0	0
2012	1	6	0	0	1	6	0	0	0	0	0	0
2013	2	13	0	0	1	4	2	19	0	0	0	0
2014	0	4	0	0	2	5	2	17	0	0	0	0
2015	3	22	0	0	1	6	0	0	0	0	0	0
2016	1	3	0	0	3	14	4	16	1	4	0	0
2017	1	3	0	0	2	19	4	20	0	5	0	0

4.1.1 Leatherback sea turtle

Tables 4.2 and 4.3 report the statistics for the different requested ATLs: ATL_{10} and ATL_{12}. Although the amount of effort has decreased through the years, the t_{yr}s do not appear to have decreased.

Table 4.2. The mean and 95th percentile of the specified leatherback sea turtle's posterior ATLs when using 2010–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th Percentile
Annual	7.9	25
3-year	24.0	56

Table 4.3. The mean and 95th percentile of the specified leatherback sea turtle's posterior ATLs when using 2012–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th Percentile
Annual	9.7	30
3-year	29.2	69

4.1.2 Loggerhead sea turtle

Although there were no observed bycatch events of a loggerhead sea turtle during 2010–2018, we cannot conclude there were no bycatch events or that there will be no events in the future. To estimate the ATLs, the Bayesian model for extremely rare events described in Section 3.2.1 is used. Tables 4.4 and 4.5 report the statistics for the different requested ATLs. As one of the ATLs has $P(T_{ATL} \leq \tilde{t}_{(0.95)}) > 0.95,$ these probabilities are provided. The slightly higher values of the estimated 95th percentiles when 2010–2011 data are excluded is partially a consequence of excluding the 66 observations of 0.

Table 4.4. The mean and 95th percentile of the specified loggerhead sea turtle's posterior ATLs when using 2010–2018 data. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th Percentile
annual	0.2	1 (0.972)
3-year	0.6	3 (0.971)

Table 4.5. The mean and 95th percentile of the specified loggerhead sea turtle's posterior ATLs when using 2012–2018 data. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th Percentile
annual	0.2	2 (0.978)
3-year	0.4	4 (0.957)

4.1.3 Olive ridley sea turtle

Tables 4.6 and 4.7 report the statistics for the different requested ATLs. The $\hat{t}_{yr}$s for 2016 and 2017 are higher than the previous years, but this could be a consequence of sampling error.

Table 4.6. The mean and 95th percentile of the specified olive ridley sea turtle's posterior ATLs when using 2010–2017 takes estimates as realizations of T_{ATL} **.**

Period of ATL	Mean	95th percentile
annual	10.9	27
3-year	32.8	60

Table 4.7. The mean and 95th percentile of the specified olive ridley sea turtle's posterior ATLs when using 2012–2017 takes estimates as realizations of T_{ATL} **.**

Period of ATL	Mean	95th percentile
annual	11.0	27
3-year	33.6	61

4.1.4 Green sea turtle

The green sea turtle's 2010–2011 $\hat{t}_{yr}$s are noticeably larger than the 2012–2017 $\hat{t}_{yr}$s . However, we are comparing point estimates which have a measure of uncertainty around them that is difficult to quantify, especially for the 2010–2011 $\hat{t}_{yr}$s. To quickly gather information on takes in the ASLL fishery so that more informed recommendations on the appropriate level of observer coverage could be provided, the ASOP received funding to increase observer coverage in 2010, but this funding was discontinued in 2011 before maintaining high coverage for at least 12 consecutive months. Consequently, there is substantial variability in observer coverage during these two years that is difficult to accurately quantify. At the beginning of 2010, observer coverage was low, approximately 8%, until around early May 2010 when it started to increase as more observers were assigned to the ASOP. Around late October 2010, observer coverage was approximately 37%, and around mid-January 2011, observer coverage was approximately 67%. Then, around mid-March 2011, observer coverage started to decline as observer's left the ASOP. Observer coverage was approximately 39% around late March 2011, but by the middle of

October that year observer coverage had dropped to approximately 19%. Tables 4.8 and 4.9 report the statistics for the different requested ATLs.

Table 4.8. The mean and 95th percentile of the specified green sea turtle's posterior ATLs when using 2010–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	20.1	61
3-year	59.3	134

Table 4.9. The mean and 95th percentile of the specified green sea turtle's posterior ATLs when using 2012–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	14.3	45 (0.953)
3-year	42.9	101 (0.951)

4.1.5 Hawksbill sea turtle

In 2018, there were 2 observed hawksbill sea turtle bycatch events. As the number of hawksbill sea turtle bycatch events is known for all ASLL trips landing in 2018, it was possible to include these observations into the computation of the ATL. As observing a hawksbill sea turtle bycatch event is extremely rare, the ATL is estimated using the Bayesian model for extremely rare events. Because a hawksbill bycatch event was not observed until 2016, including all the *y*-values of 0 from 2010 to 2015 resulted in ATLs with estimated means and 95th percentiles that seemed too low considering that there have been 3 observed bycatch events in recent years. Therefore, the ATL was estimated assuming that only the 2016–2017 t_{yr}s are realizations of T_{ATL}. Tables 4.10 and 4.11 report the statistics for the ATL that assumed 2016–2017 t_{yr}s are realizations of T_{ATL} and the ATL_{12}. As at least one of the ATLs has a $P(T_{ATL} \le \tilde{t}_{(0.95)}) > 0.95$, these probabilities are provided.

Table 4.10. The mean and 95th percentile of the specified hawksbill sea turtle's posterior ATLs when using 2016–2018 data. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \le \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th percentile
annual	6.3	14 (0.951)
3-year	19.1	40 (0.952)

Table 4.11. The mean and 95th percentile of the specified hawksbill sea turtle's posterior ATLs when using 2012–2018 data. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \le \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th percentile
annual	3.0	8 (0.970)
3-year	8.9	20 (0.959)

4.1.6 Unidentified hardshell sea turtle

Although there were no observed bycatch events of an unidentified sea turtle during 2010–2018, it is possible that 100% coverage could lead to at least 1 event in which the turtle could not be identified to the species level. To estimate the ATL, the Bayesian model for extremely rare events is used. Tables 4.12 and 4.13 report the requested statistics for the different requested ATLs. As at least one of the ATLs has a $P(T_{ATL} \leq \tilde{t}_{(0.95)}) > 0.95$, these probabilities are provided. The slightly higher values of the estimated 95th percentiles of the ATL_{12}s are partially a consequence of excluding the 66 observations of 0.

Table 4.12. The mean and 95th percentile of the specified unidentified hardshell sea turtle's posterior ATLs when 2010–2018 data are used. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th percentile
annual	0.2	1 (0.972)
3-year	0.6	3 (0.971)

Table 4.13. The mean and 95th percentile of the specified unidentified hardshell sea turtle's posterior ATLs when 2012–2018 data are used. In the percentile columns, the numbers in parentheses are the cumulative probabilities at the percentile; i.e., $P(T_{ATL} \leq \tilde{t}_{(0.95)})$.

Period of ATL	Mean	95th percentile
annual	0.2	2 (0.963)
3-year	0.5	5 (0.951)

4.2 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 4.8 gives the observed takes $(t_{obs,yr})$ and $\hat{t}_{yr}$s for the rays of interest. For 2015–2017, there were no observed bycatch events of the giant manta ray but there were observed bycatch events where the species identification could only be made to the classification level of a manta/mobula or unidentified ray.

Table 4.14. The observed takes (obs) and $\hat{t}_{yr}$ (est) for the giant manta ray and the two other ray classifications of concern.

Year	Giant Manta Ray		Manta/Mobula		Unidentified Ray	
	obs	est	obs	est	obs	Est
2010	3	11	1	12	0	0
2011	3	11	1	4	6	16
2012	3	29	0	0	0	0
2013	2	8	0	0	1	9
2014	1	2	1	3	0	5
2015	0	3	0	0	3	13
2016	0	0	2	9	0	4
2017	0	0	0	11	1	4

4.2.1 Giant manta ray

Tables 4.15 and 4.16 report the statistics. The reported estimated mean and 95th percentiles for ATL_{10} and ATL_{12} are very similar. The higher value of $\hat{t}_{2012}$ would influence the extent of the right tail of the ATLs.

Table 4.15. The mean and 95th percentile of the specified giant manta ray's posterior ATLs when using 2010–2017 estimates takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	9.0	29
3-year	26.8	61

Table 4.16. The mean and 95th percentile of the specified giant manta ray's posterior ATLs when using 2012–2017 estimates takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	8.7	28
3-year	25.7	60

4.2.2 Manta/Mobula ray

Tables 4.17 and 4.18 report the statistics. The value of $\hat{t}_{2017}$ may appear to be high considering that there were no observed takes for this species classification in 2017. However, at the end of 2016, when these takes occurred, observer coverage was low. Since this stratum involved trips that ended in 2017, the 2016 takes were involved in estimating the take rate for $\hat{t}_{2017}$ (see Section 3.1).

Table 4.17. The mean and 95th percentile of the specified manta/mobula's posterior ATLs when using 2010–2017 estimates takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	5.4	17
3-year	16.2	38

Table 4.18. The mean and 95th percentile of the specified manta/mobula's posterior ATLs when using 2012–2017 estimates takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	4.9	16
3-year	14.7	36

4.2.3 Unidentified ray

Tables 4.19 and 4.20 report the statistics. The reported estimated mean and 95th percentiles for ATL_{10} and ATL_{12} are very similar.

Table 4.19. The mean and 95th percentile of the specified unidentified ray's posterior ATLs when using 2010–2017 estimates takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	7.6	24
3-year	23.2	53

Table 4.20. The mean and 95th percentile of the specified unidentified ray's posterior ATLs when using 2012–2017 estimates takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	7.5	24
3-year	22.3	52

4.3 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. Similarly, the $\hat{t}_{yr}$s are estimates of total catch for $yr = 2010,\ldots,2017$. Tables 4.21 and 4.22 report the observed catches $(t_{obs,yr})$ and $\hat{t}_{yr}$s for the sharks of interest.

Table 4.21. 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
2010	124	1,176	4	17	1	5
2011	107	319	2	7	0	0
2012	68	470	0	0	1	6
2013	87	407	0	0	0	0
2014	104	464	1	6	0	0
2015	168	827	1	3	1	7
2016	197	899	1	6	2	9
2017	63	458	1	4	0	0

4.3.1 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 datasets of 500 *T* outcomes conveyed too much confidence in the prior distribution, whereas datasets of 20 *T* outcomes appeared to capture a more realistic level of uncertainty. Hence, datasets of 20 *T* outcomes are generated. Tables 4.22 and 4.23 report the statistics. The reported estimated mean and 95th percentiles from ATL_{10} and ATL_{12} are very similar. The yearly number of observed and estimated oceanic whitetip sharks appear to vary considerably and do not seem to be declining.

Table 4.22. The mean and 95th percentile of the specified oceanic whitetip shark's posterior ATLs when using 2010–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	620.8	1,119
3-year	1,878.5	2,784

Table 4.23. The mean and 95th percentile of the specified oceanic whitetip shark's posterior ATLs when using 2012–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	619.9	1,110
3-year	1,836.9	2,662

4.3.2 IWP scalloped hammerhead shark

Tables 4.24 and 4.25 report the statistics. The higher estimated takes in 2010 would influence the extent of the right tail of the ATL_{10}. However, if one considers the yearly combined estimated takes of this species and the IWP unidentified hammerhead sharks, the 2010 observation does not seem that abnormal.

Table 4.24. The mean and 95th percentile of the specified IWP scalloped hammerhead shark's posterior ATLs when using 2010–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	6.0	19
3-year	18.1	42

Table 4.25. The mean and 95th percentile of the specified IWP scalloped hammerhead shark's posterior ATLs when using 2012–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	4.5	15
3-year	13.4	33

4.3.3 IWP unidentified hammerhead sharks

Tables 4.26 and 4.27 report the statistics. Although the estimated mean and 95th percentiles from ATL_{10} and ATL_{12} do differ, it is unclear how much of this difference is due to the uncertainty around the estimated mean and 95th percentiles and the reduced sample size of realizations of T_{ATL} for ATL_{10}.

Table 4.26. The mean and 95th percentile of the specified IWP unidentified hammerhead shark's posterior ATLs when using 2010–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	5.1	16
3-year	15.4	37

Table 4.27. The mean and 95th percentile of the specified IWP unidentified hammerhead shark's posterior ATLs when using 2012–2017 estimated takes as realizations of T_{ATL}.

Period of ATL	Mean	95th percentile
annual	5.8	19
3-year	17.1	41

5 Discussion

Bayesian modeling is convenient and useful when estimating the ATL; however, the knowledge and information on the process generating *T* outcomes in the ASLL fishery is insufficient to accurately model what is likely a complex process, 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.

6 References

Berger, J. O., Bernardo, J. M., and Sun, D. (2012). Objective priors for discrete parameter spaces. Journal of American Statistical Association 107(498), 636-648.

Chanialidis, C., Evers, L., Neocleous, T., and Nobil, A. (2018). Efficient Bayesian inferences for COM-Poisson regression models. *Statistics and Computing*, 28(3).

Conway, R. W. and Maxwell, W. L. (1962). A queuing model with state dependent service rates. *Journal of Industrial Engineering*, 12, 132-136.

Dalthorp, D., Huso, M., and Dail, D. (2017). Evidence of absence (v2.0) software user guide: U.S. Geological Survey Data Series 1055.

Gelman, A. and Carlin, J. B. and Stern, S. S. and Rubin, D. B. (2004). *Bayesian Data Analysis*, (2nd.ed). New York: Chapman and Hall.

Guikema, S. D. and Coffelt, J. P. (2008). A flexible count data regression model for risk analysis. *Risk Analysis* 28, 213-223.

Lohr, S. L. (2010). *Sampling: Design and Analysis* (2nd ed.). Boston: Brooks/Cole.

Minke, T. P., Shmueli, G., Kadane, J. B., Borle, S., Boatwright, P. (2003). Computing with the COM-Poisson distribution. Technical. Report 776, Dept. Statistics, Carnegie Mellon Univ., Pittsburgh, PA.

Pacific Islands Fisheries Science Center, (2019): Hawaii Longline Logbook, https://inport.nmfs.noaa.gov/inport/item/2721.

Pacific Islands Regional Observer Program (2017), American Samoa Longline Observer Program Field Manual: AS 17.10.00.02, Pacific Islands Regional Office, National Marine Fisheries Service, Honolulu, Hawaii. URL: https://www.fisheries.noaa.gov/pacific-islands/pacific-islands-fishery-observer-program**Error! Hyperlink reference not valid.**.

Pacific Islands Regional Office (2019), Longline Observer Data System, https://inport.nmfs.noaa.gov/inport/item/9027.

Shmueli, G., Minka, T. P., Kadane, J. B., Borle, S. and Boatwright, P. (2005). A useful distribution for fitting discrete data: Revival of the Conway-Maxwell-Poisson distribution. *Applied Statistics* 84, 127-142.

Thompson, S. K. (1992). *Sampling*. New York: Wiley.